Multi-Objective Modeling of Relief Items Distribution Network Design Problem in Disaster Relief Logistics Considering Transportation System and CO_2 Emission

Mahdi Modiri[a*], Mohammad Eskandari[b], Samira Hasanzadeh[c]

[a] Full professor at Malek Ashtar University of technology, Tehran, Iran, Email: m_modiri@mut.ac.ir

[b] Assistant professor, Faculty of Passive Defense, Malek Ashtar University of Technology, Tehran, Iran, Email: eskandarim@ut.ac.ir

[c] Ph.D student in Crisis Management, Malek Ashtar University of Technology, Tehran, Iran, Email: s.hasanzadeh260@gmail.com

***Corresponding author:** Mahdi Modiri, Email: m_modiri@mut.ac.ir, Mobile number: 0912 132 9179

Abstract

The present study aims to propose a multi-objective mixed integer mathematical programming model for designing a relief items distribution network in sustainable disaster relief logistics. The first objective function minimizes the total network costs. Which are divided into two parts: 1- relief costs including (transportation costs, inventory costs and fixed costs of facilities) 2- social costs (deprivation cost). The second objective function minimizes the amount of pollution generated by the network. Considering the related literature review, this is the first study that to propose a robust fuzzy optimization approach for relief items distribution network design problem considering environmental (CO_2 emission), social (deprivation cost) and economic impacts under reliability and uncertainty. Then, the multi-objective model was solved using the multi-choice goal programming. To indicate the validity of the proposed model, a case study was evaluated based on real data (2019 flood in Sari city, Mazandaran Province). Using the proposed model, decision-makers and managers are able to make strategic and tactical decisions with the least cost and time, and in relief planning can enhance the structure of distribution networks and inventory and reduce victims' dissatisfaction.

Keywords: Distribution Network, Relief Items, Disaster Relief Logistics, CO_2 Emission, Robust Fuzzy Optimization.

1. Introduction

Natural disasters are uncontrollable conditions that directly affect human lives. Despite research and technological advances, predicting the time or location of natural disasters is not possible [1]. The international disaster database provides the total number of natural disasters and affected people, which have significantly increased since 1900 [2]. Large-scale natural disasters have frequently occurred, including earthquakes and tsunami in Indonesia in 2018, earthquake in Nepal in 2015 that lead to human casualties, financial damages, disruption in the environment, and consequently adverse impacts on sustainable development [3]. Since the number of large-scale natural disasters has extremely increased, the vital need for a sustainable disaster supply chain to save human lives, reduce human suffering, and help the development as much as possible has remained an issue [2]. Therefore, it is vital to take the economic, social, and environmental issues into account in the disaster relief logistics problem to reduce the harmful effects of a disaster [4]. During natural disasters, the fundamental issue that has lately caught the attention of many researchers is to decide on the proper location for the relief items distribution centers in the affected area [5]. In the event of a catastrophe, the necessary products are sent from the supply centers to the distribution centers so that they can distribute them to the affected population [6]. Thereby, it is required to create a certain number of emergency distribution centers in suitable places to store and allocate relief items. It is also necessary to dispatch appropriate vehicles to distribute the relief items from the distribution centers to the demand points. When distributing the relief aids, the vehicles emit a certain amount of carbon dioxide, intensifying climate change [7]. Environmental deterioration is one of the major reasons behind frequent natural disasters [8]. Thereby, to create a long-term relative balance between the relief and rescue activities and environment protection, it is essential to take the carbon emissions into account while optimizing the relief items distribution management problem in disaster relief logistics. In this research, a multi-objective mixed integer mathematical programming model is presented to design a decision support model for the relief items distribution network in disaster relief logistics. The first objective function minimizes the total network costs, which are divided into two parts: 1- relief costs including (transportation costs, inventory costs and fixed costs of facilities) 2- social costs (deprivation cost). The second objective function of this research is to reduce environmental pollution. An important issue that has rarely been addressed in previous research is that during a disaster, distribution centers may face disruptions and fail to provide services because they are disrupted after the disaster. These centers are called unreliable centers. Reliability was considered in the problem to deal with disorders. Considering the inherent uncertainty in this issue, especially in critical situations, such as large-scale disasters, the amount of demand, costs, etc. are not specified. Therefore, this issue will be examined with uncertainty, and a robust fuzzy optimization approach is utilized to deal with the uncertainty. Further, multi-choice goal programming is used to solve the multi-objective model. Finally, a case study was conducted on Sari city, Mazandaran Province, which has been affected by a flood in 2019, to verify the model performance. Considering the related literature review, this is the first study that to propose a robust fuzzy optimization approach for relief items distribution network design problem in sustainable disaster relief logistics considering environmental (CO_2 emission), social (deprivation cost) and economic impacts under reliability and uncertainty. The rest of the article is organized as follows: Section 2 presents studies related to the strategic models used in sustainable disaster relief logistics. Section 3 defines the problem. The research methodology, including model formulization, uncertainty modeling, and the solution method are presented in Section 4. Section 5 discusses the application of the model in the Sari region and provides the obtained results from solving the research problem. Section 6 presents the managerial implications derived from the results. Finally, concludes the research, limitations and suggestions for future research are provided in Section 7.

2. Literature review

In this section, relevant research on relief items distribution network design is reviewed. This investigation falls into two main streams: humanitarian logistics studies and sustainability models.

1.2. Humanitarian logistics studies

Loree and Aros-Vera [5] provided a mathematical model to locate the distribution and allocate the inventory after the disaster in a humanitarian manner. This model minimizes the deprivation, logistics, and facilities costs; and allows demand groups to use multiple demand points. Bozorgi-Amiri et al [9] developed a multi-objective robust stochastic model for disaster relief logistics under uncertainty and solved it using a compromise programing method. Hatefi and Jolai [10] presented a robust and reliable model for an integrated forward–reverse logistics network design under demand uncertainty and facility disruptions, which simultaneously takes uncertain parameters and facility disruptions into account. The proposed model is formulated based on a recent robust optimization approach to protect the network against uncertainty. An et al [11] suggested a relief facilities allocation location model to reduce the costs. To this aim, they stated the facility disruption, support facilitation, and service time as Bernoulli and Poisson statistical distribution functions in a single-objective model and considered route congestion. Huang and Song [12] proposed an emergency logistics distribution routing model for unexpected events. An emergency logistics distribution routing model is developed based on uncertainty theory. To solve the problem, the equivalent model is provided and a cellular genetic algorithm is designed. In addition, an example is presented to illustrate the application of the proposed model and the effectiveness of the proposed algorithm**.** Hu et al. [13] implemented a mathematical model with two objectives of efficiency and justice in giving aid in the accidents and natural disasters, with the assumption that the rescue items should be distributed by a relief center fairly and efficiently to the affected areas, regarding the limited upstream resources. Haghi et al. [14] developed a multi-objective programming model for locating the relief items supply and health centers, aiming to distribute the relief items and transfer the injured people to the health centers. Furthermore, stochastic demands, supply, and cost parameters were addressed to bring the model closer to reality. The proposed model maximizes the response to the medical needs of the injured people, in addition to targeting the proper distribution of relief items and minimizing the total costs of the entire preparation and response phase. Liu et al. [15] studied a multi-product and multi-period distribution model that considered both relief items and injured people to minimize the total unmet demands. To analyze the application of the model and proposed framework, they used the data from the Wenchuan earthquake. Lin et al [16] developed a multi-period, multi-items, and multi-vehicle model to logistically model the essential and prior goods in the response phase of the disaster. The model has two objective functions, the first of which was to minimize unfulfilled demands and the second one was to minimize travel time. In a study, Wang et al [17] presented a routing model to help the relief distribution with regards to time, costs, and reliability. Balcik and Yanıkoğlu [18] provided a stochastic programming model to determine the optimal sequence of visiting affected areas for humanitarian needs assessment teams considering travel time uncertainty. Aghajani et al [19] provided a novel option contract integrated with supplier selection and inventory prepositioning for humanitarian relief supply chains their proposed a novel two-period option contract integrated with supplier selection and inventory prepositioning. A two-stage scenario-based mixed possibilistic-stochastic programming model is developed to cope with various uncertainties. The first stage's decisions include supplier selection and capacity reservation level at each supplier/period and the level of inventory prepositioning. The next section presents studies related to the issue of sustainability in disaster relief logistics.

2.2. Sustainable humanitarian logistics

Over the past few decades, sustainable disaster relief chains have increasingly captured the attention of academics and individuals. A great deal of research has been conducted on sustainability in commercial supply chains, but investigations on this issue in disaster supply chains are still limited [20]. A vast majority of researchers have attempted to answer the question of what indicators are available to measure the sustainability of the disaster supply chain. However, how to describe these potential indicators through quantitative methods has barely been regarded. The aid distribution problem is extremely appealing in the sustainable disaster supply chain. Although some researchers have addressed the importance of this problem in the disaster supply chain, the means through which some of these indicators are combined to measure the sustainability in the relief distribution strategies still call for further investigations to be conducted [21]. Carter and Rogers [22] explained that sustainability can be measured by the three-dimensional model consisting of the social, economic and environmental dimensions. In recent years, both relief distribution and sustainable disaster supply chain for saving humans lives, reducing the victims' suffering, and also helping the development have increasingly captured the interest of researchers. Kaivo-oja et al. [23] discussed Sustainability as a hot topic. Different researchers in different fields do not have a unique understanding of its definition and nature. This subject can only be found in some papers. For instance, Weerawardena et al. [24] believed that sustainability could be understood as maintaining operation in non-profit organizations. Ibegbunam and D. McGill [25] mentioned that the sustainability of humanitarian supply chains consists of responsible cooperation and communication. Haavisto and G. Kovacs [26] explained and described the sustainability of the humanitarian supply chain from the social perspectives, beneficiary, supply chain, and plan. Kunz and S. Gold [27] also exchanged ideas and discussed the sustainability of the humanitarian supply chain during the reconstruction phase. Dubey and Gunasekaran [28] refer to agility, compatibility, and coordination as the vital properties of the sustainable humanitarian supply chain. The sustainability of the emergency logistics network must take not only the economic and social aspects but also the environmental aspects into account. Recently Boostani et al [4] Developed a sustainable humanitarian relief logistics model that minimizes the costs of the total humanitarian relief supply chain (costs of the preparedness and response phases), with a view to strategic and tactical planning issues regarding facility location, procurement, and resource allocation. Maximizes the social welfare (by maximizing the minimum level of satisfaction in disaster areas) and minimizes environmental impacts. Zhang et al [29] presented a model for sustainable last mile relief network problem that maximizes equitable distribution of relief resources and minimizes the transportation time and operation cost. In addition, they considered uncertainty in their last-mile network. The results show that their proposed model can achieve an exchange between the equitability, timeliness and economics for the distribution of relief in a relief network. Jamali et al [30] proposed a multi-objective stochastic programming model to configure a relief logistics in relation to sustainability. Three levels of severity of injury are considered and the number of victims of each severity is subject to uncertainty. This model can simultaneously determine the location and capacity of shelters, the assignment of patients, type of transportation modes and the amount of flow from each medical supply center to shelters. Based on the findings of sensitivity analysis, several suggestions have been presented with the aim of creating an optimal exchange between different aspects of sustainability. The results show that the application of environmental issues to humanitarian logistics does not necessarily increase relief costs, but may be in conflict with the social aspect. In addition, a small increase in the budget for the preparation phase drastically reduces response costs. Cao et al [2] proposed a multi-objective mathematical model for the sustainable disaster supply chain in order to maximize victim satisfaction and minimize maximum deviation in victim satisfaction for all demand points and to propose a genetic algorithm to solve this mathematical model. A case study of the Wenchuan earthquake has also been shown for validation. Table 1 presents a comparison of the conducted researches related to the literature on the subject of the study. The characteristics of the present study are also given in the last row.

Considering the related literature review, the research gaps and contributions of this research could be summarized as follows:

- Sustainability is now a social concern for development due to increasing pressure of environmental and social requirements. Within this context, designing a sustainable emergency logistics network is a challenge for decision makers. To respond to these challenges, the sustainability of emergency logistics network must consider not only economic aspects but also social and environmental aspects. Much research has been done on sustainability in the commercial supply chain, but the issue of sustainability is still very limited in disaster relief logistics research. Recently, sustainable modeling of disaster relief logistics has received increasing attention. Most studies such as Cantillo et al [40], Cotes and Cantillo [41], Paul and Wang [42], Zhang et al [29] have considered only one or two dimensions of sustainability in humanitarian supply chain models. The significance of simultaneously considering three aspects of sustainability and presenting a multi-objective optimization model is defined by Boostani et al [4] and Jamali et al [30]. Because, it is vital to take the economic, social, and environmental issues into account in the disaster relief logistics problem to reduce the harmful effects of a disaster. By combining relief costs (economic aspect), deprivation costs (social aspect), and Carbon emissions (environmental aspect), we have integrally considered sustainability in this study
- Some studies related to network designing models in sustainable disaster relief logistics focus on minimizing transportation time and operating costs without considering the environmental effects, such as Zhang et al [29]. Environmental issues, such as CO_2 emissions, must be taken into account in designing a disaster relief logistics network. Because transportation is the most important source of CO_2 emissions and air pollution in logistics and supply chains networks. In addition to road transportation, other transportation ways, including relief items transportation by motorboats and rescue helicopters are also considered in this research. The proposed model aims at reducing the environmental pollutions in addition to reducing operating costs.
- An important issue that has rarely been addressed in previous research such as Paydar et al [38], Eshghi et al [43], Jamali et al [30], Cao et al [3] and Zhang and Cui [45] is that

during a disaster, distribution centers may face disruptions and fail to provide services because they are disrupted after the disaster. These centers are called unreliable centers. In this research, it is assumed that there are reliable centers that send the relief items in case of the inability of unreliable centers to decrease the risk and unsatisfied demands.

- Despite the uncertain and unpredictable nature of disasters, many articles have not considered various uncertainties as key challenges in emergency logistics planning; Cantillo et al [40], Cotes and Cantillo [41] and Madani et al [44] proposed a purely deterministic model and did not use an uncertain approach. In critical situations, accurate information about the parameters is not available, for example during large-scale disasters, we don't know the amount of demand, costs, etc. in other words, there is uncertainty in the nature of the research problem. Therefore, in this research, in order to be more compatibility with the real world and increase network efficiency, we have considered uncertainty of parameters such as (demand of affected areas, logistics costs).
- In studies such as Aghajani et al [19], Boostani et al [4], Nayeem and Lee [47] and Cheng et al [46] there are different methods to deal with various types of uncertainty in existing literature of disaster relief logistics, but the approach that has not been done in any of these studies is the robust fuzzy multi-objective approach that utilized in this research for the first time to deal with uncertainty. In general, the current study is the first study that to propose a robust fuzzy model for relief items distribution network design problem considering environmental (CO_2 emission), social (deprivation cost) and economic impacts under reliability and uncertainty. To verify the model performance, a real case study was conducted on Sari city, Mazandaran Province, which has been affected by a flood in 2019.

3. Problem definition

During natural disasters, the fundamental issue is to decide on the proper location for the relief items distribution centers in the affected area. The distribution centers are the critical links between supply centers and demand points and should be strategically constructed immediately after the disaster to provide a proper response. Decisions on strategic deployment and inventory allocation to the distribution centers are usually made after the disaster. Until this time, the survivors would face injury and suffering due to lack of access to the vital resources and hence, the selected locations for distribution centers directly affect the response time of providing essential goods for the affected areas. A measure must be introduced to indicate the survivors' suffering because of not having access to vital goods over time. This measure is known as the deprivation cost, which has to be accounted for in decision-making processes. Figure 1 illustrates a network of disaster relief logistics used in this research. This network consists of one primary source of relief items supply as the supply center, multiple suggested locations as the distribution centers, and various affected centers as the demand points. In this study, there are different transportation modes to ship the relief items between supply centers, distribution centers, and demand points, with different costs and capacities. Moreover, each transportation type has a specific CO_2 emission rate. Concerning the problem of the distribution management of relief items, these items should be transferred from the undestroyed areas to the supply centers after a disaster. Supply centers should be in the areas that are not susceptible to earthquakes or natural disasters and should be as near as possible to the communication centers like airports, ports, etc. Afterward, the relief items are transferred from the supply centers to the local distribution centers to be sent to the demand points. However, the relief and rescue centers can become damaged and inaccessible in case of large-scale natural disasters, which has been less considered in previous research, Effective distribution of relief goods after a disaster plays a pivotal role in the rescue operation. The reliable distribution of relief goods not only protects the relief and rescue workers but also ensures the on-time delivery of the relief items to individuals. Therefore, building distribution centers that are less subject to disruptions and damages can increase the efficiency of disaster relief logistics and the network's reliability. To assimilate the problem to a real-world one, disturbances such as delayed distribution or the possibility of failure in some distribution center inventories are considered. Moreover, the reliability issue was addressed in the problem to deal with these disorders. Thus, our distribution centers are divided into two reliable and unreliable segments, each of which with its own cost and capacity. Although reliable centers are more expensive, it can be assured that there will be no problem in terms of overcoming the disorders in their performance. Unreliable centers are much less expensive but they can be damaged or disrupted in terms of distribution capacity. To be more compatible with the real world, this research has included the uncertainty of parameters such as affected areas demands and logistic costs.

The model has been proposed based on assumptions below:

- The network of disaster relief logistics consists of three levels of supply center, distribution center, and damaged points.
- The demand points and supply centers are specified.
- Potential points are determined for constructing reliable and unreliable centers.
- The probability of failure is assumed for unreliable distribution centers.
- Reliable distribution centers do not have a probability of failure.
- Each distribution center has a different capacity.
- Multiple relief items are considered for the proposed model.
- The demand for relief items is uncertain.
- Deprivation costs are considered in the model, in addition to the private costs of the disaster relief logistics network consisting of transportation costs, the storage cost of each item type, and fixed costs of the reliable and unreliable centers.
- The maximum time of relief items deprivation time has been considered in the model.
- The distance between the affected areas, distribution centers, and supply center is determined.
- In addition to road transportation, other transportation ways, including relief items transportation by motorboats and rescue helicopters are also considered in this research. Regarding the topographic conditions of the affected area in this study (Sari city flood), sending the relief items from distribution centers to the affected areas is not possible through highways or the main roads. Therefore, the affected people cannot receive relief items through high-capacity trucks and trailers.
- The emission rate of CO_2 for each vehicle is taken into account.
- Each vehicle has a specific capacity to carry relief items.

4. Methodology

This section has three main parts of formulizing the model, modeling the uncertainty, and providing the solution method. The detailed information of each part is as follows:

4.1. Model formulation

The multi-objective mixed integer mathematical programming was formulated to design the relief items distribution network in sustainable disaster relief logistics. Indices, parameters, decision variables, and the mathematical model are as follows:

Sets

I	Index of supply centers (i:1,…, I)
J	Index of distribution centers (j:1,…, J)
K	Index of demand points (affected) (k:1,…, K)
M	Index of Relief Items (m:1,…, M)
L	Index of vehicles (l: 1,…, L)

Parameters

C_{ijk}^{ml}	Transportation cost for the item type m from the supply center i to the demand point k through the distribution center j by the vehicle l
C_{jk}^{ml}	Transportation cost of the item type m from the distribution center j to the demand point of k by the vehicle l
Q_k	Population in demand point k
γ_k	Deprivation cost function that depends on the deprivation time in demand point k
$T_{\max}$	Maximum deprivation cost in such a way that there are no casualties.
t_{ijk}^{l}	Travel time from the supply center i to the demand point k through the distribution center j using the vehicle l
t_{jk}^{l}	Travel time from the distribution center j to the demand point k using the vehicle l
W_{km}	Demand for the item m in each demand point k

e_l	CO_2 emission per kilometer traveled by the vehicle l
DI_{ij}	Distance between supply center i and the distribution center j
DI_{jk}	Distance between distribution center j and the demand point k
$capl_l$	Capacity of transportation type l
H_m	Minimum amount of item m stored in a center
S_m	Storage cost of each item type m
Fr_j	Fixed cost of reliable distribution centers j
Fu_j	Fixed cost of unreliable distribution centers j
qu_j	Capacity of distribution centers j
a	Capacity disruption rate
$BigM$	A big positive number

Decision Variables

P_{jk}^{ml}	Demand ratio in each type of good *m,* which is transferred from the distribution center *j* to the demand point *k* using the vehicle *l*
P_{ijk}^{ml}	Demand ratio in each type of good *m,* which is transferred from the supply center *i* to the demand point k through the distribution center *j* using the vehicle *l*
A_{j}^{m}	The amount of item *m* stored in distribution center *j*
Yr_{j}	Equal to 1, if the reliable distribution center *j* is constructed in *j*; otherwise, zero.
Yu_{j}	Equal to 1, if the unreliable distribution center *j* is constructed in *j*; otherwise, zero.
X_{ijk}	Equal to 1, if the demand point *k* receives the goods from the supply center *i* through the distribution center j; otherwise, zero.
X_{jk}	Equal to 1, if the demand point *k* receives the goods from the distribution center *j*; otherwise, zero.
TM_{ijk}^{ml}	Equal to 1, if the vehicle type *l* is chosen to transport each item type *m* from the supply centers *i* to the demand point *k* through the distribution center *j*; otherwise, zero.
TM_{jk}^{ml}	Equal to 1, if the vehicle type *l* is chosen to transport each item type *m* from the distribution center *j* to the demand point *k*; otherwise, zero.

Mathematical Formulation

$$Min\ Z_1 = \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L} C_{jk}^{ml}.W_{km}.P_{jk}^{ml} + \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{I}\sum_{l=1}^{L} C_{ijk}^{ml}.W_{km}.P_{ijk}^{ml}$$
$$+\sum_{j=1}^{J} Fr_j.Yu_j + \sum_{j=1}^{J} Fu_j.Yr_j + \sum_{m=1}^{M}\sum_{j=1}^{J} S_m.A_j^m + \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L} \gamma_k(t_{jk}^l).Q_k.P_{jk}^{ml}$$
$$+\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L} \gamma_k(t_{ijk}^l).Q_k.P_{ijk}^{ml} \quad (1)$$

$$Min\ Z_2 = \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{i=1}^{I} DI_{ij}.e_l.P_{ijk}^{ml} + DI_{jk}.e_l.P_{jk}^{ml} \quad (2)$$

Subject to:

$$\sum_{j=1}^{J} X_{jk} = 1 \qquad \forall k \in K \quad (3)$$

$$P_{jk}^{ml} \le X_{jk} \qquad \forall j \in J, k \in K, m \in M, l \in L \quad (4)$$

$$P_{ijk}^{ml} \le X_{ijk} \qquad \forall i \in I, j \in J, k \in K, m \in M, l \in L \quad (5)$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} P_{jk}^{ml} + \sum_{l=1}^{L}\sum_{j=1}^{J}\sum_{i=1}^{I} P_{ijk}^{ml} = 1 \qquad \forall k \in K, m \in M \quad (6)$$

$$\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{k=1}^{K} W_{km}.P_{jk}^{ml} \le \left(qu_j.yr_j + a.qu_j.yu_j\right) \qquad \forall j \in J \quad (7)$$

$$A_j^m \ge H_m.(Yr_j + Yu_j) \qquad \forall j \in J, m \in M \quad (8)$$

$$X_{jk} \le (Yr_j + Yu_j) \qquad \forall j \in J, k \in K \quad (9)$$

$$X_{ijk} \le (Yr_j + Yu_j) \qquad \forall i \in I, j \in J, k \in K \quad (10)$$

$$t_{jk}^l.X_{ijk} \le T_{\max} \qquad \forall j \in J, k \in K, l \in L \quad (11)$$

$$t_{ijk}^l.X_{ijk} \le T_{\max} \qquad \forall i \in I, j \in J, k \in K \quad (12)$$

$$TM_{jk}^{ml} \le X_{jk} \qquad \forall j \in J, k \in K, m \in M, l \in L \quad (13)$$

$$TM_{ijk}^{ml} \le X_{jk} \qquad \forall i \in I, j \in J, k \in K, l \in L, m \in M \quad (14)$$

$$P_{ijk}^{ml} \le capl_l . TM_{ijk}^{ml} \qquad \forall i \in I, j \in J, k \in K, l \in L, m \in M \qquad (15)$$

$$P_{jk}^{ml} \le capl_l . TM_{jk}^{ml} \qquad \forall j \in J, k \in K, l \in L, m \in M \qquad (16)$$

$$TM_{ijk}^{ml} \le (Yr_j + Yu_j) \qquad \forall i \in I, j \in J, k \in K, l \in L, m \in M \qquad (17)$$

$$TM_{jk}^{ml} \le (Yr_j + Yu_j) \qquad \forall j \in J, k \in K, l \in L, m \in M \qquad (18)$$

$$\sum_{l=1}^{L} \sum_{k=1}^{K} W_{km} \cdot P_{jk}^{ml} - A_j^m = 0 \qquad \forall j \in J, m \in M \qquad (19)$$

$$A_j^m \le BigM.(Yr_j + Yu_j) \qquad \forall j \in J, m \in M \qquad (20)$$

$$Yr_j, Yu_j, X_{ijk}, X_{ij}, \in \{0,1\} \qquad \forall i \in I, j \in J, k \in K \qquad (21)$$

$$0 \le P_{jk}^{ml} \le 1 \qquad \forall j \in J, k \in K, m \in M, l \in L \qquad (22)$$

$$0 \le P_{ijk}^{ml} \le 1 \qquad \forall i \in I, j \in J, k \in K, m \in M \qquad (23)$$

$$A_j^m \ge 0 \qquad \forall j \in J, m \in M \qquad (24)$$

Equation (1) shows the objective function that minimizes all the incurred costs during the emergency response. The presented formula involves private costs such as transportation costs from the supply centers to the distribution centers and from the distribution centers to the demand points, fixed costs of facilitates location, and pre-determined inventory costs, as well as deprivation costs, which are due to lack of access to sustainable items required for a living. In this formula, decision variables such as demand ratio are present because they are related to two different costs in the objective function. Transportation costs are related to each product's demand while deprivation costs rely on the population (number of people) and travel time and are related to the deprivation time. Equation (2) presents the second objective function that minimizes the amount of pollution generated by the network. Constraint (3) ensures that each distribution center gives service to each demand point. Constraint (4) guarantees that if a distribution center does not explicitly serve the demand, no shipments are assigned to it. Constraint (5) ensures that if a supply center does not help a distribution center, no shipment is transferred from the supply centers to the distribution center. Constraint (6) indicates that the total demand ratio for each item that is sent to the demand point's *k* is equal to one. Constraint (7) refers to the capacity of the distribution center and assures that if no one is located in site *j*, no shipments can be sent. Constraint (8) states that if there is a distribution center, it should store a minimum amount of item type *m* so that it is worth to open the facility. Constraints (9) and (10) express that X *has* a value only when Y *has* a value. In other words, no region can be assigned to the distribution center if no facility is built. Constraints (11) and (12) ensures that the travel time from the supply center or the distribution center is less than or maximum equal to the deprivation time such that no casualties are occurred. Constraints (13) and (14) show that until X takes a value equal to one, *TM* cannot accept any values; that is, no transportation types can be used until a value is assigned to X. Constraints (15) and (16) state the capacity constraints of the vehicles. Constraints (17) and (18) state that if a center is not constructed, and Y is not equal to one, we cannot have a transportation type. Constraint (19) provides the possibility to maintain the flow of products. Constraint (20) illustrates that if the center is not established, no items can be stored in the center. Constraint (21) forces the variables to be an integer. Constraints (22) and (23) ensure that the value of the variables varies between zero and one. Constraint (24) is a non-negativity constraint.

4.2. Uncertainty modeling

4.2.1. The chance constrained fuzzy programming model

Some of the proposed mathematic parameters in the previous section have uncertainty. So far, various approaches have been developed to deal with uncertainty and risk in mathematical optimization problems, such as stochastic optimization, fuzzy optimization, robust optimization, and hybrid approaches. Fuzzy reliability coefficients and membership functions are employed in the fuzzy programming models for the expression of uncertainty or lack of knowledge into parameters, which are divided into two categories of possibilistic programming and flexible programming. In possibilistic programming, a lack of adequate knowledge about the accurate values of the parameters is modeled using the existing objective data and the decision maker's knowledge. In flexible programming, the flexibility degrees of the objective function and constraints are employed to control uncertainty, and the modeling will be based on fuzzy or priority sets [48]. In this article, the chance constrained fuzzy programming model (CCFP) introduced by Talaei et al. [49] is used to deal with the uncertainty of the problem's different parameters. The chance constraints approach is one of the major methods to solve the optimization problems under different uncertainties, based on which the model designer makes sure that the possibility of satisfying a constraint is higher than a certain level. In other words, based on that, the feasible region of the problem is limited for the confidence level of the solution to be high. This method is a fundamental approach that relies on deep mathematical concepts such as the expected value of fuzzy numbers and criteria such as possibility (Pos) and necessity (Nec). This model enables the decision-maker to control conservatism to eliminate the constraints, in addition to supporting different forms of fuzzy numbers such as triangular and trapezoidal [50]. For better understanding, consider the following optimization model:

$$
\begin{aligned}
&Min\ \mathrm{Z} = fy + cx \\
&s.t. \\
&Ax \geq d \\
&Bx = 0 \\
&Sx \leq Ny \\
&y \in \{0,1\},\ x \geq 0
\end{aligned}
\tag{25}
$$

Assume that the vector *f* (fixed costs) is a certain parameter and vectors c (variable costs) and *d* (market demand), as well as the matrix of coefficients *N* (facility capacity), are the uncertain parameters of the problem. To build the base model of CCFP, they used the expected value operator to model the uncertain parameters of the objective function and necessity measure (*Nec)* to model the chance constraints. The *Nec* measure can be directly used to convert fuzzy chance constraints to their deterministic equivalents. Since the use of *Nec* is more meaningful in eliminating the chance constraints [50], the trapezoidal fuzzy distribution is used in the modeling process because it can be defined by four sensitive points (i.e. $\tilde{\theta} = \tilde{\theta}_{(1)}, \tilde{\theta}_{(2)}, \tilde{\theta}_{(3)}, \tilde{\theta}_{(4)}$) (Figure 2). Therefore, the basic CCFP model can be formulated as follows:

$$
\begin{aligned}
&Min\ E[Z] = E[f]y + E[\tilde{c}]x \\
&s.t.
\end{aligned}
$$

$$Nec\left\{Ax \geq \tilde{d}\right\} \geq \alpha_m \qquad \forall m \in M \tag{26}$$

$$Bx = 0$$

$$Nec\left\{Sx \leq \tilde{N}y\right\} \geq \alpha_m \qquad \forall m \in M$$

$$y \in \left\{0,1\right\},\ x \geq 0$$

The objective function and first and third constraints (which have uncertain parameters) are considered as fuzzy distributions. Knowing that the constraints with uncertain parameters need to be created with a minimum satisfaction level α_i, the deterministic model can be defined as follows:

$$Min\ E\left[z\right] = fy + \left(\frac{c_{(1)} + c_{(2)} + c_{(3)} + c_{(4)}}{4}\right)x$$

$s.t.$

$$Ax \geq \left(1-\alpha_m\right)d_{(3)} + \alpha_m d_{(4)} \qquad \forall m \in M \tag{27}$$

$$Bx = 0$$

$$Sx \leq \left[(1-\alpha_m)N_{(2)} + \alpha_m N_{(1)}\right]y \qquad \forall m \in M$$

$$y \in \left\{0,1\right\},\ x \geq 0$$

This approach is used to overcome the uncertainty in this research. The model presented in (27) is converted to its deterministic equivalent as follows:

$$Min\ \mathrm{E}[Z_1] = \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L}\left(\frac{C_{jk(1)}^{ml} + C_{jk(2)}^{ml} + C_{jk(3)}^{ml} + C_{jk(4)}^{ml}}{4}\right).\left(\frac{W_{km(1)} + W_{km(2)} + W_{km(3)} + W_{km(4)}}{4}\right).P_{jk}^{ml}$$
$$+\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L}\sum_{i=1}^{I}\left(\frac{C_{ijk(1)}^{ml} + C_{ijk(2)}^{ml} + C_{ijk(3)}^{ml} + C_{ijk(4)}^{ml}}{4}\right).\left(\frac{W_{km(1)} + W_{km(2)} + W_{km(3)} + W_{km(4)}}{4}\right).P_{ijk}^{ml}$$
$$+\sum_{j=1}^{J1} Fr_j.Yu_j + \sum_{j=j1+1}^{J2} Fu_j.Yr_j + \sum_{m=1}^{M}\sum_{j=1}^{J} S_m.A_j^m + \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L}\gamma(t_{jk}^l).Q_K.P_{jk}^{ml} + \sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L}\gamma(t_{ijk}^l).Q_K.P_{ijk}^{ml}$$

$$s.t. \tag{28}$$

$$\sum_{m=1}^{M}\sum_{k=1}^{K}\left[\left(1-\alpha_1\right).W_{km(3)} + \alpha_1.W_{km(4)}\right].P_{jk}^{ml} \leq \left(qu_j.yr_j + qu_j.yu_j\right) \qquad \forall j \in J$$

$$0.5 \leq \alpha_m \leq 1 \qquad \forall m \in M$$

Equations (3-6) and (8-24)

4.2.2. Robust fuzzy programming

In addition to having characteristics of robust optimization, robust fuzzy programming (RFP) can take fuzzy assumptions into account, contrary to the conventional robust programming methods in which some ranges have been provided for the uncertain considerations [49]. The proposed (RFP) model is presented as follows:

$$Min\ \mathrm{E}\left[Z_1\right]+\eta\left(Z_{\max}-E\left[Z\right]\right) \tag{29}$$
$$+\varphi\left[\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{l=1}^{L}\left(W_{km(4)}-\left(1-\alpha_1\right).W_{km(3)}-\alpha_1.W_{km(4)}\right).P_{jk}^{ml}\right]$$

s.t.

$$\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{l=1}^{l}\left[\left(1-\alpha_1\right).W_{km(3)}+\alpha_1.W_{km(4)}\right].P_{jk}^{ml}\le\left(qu_j.yr_j+qu_j.yu_j\right) \qquad \forall j\in J \tag{30}$$

$$0.5\le\alpha_m\le 1 \qquad \forall m\in M \tag{31}$$

Equations (3-6) and (8-24)

Where $Z_{\max}$ is defined as follows:

$$Z_{\max}=\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L}C_{jk(4)}^{ml}.W_{km(4)}.P_{jk}^{ml}+\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{I}C_{ijk(4)}^{ml}.W_{km(4)}.P_{ijk}^{ml} \tag{32}$$
$$+\sum_{j=1}^{J}Fr_j.Y_j+\sum_{j=1}^{J}Fu_j.Y_j+\sum_{m=1}^{M}\sum_{j=1}^{J}S_m.A_j^m+\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L}\gamma(t_{jk}^l).Q_K.P_{jk}^{ml}$$
$$+\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{l=1}^{L}\gamma(t_{ijk}^l).Q_K.P_{ijk}^{ml}$$

The first term in equation (29), similar to the CCFP base model, minimizes the expected value of the objective function. The second term minimizes the difference between pessimistic value and the expected value in the objective function. Further, η indicates the weight or importance of this term against the other terms in the objective function and controls the robustness of the optimization for the solution vector. The third term determines the level of conservatism for each chance constraint and φs are the unit penalties for possible deviations of each chance constraint with uncertain parameters. The coefficients are the difference between the most pessimistic uncertain parameters and the ones that are used in these constraints. In fact, this term controls the robustness of the solution vector.

4.2.3. Linearization of the nonlinear constraints and functions

It should be noted that in the above approaches when technical coefficients are assumed to be uncertain, the linearity of the proposed model chance constraints and the objective function is eliminated. Therefore, it can be said that when the technical coefficients face uncertainty, the model becomes a nonlinear programming. In such cases, the nonlinear terms convert to the linear ones, by adding some constraints and defining new variables for the model; therefore, to avoid the complexity of a nonlinear model, new variables are defined as follows:

$$
\begin{aligned}
&LP_{jk}^{ml} \le \alpha_1 && \forall j \in J, k \in K, m \in M, l \in L \\
&LP_{jk}^{ml} \le Bigm.P_{jk}^{ml} && \forall j \in J, k \in K, m \in M, l \in L \\
&LP_{jk}^{ml} \ge \alpha_1 - Bigm(1 - P_{jk}^{ml}) && \forall j \in J, k \in K, m \in M, l \in L \qquad (33) \\
&LP_{jk}^{ml} = P_{jk}^{ml}.\alpha_1 && \forall j \in J, k \in K, m \in M, l \in L \\
&LP_{jk}^{ml} \ge 0 && \forall j \in J, k \in K, m \in M, l \in L
\end{aligned}
$$

The objective function and nonlinear constraint in the proposed model change as follows:

$$
\begin{aligned}
&Min\ \mathrm{E}[Z_1] + \eta\left(Z_{\max} - E[Z]\right) \qquad (34) \\
&+\varphi\left[\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{m=1}^{M}\sum_{l=1}^{L}\left(W_{km(4)}.P_{jk}^{ml} - W_{km(3)}.P_{jk}^{ml} + W_{km(3)}.LP_{jk}^{ml} - W_{km(4)}.LP_{jk}^{ml}\right)\right]
\end{aligned}
$$

$$
\sum_{m=1}^{M}\sum_{k=1}^{K}\sum_{l=1}^{l} W_{km(3)}.P_{jk}^{ml} - W_{km(3)}.LP_{jk}^{ml} + W_{km(4)}.LP_{jk}^{ml} \le \left(qu_j.yr_j + qu_j.yu_j\right) \qquad \forall j \in J \qquad (35)
$$

4.3. Goal programming

Decision making is a part of our daily life. Almost all managerial decision making problems have multiple and often contradictory criteria for the solutions. Charnes et al. [51] introduced the goal programming concept. Goal programming is one of the most typical methods used when dealing with multi-criteria and multi-objective decision-making (MODM/MCDM) problems. However, a limitation of using goal programming to solve the MODM problems is that the structure of decision-maker priority is not considered easily. The utility function is one of the most extensive methods used for demonstrating the preferences of decision-makers [52]. Multi-choice programming is a method proposed by Chang [53] to solve the problems at the multi-choice goal programming levels. Since the 1970s, many efforts have been made on multi-objective programming. So far, there have been many types of research regarding how to solve the problems surrounding linear multi-objective programming. The goal programming approach is a broadly used technique to solve the multi-objective and multi-criteria decision-making problems by finding a set of satisfactory solutions. The chief reason for its popularity is its intrinsic flexibility that enables the decision-makers to formulate the problems related to the multi-objective decision making, including several criteria, incomplete information, most decision-making variables, and resource constraints [54]. It is introduced by Charnes et al. for the first time, and then developed by Charnes and Cooper [55], Lee [56], Ignizio[57], Tamiz et al. [58] and Romero[59]. In the usual goal programming method, the objective is to minimize the sum of positive and negative deviations of each objective from the goal, and it is defined for each of them. Chang [60] stated that concerning the environmental uncertainties and also the existing disagreements, the decision-makers prefer considering multiple goal levels for each objective function to a single goal. Chang [53] stated that the existence of zero-one variables in the previous model has brought about the complexity of the problem. In order to overcome this problem, Chang provided a model named revised multi-choice goal programming (RMCGP).

$$
\begin{aligned}
& Min \sum_{k} \left[\beta_k^d (d_k^+ + d_k^-) + \beta_k^e (e_k^- + e_k^+) \right] && \\
& S.T. && \forall_k \\
& f_k(X) + d_k^- - d_k^+ = y_k && \forall_k \\
& y_k + e_k^- - e_k^+ = U_{k,\min} && \forall_k \\
& U_{k,\min} \le y_k \le U_{k,\max} && \forall_k \\
& d_k^- . d_k^+ = 0 && \forall_k \\
& d_k^-, d_k^+, e_k^+, e_k^- \ge 0 && \forall_k
\end{aligned}
\tag{36}
$$

Model constraints

In the model above, $U_{k,\min}$ and $U_{k,\max}$ are the range k of the aspiration levels y_k, that is a continuous variable. d_k^+ and d_k^- are the positive and negative deviations of $f_x(X)$ from y_k, respectively. e_k^+ and e_k^- are the positive and negative deviations values from $U_{k,\min}$, respectively. Also, β_k^d and β_k^e indicate the significance level (weight) of ordered pairs (d_k^+, d_k^-) and (e_k^+, e_k^-), respectively. Chang [61] stated that the revised multi-choice goal programming (RMCGP) does not consider the preference level of the decision-makers. Therefore, aiming to maximize the decision-makers' desired utility, he added the utility function to the previous model. The new model is as follows.

$$
\begin{aligned}
& Min \sum_k \left[\beta_k^d (d_k^+ + d_k^-) + \beta_k^\delta \delta_k^- \right] \\
& S.T. \\
& \lambda \le \frac{U_{k,\max} - y_k}{U_{k,\max} - U_{k,\min}} && \forall_k \\
& f_k(X) + d_k^- - d_k^+ = y_k && \forall_k \\
& \lambda_k + \delta_k^- = 1 && \forall_k \\
& U_{k,\min \le y_k} \le U_{k,\max} && \forall_k \\
& d_k^- . d_k^+ = 0 && \forall_k \\
& d_k^-, d_k^+, \delta_k^-, \lambda_k \ge 0 && \forall_k
\end{aligned} \tag{37}
$$

Model constraints

In which δ_k^- indicates the normalized deviation of y_k from $U_{k,\min}$, β_k^δ is the significance level (weight), and λ_k is the utility value. Since Chang's last goal programming model considers the preferences of the decision-makers, in addition to the previous models' merits, this method is used in this study.

4.3.1. Implementing RMCGP with utility function on the problem

In this research, we used the latest goal-programming model introduced by Chang [61] that considers the preferences of decision-makers. According to the definitions and concepts, the multi-choice goal programming model considers the utility function for relief items distribution in sustainable relief logistics as follows:

$$Min \beta_1^d (d_1^+ + d_1^-) + \beta_2^d (d_2^+ + d_2^-) + \beta_1^\delta \delta_1^- + \beta_2^\delta \delta_2^- \quad (38)$$

S.T.

$$\lambda_1 \le \frac{U_{1,\max} - y_1}{U_{1,\max} - U_{1,\min}} \quad (39)$$

$$\lambda_2 \le \frac{U_{2,\max} - y_2}{U_{2,\max} - U_{2,\min}} \quad (40)$$

$$Z_1 + d_1^- - d_1^+ = y_1 \quad (41)$$

$$Z_2 + d_2^- - d_2^+ = y_2 \quad (42)$$

$$\lambda_1 + \delta_1^- = 1 \quad (43)$$

$$\lambda_2 + \delta_2^- = 1 \quad (44)$$

$$U_{1,\min} \le y_1 \le U_{1,\max} \quad (45)$$

$$U_{2,\min} \le y_2 \le U_{2,\max} \quad (46)$$

Model constraints (47)

5. Research area

The city of Sari, with an area of 3248.4 km, is the largest city in Mazandaran province. The center of this city is the Sari town, with a population of more than 504,298 people in 2016, from which 403,307 people are living in Sari City. This city is one of the most populated cities in northern Iran and its geographical coordinates are 36.335974° northern latitude and 53.031981 eastern longitudes. Sari city is bounded by the Caspian Sea on the north, the cities of Mianrood and Neka on the east, the cities of Ghaemshahr and Savadkuh on the west, and Juybar on the northwest. The following map displays the location of Sari city in the Iran and Mazandaran province (Figure 3).

Sari city is located in the east of Mazandaran province and consists of 6 parts: Central, Northern RoudPey, Southern Roudpey, Chahardangeh, Dodangeh, and Kalijan Rustaq. In this study, twelve villages were considered as demand points. Table 2 reports the affected villages and the population of each demand point to receive relief goods.

Five potential points in Sari city were considered as the candidate points for constructing reliable and unreliable relief goods distribution centers. Each of these centers has specific capacities and costs. Criteria for determining these centers include: access way to damaged areas, distance from rivers and dams, and proximity to the crisis area in Sari city. In this study, the Red Crescent warehouse was selected as the supply center. Figure 4 demonstrates the supply center, candidate points for distribution centers construction, and demand points.

According to the information received from the Red Crescent center of Mazandaran province, 72-hour food packages, blankets, carpets, rice bags, oil, tents, and washing powder were the relief items for the injured people of Sari city in the 2019 flood in the villages. The standard set for the storage of relief goods is to provide relief goods for 2% of the population and store relief items for critical times. The storage cost for each item is approximately equal to 25% of the purchase price (Table 3).

Considering the topographic condition of the area, three transportation ways (road, air, and sea) were utilized to distribute the relief goods in critical situations. Table 4 presents the vehicle types and capacities while table 5 provides the CO_2 emission of each type. The distance between supply center *i* and the distribution centers *j* and the distance between the distribution centers *j* and the demand points *k* were estimated by Google Maps.

The item transportation cost from each distribution center to demand points by each road vehicle is estimated in terms of the ton/km unit. Table 6 shows the motorboat and helicopter transportation costs for each trip. Considering the dimensions of each relief good, the capacity of each distribution center is calculated as 0.3829 cubic meters. Table 7 presents the volume of each item. The information about capacity, fixed cost (the fixed cost includes rent, insurance and public services and is related based on one month), and area of each distribution center are described in Table 8.

5.1. Computational results

This section discusses the results of solving the case study with the multi-choice goal programming method. All of the calculations were performed in GAMS software on a personal computer with a processor 2.40 GHz using 4 GB RAM on Windows 8. Table 9 provides the results of the upper and lower bounds of the goal levels. In the following, the results of solving the model with multi-choice goal programming are shown. Table 10 shows the optimal values of the first objective function (Z_1), the second objective function (Z_2), and the goal objective function (Z), as well as deviations. According to the results of Table 10, the first and second objective functions create complete satisfaction, because their deviations (d_1^+, d_1^-), (d_2^+, d_2^-) are zero. After implementing the model, decision variables are obtained and described in Tables 11 and 12. As observed, the distribution centers j_3 and j_4 are selected to construct reliable and unreliable distribution centers, respectively. Table 13 describes the pre-inventory amounts of relief items that should be stored in the distribution center. Table 14 shows that each demand point *k* will receive relief items from which constructed distribution center *j*. Figure 5 shows the flow allocation process as a result of implementing the model. Table A in the Appendix shows the type of vehicle assigned to transport each good from established distribution centers to demand points with respect to the minimum pollution amount.

5.2. Sensitivity analysis

Sensitivity analysis is studying the impressibility of the output variables from the input variables of a statistical model. In other words, it is a method to systematically change the inputs of a statistical model to predict the effects of these variations in the model's output.

In this section, the model's sensitivity to the parameters like transportation costs and demand level is examined in the first objective function. In the second objective function, the model's sensitivity to the distance parameter between the centers is investigated, which can be seen in figures 6, 7 and 8 respectively. The resulting graphs from this analysis demonstrate how each objective function changes if the value of parameters alters. For sensitivity analysis, the coefficients 0.8, 0.9, 1.1, and 1.2 have been used.

According to Figure 6, the demand enhancement of the damaged points leads to an increase, and the demand reduction in such places brings about a decline in the value of the first objective function. As an illustration, the objective function value is 72,220,100 Rials under the base case. A decline of 20% in the demand quantity leads to objective function reduction to 621,606,100 Rials, while an increase in the demand by 20% brings about the objective function enhancement to 822,834,200 Rials. Also, a 10% reduction and 10 % increase have led the objective function to be 671,913,100 Rials and 772,527,100 Rials, respectively.

As demonstrated in Figure 7, reducing the transportation cost leads to the decline of the first objective function, while as it increases the value of the objective function rises. A decline of

20% in the transportation cost leads to objective function reduction to 706,987,000Rials, while an increase in the transportation cost by 20% brings about the objective function enhancement to 737,453,300 Rials. Also, a 10% reduction and 10 % increase have led the objective function to be 712,562,900 Rials and 729,836,700 Rials, respectively.

Figure 8 shows the distance variation value between the centers in the second objective function. According to the predictions, as the distance increases, the second objective function rises. Also, the distance reduction decreases the second objective function.

6. Managerial implications

Different literature reviews have addressed the design problem of disaster relief logistics networks. In this problem, a set of decision-making parameters, including the number, location, and capacity of different centers in the network, is specified. Environmental issues, such as CO_2 emissions, must be taken into account in designing a disaster relief logistics network. In disaster relief logistics, when people do not have access to vital resources for a period, the human suffering and pain cost (deprivation cost) must be considered. Some of the conducted investigations have proposed the humanitarian logistic models based on the social costs (deprivation cost), such as Holguin et al. [65], Cantillo et al. [40]. Conventionally, the network designing models in disaster relief logistics focus on the fixed and operational costs without considering the environmental effects and deprivation costs. The expansion of the knowledge frontier from the conventional supply chains to the green networks has had an important effect on the sustainability of logistics and supply chain networks. There are various indicators to achieve sustainability in disaster relief environments Haavisto & Kovács [21], Dubey & Gunasekaran [28]. By combining relief costs (economic aspect), deprivation costs (social aspect), and Carbon emissions (environmental aspect), we have integrally considered sustainability in this study. The significance of simultaneously considering three aspects of sustainability and presenting a multi-objective optimization model is defined by Boostani et al. [4] and Cao et al. [2]. This study introduces a model for designing a disaster relief network in the operational planning step. The proposed model can determine the optimal position of the distribution centers such that the economic and social impacts of emergency reaction, as well as the environmental contaminations level, are minimized. This study proposes facilities locating model to forecast the required relief items for preparation against disasters, provided at the initial hours of emergency situation. This modeling determines the amount of each product type for providing services to the locations subject to a disaster during the initial reaction. The proposed model in this study leads this decision toward the appropriate number and location of distribution centers and also a proper delivery strategy for each demand point. In this investigation, the optimal number and location of distribution centers are determined such that the social costs are minimized, and each distribution center provides services concerning its particular capacity to a set of demand points with different types of commodities. This model provides a piece of information for the planners and managers of the emergency reaction to decide on the relief items distribution plan. Using the proposed model, decision-makers involved in relief planning can enhance the structure of distribution networks and inventory and reduce victims' dissatisfaction. The results of this study enable planners to improve their preparedness and response operation while considering the best locations for distribution of relief items because the number and location of distribution centers directly affect response time, costs arisen during the disaster relief logistics operation and Carbon emission rate based on transportation mode.

7. Conclusions and suggestions

The humanitarian logistics goals include guaranteeing on-time delivery of resources to injured individuals in the disaster at the response stage, reducing human suffering, and minimizing casualties. In this regard, the design of the appropriate models is necessary for minimizing social, economic, and environmental costs of response operation and distribution of relief items to the harmed population. In this research, a multi-objective mixed integer mathematical programming model is presented to design a decision support model for the relief items distribution network in sustainable disaster relief logistics. The proposed model aims at reducing the relief costs and environmental pollutions in addition to reducing social costs (deprivation cost). Reliability is taken into account in the problem to overcome the disruptions. To overcome the uncertainties, a robust fuzzy optimization approach was utilized and an equivalent robust model was proposed for the studied problem. Then, the multi-objective model was solved using the multi-choice goal programming. To evaluate the performance of the model, a case study was evaluated based on real data. In addition to road transportation, other transportation modes, including relief items transportation by motorboats and rescue helicopters are also considered in this research. Regarding the topographic conditions of the affected area in this study (Sari city flood), sending the relief items from distribution centers to the demand points is not possible through highways or the main roads. Therefore, the affected people cannot receive relief items through high-capacity trucks and trailers. In this study, different relief items are transferred among the distribution and supply centers and demand points by different types of transportations. Each vehicle emits a different amount of CO_2 according to the traveled distance. The emission rate of CO_2 for each vehicle is taken into account and each vehicle has a specific capacity to carry relief items. The obtained results specify the type of vehicle assigned to transport each good from established distribution centers to demand points with respect to the minimum pollution amount (Appendix). Besides, the results indicate that from which constructed distribution center each demand point receives the relief items and how much is the pre-inventory of relief goods is in the distribution centers. The computational results from solving the case study with a multi-choice goal programming method reveal the proper performance of the model. It can be concluded that the proposed model can provide an effective way to manage relief items distribution under uncertainty. Accordingly, a sensitivity analysis was performed on some of the model parameters to the objective function, and changes in the objective function were presented concerning the changes of each parameter. Despite the mentioned contribution, our study is not free of limitations. One of the research limitations is solving model in the large-scale. Therefore, using the metaheuristic algorithms to solve larger problems is way to develop the model. In order to develop the current model, it is proposed that vehicle routing is considered in accordance with environmental purposes. Carrying out the routing and facilities location assists the relief time reduction and more reliable route selection, which will be addressed in further studies. The proposed model can determine other variables and constraints for achieving more compatibility with the real world. Our model only considers the disruption in facilities, whereas disconnections of networks such as routes or roads can also be taken into account. In addition to transporting relief items to the damaged points, evacuating such individuals from these places and transferring them to the emergency units, like the emergency departments, can be considered in this model. The routing of relief items transportation vehicles from supply centers to the distribution centers and demand points are topics that can be considered in further studies.

References

1. Gökçe, M. A., and Ercan, E. “Multi-period vehicle routing & replenishment problem of neighborhood disaster stations for pre-disaster humanitarian relief logistics”, *IFAC-Papers Online*, **52**(13), pp. 2614-2619 (2019).

2. Cao, C., Li, C., Yang, Q., Liu, Y., et al. “A novel multi-objective programming model of relief distribution for sustainable disaster supply chain in large-scale natural disasters”, *Journal of Cleaner Production*, **174**, pp. 1422-1435 (2018).

3. Cao, C., Liu, Y., Tang, O., et al. “A fuzzy bi-level optimization model for multi-period post-disaster relief distribution in sustainable humanitarian supply chains”, *International Journal of Production Economics*, **235**, p. 108081 (2021).

4. Boostani, A., Jolai, F., and Bozorgi-Amiri, A. “Designing a sustainable humanitarian relief logistics model in pre-and postdisaster management”, *International Journal of Sustainable Transportation*, **15**, pp. 1-17 (2020).

5. Loree, N., and Aros-Vera, F. “Points of distribution location and inventory management model for Post-Disaster Humanitarian Logistics”, *Transportation Research Part E: Logistics and Transportation Review*, **116**, pp. 1-24 (2018).
6. Rahmani, D., Zandi, A., Peyghaleh, E., et al. “A robust model for a humanitarian relief network with backup covering under disruptions: A real world application”, *International journal of disaster risk reduction*, **28**, pp. 56-68 (2018).
7. Theeraviriya, C., Pitakaso, R., Sillapasa, K., et al. “Location decision making and transportation route planning considering fuel consumption”, *Journal of Open Innovation: Technology, Market, and Complexity*, **5**(2), p. 27 (2019).
8. Shen, L., Tao, F., Shi, Y., et al. “Optimization of location-routing problem in emergency logistics considering carbon emissions”, *International journal of environmental research and public health*, **16**(16), p. 2982 (2019).
9. Bozorgi-Amiri, A., Jabalameli, M. S., and Al-e-Hashem, S. M. “A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty”, *OR spectrum*, **35**(4), pp. 905-933 (2013).
10. Hatefi, S. M., and Jolai, F. “Robust and reliable forward–reverse logistics network design under demand uncertainty and facility disruptions”, *Applied Mathematical Modeling*, **38**(9-10), pp. 2630-2647 (2014).
11. An, S., Cui, N., Bai, Y., et al. “Reliable emergency service facility location under facility disruption, en-route congestion and in-facility queuing”, *Transportation research part E: logistics and transportation review*, **82**, pp. 199-216 (2015).
12. Huang, X., and Song, L. “An emergency logistics distribution routing model for unexpected events”, *Annals of Operations Research*, **269**(1), pp. 223-239 (2018).
13. Hu, C. L., Liu, X., and Hua, Y. K. “A bi-objective robust model for emergency resource allocation under uncertainty”, *International Journal of Production Research*, **54**(24), pp. 7421-7438. (2016).
14. Haghi, M., Ghomi, S. M. T. F., and Jolai, F. “Developing a robust multi-objective model for pre/post disaster times under uncertainty in demand and resource”, *Journal of Cleaner Production*, **154**, pp. 188-202 (2017).
15. Liu, Y., Lei, H., Wu, Z., et al. “A robust model predictive control approach for post-disaster relief distribution”, *Computers & Industrial Engineering*, **135**, pp. 1253-1270 (2019).
16. Lin, Y. H., Batta, R., Rogerson, P. A., et al. “A logistics model for emergency supply of critical items in the aftermath of a disaster”, *Socio-Economic Planning Sciences*, **45**(4), pp. 132-145 (2011).

17. Wang, H., Du, L., and Ma, S. “Multi-objective open location-routing model with split delivery for optimized relief distribution in post-earthquake”, *Transportation Research Part E: Logistics and Transportation Review*, **69**, pp. 160-179 (2014).

18. Balcik, B., and Yanıkoğlu, İ. “A robust optimization approach for humanitarian needs assessment planning under travel time uncertainty”, *European Journal of Operational Research*, **282**(1), pp. 40-57 (2020).

19. Aghajani, M., Torabi, S. A., and Heydari, J. “A novel option contract integrated with supplier selection and inventory prepositioning for humanitarian relief supply chains”, *Socio-Economic Planning Sciences*, **71**, p. 100780 (2020).

20. Habib, M. S., Lee, Y. H., and Memon, M. S. “Mathematical models in humanitarian supply chain management: A systematic literature review”, *Mathematical Problems in Engineering*, (2016).

21. Haavisto, I., and Kovács, G. “Perspectives on sustainability in humanitarian supply chains”, *Disaster Prevention and Management*, **23**(5), pp. 610-631 (2014).

22. Carter, C. R., and Rogers, D. S. “A framework of sustainable supply chain management: moving toward new theory”, *International journal of physical distribution & logistics management*, **38**, pp. 360-387 (2008).

23. Kaivo-oja, J., Panula-Ontto, J., Vehmas, J., et al. “Relationships of the dimensions of sustainability as measured by the sustainable society index framework”, *International Journal of Sustainable Development & World Ecology*, **21**(1), pp. 39-45 (2014).

24. Weerawardena, J., McDonald, R. E., and Mort, G. S. “Sustainability of nonprofit organizations: An empirical investigation”, Journal *of World Business*, **45**(4), pp. 346-356 (2010).

25. Ibegbunam, I., and McGill, D. “Health commodities management system: priorities and challenges”, *Journal of Humanitarian Logistics and Supply Chain Management*, **2**(2), pp. 161-182 (2012).

26. Haavisto, I., and Kovacs, G. “Sustainability in humanitarian operations”, *Sustainable Value Chain Management Analyzing, Designing, Implementing, and Monitoring for Social and Environmental Responsibility*, pp. 489-507 (2013).

27. Kunz, N., and Gold, S. “Sustainable humanitarian supply chain management–exploring new theory”, *International Journal of Logistics Research and Applications*, **20**(2), pp. 85-104 (2017).

28. Dubey, R., and Gunasekaran, A. “The sustainable humanitarian supply chain design: agility, adaptability and alignment”, *International Journal of Logistics Research and Applications*, **19**(1), pp. 62-82 (2016).

29. Zhang, P., Liu, Y., Yang, G., et al. “A multi-objective distributionally robust model for sustainable last mile relief network design problem”, *Annals of Operations Research*, pp. 1-42 (2020).

30. Jamali, A., Ranjbar, A., Heydari, J., et al. "A multi-objective stochastic programming model to configure a sustainable humanitarian logistics considering deprivation cost and patient severity", *Annals of Operations Research*, pp.1-36 (2021).

31. Haghani, S. C. O. A. "Testing and evaluation of a multi-commodity multi-modal network flow model for disaster relief management", *Journal of Advanced Transportation*, **31**(3), pp. 249-282 (1997).

32. Fiedrich, F., Gehbauer, F., and Rickers, U. "Optimized resource allocation for emergency response after earthquake disasters", *Safety science*, **35**(1-3), pp. 41-57 (2000).

33. Özdamar, L., Ekinci, E., and Küçükyazici, B. "Emergency logistics planning in natural disasters", *Annals of operations research*, **129**(1-4), pp. 217-245 (2004).

34. Yi, W., and Kumar, A. "Ant colony optimization for disaster relief operations", *Transportation Research Part E: Logistics and Transportation Review*, **43**(6), pp. 660-672 (2007).

35. Mete, H. O., and Zabinsky, Z. B. "Stochastic optimization of medical supply location and distribution in disaster management", *International Journal of Production Economics*, **126**(1), pp. 76-84 (2010).

36. Najafi, M., Eshghi, K., and Dullaert, W. "A multi-objective robust optimization model for logistics planning in the earthquake response phase", *Transportation Research Part E: Logistics and Transportation Review*, **49**(1), pp. 217-249 (2013).

37. Veysmoradi, D., Vahdani, B., Farhadi Sartangi, M., et al. "Multi-objective open location-routing model for relief distribution networks with split delivery and multi-mode transportation under uncertainty", *Scientia Iranica*, **25**(6), pp. 3635-3653 (2018).

38. Paydar, M. M., Molladavoodi, H., and Safaei, A. S. "Distribution planning of relief commodities considering the features of demand areas: A robust multi-objective approach", *Scientia Iranica*, **25**(6), pp. 3776-3793 (2018).

39. Shahparvari, S., and Bodaghi, B. "Risk reduction for distribution of the perishable rescue items; A possibilistic programming approach", *International journal of disaster risk reduction*, **31**, pp. 886-901 (2018).

40. Cantillo, V., Serrano, I., Macea, L. F., et al. "Discrete choice approach for assessing deprivation cost in humanitarian relief operations", *Socio-Economic Planning Sciences*, **63**, pp. 33-46 (2018).

41. Cotes, N., and Cantillo, V. "Including deprivation costs in facility location models for humanitarian relief logistics", *Socio-Economic Planning Sciences*, **65**, pp. 89-100 (2019).

42. Paul, J. A., and Wang, X. J. "Robust location-allocation network design for earthquake preparedness", *Transportation research part B: methodological*, **119**, pp. 139-155 (2019).

43. Eshghi, A., Tavakkoli-Moghaddam, R., Ebrahimnejad, S., et al. "Multi-objective robust mathematical modeling for emergency relief in disaster under uncertainty", *Scientia Iranica*, (2020).

44. Madani, H., Arshadi Khamseh, A., and Tavakkoli-Moghaddam, R. “Solving a new bi-objective model for relief logistics in a humanitarian supply chain by bi-objective meta-heuristic algorithms”, *Scientia Iranica*, **28**(5), pp. 2948-2971 (2021).

45. Zhang, L., and Cui, N. “Pre-Positioning Facility Location and Resource Allocation in Humanitarian Relief Operations Considering Deprivation Costs”, *Sustainability*, **13**(8), 4141 (2021).

46. Cheng, J., Feng, X., and Bai, X. “Modeling equitable and effective distribution problem in humanitarian relief logistics by robust goal programming”, *Computers & Industrial Engineering*, **155**, 107183 (2021).

47. Nayeem, M. K., and Lee, G. M. “Robust Design of Relief Distribution Networks Considering Uncertainty”, *Sustainability*, **13**(16), 9281 (2021).

48. Pishvaee, M. S., Rabbani, M., and Torabi, S. A. “A robust optimization approach to closed-loop supply chain network design under uncertainty”, *Applied mathematical modelling*, ***35***(2), pp. 637-649 (2011).

49. Talaei, M., Moghaddam, B. F., Pishvaee, M. S., et al. “A robust fuzzy optimization model for carbon-efficient closed-loop supply chain network design problem: a numerical illustration in electronics industry”, *Journal of Cleaner Production*, **113**, pp. 662-673 (2016).

50. Inuiguchi, M., and Ramık, J. “Possibilistic linear programming: a brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem”, *Fuzzy Sets and Systems*, **111**(1), pp. 3-28 (2000).

51. Charnes, A., Cooper, W. W., and Ferguson, R. O. “Optimal estimation of executive compensation by linear programming”, *Management Science*, **1**(2), pp. 138-151 (1955).

52. Podinovski, V. V. “Set choice problems with incomplete information about the preferences of the decision maker”, *European journal of operational research*, **207**(1), pp. 371-379 (2010).

53. Chang, C. T. “Revised multi-choice goal programming”, *Applied mathematical modelling*, **32**(12), pp. 2587-2595 (2008).

54. Urı́a, M. V. R., Caballero, R., Ruiz, F., et al. “Meta-goal programming”, *European Journal of Operational Research*, **136**(2), pp. 422-429 (2002).

55. Charnes, A., and Cooper, W. W. “Management models and industrial applications of linear programming”, *Management Science*, **4**(1), pp. 38-91(1957).

56. Lee, S. M. “Goal programming for decision analysis”, *Philadelphia: Auerbach Publishers*, **6**(14), pp. 252-260 (1972).

57. Ignizio, J. P. “Introduction to linear goal programming”, *Beverly Hills, CA: Sage*. pp. 1-96 (1985)

58. Tamiz, M., Jones, D., and Romero, C. “Goal programming for decision making: An overview of the current state-of-the-art”, *European Journal of operational research*, **111**(3), pp. 569-581 (1998).

59. Romero, C. “Extended lexicographic goal programming: a unifying approach”, *Omega*, **29**(1), pp. 63-71 (2001).
60. Chang, C. T. “Multi-choice goal programming”, *Omega*, **35**(4), pp. 389-396 (2007).
61. Chang, C. T. “Multi-choice goal programming with utility functions”, *European Journal of Operational Research*, **215**(2), pp. 439-445 (2011).
62. Mohammed, F., Selim, S. Z., Hassan, A., et al. “Multi-period planning of closed-loop supply chain with carbon policies under uncertainty”, *Transportation Research Part D: Transport and Environment*, **51**, pp. 146-172 (2017).
63. Columbia, B. “2012 BC Best Practices Methodology for Quantifying Greenhouse Gas Emissions Including Guidance for Public Sector Organizations, Local Governments and Community Emissions”, Ministry of Environment, (2012).
64. Jun, P., Gillenwater, M., and Barbour, W. “CO2, CH4, and N2O emissions from transportation-water-borne-navigation [Background paper]”, Good practice guidance and uncertainty management in national greenhouse gas inventories, pp.71-92(2002).
65. Holguín-Veras, J., Jaller, M., Van Wassenhove, L. N., et al. “On the unique features of post-disaster humanitarian logistics”, *Journal of Operations Management*, **30**(7-8), pp. 494-506 (2012).

Mahdi Modiri received his Ph.D. degree from the University of Tehran, Tehran, Iran. He is a full professor at MUT, Tehran, Iran. He has authored/co-authored more than 230 scientific publications (ISI listed publications and national and international conferences proceeding) on a wide range of topics such as Passive defense, Sustainable urban planning, Natural hazard vulnerability mitigation, Land management plan, Urban planning and Smart city.

Mohammad Eskandari his master's and PHD majors are Disaster Management and Civil Engineering -GIS, respectively. He has been teaching for about 10 years. His research interests are emergency management plan (EAP, EOP and ERP), earthquake hazard analysis, vulnerability assessment, risk assessment, loss estimation, modeling in GIS, civil defense and et al. According to this have written some papers related to these subjects. Currently, he has 21 published research articles on disaster management and GIS in various journals. Also he has presented 16 research articles in high-level conferences as well.

Samira Hasanzadeh is a Ph.D student of Crisis Management at Malek Ashtar University of Technology, Tehran, Iran. The title of her thesis is “Optimal Model of the Distribution Management of Relief Items in Disaster Relief Logistics (Case Study: Mazandaran Province, SARI)”. Her research interests include crisis management, earthquake damage estimation, risk management and decision making techniques. She has published a number of research articles in journals and conferences.

Tables

Figures

Figure 3. Sari city location in the country and Mazandaran province
Figure 4. Supply center, candidate points to construct distribution centers and demand points
Figure 5. Network status after modeling
Figure 6. The sensitivity analysis of the first objective function on the demand
Figure 7. The sensitivity analysis of the first objective function on transportation cost
Figure 8. The sensitivity analysis of the second objective function on distanc

Tables

Table 1. Comparison of the related published papers with the proposed model

Reference	Model		Sustainability	Main objective			Deprivation costs	Reliability	Uncertainty	Transportation mode	Modeling method	Solution methodology	Type of mathematical programming to deal with the parameter uncertainty
	Multi objective	Single objective		Economic	Environmental	Social							
Haghani [31]	*					*				*		Heuristic	
Fiedrich et al [32]		*								*		Heuristic	
Özdamar et al [33]		*								*		Heuristic	
Yi & Kumar [34]		*									MIP	Meta heuristic	
Mete and Zabinsky[35]	*					*			*	*	MIP		Stochastic
Najafi et al [36]	*								*	*	LP and NLP	Heuristic & Meta heuristic	Robust
Veysmoradi et al[37]	*					*			*	*	MINLP		Robust
Paydar et al[38]	*					*			*			Multi-choice goal programming	Robust
Rahmani et al [6]	*					*		*	*			Heuristic	Robust
Shahparvari and Bodaghi [39]	*					*			*	*		Meta heuristic	Fuzzy

Cantillo et al [40]		*	*	*		*						Discrete choice approach	
Cotes and Cantillo[41]		*		*		*						Exact	
Paul and Wang[42]		*		*		*			*				Robust
Eshghi et al[43]	*					*			*	*	MINLP	Meta heuristic	Robust
Boostani et al [4]	*		*	*	*	*	*		*		MILP	Exact	Stochastic
Aghajani et al [19]						*			*			Exact	Fuzzy
Madani et al[44]	*					*		*		*	MIP	Meta heuristic	
Jamali et al [30]	*		*	*		*	*		*	*	MIP	Multi-choice goal programming	Stochastic
Cao et al [3]	*		*	*		*	*		*		MIP	Exact	Fuzzy
Zhang and Cui[45]	*			*		*	*		*	*	MIP		stochastic
Cheng et al [46]	*								*			goal programming	Robust
Nayeem and Lee [47]	*					*			*	*	MIP		Robust
Current study	*		*	*	*	*	*	*	*	*	MIP	Multi-choice goal programming	Robust Fuzzy

Table 2. Demand points

Demand points k	Village name	District	Number of people in need of relief goods	Demand points k	Village name	District	Number of people in need of relief goods
k_1	Sheykh Ali Mahalleh	Southern Roudpey	52	k_7	Moozi Bagh	Northern RoudPey	64
k_2	Akand	Southern Roudpey	52	k_8	Hamidabad	Northern RoudPey	20
k_3	Kordkhel	Northern RoudPey	60	k_9	Sooteh	Northern RoudPey	100
k_4	Abmal	Northern RoudPey	20	k_{10}	Taherabad	Northern RoudPey	32
k_5	Panbeh Chooleh	Northern RoudPey	100	k_{11}	Sharifabad	Northern RoudPey	60
k_6	Esfandan	Northern RoudPey	100	k_{12}	Hassanabad	Northern RoudPey	140

Table 3. Storage cost of each item type

necessary goods	tent	carpet	blanket	rice bag	oil	72-hour food packages	washing powder
Storage cost	1750000	875000	600000	37500	17500	250000	15000

Table 4. Transportation methods, capacity, and co_2emission of each vehicle

Transportation Method	Vehicle Type	Capacity
Road	1- Lightweight cars like Nissan pickup truck	2 Tones
	2- Semi-heavy cars like the mini truck	10 Tons
	3- Heavy cars like the trailer	22 Tones
Air	4- Helicopter	4 Tones
Sea	5- Boat	566 kilograms

Table 5. CO_2 Emission of each vehicle

Transportation Method	Vehicle Type	CO_2 emission (kg/ton-km)	Reference
Road	1- Lightweight cars like Nissan pickup truck	0.048	[62]
	2- Semi-heavy cars like mini truck	0.0252	
	3- Heavy cars like the trailer	0.297	
Air	4- Helicopter	0.447	[63]
Sea	5- Boat	0.0032	[64]

Table 6. Transportation cost of motorboat and helicopter

Transportation method	Velocity	Transportation cost per travel/(Rial)
Motorboat	45 km/hour	900000
Helicopter	250 km/hour	200000000

Table 7. Each item's volume ($\mathbf{m^3}$)

Item	Tent	Carpet	Blanket	Rice (5 kg)	Oil (1 kg)	Food package	Washing powder
Dimensions	80×50×50	20×70×70	20×60×40	10×10×17	10×10×30	40×30×25	22×20×5
volume (m^3)	0.2	0.098	0.048	0.0017	0.003	0.03	0.0022

The total is equal to 0.3829 cubic meters.

Table 8. Distribution centers' information

Distribution center number	Area (square meter)	Capacity (relief goods quantity)	Fixed costs (Rial)
1	200	522	36000000
2	350	914	63000000
3	500	1305	90000000
4	750	1958	135000000
5	900	2350	162000000

Table 9. Upper/lower goal levels

$U_{2,\max}$	$U_{2,\min}$	$U_{1,\max}$	$U_{1,\min}$
949.804	1.019	7.50006E+11	7.222201E+8

Table 10. Results of the multi-choice goal programming method

Z	**0.003**
Z_1	4.617356E+9
Z_2	1.468
y_1	4.617356E+9
y_2	1.468
d_1^+	0.000
d_1^-	0.000
d_2^+	0.000
d_2^-	0.000
δ_1^-	0.005
δ_2^-	4.725047E-4

Table 11. Selected points to construct reliable distribution centers

j	**1**	**2**	**3**	**4**	**5**
Yr	0	0	1	0	0

Table 12. Selected points to construct unreliable distribution centers

j	**1**	**2**	**3**	**4**	**5**
Yu	0	0	0	1	0

Table 13. Pre-inventory amount of relief items in distribution centers

$a(m, j)$	j_3	j_4
m_1	220	**342**
m_2	68	**152**
m_3	267	**157**
m_4	408	**530**
m_5	100	**371**
m_6	55	**143**
m_7	187	**248**

Table 14. Allocating demand points to the distribution centers

$x(j,k)$	k_1	k_2	k_3	k_4	k_5	k_6	k_7	k_8	k_9	k_{10}	k_{11}	k_{12}
j_3	1	1	1	1	1	1						
j_4							1	1	1	1	1	1

Figures

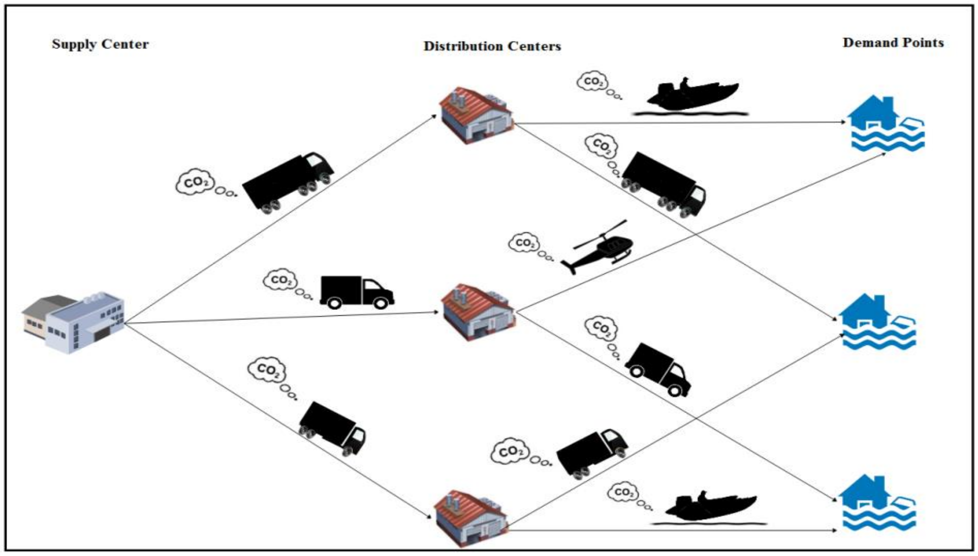

Figure 9. Disaster Relief Logistics Network

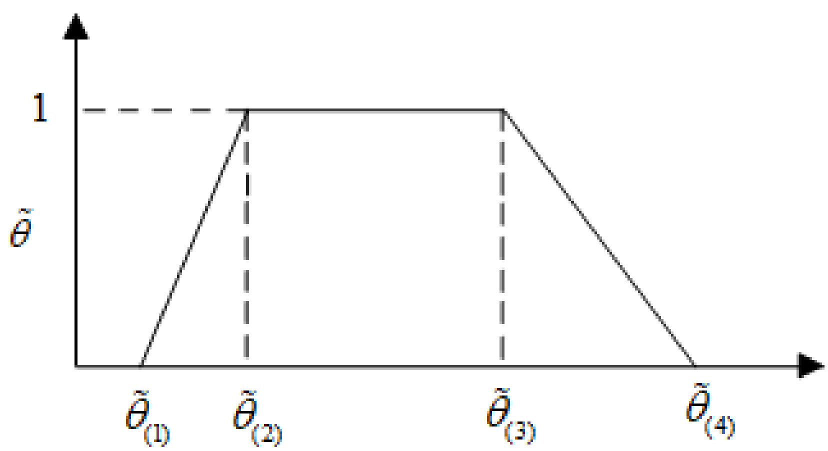

Figure 10. Fuzzy parameter $\tilde{\theta}$

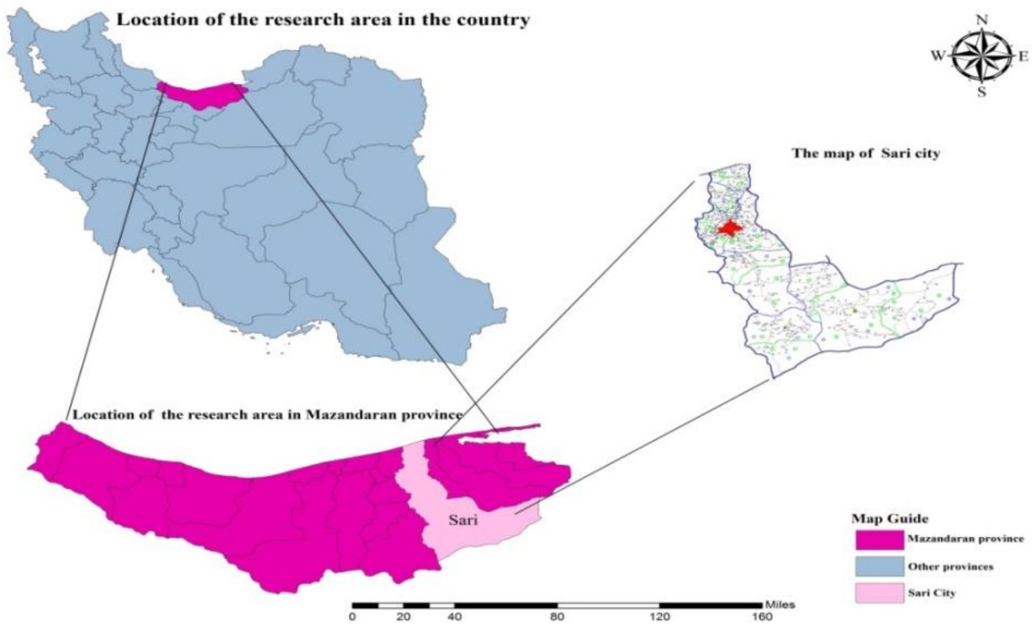

Figure 11. Sari city location in the country and Mazandaran province

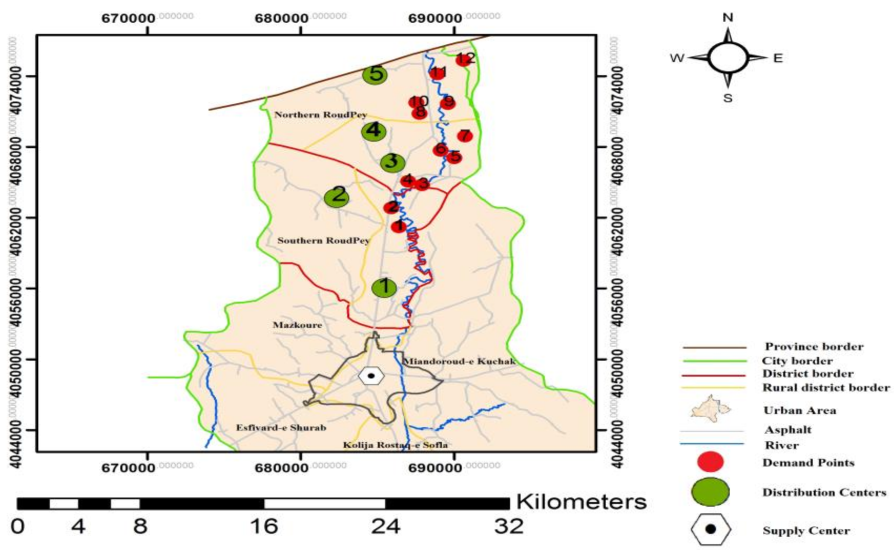

Figure 12. Supply center, candidate points to construct distribution centers and demand points

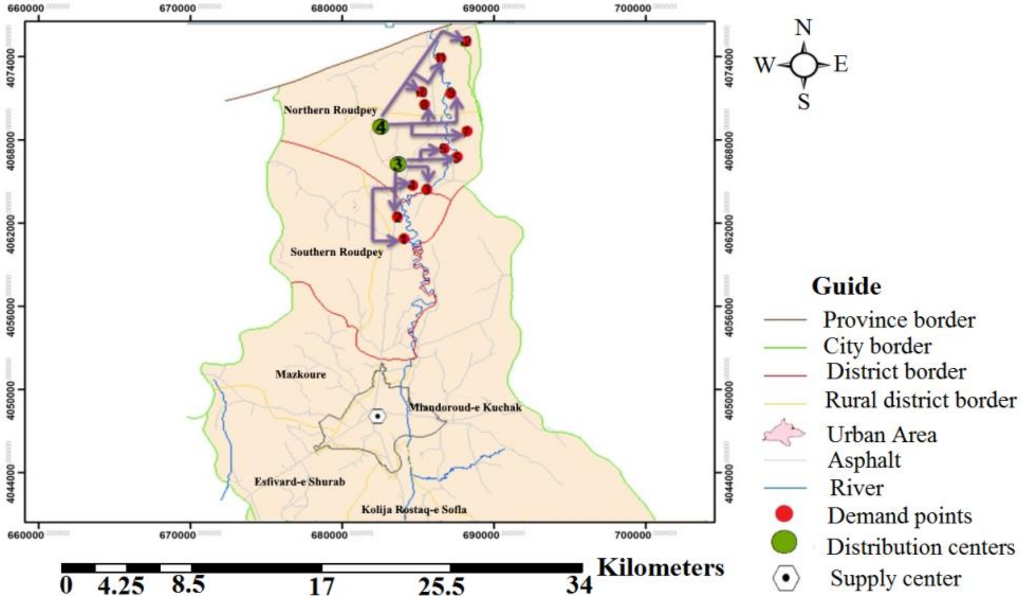

Figure 13. Network status after modeling

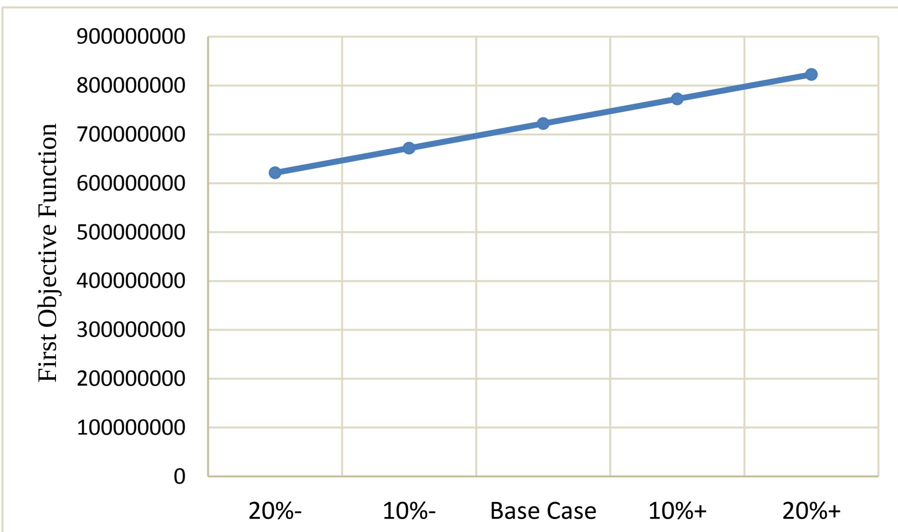

Figure 14. The sensitivity analysis of the first objective function on the demand

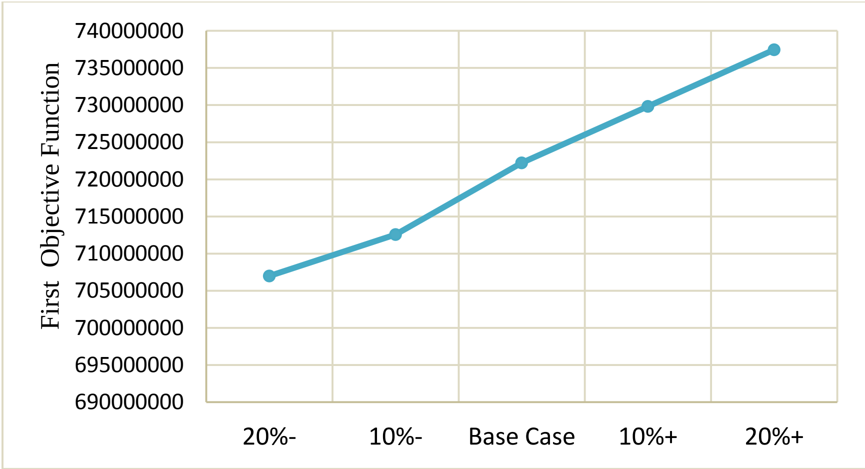

Figure 15. The sensitivity analysis of the first objective function on transportation cost

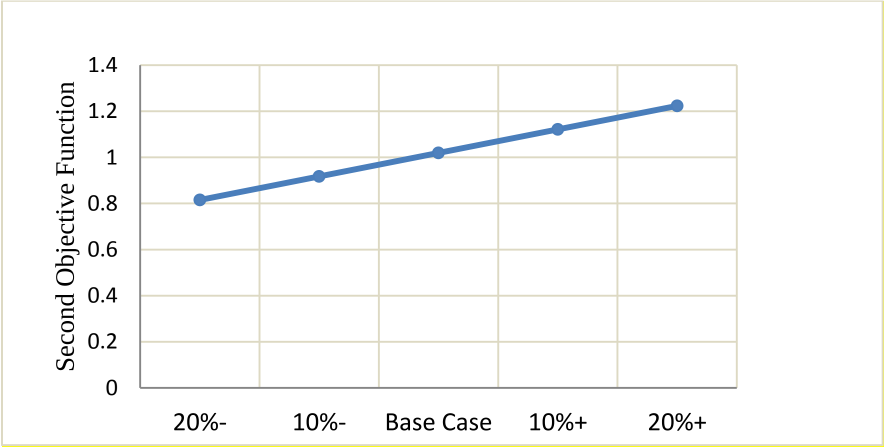

Figure 16. The sensitivity analysis of the second objective function on distance

Appendix

Table A. the type of vehicle l assigned to transport each item type *m* from the distribution center *j* to the demand point *k*

$TM(j,k,m,l)$	Value	$TM(j,k,m,l)$	Value	$TM(j,k,m,l)$	Value
$TM(3,2,1,2)$		$TM(3,4,3,2)$		$TM(3,6,4,1)$	
$TM(3,2,1,5)$	1	$TM(3,4,3,5)$	1	$TM(3,6,4,5)$	1
$TM(3,2,2,2)$		$TM(3,4,4,1)$		$TM(3,6,5,1)$	
$TM(3,2,2,5)$	1	$TM(3,4,4,5)$	1	$TM(3,6,5,5)$	1
$TM(3,2,3,2)$		$TM(3,4,5,2)$		$TM(3,6,6,1)$	
$TM(3,2,3,5)$	1	$TM(3,4,5,5)$	1	$TM(3,6,6,5)$	1
$TM(3,2,4,5)$	1	$TM(3,4,6,2)$		$TM(3,6,7,1)$	
$TM(3,2,5,1)$		$TM(3,4,6,5)$	1	$TM(3,6,7,5)$	1
$TM(3,2,5,5)$	1	$TM(3,4,7,2)$		$TM(3,12,1,5)$	1
$TM(3,2,6,2)$		$TM(3,4,7,5)$	1	$TM(3,12,2,5)$	1
$TM(3,2,6,5)$	1	$TM(3,5,1,1)$		$TM(3,12,3,5)$	1
$TM(3,2,7,2)$		$TM(3,5,1,5)$	1	$TM(3,12,4,5)$	1
$TM(3,2,7,5)$	1	$TM(3,5,2,2)$		$TM(3,12,5,5)$	1
$TM(3,3,1,2)$		$TM(3,5,2,5)$	1	$TM(3,12,6,5)$	1
$TM(3,3,1,5)$	1	$TM(3,5,3,2)$		$TM(3,12,7,5)$	1
$TM(3,3,3,1)$		$TM(3,5,3,5)$	1	$TM(4,1,1,1)$	
$TM(3,3,3,5)$	1	$TM(3,5,4,1)$		$TM(4,1,1,5)$	1
$TM(3,3,4,1)$		$TM(3,5,4,5)$	1	$TM(4,1,2,2)$	
$TM(3,3,4,5)$	1	$TM(3,5,5,2)$		$TM(4,1,2,5)$	1

$TM(j,k,m,l)$	Value	$TM(j,k,m,l)$	Value	$TM(j,k,m,l)$	Value
$TM(3,3,5,2)$		$TM(3,5,5,5)$	1	$TM(4,1,3,2)$	
$TM(3,3,5,5)$	1	$TM(3,5,6,2)$		$TM(4,1,3,5)$	1
$TM(3,3,6,2)$		$TM(3,5,6,5)$	1	$TM(4,1,4,1)$	
$TM(3,3,6,5)$	1	$TM(3,5,7,1)$		$TM(4,1,4,5)$	1
$TM(3,3,7,2)$		$TM(3,5,7,5)$	1	$TM(4,1,5,2)$	
$TM(3,3,7,5)$	1	$TM(3,6,1,2)$		$TM(4,1,5,5)$	1
$TM(3,4,1,1)$		$TM(3,6,1,5)$	1	$TM(4,1,6,2)$	
$TM(3,4,1,5)$	1	$TM(3,6,2,1)$	1	$TM(4,1,6,5)$	1
$TM(3,4,2,2)$		$TM(3,6,2,5)$	1	$TM(4,1,7,2)$	
$TM(3,4,2,5)$	1	$TM(3,6,3,1)$	1	$TM(4,1,7,5)$	1
$TM(4,7,1,5)$	1	$TM(4,9,1,5)$	1	$TM(4,10,5,5)$	
$TM(4,7,2,5)$	1	$TM(4,9,2,2)$		$TM(4,10,6,2)$	
$TM(4,7,3,5)$	1	$TM(4,9,2,5)$	1	$TM(4,10,6,5)$	1
$TM(4,7,4,5)$	1	$TM(4,9,3,2)$		$TM(4,10,7,1)$	
$TM(4,7,5,5)$	1	$TM(4,9,4,1)$		$TM(4,10,7,5)$	1
$TM(4,7,6,5)$	1	$TM(4,9,4,5)$	1	$TM(4,11,1,1)$	
$TM(4,7,7,5)$	1	$TM(4,9,5,2)$		$TM(4,11,1,5)$	1
$TM(4,8,1,1)$		$TM(4,9,5,5)$	1	$TM(4,11,2,2)$	
$TM(4,8,1,5)$	1	$TM(4,9,6,2)$		$TM(4,11,2,5)$	1
$TM(4,8,2,2)$		$TM(4,9,6,5)$	1	$TM(4,11,3,2)$	
$TM(4,8,2,5)$	1	$TM(4,9,7,2)$		$TM(4,11,3,5)$	1
$TM(4,8,3,2)$		$TM(4,9,7,5)$	1	$TM(4,11,4,2)$	

$TM(j,k,m,l)$	Value	$TM(j,k,m,l)$	Value	$TM(j,k,m,l)$	Value
$TM(4,8,3,5)$	1	$TM(4,10,1,1)$		$TM(4,11,4,5)$	1
$TM(4,8,4,1)$		$TM(4,10,1,5)$		$TM(4,11,5,1)$	
$TM(4,8,4,5)$	1	$TM(4,10,2,2)$		$TM(4,11,5,5)$	1
$TM(4,8,5,2)$		$TM(4,10,2,5)$	1	$TM(4,11,6,2)$	
$TM(4,8,5,5)$	1	$TM(4,10,3,1)$		$TM(4,11,6,5)$	1
$TM(4,8,6,2)$		$TM(4,10,3,5)$	1	$TM(4,11,7,5)$	1
$TM(4,8,6,5)$	1	$TM(4,10,4,1)$	1		
$TM(4,8,7,5)$	1	$TM(4,10,4,5)$			
$TM(4,9,1,2)$		$TM(4,10,5,1)$	1		