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Introducing a Fuzzy Robust Integrated Model for Optimizing Humanitarian Supply Chain Processes

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Abstract

The natural disasters of the last few decades clearly reveal that natural disasters impose high financial and human costs on governments and communities. Concerns in this regard are growing day by day. Making the right decisions and taking appropriate and timely measures in each phase of the crisis management cycle will reduce potential damage at the time of the disaster and reduce the vulnerability of society. Therefore, in this research, a mathematical model of crisis logistics planning considering the problem of primary and secondary crisis in disaster relief is introduced, which is the innovation of this research. In the primary crisis, the goal is to provide services and relief goods to crisis areas, and in the second stage, the secondary crisis that occurs after the primary crisis seeks to provide relief to crisis centers and transfer the injured to relief centers. Therefore, this research proposes a mathematical fuzzy ideal programming model in two primary and secondary crises. In the primary crisis, the goal is to provide services and relief goods to crisis-stricken areas. The secondary crisis, which occurs after the primary crisis, aims to support crisis-stricken centers and move injured people to relief bases in the second step. According to the proposed model, Bertsimas-Sim's fuzzy programming that formulation proposed by Bertsimas and Sim [1] and robust approach we initially used. The Epsilon constraint method was used to solve the low-dimensional model. Multi-objective meta-heuristic algorithms have been designed to handle the computational complexity of large-scale real-time problems. Multiple comparisons and analyses have been proposed to assess the performance of the model and problem-solving capabilities. The results indicate that the proposed approach can be applied and implemented to develop a real-world humanitarian logistics network.

Keywords: Critical logistics, Primary and secondary crises, Fuzzy robust integrated programming, Meta-heuristic algorithm.

1 | Introduction

Natural disasters strike the world at various times of the year, killing countless people and causing massive financial losses to governments [2]. Floods, earthquakes, tsunamis, hurricanes, tornadoes, meteorite strikes, etc., are among natural disasters.

Any of these natural disasters can have certain adverse effects depending on their magnitude and Location. Accordingly, it is crucial to prepare for, plan for, predict, and take preventative measures in the event of a natural disaster [3]. Catastrophes, as previously stated, cause significant loss of life and property in societies and nations. Thus, getting proper emergency logistics planning in place to cope with natural disasters and crisis management is critical. Such disasters are unexpected and unpredictable in nature as science and technology advance, necessitating the availability of preventative plans as well as post-disaster emergency responses. Therefore, the minimal resources

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available should be distributed among victims in the most efficient manner possible to address their most pressing needs [4]. Natural disasters, such as floods and earthquakes, have struck many countries, including our country, with varying degrees of severity, resulting in significant financial and human losses. Clearly, planning for a post-disaster emergency response is essential, as it further improves the efficiency and effectiveness of rescue operations. A major focus of relief responses and reactions would be to minimize the loss of life and property by having preparations and plans in place to cope with the implications of disasters, as well as raising public awareness. When devising these plans, one thing to keep in mind is that the nature of natural disasters like earthquakes necessitates a swift and efficient response.

To put it another way, in such a complicated and emergency situation, the decision-maker must conduct rescue operations and resolve the injured's situation quickly and efficiently. To achieve this important goal and take timely action, it appears that having access to an effective and systematic pre-defined program with all of the required activities, sequences, and communications is required [5]. Thus, logistical preparation for the transportation of critical items needed in affected areas is one of these tasks that are also very significant. Aid provision to disaster-stricken regions, the importance of the distribution of relief goods, and the evacuation of the injured is essential and strategic, as increased efficiency of transportation of goods and casualties has a great effect on the number of survivors after the disaster [6]. Consequently, the majority of disaster relief problems have focused on optimizing routing decisions and locating ground vehicles with a variety of modeling approaches. Helicopters are used for contingency purposes due to their widespread use in medical emergencies and disaster relief. In this research, the importance of disaster relief, taking humanitarian medical aid, vaccinations, and other auxiliary products, such as tents, blankets, medicines from located warehouses and distribute them to affected areas following the sudden occurrence of natural disasters and for evacuation operations, the relocation of the wounded from affected areas and transferring them to hospitals, are taken into account sites. The aim is to find a series of routes that start and end at hospitals and take the shortest flight time possible. Another goal is for helicopters to use as little fuel as possible. Humanitarian supply chain management should be able to respond to a crisis in the shortest amount of time possible. The "last-mile delivery problem," which is becoming more prevalent in disaster relief, is also addressed in this study, in addition to the last step of the relief supply chain. Thus, a mathematical model based on last-mile distribution concepts will be considered in this research. This research aims to establish a new model for rapid response to natural disasters in the process of rapid relief to [affected] regions. The development of such measures focused on the phase of rapid response to disasters while considering real limitations is one of the fuzzy robust integrated model goals in this study. In this research, the collection and distribution of medical aids, vaccines and other auxiliary items such as tents, blankets, medicine and, … From the warehouses we have located to the damaged places after the sudden occurrence of natural disasters, and for evacuation operations, we consider the removal of the injured from the damaged areas and their transfer to hospitals. The goal is to determine the set of routes that have the shortest flight time, which should start from hospitals and end in hospitals, and also the other goal is to minimize the amount of fuel consumption by helicopters.

Efficient humanitarian supply management must be able to respond to the situation as quickly as possible and in the shortest possible time frame.

2 | Literature Review

Since critical logistics are so crucial in relief efforts, this section examines international research in crisis logistics. The following is a study of research based on the interpretation of studies published in recent years in journals. According to Rodriguez [7], to alleviate distress, resource provisioning for disaster victims must be established, as well as proper planning for these activities. To cope with crises, crisis management brings together several organizations and shares resources. As a consequence, successful operations are highly reliant on cross-organizational collaboration. Chapman [8] argued that it's vital to ensure that post-disaster relief operations are well-organized and effective and the affected population's

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basic needs are met. However, uncertainty also affects all facets of rescue operations in the aftermath of a disaster. The location of relief distribution centers, as well as public awareness of these locations, are critical for the pace and efficiency of relief operations. Yu [9] often used the cost of deprivation as a primary economic measure of human misery in the context of emergency supplies (logistics). An enhanced method for the effective and fair allocation of critical resources in emergency supplies has been proposed, which incorporates this economic agency to account for human suffering.

To explain the disaster response process, a dynamic planning model for a retransmission problem of extracted multi-period resource allocation is presented, with specific attention to human distress caused by delayed delivery. Vahdani [10] proposed a multi-objective two-stage integer mathematical model in which the establishment of distribution centers and warehouses with varying capacities, as well as decisions about products stored in warehouses and distribution centers built in the first step, were taken into account. Due to emergency restrictions, operational preparation was undertaken in the second step to route and distribute merchandise in affected areas, increasing overall expense, travel time, and route reliability. Then, two metacognitive algorithms, NSGA-II and MOPSO, were used to check the accuracy of the mathematical model and the performance of the proposed algorithms by numerical samples. The results of the algorithms are presented for 35 different problems. Mohammadi et al. [11] developed a two-level model for the location of transport points and distribution centers of relief goods in earthquake situations. The first level involves locating relief facilities and transport points, and the second level includes routing for transporting the injured and bodies to certain pre-determined points. In addition, three scenarios (Masha fault, Rey fault, and North fault) with probabilities of 0.35, 0.30, and 0.35 are considered based on the conditions of Tehran faults. Finally, the Epsilon constraint method and GAMZ software were used to solve this model as it was multi-objective in nature. According to the findings, ten points should be chosen for transport point establishment along highways. Zahiri et al. [12] created a multi-level model under uncertainty for planning relief goods distribution centers. Uncertainty is taken into account in parameters like demand and facility capacity, treated as triangular fuzzy.

The inventory volume of each warehouse, the number of products flow from the retailer to each warehouse and from there to the affected area are among the research variables. This research yielded the following conclusions: 1) supplier/warehouse capacity is inversely correlated with the overall cost, and growing warehouse and supplier capacity reduces costs in this model, and 2) penalty cost for unsatisfied demand plays an important role in system efficiency. By raising the penalties, all requirement points can be covered. Salehi et al. [13] proposed a probabilistic multi-period model for designing a blood distribution network in the aftermath of an earthquake. A number of blood derivatives, such as plasma and possible platelets, are also in demand. In this research, a three-level blood supply chain is considered, including: 1) donors, 2) blood collection centers, and 3) blood transfusion base. The proposed two-level model is proposed for the city of Tehran, before and after the earthquake. The number of temporary blood collection facilities is calculated at the first level, and post-earthquake scenarios, including the distribution of blood products, are run at the second level. Finally, the performance of the model is validated by Monte Carlo simulation. Khatami et al. [14] proposed a probabilistic two-level model for crisis management before and after an earthquake. The first level of this model involves locating relief stations, and the second level involves allocating these stations to crisis-stricken regions. The number of goods stored and shortage volume in each center are among the decision variables of this research. A potential earthquake in Tehran was used to assess the accuracy of the proposed multi-commodity, multi-period model. In their research, Zokaee et al. [15] introduced a three-level (tier) supply chain that included suppliers, relief distribution centers, and affected areas. This study aimed to improve victim satisfaction while also lowering prices; for this purpose, certain penalties are considered in the event of a shortage of products. Robust optimization is used to solve the proposed model, which has uncertainties in demand and cost parameters. The Alborz area, which is prone to earthquakes and other natural disasters, was used as a case study in this research. Douglas et al. [16] proposed a two-level inventory (warehouse) distribution model in the disaster relief supply chain. One of their innovations has been location risk. The transportation vehicles used in this research are heterogeneous and have varying capacities. To demonstrate the efficacy of the model, they performed a case study in Brazil. They used an advanced algorithm to solve the case study. Cavdur et al. [17] developed a two-level model for distributing relief goods in earthquake-prone areas to those affected. This research aims to reduce the distance traveled as well as to minimize the amount of unmet demand. Some scenarios based on the time of the disaster and environmental situations, such as traffic, have been defined to achieve this aim. Consideration of supply and demand equilibrium, service level, and productivity of manufacturing operation are among the innovations of this research. Finally, the proposed earthquake model is based on a case study in Turkey. Xu et al. [18] used statistical modeling and electronic systems to locate earthquake shelters after acquiring geographic information.

The proposed model is of the P-middle type, and it aims to maximize coverage while minimizing the distance to the shelter. The proposed algorithm involves three steps: 1) selection of candidate shelters, 2) analysis of the coverage range of each shelter, and 3) selection of the final shelter site. The results obtained from the implementation of the model in Yangzhou indicated the accuracy and precision of the proposed model. Ouyed and Allili [19] in her research considers a six-level chain including blood donors, blood collection centers, laboratories, blood centers, hospitals and accident centers. In order to investigate the uncertainty in the model parameters, the possibility planning method has been used. The results of numerical analysis indicate the good performance of the possibility method compared to the definitive method and the possibility of 0.9 has the best performance compared to other values. Ling et al. [20] introduced the mathematical model of the medical equipment supply chain for the prevention and control of the COVID-19 epidemic, which aimed to maximize the overall satisfaction of medical equipment and minimize the total cost of planning.

Madani et al. [21] presents a multi-stage, multi-objective back-and-forth relief network that considers the location of hospitals, local warehouses, and hybrid centers that the hospital warehouse center is in the pre-disaster stage. In the post-disaster phase, the routing of relief goods in the forward path is considered. On the way back, there are some vehicles that can transport the injured after delivery. Combined transportation facilities will transport the injured to hospitals and combined centers. Depending on the degree of difficulty, a Non-dominated Sorting Genetic Algorithm (NSGA-II) with Simulated Algorithm (SA) and Variable Neighborhood Search (VNS) is proposed to solve the proposed problems. Hallak and Miç [22], in a case study conducted north of Aleppo in Syria to locations of the relief warehouses. At first, human and economic criteria were selected by three experts and then the weight of the criteria was determined by Fuzzy Analytic Hierarchical Process (F-AHP). Finally, warehouses were evaluated and ranked by MULTIMOORA technique as Multi-Criteria Decision Making (MCDM) method. Abazari et al. [23], in their research, in the pre-disaster stage, they determined the location and number of relief centers with a specific inventory level, and then after the disaster based on the distribution program, the amount of Relief Items (RI) that should be transferred to the Demand Points (DP) and the number of the required equipment is determined. Objective functions minimize the total distance traveled by RI, the total cost, the maximum transport time between relief centers and DP, and the number of perished items. Momeni et al. [24], reducing response time with high reliability has been introduced as the main goal of their research. In this research, after the disaster, the latest information on the condition of the roads is collected by drones and motorcycles then this information analyzed by disaster management to determine the probability of each scenario. By evaluating and analyzing the collected data, route repair teams are sent to increase the reliability of the route and in the final stage, they allocate RI to the DP.

Sarma et al. [25], in their research, they have introduced a three-step model in which the demand is done with the highest priority by local agencies in the first step and other remaining demands by national and international agencies in the second step along with the restoration of local agencies in the third step is done. To illustrate the performance of their proposed model, they have provided a numerical example that has tested its convergence using LINGO software and CPLEX optimization solvers. In Dachyar and Nilsari [26], the goal of his research design improvement in disaster relief distribution information system by utilizing the Internet of Things (IoT). The method used in this research is the development of a structure system with Entity-Relationship Diagram (ERD) and Data Flow Diagram (DFD). This study reduces the cycle time of the disaster relief distribution process at the rate of 59.4% and proposes an information system design that is expected to improve accountability in the disaster relief distribution system. In Cao et al. [27], they presented a fuzzy two-level optimization model using Wenchuan earthquake data. This study presents the problem as a fuzzy tri-objective bi-level integer programming model to minimize the unmet demand rate, potential environmental risks, emergency costs on the upper level of decision hierarchy and maximize survivors' perceived satisfaction on the lower level of decision hierarchy. *Table 1* summarizes the study assessment based on the evaluation of international research on critical logistics.

Table 1. A review of international literature.

Row	Author	Single-Objective	Multi-Objective	Definitie	Robust	Probable	Fuzzy	Ordinary Logistics	Relief Logistics	Accurate Solution	Meta-Heuristic Solution
1	Abounacer et al. [28]		*	*					*	*	
2	Aghajani and Torabi [29]		*						*	*	
3	Binbin and Songchen [30]		*						*	*	
4	Boonmee et al. [31]		*						*	*	*
5	Boltürk et al. [32]		*				*		*	*	
6	Barbarosoğlu et al. [33]			*					*	*	
7	Cao et al. [2]		*						*		*
8	Chapman and Mitchell [8]		*	*					*	*	
9	Cavdur et al. [17]		*			*			*		*
10	Chen and Yu [34]		*	*					*	*	
11	Chu and Yan Zhong [35]		*			*			*		*
12	De Angelis et al. [36]		*						*		*
13	Alem et al. [16]		*						*		*
14	Fahimnia et al. [37]		*			*			*		*
15	Fereiduni and Shahanaghi [38]		*		*				*		*
16	Jha et al. [5]		*						*		*
17	Madani et al. [21]		*						*		*
18	Khatami et al. [14]		*	*			*		*		
19	Ming Zhao and Xiang Liu [39]		*	*		*					
20	Papi et al. [40]		*	*		*				*	
21	Roh et al. [41]		*		*	*		*			
22	Safaei et al. [3]		*		*	*				*	
23	Samani et al. [4]		*	*		*			*		
24	Salehi et al. [13]		*	*		*			*	*	
25	Vahdani et al. [10]		*	*		*				*	
26	Yu et al. [9]		*	*		*					
27	Zahiri et al. [12]		*		*	*		*			
28	Zokaee et al. [15]		*		*	*				*	
29	Ouyed and Allili [19]		*	*		*				*	
30	Ling et al. [20]		*	*		*				*	
31	Madani et al. [21]		*	*		*					*
32	Hallak and Miç [22]		*		*	*		*			
33	Abazari et al. [32]		*	*		*			*		
34	Momeni et al. [24]		*	*		*			*		
35	Sarma et al. [25]		*	*		*					*
36	Dachyar and Nilsari [26]	*			*	*					*
37	Cao et al. [27]		*	*		*		*			
38	Current study		*	*		*		*		*	

The application of relief logistics in crises induced by natural disasters will be addressed in this study, based on the above-mentioned national and international studies. The need to make swift decisions and carry out operations with minimal resources has contributed to developing a type of knowledge known as crisis management. In this regard, research undertaken on recent crises in various parts of the world indicates that the need to investigate and model successive developments is greater than ever. As previously mentioned, such incidents neutrally occur in a cascading fashion as a chain of interrelated disasters. They are referred to as primary and secondary crises in the literature on crisis management because the occurrence of a crisis in one region triggers a secondary crisis in the regions affected by the primary crisis.

A secondary disaster, such as a flood crisis, is possible after a primary earthquake crisis that destroys infrastructure, including water supply facilities. Thus, steps must be taken to locate, route, and allocate relief distribution centers, relief bases, temporary shelters, and optimal routes to reach the affected areas.

Given the nature of relief in major consecutive events and the importance of relief pace during the relief management process in the current model, an effort has been made to minimize relief time as much as possible in both primary and secondary crisis phases. This is achieved in the primary crisis by locating facilities to deliver RI to affected areas and routing to transport wounded people to medical centers. It is assumed that a secondary crisis occurs in the same area as the primary crisis, and it is impossible to relocate for the deployment of equipment to respond to the second incident. Following the secondary crisis outbreak, we would concentrate on minimizing relief time and transferring people whose homes have been demolished to shelters, optimizing routing for the relocation of homeless people, and maximizing relief coverage, to carry out more equitable operations. As discussed in the research literature, most studies have discussed pre-disaster components or disaster occurrences in the present case, and yet no research has been conducted on secondary disaster. Therefore, in this research, a new mathematical model in the field of secondary disaster analysis is presented, which is much more effective in terms of the volume of destruction than the primary disaster.

3 | Problem Description and Formulation

Following natural disasters, the most significant factor in determining the effectiveness of relief measures is the pace at which relief facilities and goods are made available in the affected region. According to the above, the rate of transfer of the injured are transported to treatment facilities and the homeless to temporary shelters may also be indicative of the speed at which relief is provided. Another aspect that causes more and more injured people to be satisfied is the equitable distribution of relief in the affected areas. This is especially critical when disasters like floods strike, which typically impact a wide geographic area and necessitate balancing relief services across all affected areas.

We consider a four-level supply chain structure when shipping RI to affected areas (*Fig. 1*). The key warehouses for relief supplies can be found on the first level. These warehouses are permanent or temporary facilities whose number and location are identified prior to the disaster. Relief distribution centers, shelters, and temporary medical centers are located on the second level. The number and potential location of these facilities are pre-determined. The best are chosen to be activated from among these locations to finally minimize the time it takes to transport relief goods and wounded people to medical centers. Disaster-stricken areas make up the third level. The precise number of casualties is unknown immediately after a disaster. Hence, demand for relief goods, as well as subsequent voluntary public contributions and support, are considered uncertainty parameters. Donations from the general public (voluntary public contributions) are sent to distribution centers. Warehouses contain a basic inventory of different relief goods, and government assistance is sent to warehouses at the start of the relief period.

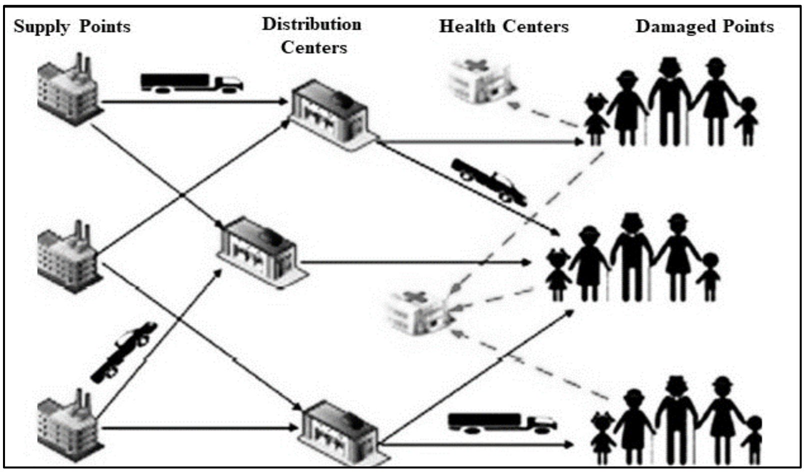

Fig. 1. Relief network investigated in this research.

3.1 | Assumptions

The assumptions of the model are as follows:

I. The number and location of key warehouses are well-defined.
II. The number and candidate location for temporary distribution centers (midpoints), medical centers, and shelters are well-defined.
III. The number and location of affected areas are well-known after the disaster.
IV. Supply points or warehouses have a certain capacity for receiving and sending goods.
V. Midpoints, or temporary distribution centers, shelters, and temporary medical centers, have a certain capacity to receive and send supplies and casualties.
VI. Network arcs are linking ways from supply points to distribution centers, from distribution centers to affected points, from affected points to shelters and medical centers, and from supply points to affected points.
VII. Various types of relief goods are considered.
VIII. A multi-period mathematical model is considered.
IX. The products' volume and weight are well-defined.
X. Each vehicle has a certain transportation capacity.
XI. Each mode of transportation has its own set of routes to follow.
XII. Roads can be blocked after a disaster.
XIII. Affected point demand is taken into account as a reliable uncertainty parameter.
XIV. Since primary and secondary crises are possible, the response phases to primary and secondary crises will be scheduled separately.
XV. A secondary crisis has a certain probability of occurring, but it may not occur in the same region even after the primary crisis.
XVI. A two-stage crisis occurs, with the second stage occurring after the first.
XVII. People who have been injured are separated into two categories: those who need medical attention and those who need shelter.

3.2 | Notations

Indexes

I: the warehouse node.

J: the temporary procurement center node.

K: the node of the damaged place in the primary and secondary disasters.

M: the set of candidate nodes of the temporary medical center.

N: the shelter node.

L: the type of vehicles (i.e., trucks and helicopters).

C: the relief commodity.

D: the type of injury (i.e., injuries classification based on treatment or their transfer to shelters).

S: the scenario in the primary and secondary disasters–two scenarios are considered in the mathematical model, which are the first scenario (an earthquake as the primary disaster and flood as the secondary disaster), and the second scenario (an earthquake as the primary disaster and fire as the secondary disaster).

Parameters

P_s: the probability of scenario s in the primary and secondary crises.

$T\delta_{lij}$: the transfer-shipment time of vehicle L between nodes i and j.

$\delta\prime_{ljj\prime}$: the transfer-shipment time of vehicle L between nodes j and j'.

Tc_{ljk} : the transfer-shipment time of vehicle L between nodes j and k.

$Tcc_{lkk\prime}$: the transfer-shipment time of vehicle L between nodes k and k'.

U_{knd}: the transfer time of injured individuals of type d from demand node k to shelter n in the secondary disaster.

z_{kmd}: the transfer time of injured individuals of type d from demand node k to medical center m in the primary disaster.

B_0: the relief time in the primary disaster.

B_1: the relief time in the secondary disaster.

dem_{kcs}: the demand for commodity c in node k under scenario s.

$capp_{ic}$: the amount of commodity c that can be supplied by node i.

o_{kd}: the number of injured individuals of type d in node k in the primary and secondary disasters.

ca_{nd}: the capacity of shelter n for receiving injured individuals of type d in the secondary disaster.

se_{md}: the capacity of medical center m for receiving injured individuals of type d in the primary disaster.

$ccap_j$: the volumetric capacity of temporary procurement center j.

β_{kd}: the percentage of injured individuals type d in disaster center k.

MM: is a large number.

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Decision parameters

Q_{lijcs}: the amount of commodity c supplied from I and stored in node I, by vehicle l under scenario s.

$Q^1_{lijj'cs}$: the amount of commodity c sent by temporary procurement center j to procurement center j' through vehicle L under scenario s.

Y_{ljkcs}: the amount of commodity c transported by vehicle L from node j to node k under scenario s.

$Y^1_{ljk'kcs}$: the amount of commodity c transported by vehicle L from center k' to center k under scenario s.

T_{LKs}: the arrival time of vehicle L in disaster center k under scenario s.

X_{kcs}: the stored amount of commodity c in node k under scenario s.

AA_{lkmds}: the number of injured individuals type d transferred by vehicle L from node k to medical center m under scenario s.

A_{lknds}: the number of injured individuals type d transferred by vehicle L from node k to shelter n under scenario s.

b_{kcs}: the shortage of commodity c in node k under scenario s.

e_{kds}: the number of the unhandled injuries type d in node k under scenario s.

ZZ_{js}: is 1 if a temporary procurement center is established in node j under scenario s, otherwise, it is zero.

H_{ms}: is 1 if a medical center is established in node m under scenario s, otherwise, it is zero.

D_i^+: is the positive deviation from the goal considered by the objective function i.

D_i^-: is the negative deviation from the goal considered by the objective function i.

Hs_{ns}: is 1 if shelter n is established under scenario s, otherwise, it is zero.

X^1_{lijs}: is 1 if vehicle L moves from supplier i to temporary procurement center j under scenario s, otherwise it is zero.

$X^2_{lijj's}$: is 1 if vehicle L moves from temporary procurement center j to temporary procurement center j' under scenario s, otherwise it is zero.

X^3_{ljks}: is 1 if vehicle L moves from temporary procurement center j to disaster center k under scenario s, otherwise it is zero.

$X^4_{ljkk's}$: is 1 if vehicle L moves from disaster center k to disaster center k'under scenario s; otherwise it is zero.

X^5_{lkms}: is 1 if vehicle L moves from disaster center k to medical center m under scenario s, otherwise it is zero.

X^6_{lkns}: is 1 if vehicle L moves from disaster center k to shelter n under scenario s, otherwise it is zero.

3.3 | Mathematical Modeling

$$MIN\ Z1C =$$

$$p_s\left(\sum_i\sum_j\sum_k\sum_l\sum_m\sum_n T_{lij} * X^1_{lijs} + {}^{'}_{ljj'} * X^2_{lijjs'} + Tc_{ljk} * X^3_{ljks} + Tcc_{lkk'} * X^4_{ljkk's} + U_{knd} * X^6_{lkns} + z_{kmd} * X^5_{lkms}\right) \quad (1)$$

$$MIN\ Z2C =$$

$$p_{kc} + q_{kcs} \geq dem_{kcs} \quad \text{for all } k, c. \quad (2)$$

The first objective function is to minimize vehicle routing scheduling (time) for the phase of responding to the primary crisis and the location of temporary relief logistics centers during the primary crisis, while the second objective function is to minimize the time it takes to move wounded people to shelter during the secondary crisis.

$$MIN\,C = p_s\left(\sum_L\sum_K T_{LKs}\right). \quad (3)$$

The third objective function is to minimize the golden relief time and movement of the wounded to a temporary medical center in the secondary crisis.

$$MAX\,C = p_s\left(\sum_i\sum_j\sum_k\sum_l\sum_m\sum_n X^1_{lijs} + X^2_{lijj's} + X^3_{ljks} + X^4_{ljkk's} + X^6_{lkns} + X^5_{lkms}\right) + D^-_4 + D^+_4. \quad (4)$$

The fourth objective function is to maximize the coverage of disaster-stricken areas by routing vehicles, transferring relief goods, and transferring wounded people in secondary crises.

Table 2. The objective function identifier of the problem is as follows.

	Objective Function	Method
Primary crisis	Minimizing the amount of time it takes to transport relief supplies and transfer injured people to medical centers	Location of the temporary procurement (logistics) center Location of the shelter Location of the medical center Optimal routing between the warehouse and the temporary procurement center Routing between temporary procurement centers (transfer shipment) Routing between procurement center and crisis centers
Secondary crisis	Minimizing the time it takes for injured people to be transferred to a shelter. Maximizing the coverage of crisis-stricken areas	Routing the transportation of the injured people to the shelter Allocation of temporary warehouses to crisis centers and shelter centers to crisis-stricken areas

3.4 | Fuzzy Programming

$$\sum_l\sum_j Q_{lijcs} + \sum_l\sum_{j'\neq j}\sum_J Q^1_{lij'cs} \leq capp_{ic} \qquad \text{for all } i, c, s. \quad (5)$$

In *Constraint (5)*, the volume of merchandise passing between the warehouse and the temporary procurement centers should be less than the transportation vehicles' capability.

$$\sum_l\sum_i\sum_c Q_{lijcs} + \sum_l\sum_{j'\neq j}\sum_c\sum_i Q^1_{lij'jcs} \leq ccap_j \qquad \text{for all } j, s. \quad (6)$$

In *Constraint (6)*, the volume of merchandise submitted to temporary procurement centers should be smaller than the available storage space to temporary distribution centers.

$$\sum_{l}\sum_{i} Q_{lijcs} + \sum_{l}\sum_{j'\neq j}\sum_{i} Q^{1}_{lij'jcs} = \sum_{l}\sum_{k} Y_{ljkcs} + \sum_{l}\sum_{k'\neq k}\sum_{K} Y^{1}_{lJkk'cs} \qquad \text{for all } j, c, s. \tag{7}$$

In *Constraint (7)*, according to this constraint, the volume of goods arriving at each temporary procurement center from a warehouse or other temporary procurement centers should be directed to the crisis center, or excess goods may be sent to other temporary procurement centers.

$$\sum_{l}\sum_{i} Q_{lijcs} + \sum_{l}\sum_{j'\neq j}\sum_{i} Q^{1}_{lij'jcs} = \sum_{l}\sum_{k} Y_{ljkcs} + \sum_{l}\sum_{k'\neq k}\sum_{K} Y^{1}_{lJkk'cs} \qquad \text{for all } j, c, s. \tag{8}$$

Demands of crisis centers are received either directly from supply centers (the sender), or they must be satisfied by equipment sent to another crisis center. On the other side, crisis centers may store inventory or require a deficit.

$$\sum_{l}\sum_{m} AA_{lkmds} + e_{kd} = o_{kd} \qquad \text{for all } k, d, s. \tag{9}$$

Constraint (9) transfer of the injured people from every region struck by a primary crisis to medical centers.

$$\sum_{l}\sum_{n} A_{lknds} + e_{kd} = o_{kd} \qquad \text{for all } k, d, s. \tag{10}$$

In *Constraint (10)*, the injured people from any region struck by a secondary crisis can be taken to shelter centers by equipment that delivers goods.

$$\beta_{kd}\sum_{l}\sum_{m} AA_{lkmds} + \left(1-\beta_{kd}\right) * \sum_{l}\sum_{n} A_{lknds} \leq o_{kd} \qquad \text{for all } k, d, s. \tag{11}$$

In *Constraint (11)*, this constraint specifies the number of wounded persons.

$$\sum_{l}\sum_{k} AA_{lkmds} \leq se_{md} \qquad \text{for all } m, d, s\ . \tag{12}$$

In *Constraint (12)*, the number of injured people transferred to medical centers must be smaller than the admission capacity of the medical center.

$$\sum_{l}\sum_{k} A_{lknds} \leq ca_{nd} \qquad \text{for all } n, d, s. \tag{13}$$

In *Constraint (13)*, the number of injured persons who have become homeless due to a secondary crisis and need to be moved to shelter centers must be smaller than the admission capacity of the shelter.

$$\sum_{i}\sum_{j}\sum_{k}\sum_{l}\sum_{m}\sum_{n} T_{lij} * X^{1}_{lijs} + '_{ljj'} * X^{2}_{lijj's} + Tc_{ljk} * X^{3}_{ljks} + Tcc_{lkk'} * X^{4}_{ljkk's} + z_{kmd} * X^{5}_{lkms} \leq B_{0} \tag{14}$$

$$\text{for all } s.$$

According to *Constraint (14)*, the pre-secondary crisis timetable for shipping relief supplies transversely must be shorter than the permitted time.

$$\sum_{i}\sum_{j}\sum_{k}\sum_{l}\sum_{m}\sum_{n} T_{lij} * X^{1}_{lijs} + '_{ljj'} * X^{2}_{lijj's} + Tc_{ljk} * X^{3}_{ljks} + Tcc_{lkk'} * X^{4}_{ljkk's} + U_{knd} * X^{6}_{lkns} \leq B_{1}. \tag{15}$$

Constraint (15) specifies that both transport and displacement times in secondary crisis management should be shorter than the permitted time.

$$\sum_{c} Q_{lijcs} \leq MM * X^{1}_{lijs} \quad \text{for all } l,i,j,s. \tag{16}$$

In *Constraint (16)*, there is limited communication between routing and the volume of merchandise shipped from the supplier to the temporary procurement site.

$$\sum_{c} Q_{lijcs} \leq MM * X^{1}_{lijs} \quad \text{for all } l,i,j,s. \tag{17}$$

In *Constraints (17)*, there is limited communication between routing and the volume of merchandise shipped from the supplier and temporary procurement to the temporary procurement site.

$$\sum_{c} Y_{ljkcs} \leq MM * X^{3}_{ljks} \quad \text{for all } l,j,k,s. \tag{18}$$

In *Constraints (18)*, there is limited communication between routing and the volume of merchandise shipped from the temporary procurement center to disaster-stricken areas.

$$\sum_{c} Y^{1}{}_{ljkk'cs} \leq MM * X^{4}_{ljkk's} \quad \text{for all } l,j,k,k' \neq k,s. \tag{19}$$

In *Constraints (19)*, there is limited communication between routing and the volume of merchandise shipped from the temporary procurement center and disaster-stricken areas to disaster-stricken areas.

$$\sum_{j} X^{1}_{lijs} \leq 1 \quad \text{for all } l,i,s. \tag{20}$$

Constraint (20) specifies the limited number of times the equipment will leave the supplier. Based on this constraint, the equipment can only depart the supplier once and move toward the temporary procurement center.

$$\begin{aligned} &\sum_{l} X^{1}_{lijs} + \sum_{j' \neq j}\sum_{l} X^{2}_{lj'js} \leq 1 \quad \text{for all } i,j,s, \\ &\sum_{j' \neq j}\sum_{L} X^{2}_{lijj's} \leq 1 \quad \text{for all } i,j,s. \end{aligned} \tag{21}$$

Constraint (21) limited number of times equipment arrives at the temporary procurement center.

$$\sum_{i}\sum_{l} X^{1}_{lijs} + \sum_{i}\sum_{j' \neq j}\sum_{l} X^{2}_{lij'js} = \sum_{k}\sum_{l} X^{3}_{ljks} + \sum_{i}\sum_{j' \neq j}\sum_{l} X^{2}_{lijj's} \quad \text{for all } j\ ,s\ . \tag{22}$$

Constraint (22) states that the number of arrivals to temporary procurement centers should be equal to the number of departures from these centers, as they do not store transportation vehicles.

$$\sum_{k} X^{3}_{ljks} \leq 1 \quad \text{for all } l,j,s. \tag{23}$$

Constraint (23) limited number of times equipment is brought into the crisis center.

$$\sum_{i}\sum_{l} X^{1}_{lijs} + \sum_{i}\sum_{j' \neq j}\sum_{l} X^{2}_{lij'js} = ZZ_{j} \quad \text{for all } j,s. \tag{24}$$

Constraint (24) constrained construction of temporary procurement centers.

$$\sum_{l}\sum_{k}\sum_{d} AA_{lkmds} \leq MM * H_{ms} \quad \text{for all } m,s. \tag{25}$$

Constraint (25) constrained construction of temporary medical centers.

$$\sum_{i} X^{1}_{lijs} \geq \sum_{i}\sum_{j' \neq j} X^{2}_{lijj's} \qquad \text{for all } j,l,s. \tag{26}$$

Constraint (26) requiring early routing between suppliers and temporary procurement centers

$$\sum_{j} X^{3}_{ljks} \geq \sum_{j}\sum_{k' \neq k} X^{4}_{ljkk's} \quad \text{for all } l,K,s\ . \tag{27}$$

Constraint (27) requiring early routing between temporary distribution centers and disaster-stricken areas.

$$\sum_{d} AA_{lkmds} \leq MM * X^{5}_{lkms} \qquad \text{for all } l,k,m,s. \tag{28}$$

Constraint (28) routing between the disaster-stricken area and the medical center.

$$\begin{aligned} &\sum_{d} A_{lknds} \leq MM * X^{6}_{lkns} \qquad \text{for all } l,k,n,s, \\ &\sum_{l}\sum_{k}\sum_{d} A_{lknds} \leq MM * Hs_{ns} \qquad \text{for all } n,s. \end{aligned} \tag{29}$$

Constraint (29) routing between the crisis-stricken area and the shelter, as well as the erection of the shelter center.

$$\begin{aligned} &T_{LK} \leq \sum_{I}\sum_{J}\sum_{C} T_{lijc} * X^{1}_{lijs} + \sum_{J}\sum_{C} Tc_{ljkc} * X^{3}_{ljks} + \sum_{K' \neq K}\sum_{J}\sum_{C} Tcc_{lk'Kc} * X^{4}_{ljk'ks}. \\ &T_{LK} \leq 48 \end{aligned} \tag{30}$$

In *Constraint (30)*, the equipment transportation time for distributing goods among crisis area and the golden time for relief should be less than 48 hours.

According to Inuiguchi and Ramık [42], the above model can be rewritten as

$$\begin{aligned} &\text{Min } Z = f.y + \left(\frac{c_{(1)} + c_{(2)} + c_{(3)} + c_{(4)}}{4} \right).x, \\ &A.x \geq \left(1 - \alpha_m\right).d_{(1)} + \alpha_m.d_{(2)} \ \text{ for all } m, \\ &B.x = 0, \\ &s.x \leq N.y, \\ &0.5 \leq \alpha_m \leq 1, \\ &x \geq 0 \text{ for all } m, \\ &y \in \{0,1\}. \end{aligned} \tag{31}$$

As previously mentioned, the model proposed in the previous section is a fuzzy linear model. This section will use robust programming and Bertsimas-Sim approach to add demand uncertainty to the model.

Thus, *Constraint (8)* will be modified to the Bertsimas model. Hence, the proposed model will be linear. According to the findings of this research, customer demand is one of the significant parameters whose values can surpass nominal values. Therefore, taking this parameter into account in uncertain situations will help the proposed model get closer to the problem reality. Customer demand uncertainty will be addressed using robust programming and the Bertsimas-Sim approach.

The robust optimization approach looks for solutions that are either optimal or near-optimal and are likely to be justified. One of four approaches to considering uncertainty in robust programming is the Bertsimas-Sim approach. We will briefly discuss this method in this section. The following linear programming model is considered for this purpose:

$$
\begin{aligned}
&\text{Min } Z \sum_j C_j X_j, \\
&\text{s.t,} \\
&\quad Ax \;\; b.
\end{aligned} \tag{32}
$$

In this model, it is assumed that only the right-hand coefficients in the constraints, i.e., matrix A, have non-crisp values, and the entries of this matrix, i.e., a_{ij} s, fluctuate in the $[\tilde{a}_{ij} - \hat{a}_{ij}, \tilde{a}_{ij} + \hat{a}_{ij}]$ range, where $\tilde{a}_{ij}$ and $\hat{a}_{ij}$ represent the nominal values and maximum deviation of parameter a_{ij}, respectively. Bertsimas and Sim's proposed robust model is in the form of *Eq. (33)*.

$$
\begin{aligned}
&\text{Min } Z \sum_j C_j X_j, \\
&\text{s.t.} \sum_j \tilde{a}_{ij} x_j + z_i \Gamma_i + \sum_{j \in J_i} \mu_{ij} \le b_i \qquad \text{for all } i, \\
&z_i + \mu_{ij} \ge \hat{a}_{ij} x_{ij} \qquad \text{for all } i, j, \\
&z_j, \mu_{ij} \ge 0 \qquad \text{for all } i, j.
\end{aligned} \tag{33}
$$

In these equations, and μ_{ij} are dual slack variables, and Γ_i, or the uncertainty budget, represent the degree of conservatism chosen based on the importance of the constraint as well as the decision-maker's risk-taking. The mathematical model presented in the demand section is taken as fuzzy by the proposed procedure. Thus, the demand-associated constraint is modified as follows:

$$
\begin{aligned}
&\sum_l \sum_j Y_{ljkcs} + \sum_l \sum_{k1 \neq k} \sum_J Y^1_{lJk'kcs} \ge (1-\alpha)\text{dem}_{kcs(1)} + \alpha.\text{dem}_{kcs(2)} + \Gamma_{kc} p_{kc} + q_{kcs} + X_{kcs} - b_{kcs} \text{ for all } k, c, s, \\
&\sum_l \sum_j Y_{ljkcs} + \sum_l \sum_{k1 \neq k} \sum_J Y^1_{lJk'kcs} \le (1-\alpha)\text{dem}_{kcs(4)} + \alpha.\text{dem}_{kcs(3)} + \Gamma_{kc} p_{kc} + q_{kcs} + X_{kcs} - b_{kcs} \text{ for all } k, c, s, \\
&p_{kc} + q_{kcs} \ge \text{dem}_{kcs} \qquad \text{for all } k, c.
\end{aligned} \tag{34}
$$

4 | Findings

The relief logistics and crisis management are of paramount importance since the disaster response phase in crisis management must occur in the shortest possible time. The emergence of primary crises, according to evaluations, also triggers and intensifies secondary crises. The longer the response phase of the primary crisis is postponed, the more detrimental the effect of the secondary crisis will be on the crisis-stricken region. In this problem, one of the fundamental principles under consideration when it comes to primary and secondary crises is humanitarian logistics. There are four levels to this evaluation: Warehouses for the storage of relief supplies in large quantities, temporary procurement centers to support the logistical processes of delivering relief goods to crisis-stricken areas during both primary and secondary crises, crisis-stricken areas in need of prompt and effective treatment, and medical centers responsible for treating the injured people during the primary crisis, and shelter centers responsible for treating the injured people during the secondary crisis. Since critical incidents occur in both the primary and secondary stages, two types of transportation equipment are used in this evaluation: land and airborne. The volume of portable RI, as well as the cost and timing of relocation, all influence the equipment selection. Two scenarios have been considered likely in this evaluation. A major earthquake is expected in the first scenario. The occurrence of one of the flood or fire components is considered in the second scenario or secondary incident. Transportation capacity and golden relief time are the two fundamental constraints that are considered for transportation equipment.

In addition, the formulated mathematical model is multi-objective. The first objective [function] is vehicle routing time for the crisis response phase. This evaluation seeks to minimize the time it takes to transport the relief cargo, provide relief to the wounded, and move them to temporary medical centers.

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The second objective function is to minimize the golden time for relief, with a maximum of 48 h. The third objective function is to minimize routing during the secondary crisis and relocate victims to pre-determined shelters. In general, natural disasters are so complex that humans are still unable to predict the exact time of a disaster, despite the implementation of thousands of prevention techniques in the form of networks all around the world and continuous data analysis using powerful machines. This section will evaluate and analyze the results of the model.

4.1 | Numerical Examples

An example with random data was examined to validate the model's accuracy, according to the modeling. Thus, the most important parameters of the model are:

I. Time spent transporting equipment L from the ith warehouse to the jth node (in min).

Table 3. Time spent on transporting from the warehouse to the middle node.

	J1	J2	J3	J4
L1.S1	12	15	15	14
L1.S2	13	14	15	12
L1.S3	12	13	13	15
L2.S1	14	12	13	14
L2.S2	14	12	13	14
L2.S3	15	13	14	12
l3.S1	14	12	15	14
l3.S2	14	13	13	12
l3.S3	13	13	13	14
l4.S1	12	15	13	13
l4.S2	14	13	13	12
l4.S3	12	14	14	13

This parameter represents the time it takes for the shipment from the supplier to the temporary procurement center in the primary crisis scenario. Depending on the volume of demand, relief supplies are distributed to temporary procurement centers.

II. Time spent transporting equipment L from the jth node to the j'th node (in min).

Table 4. Transfer shipment time between j and X.

	J1	J2	J3	J4
L1.J1	-	8	10	10
L1.J2	8	-	11	8
L1.J3	11	9	-	10
L1.J4	13	11	11	-
L2.J1	-	10	12	12
L2.J2	13	-	9	13
L2.J3	9	11	-	10
L2.J4	11	9	11	-
l3.J1	-	9	11	13
l3.J2	9	-	13	9
l3.J3	9	10	-	13
l3.J4	10	12	9	-
l4.J1	-	9	11	8
l4.J2	12	-	11	10
l4.J3	11	10	-	10
l4.J4	11	11	10	-

Table 4 indicates the length of transportation based on primary and secondary incidents during the primary crisis. Following the secondary crisis, the same strategy is followed for a shorter time. As we all know, during the primary crisis, procurement centers' stockpiles (inventory) are larger than the needs of crisis-stricken regions. Hence, in the event of a secondary crisis, inventory is transferred between temporary

Procurement centers to reduce the response time phase to the secondary crisis. Thus, relief supplies arrive at crisis centers in a shorter period of time during the secondary crisis phase.

III. Time spent transporting equipment L from the jth node to the kth node (in min).

Table 5. Time spent transporting equipment L from the jth node to the kth node.

	K1	K2	K3
L1.J1	7	9	9
L1.J2	5	10	7
L1.J3	8	11	11
L1.J4	6	5	11
L2.J1	12	9	6
L2.J2	11	10	6
L2.J3	9	11	5
L2.J4	9	12	9
l3.J1	7	9	10
l3.J2	8	12	11
l3.J3	7	6	6
l3.J4	7	8	10
l4.J1	6	8	11
l4.J2	9	9	5
l4.J3	11	8	9
l4.J4	10	6	11

This parameter is set in the event of a primary or secondary crisis. Since the transport distance does not change in either case, the transport time remains constant. Two types of road vehicles (vans and trucks) and two types of airborne equipment (helicopter and quadrotor) are taken into account in this parameter.

IV. Time spent transporting equipment L from the kth node to the k'th node (in min).

Table 6. Transfer shipment time for k.

	K1	K2	K3
L1.K1	6	4	4
L1.K2	6	7	5
L1.K3	6	4	7
L2.K1	7	4	5
L2.K2	5	6	5
L2.K3	6	6	5
l3.K1	5	4	4
l3.K2	6	5	6
l3.K3	7	4	5
l4.K1	5	5	5
l4.K2	6	6	6
l4.K3	6	6	6

According to the definition of transfer shipment status between crisis-stricken nodes during primary and secondary crises, the status of transmission of relief goods is considered to be exchanging relief goods. *Table 6* displays the time spent transporting this parameter.

V. Time spent transporting a d-type injured person from the kth demand node to the nth shelter during a secondary crisis (in min).

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Table 7. Time spent transporting a d-type injured person from the kth demand node to the nth shelter during a secondary crisis.

	D1	D2
K1.N1	15	13
K1.N2	13	15
K2.N1	12	14
K2.N2	14	15
K3.N1	14	14
K3.N2	13	15

It is assumed that the wounded need medical attention during the primary crisis. This parameter specifies the time it takes for wounded people to be transported to temporary medical centers.

VI. Time spent transporting a d-type injured person from the kth demand node to the mth medical center during a primary crisis.

Table 8. Time spent transporting a d-type injured person from the kth demand node to the mth medical center during a primary crisis.

	D1	D2
K1.M1	14	13
K1.M2	14	15
K2.M1	13	12
K2.M2	14	12
K3.M1	15	13
K3.M2	15	15

This parameter takes into account two different types of injury. M1 injury: during the primary crisis, it is assumed that the wounded need medical attention. M2 injury: during a secondary crisis, it is assumed that people need shelter and are moved there.

VII. Demand for the product C in the Kth node under scenario s.

Table 9. Demand for the product c in the kth node under scenario s (θ = 1).

	SS1	SS2
K1.C1	32	63
K1.C2	74	42
K1.C3	44	67
K2.C1	54	79
K2.C2	39	36
K2.C3	50	66
K3.C1	68	54
K3.C2	76	57
K3.C3	66	48

Table 10 introduces the required demand in crisis-stricken areas assumed in two primary crisis scenarios.

Table 10. Demand for the product c in the kth node under scenario s (θ = 2).

	SS1	SS2
K1.C1	89	81
K1.C2	89	97
K1.C3	83	90
K2.C1	99	86
K2.C2	92	99
K2.C3	88	91
K3.C1	99	91
K3.C2	87	92
K3.C3	98	93

Table 11 introduces the required demand in crisis-stricken areas assumed in two primary crisis scenarios.

Table 11. Demand for the product c in the kth node under scenario s (θ = 3).

	SS1	SS2
K1.C1	117	117
K1.C2	126	136
K1.C3	109	137
K2.C1	101	128
K2.C2	123	120
K2.C3	121	102
K3.C1	132	101
K3.C2	113	129
K3.C3	102	125

Table 12. Demand for the product c in the kth node under scenario s (θ = 4).

	SS1	SS2
K1.C1	148	160
K1.C2	168	168
K1.C3	173	162
K2.C1	179	161
K2.C2	167	159
K2.C3	176	171
K3.C1	176	143
K3.C2	170	156
K3.C3	144	157

Table 12 introduces the required demand in crisis-stricken areas assumed in two secondary crisis scenarios.

The collected information was divided based on two primary and secondary incident scenarios based on incidents, e.g., floods, earthquakes, fires, and hurricanes. According to the papers evaluated, 70% of the last 20 events were primary crises, and 30% of primary crises had turned into secondary crises. Therefore, the likelihood of scenarios occurring is adjusted. Following the GAMS coding, the following conclusions are initially drawn:

4.2 | Computational Experiments

We always maximize one of the objectives in solving a mathematical model accurately using the augmented epsilon-constraint method, as long as we define the maximum permissible limit for the other objectives as constraints. The mathematical representation of a bi-objective problem will be as follows:

$$\text{Min } f_1(x) \quad \text{Subject to} \quad f_2(x) \leq \varepsilon_2, f_3(x) \leq \varepsilon_3, \ldots, f_p(x) \leq \varepsilon_p, x \in S. \tag{35}$$

The Pareto edge of the problem can be found by shifting the values of the right-hand side of the new constraints of εs. One of the main drawbacks of the epsilon-constraint method is the high volume of computations needed since several different ε_i values (p-1) must be tested for each of the objective functions translated to constraint. Obtaining the maximum and minimum of each objective function without considering other objective functions in the $x \in S$ space is one of the most common approaches to implementing the epsilon-constraint method. The range associated with each objective function is then calculated using the values obtained in the previous step. If the maximum and minimum values of the objective functions are referred to as f_i^{max} and f_i^{min}, respectively, the range of each is determined as follows:

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$$r_i = f_i^{max} - f_i^{min}. \quad (36)$$

The r_i range is divided into the q_i range. Then, we can get $q_i + 1$ different values for ε_i using the following formula:

$$\varepsilon_i^k = f_i^{max} - \frac{r_i}{q_i} \times k \quad k = 0,1,\dots,q_i. \quad (37)$$

In the equation above, K represents the number of the new point associated with ε_i. The above multi-objective optimization problem can be reduced to $\prod_{i=2}^{p}(q_i+1)$ single-objective optimization sub-problems using the epsilon-constraint method. Each sub-problem has an S solution space since they will even be more constrained by inequalities related to objective functions $f_2,\dots,f_p$. Finally, the following values are obtained for each variable:

Table 13. Parameters of the Epsilon-constraint method.

r2	72	r3	942	r4	3072
Li	4	Li	4	Li	4
NIS2	110	NIS3	258	NIS4	5928
PISF2	182	PISF3	1200	PISF4	9000
ϑ	0.0001	ϑ	0.0001	ϑ	0.0001

The values of εs are then calculated using *Eq. (37)*.

Table 14. Epsilon values.

ε4	ε3	ε2
5928	258	110
6696	493.5	128
7464	729	146
8232	964.5	164
9000	1200	182

Finally, we used GAMS software to solve the augmented epsilon-constraint model for each of the obtained εs. *Table 15* lists the Pareto optimal solutions found:

Table 15. Pareto optimal solutions in the augmented epsilon-constraint method.

ε	First Objective Function	Second Objective Function	Third Objective Function	fourth Objective Function
1	73536	110	258	5928
2	80601	128.2	494.1	6696
3	87667	146.4	729	7464
4	94848	164	964	8232
5	96546	173	1034	9431

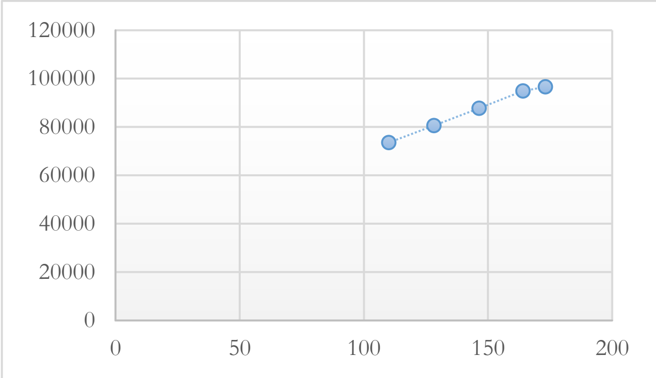

Fig. 2. Pareto boundary of optimal solutions of the first and second objective functions.

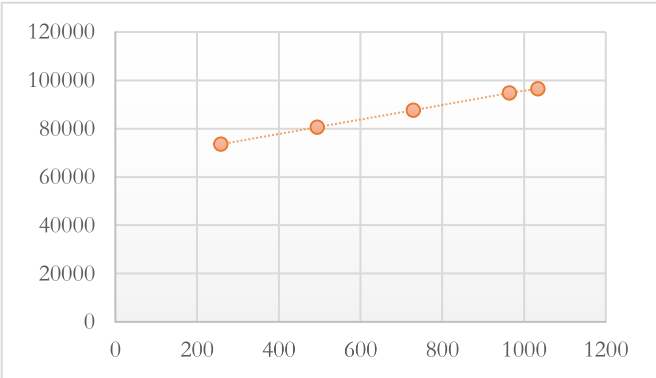

Fig. 3. Pareto boundary of optimal solutions of the first and third objective functions.

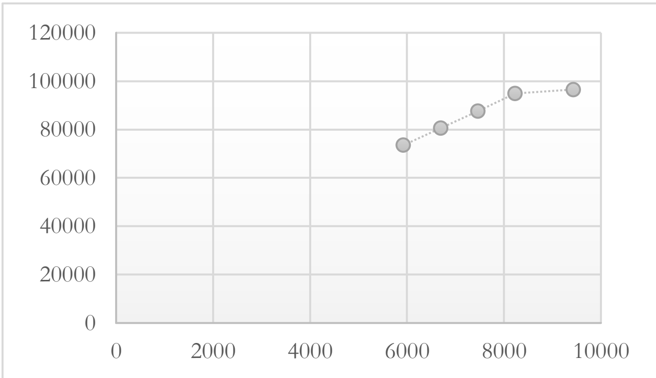

Fig. 4. Pareto boundary of optimal solutions of the first and fourth objective functions.

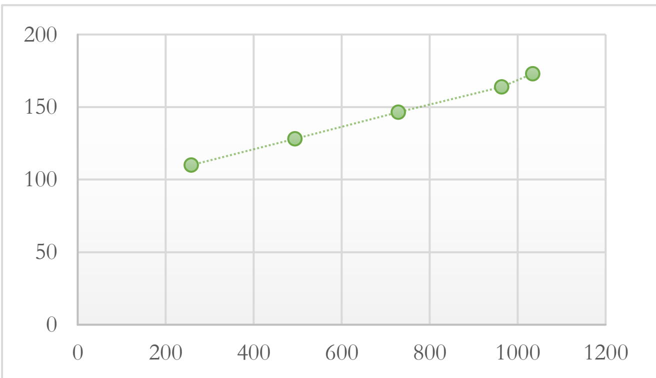

Fig. 5. Pareto boundary of optimal solutions of the second and third objective functions.

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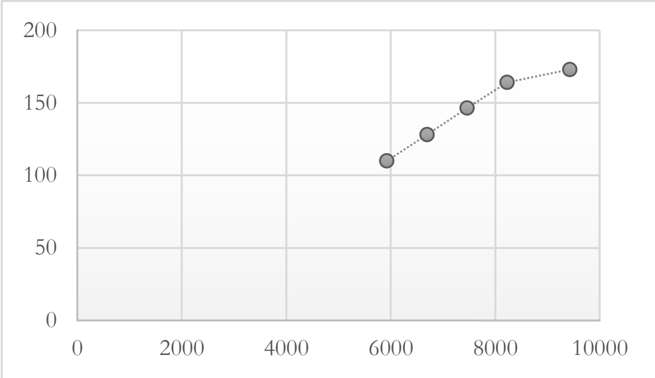

Fig. 6. Pareto boundary of optimal solutions of the second and fourth objective functions.

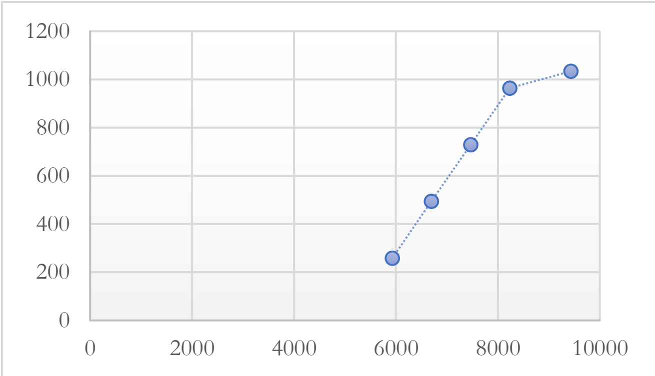

Fig. 7. Pareto boundary of optimal solutions of the third and fourth objective functions.

4.3 | Parameters Tuning

The use of performance measures is one way to address such problems. The following are some of these measures:

Number of Pareto solutions

This criterion is the number of output solutions per algorithm execution. This criterion is defined as the number of output solutions produced while running each algorithm in comparing several algorithms. Obviously, the more Pareto solutions a method has, the more desirable it is.

Average distance to the optimal solution (Mean Ideal Distance (MID))

This criterion is used to determine the average distance of Pareto solutions from the origin of coordinates. The lower the value of this criterion, the higher the efficiency of the algorithm, as seen in the following equation.

$$\mathrm{MID}=\frac{\sum_{i=1}^{n}\sqrt{\left(\frac{f1_i-f1_{best}}{f1_{total}^{max}-f1_{total}^{min}}\right)^2+\left(\frac{f2_i-f2_{best}}{f2_{total}^{max}-f2_{total}^{min}}\right)^2}}{n}. \tag{38}$$

CPU time

CPU time is a critical measure in large-scale problems. Thus, the CPU time of an algorithm is used as a criterion for evaluating its quality.

Maximum Scattering (MS)

The distance index is defined as *Eq. (35)*:

$$MS = \sqrt{\sum_{i=1}^{I}\left(\min f_i - \max f_i\right)^2}. \quad (39)$$

Scattering index of non-dominated solutions (Spread of Non-dominance Solutions (SNS))

This index is used to determine the scattering and diversity of the Pareto solutions that have been found:

$$SNS = \sqrt{\frac{\sum_{i=1}^{n}\left(MID - C_i\right)^2}{n-1}}. \quad (40)$$

$$C_i = \sqrt{f1_i^2 + f2_i^2}.$$

4.4 | Results and Comparative Study of Solution Methods

It is time to design the experiment using the Taguchi method after you have designed the problem. The Taguchi method, as previously mentioned, reduces the number of experiments needed to set the parameters. We begin by determining the parameters we want to set in each algorithm. Parameter levels and orthogonal arrays for experiments are obtained using Minitab software. We tested the algorithms at the same determined levels and repeated them ten times after deciding the number of tests for each algorithm. The results of these ten experiments were then averaged. Then, we made them unweighted, plotted S/N diagrams, and determined the better parameters. We must first obtain and note the levels of each algorithm. To do so, relevant papers were studied, and candidate levels were identified from among them, as presented in *Table 16*.

Table 16. Various levels for the parameters of each algorithm.

Algorithm	Algorithm Parameters	Parameter Level Level 1	Level 2	Level 3
NSGA-II	Pc	0.7	0.8	0.9
	Pm	0.05	0.1	0.15
	N-pop	50	100	150
	Max-iteration	2*(i+j+k+l+o)	3*(i+j+k+l+o)	4*(i+j+k+l+o)
NRGA	Pc	0.7	0.8	0.9
	Pm	0.05	0.1	0.15
	N-pop	50	100	150
	Max-iteration	2*(i+j+k+l+o)	3*(i+j+k+l+o)	4*(i+j+k+l+o)

Finally, the experiments were designed, and the L9 orthogonal arrays were chosen for the NSGA-II and NRGA algorithms using the Minitab 16 software. Response values for the Taguchi method were obtained after running the algorithms for each of the preceding experiments. *Table 17* illustrates these values and orthogonal arrays.

Table 17. L9 orthogonal array and the computational results of the NSGA-II and NRGA algorithms.

Test	Pc	Pm	N-pop	Max-Iteration	NRGA Response	NSGA-II Response
1	1	1	1	1	6.4234e-006	4.497e-006
2	1	2	2	2	9.5085e-006	9.3753e-006
3	1	3	3	3	6.7366e-006	3.857e-006
4	2	1	2	3	4.3413e-006	7.0235e-006
5	2	2	3	1	5.3981e-006	9.5885e-006
6	2	3	1	2	9.4061e-006	1.594e-005
7	3	1	3	2	5.9087e-006	3.8218e-006
8	3	2	1	3	5.5662e-006	4.3919e-006
9	3	3	2	1	7.6662e-006	1.417e-005

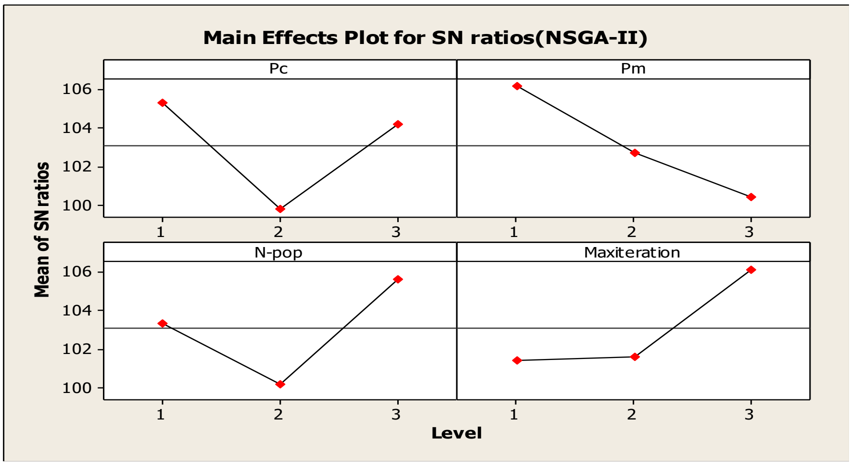

Fig. 8. Signal-noise diagram of the NSGA-II algorithm.

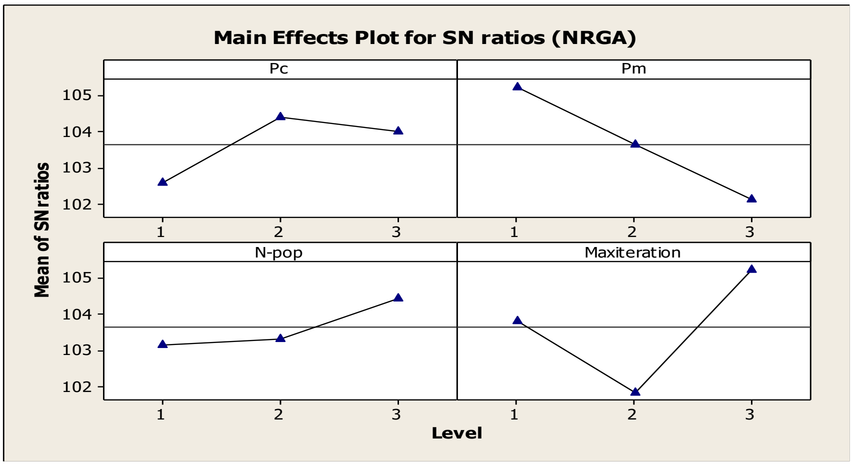

Fig. 9. Signal-noise diagram of the NRGA algorithm.

Following the design of the experiment and setting of the parameters, the appropriate parameters in each algorithm are now defined, and it is time to implement and compare the algorithms for the created problems.

Table 18. Computational results of the algorithms for 12 sub-problems.

Problem	NPS		CPU Time		MID	
	NSGA-II	NRGA	NSGA-II	NRGA	NSGA-II	NRGA
1	12	8	52.8815	58.4439	1.4909	2.3656
2	12	8	115.6659	129.4496	1.119	1.1781
3	15	14	199.8113	220.8354	2.1143	2.0267
4	8	12	302.7046	342.9649	3.6118	2.1146
5	11	7	746.2813	835.6521	3.6959	2.612
6	11	15	989.7469	1071.5596	3.1876	2.8049
7	6	7	1154.2441	1289.9778	5.0146	5.4399
8	10	15	1939.626	2179.4638	5.8759	5.6609
9	9	18	4644.4177	4215.4629	4.8438	4.797
10	17	19	5114.7147	4704.4016	3.9634	3.708
11	10	20	8779.6802	8592.3094	5.8276	4.0531
12	20	14	12039.6386	12803.8985	4.8701	6.3874

4.5 | Sensitivity Analysis

Fig. 10 to *Fig. 12* show the problem in various dimensions for a clearer understanding of certain Pareto charts.

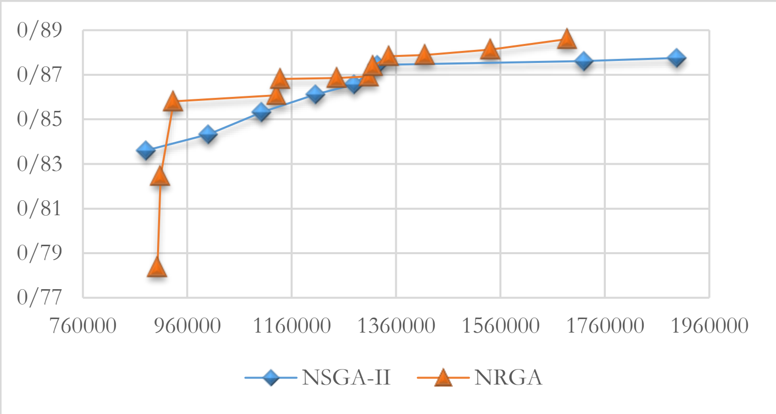

Fig. 10. Pareto chart for the low-dimensional (small-scale) problem.

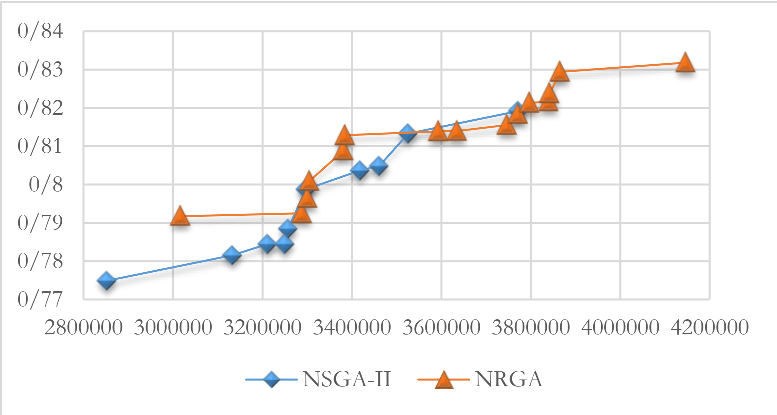

Fig. 11. Pareto chart for the mid-dimensional (medium-scale) problem.

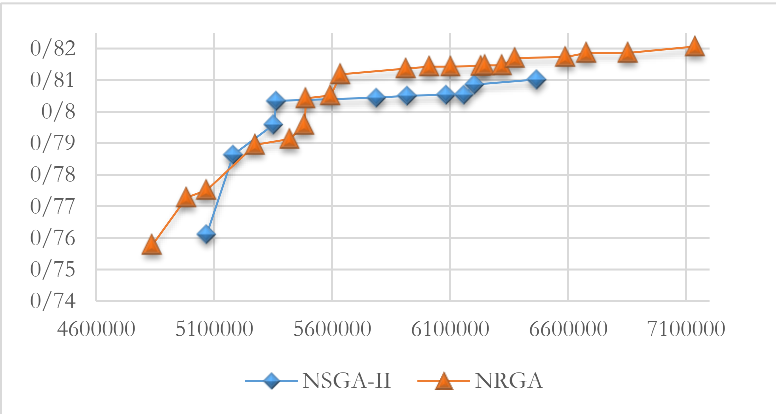

Fig. 12. Pareto chart for the high-dimensional (large-scale) problem.

According to the information provided:

NSGA-II was chosen as the best alternative on a small scale, followed by the NRGA algorithm. NRGA was chosen as the best alternative on a medium scale, followed by the NSGA-II algorithm. The NRGA algorithm was chosen as the best alternative on a large scale, followed by the NSGA-II algorithm.

5 | Managerial Insights

Natural disasters such as earthquakes, floods, hurricanes, and droughts strike various parts of the globe each year. Personal and financial losses are often associated with the occurrence of these natural disasters. Since the magnitude and scope of these disasters are often high, the demand for rescue

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operations is often uncertain. The number of relief centers available to meet the city's needs in normal conditions is often insufficient to meet demand at the appropriate time. Hence, the statistical fuzzy ideal programming model was presented in this study, which assesses the frequency of primary and secondary crises as well as accurately assesses and analyses the relief situation. Finally, using the epsilon-constraint method and metaheuristic algorithms NSGAII and NRGA, the proposed mathematical model was evaluated and analyzed to determine its validity. The findings showed that the above two algorithms are very effective in crisis management and significantly improve relief processes.

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