Journal of Engineering Managment and Soft Computing (JEMSC)

Presenting a mathematical programming model for the allocation of relief goods in crises in the humanitarian supply chain

Somayeh Khoshnami[1] and Elmira Mashayekhi[2]✉

1. Assistance Prof, Department of Industrial Management, Qa. C., Islamic Azad University, Qazvin, Iran. Email: somayeh.khoshnami@iau.ac.ir
2. Corresponding Author. Assistance Prof, Department of Industrial Management, Qa. C., Islamic Azad University, Qazvin, Iran. Email: Mashayekhi_elmira@iau.ac.ir

Article Info

Article type:
Research Article

Article history:
Received 18 September 2025
Received in revised form 14 May 2026
Accepted 1 June 2026
Published online 1 July 2026

Keywords:
Humanitarian supply chain, relief distribution, epsilon constraints.

ABSTRACT

In today's world, natural disasters and humanitarian crises are increasingly increasing, making the need for a rapid and effective response in the provision of relief goods more urgent than ever. The humanitarian supply chain, as a complex system, includes various stages, including the provision, storage, distribution, and delivery of relief goods to affected areas. In this regard, the optimal allocation of resources and relief items to different areas is one of the main challenges in crisis management. In this paper, a mathematical programming model for the distribution of relief items is presented based on the design of a multi-objective, multi-period model for fair distribution. Therefore, in this paper, an optimization model for the distribution of livelihood packages in crisis situations to deal with the crisis is presented. For this purpose, a multi-objective and multi-level humanitarian supply chain has been developed for the fair distribution of livelihood packages to deal with the crisis. Since research on the allocation of emergency supplies usually considers one to two indicators, this paper examines five dimensions of humanitarian logistics indicators, which are: access cost, transportation cost, unmet demand rate in each period and the gap between the demand filling rate and the ideal demand satisfaction rate in the entire period, environmental hazards. In addition, instead of using single-affected-area relief distribution networks or single-period or two-period distribution modes, this paper builds a model for allocating essential supplies, including water, food, medicine, equipment, clothing, and blankets, from multiple relief centers to different affected areas, which is able to treat items fairly among the areas. Because, in this case, planning for affected areas is more consistent with the actual situation. Considering the results obtained, the need for rapid and effective response in crisis situations, this research helps to improve relief processes and reduce related costs, and ultimately leads to saving lives and reducing the damage caused by crises.

Cite this article: Khoshnami, S. & et al, (2026)., Presenting a mathematical programming model for the allocation of relief goods in crises in the humanitarian supply chain. *Journal of Engineering Management and Soft Computing,* 13 (1). 20-38.

DOI: https://doi.org/10.22091/jemsc.2026.13899.1302

DOI: https://doi.org/10.22091/jemsc.2026.13899.1302

Publisher: University of Qom

1) Introduction

When a disaster occurs, humanitarian organizations can obtain relief supplies from three main sources: local suppliers, global suppliers, and distribution centers (pre-designated stockpiles). At the time of a disaster, procurement first attempts to obtain supplies from local sources, and if the relief organization has a centralized warehouse, procurement reviews the supplies available in those warehouses (Ghahremani-Nahr et. Al 2024). An initial assessment is usually conducted within the first 24 hours of a crisis to estimate the resources needed to meet the relief needs of the affected population. The initial request for cash and financial assistance is often made within 36 hours of the disaster. Anything that cannot be purchased locally or from a centralized warehouse is procured from global suppliers through a competitive bidding process. Relief agencies typically develop strong relationships with suppliers of items that are often needed in natural disasters and typically have long-term purchasing contracts with these companies (Peng et. Al 2022). One reason for pre-purchasing supplies is that they can be purchased at a reasonable price. When a disaster occurs, the demand for supplies increases dramatically, and suppliers often increase their prices in response. This is because distribution centers are located as close to the emergency as possible, depending on their strategic operations (Shao-hong et. Al 2022). Although there are additional benefits to operating pre-positioned facilities, there are also several challenges that need to be overcome to ensure the smooth flow of relief supplies. First, some of the difficulties in establishing an effective pre-positioning plan include the uncertainty about whether natural disasters will occur, and if so, where and to what extent. As a result, following a default policy can be costly, and there are only a handful of relief organizations that can support the operating costs of international distribution centers (Aghajani et. Al 2020). Non-governmental organizations (NGOs) are encouraged to focus on operational relief activities rather than disaster preparedness, as this enables them to reduce costs and make their operations more effective in the long term. Most NGOs avoid pre-positioning policies because they are both complex and costly (Narimani et. Al 2023). Another problem is that the total volume of demand met from a predetermined inventory is generally much less than the total volume of resources sent to the disaster area over the entire relief horizon. The overall goal of preparedness is to improve rapid response capabilities to enable timely food assistance in emergencies with both sudden and slow onset. The goal of pre-positioning is to minimize the expected costs in all scenarios, resulting from the selection of predetermined locations and facility sizes, purchasing and storage decisions, shipping of goods to demand points, penalties for unmet demand, and holding costs for unused materials. Improving disaster preparedness in the supply chain is critical because disruptions caused by external events can have significant financial and operational impacts when not properly prepared for. One of the reasons why humanitarian relief organizations engage in preparedness activities to enhance their logistics capabilities is that post-disaster supply logistics pose challenges and risks in obtaining and delivering sufficient resources, which are often time-consuming and costly (Mansoori et. Al 2020). In this regard, several factors need to be considered:

- The availability of relief goods, warehouse capacity and vehicles must be carefully calculated. These constraints can include the number of goods available, transport capacity and delivery time.
- Each affected area has specific needs that must be met. These needs may include food, water, medicine and other essential items. The model must be able to accurately identify and prioritize these needs.
- The costs associated with transporting goods to different areas and distributing them to the affected people must be included in the model. These costs can be affected by distance, type of vehicle and road conditions.
- Time is a critical factor in a crisis situation. The model must be designed in such a way that the delivery time of goods is minimized and the immediate needs of the affected people are met quickly.

- Crisis situations are often accompanied by many uncertainties. These uncertainties can include changes in the needs of the affected people, delays in transport and weather conditions. The model must be able to manage these risks.

Considering the presented cases, it should be kept in mind that the conditions in each country may be different based on geographical, political, and social location, and the most important of all these cases are the facilities and connections with other global aid organizations. Crisis management during crises in specific cases such as the floods that occurred in Golestan and Khuzestan provinces in 2018 and the Kermanshah earthquake in 2018 showed that in the field of crisis management, there is a need to get more help from knowledge and technology. In this regard, to prevent the occurrence of the observed cases and the discrimination that occurred in some areas of these provinces, distribution centers should be selected scientifically and free from any haste and confusion caused by management excitement. For this purpose, in this research, we will look for the following point: distribution services, casualty collection services, and transportation to hospitals and hospital centers, health centers and relief centers through the conditions experienced by individuals, and also using the fastest transportation route, which is often used for transportation in the medical sector, to mobile relief centers by vehicle and then to the hospital by helicopter. In locating warehouses, only one point should be considered, which is the distribution of people's density in different rural and urban areas, and the route before entering these areas will not be of much importance because usually the main routes usable for heavy machinery in urban areas are not more than one or two and we will have to use these routes. It is observed that considering these cases has not been seen properly in previous research, and this question arises in the mind: can these cases be achieved using mathematical modeling and achieve better results at lower cost? Considering these factors, a mathematical programming model should be designed to facilitate the optimization of the allocation of relief goods with the aim of reducing costs and increasing efficiency in responding to crises. This model can help humanitarian organizations manage their resources more effectively and respond to the needs of the affected people.

The remainder of the paper is organized as indicated. In the second section, a research background is presented to identify the research gap. In the third section, the research modeling framework is presented. In the fourth section, the findings obtained from the proposed model are presented. Finally, in the fifth section, an overall conclusion is presented along with future suggestions.

2) Literature Review

The location of facilities for disaster response has been carefully considered by decision makers. Several studies have proposed dominant and non-dominated solutions, usually based on single-objective optimization models or computational methods of multi-objective problems, in an attempt to improve the efficiency and effectiveness of humanitarian relief logistics. These facilities include shelters, medical centers, warehouses, distribution centers, disease control and prevention, and waste disposal (Boonmee et. Al 2017). Among these investigations, some studies involve subjective judgments in which decision makers define their preferences (Roh et. Al 2018). The existing literature is reviewed and grouped based on model formulation, supply chain levels, objective function, facility types, solutions, and case study. In this classification, the objective function is classified into profit-making and non-profit-making. Based on the literature review, the model formulation and problem-solving approaches are summarized in Table 1. Most of the existing papers proposed single-objective optimization models to improve profitability or non-profitability criteria, such as minimizing the number of shelters and solving the model problem with an exact algorithm by Ozbay et al., (2019), minimizing the total cost of shelter location-allocation and using a genetic algorithm to solve this model by Praneetpholkrang and Huynh (2020), and maximizing the satisfaction of decision makers and solving the model formulated using weighted goal programming by Kanoun et al. (2010). Most of these studies use weight assignment methods (i.e., weighted goal programming and weighted objective function method) to address the computational methods of multi-objective problems. These methods are not suitable for use in the field of humanitarian logistics. This makes decision makers confused when deciding which criterion is important.

Some of the most important studies recently published in this field are briefly introduced below. For example, Boonmee et al. (2017) examined pre- and post-disaster problems including the location of distribution centers, warehouses, shelters, landfills, and medical facilities. They also categorized all humanitarian problems based on different modeling methods, different problems, and considered pre- and post-disaster conditions. Maharjan and Hanaoka (2020) developed a multi-objective location allocation model under uncertainty for humanitarian supply and distribution. The proposed model considers the objectives of minimizing the total cost and maximizing the total demand coverage. The epsilon constraint method is used to solve the model. Aghajani et al. (2020) proposed a dual-objective computational model under uncertainty for a humanitarian relief supply chain. The proposed network is intended to minimize the total cost and maximize the demand. The weighted epsilon constraint method is used to solve the model (2020) developed a multimodal humanitarian supply distribution model considering different modes of transportation that tend to minimize the total delivery time and the total network cost. Mansoori et al. (2020) proposed a dual-objective model for humanitarian supply chains. In this study, relief logistics under uncertainty are carried out with the aim of minimizing the total number of victims who are not evacuated or transported to the hospital and minimizing the total unmet demand. The parameters of travel time and demand under uncertainty are considered. The proposed model is then solved using the weighted Chebyshev method. Sabouhi et al. (2020) proposed a two-stage stochastic programming model for humanitarian supply chain management considering uncertainty and disruptions. Decision-making on the location of distribution centers and decisions on timing and routing are taken in the first and second stages of the proposed approach, respectively. Mamashli et al. (2021) proposed a scenario-based multi-objective programming model in their study to investigate the sustainable-resilient routing allocation problem considering the concept of humanitarian supply chain. The objective of the proposed model is to minimize the total travel time, total environmental impacts, and total demand loss. A fuzzy robust stochastic optimization approach is used to deal with uncertain data in disaster situations. Jahangiri et al. (2023) in their study evaluated the elements of humanitarian supply chain for its successful implementation in Iranian hospitals using a hybrid decision-making method based on best-worst and TOPSIS. In this study, by determining the importance of each of the indicators affecting resources using the best-worst method, the priority of key resources was performed using the TOPSIS method. Rezaei Kallaj et al. (2021) addressed a problem of routing rescue vehicles for blood delivery in a disaster during an earthquake. In this study, a multi-objective problem is presented to control the maximum amount of blood collected in the shortest possible time using a mixed integer programming problem. Wang et al. (2021) proposed a mixed integer programming model based on time cost under uncertainty. The presented model helps solve the problem of locating and distributing emergency storage. Considering factors such as time cost, penalty cost for resource shortage, considering alternative resources from each supplier and emergency shelters, different means of transportation, and multiple resource types are involved in this study. Cao et al. (2021) formulate a fuzzy three-objective two-level integer programming model to minimize the unmet demand rate, potential environmental risks, contingency costs at the top of the hierarchy, and maximize the perceived satisfaction of the survivors at the bottom of the hierarchy. Niavand et al. (2024) analyzed the critical success factors for sustainable supply chain initiatives during the COVID-19 pandemic in India. The analysis and ranking based on the deployment of the best-worst quality composite performance are used. Shao-hong et al. (2022) present a station location algorithm for goods transfer. This method is based on the inverse nearest neighbor algorithm and local density characteristics. For this purpose, it first screens the location of the transfer station in the area to determine its location and coverage area based on the density of the appropriate distance. Finally, by calculating the necessary indicators of each station in the distribution area, the boundary of the distribution area is redefined. Peng et al. (2022) have developed a model for locating emergency resource centers with a total weighted distance objective. Then, a new multi-objective discrete particle swarm optimization is designed for it. Finally, numerical experiments of comparison algorithms and erosion experiments are carried out on 26 datasets to demonstrate the effectiveness and generality of the proposed algorithm. In this study, Narimani et al. (2023) have presented a mathematical programming model for distributing relief items in a humanitarian supply chain at two levels, upstream and downstream. For this purpose, a multi-objective and multi-level humanitarian supply chain is developed for the equitable distribution of livelihood packages to deal with the crisis. The proposed model has 3 objective functions that are solved by the weighted sum method. Ghahramaneh Nahr et al. (2024) have investigated deprivation costs in humanitarian logistics by incorporating direct and indirect effects in a robust fuzzy-probabilistic framework to optimize resource allocation and minimize response delays to disasters. Temiz et al. (2025) have formulated a model as a bi-objective probabilistic mixed integer linear programming whose objectives are to minimize the total cost (i.e., fuel cost, vehicle fixed cost, and opening fixed cost) and total travel time. A solution approach based on a clustering algorithm is also proposed to solve larger instances of the problem. The effectiveness of this heuristic is demonstrated through its application to larger scale problems.

In Table 1, the relevant papers are classified based on model type, supply chain level, objective function type, solution method, and disaster type.

Table 1. Classification of studies

Author	Model	Supply Chain Levels	Objective Function		Solution Method	Disaster Type	Uncertainty Parameter
			Profitability	Non-profitability			
Temiz et al. (2025)	Location		Total Cost	Total travel time	Clustering Algorithm	Flood	-
Ghahremani-Nahr et al. (2024)	Location	Multilevel	-	Resource allocation Disaster response delays	Epsilon Constraint	Earthquake	Cost
Narimani et al. (2023	Location	Two-level	-	Equitable distribution of items	Epsilon Constraint	Earthquake	Demand
Shao-hong et al. 2022	Location	-	-	Locating goods transfers	Nearest Neighbor	-	-
Peng et al. (2022)	Location	-	-	Locating emergency resources	PSO	-	-
Hemmati et al. (2025)	Decision-Making	Multiple	-	Sustainable success of the humanitarian supply chain	QFD-BWM	COVID-19	-
Rezaei Kallaj et al. (2021)	Multi-purpose	Multiple	-	• Maximum blood collected • Minimum blood collection time	CPLEX	Earthquake	-
Wang et al. (2021)	Multi-purpose	Multiple	Minimizing Cost	• Minimizing time	PSO-VNS	Earthquake	Time Cost
Cao et al. (2021)	Multi-purpose	Multiple	Emergency Costs	• Minimizing unmet demand • Minimizing environmental impact	Innovative	Earthquake	Unmet Demand
Mansoori et al. (2020)	Multi-purpose	Multiple	-	• Minimizing total number of victims • Minimizing unmet demand	Weighted Chebyshev	-	Travel Time and Demand
Ozbay et al. (2019)	Single-purpose	Multiple	-	Minimizing number of shelters	Exact method	Earthquake	-

In general, based on the reviewed studies shown in Table 1, most studies focus on traditional supply chains or commercial supply chains, in which case various influential aspects such as fair distribution during disasters are neglected. Existing studies on humanitarian supply chains were interested in examining the affected areas during the recovery phase. However, hardly any studies have focused on the fair rescue process in post-disaster relief distribution during the response phase. Therefore, the most important measures of the present research are:

- Reducing distribution costs during a crisis

- Selecting the right distribution location at the optimal time
- Better care for the injured and those in need of relief due to the optimal distribution and relief system
- Reducing the costs of establishing distribution warehouses due to the principled selection and the absence of the need to build new warehouses

3) Research Method

In this study, a mathematical modeling-based framework for the distribution and allocation of relief items in crisis situations is presented. The proposed model consists of two planning levels. The main elements for distribution include relief distribution centers (RDCs), emergency demand points (EDPs), and specific affected areas (ASAs). According to Figure 1, RDCs (layer 1) are established to store aid received from external suppliers such as companies. Generally, RDCs located in non-affected areas are far from the disaster site and are under the control of decision-makers in crisis command centers.
EDPs (layer 2), which are usually located in affected areas, receive aid from RDCs and dispatch items based on relief requests. Each EDP can be divided into three types of ASAs: search-and-rescue areas (SRAs), temporary treatment areas (TTAs), and temporary settlement areas with minor or no damage (TSA). In particular, ASAs (layer 3) represent a cluster of different types of survivors in SRA, TTA, and TSA. These survivors evaluate post-disaster relief distribution strategies developed by decision-makers. Different types of ASAs are considered to have different emergency tasks.

In addition, the number of RDCs and their locations are also considered. Such information can be predetermined in the strategic planning of disaster management. At the same time, the number of EDPs and ASAs under the control of local authorities and their locations are identified using advanced technologies to facilitate the analysis. The above explanation also shows that stakeholders, including decision-makers and survivors, have hierarchical relationships. Therefore, the distribution of post-disaster relief in the humanitarian supply chain can be defined as a leader-follower optimization problem. Specifically, decision-makers with higher authority determine the amounts of aid transferred to EDPs for each period and focus on reducing the rate of unmet demand, potential environmental risks, and emergency costs in all periods at the top level of the decision hierarchy. At a lower level of the decision-making hierarchy, decision-makers with less authority focus on reducing the suffering of survivors by optimizing the amounts of aid distributed to ASA for all periods to support survivors.

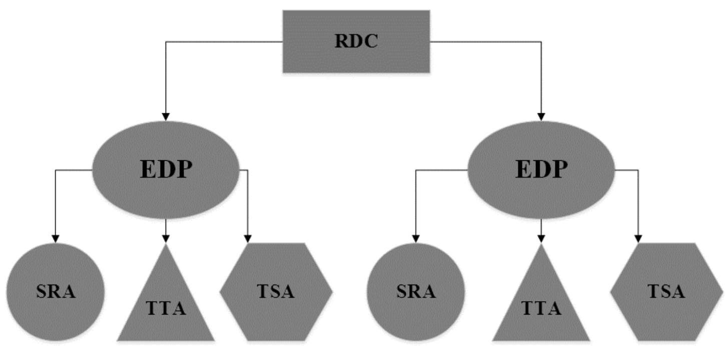

Figure 1. General mechanism of the humanitarian supply chain

Assumptions of the mathematical model

Assumption 1: Relief is provided from different relief centers to different affected centers.

Assumption 2: Relief is provided with a fair proportion of similar relief items. Thus, we assume that each survivor is allocated one relief item.

Assumption 3: There are different relief items for relief.

Assumption 4: Different time periods are considered for planning, each day is assumed to be 24 hours.

Assumption 5: A time window is considered for relief items.

Assumption 6: Complete relief is managed and distributed in ASAs and RDCs, and secondary disasters after the crisis are ignored.

Assumption 7: Relief is provided with a fair proportion of similar relief items. Thus, we assume that each survivor is allocated a similar kit.

Assumption 8: Relief is provided to each EDP and ASA based on the required demand through multiple sources.

Assumption 9: The mode of transportation is carried out by land, air and rail lines and there is no shortage when using them.

Assumption 10: The capacity of distribution centers and vehicles is limited and must be included in the model to prevent cost increases.

Assumption 11: Transportation costs per unit of product are known and fixed and depend on the distance between distribution centers and demand points.

Assumption 12: The time required to supply products from distribution centers to demand points is known and must be included in the model to avoid delays in meeting needs.

Assumption 13: Crisis conditions may cause uncertainty in demand, costs and supply time, so the model must respond to these uncertainties.

Notation

Indices:

S: First aid Period set $S = \{1,2,3\}$

I: Complex of the ist relief distribution center $i \in I$

J: Set of jth points with emergency demand $j \in J$

K: The kth set of specific regions affected by the crisis $k \in K$

M: The mth mode of transportation is by land, air, and rail, so $m \in \{1,2,3\}$

L: Collection of all affected areas $l \in L$

P: Collection of all relief centers $p \in P$

T: The entire time period $t \in T$

Q: Collection of various types of essential items $q \in Q$

Parameters:

s_{pqt}: $Supply\ quantity\ for\ essential\ items\ q\ at\ relief\ centers\ p\ in\ period\ t.$

D_{lqt}: $Demand\ for\ essential\ items\ q\ at\ damaged\ site\ l\ in\ period\ t.$

C_{plt}: Cost of access of relief centers p to the affected site l in period t.

C_{plqt}: Cost of transporting a unit of allocated essential items q from relief site p to the affected site l in period t.

G_p: $Value\ of\ essential\ items\ q\ allocated\ from\ relief\ center\ p.$

w: $Fair\ allocation\ coefficient\ of\ items.$

β_1: $Weighting\ factor\ of\ the\ first\ objective\ function.$

β_2: $Weighting\ factor\ of\ the\ second\ objective\ function.$

β_3: $Weighting\ factor\ of\ the\ third\ objective\ function.$

$[l_q; u_q]$: $Time\ window\ for\ delivery\ of\ essential\ items\ q.$

t_{ijms}: Average time spent to deliver each thousand relief kits using mode m from RDC_i to EDP_j in period s.

t_{jkms}: $Average\ time\ spent\ to\ deliver\ each\ thousand\ relief\ kits\ using\ mode\ m\ from\ EDPj\ to\ ASAk\ in\ period\ s.$

A_{1ijm}: $Carbon\ emissions\ per\ hour\ spent\ delivering\ each\ thousand\ relief\ kits\ using\ mode\ m\ from\ RDC_i\ to\ EDP_j..$

A_{2jkm}: $Carbon\ emissions\ per\ hour\ spent\ delivering\ each\ thousand\ relief\ kits\ using\ mode\ m\ from\ EDP_j\ to\ ASA_k.$

a_{1ijm}: $Cost\ of\ delivering\ per\ thousand\ relief\ kits\ using\ mode\ m\ from\ RDC_i\ to\ EDP_j.$

a_{2jkm}: $Cost\ of\ delivering\ per\ thousand\ relief\ kits\ using\ mode\ m\ from\ EDP_j\ to\ ASA_k.$

Q_{is}: $Inventory\ values\ of\ relief\ items\ in\ RDC_i\ in\ period\ s.$

D_{js}: $Expected\ values\ of\ relief\ items\ in\ EDP_j in\ period\ s.$

D_{ks}: $Expected\ values\ of\ relief\ items\ in\ ASA_k\ in\ period\ s.$

w_{js}: Weights of EDP_j determined based on the level of damage of survivors in period s.

w_{ks}: $Weights\ of\ ASA_k\ determined\ based\ on\ the\ severity\ of\ damage\ of\ survivors\ in\ period\ s.$

η_{js}: $Level\ of\ relief\ to\ survivors\ located\ in\ EDP_j\ in\ period\ s.$

η_{ks}: $Level\ of\ relief\ to\ survivors\ located\ in\ ASA_k\ in\ period\ s.$

γ_k: $Hazard\ coefficient\ of\ disaster\ losses\ per\ thousand\ units\ of\ the\ environment\ in\ ASA_k.$

k: Hazard coefficient of carbon emissions per kilogram of the environment.

Variables:

x_{ijms}: $Actual\ quantities\ of\ relief\ provided\ using\ transportation\ mode\ m\ from\ RDC_i\ to\ EDP_j\ in\ period\ s, (low - level\ chain\ planning).$

y_{jkms}: $Actual\ quantities\ of\ relief\ provided\ using\ transportation\ mode\ m\ from\ EDP_j\ to\ ASA_k in\ period\ s, (high - level\ chain\ planning). This\ variable\ is\ a\ positive\ continuous\ variable.$

d_{plqt}: $Relief\ center\ p\ allocates\ the\ quantity\ of\ essential\ items\ q\ to\ the\ affected\ area\ l\ in\ period\ t.$

u_{lqt}: $Unmet\ demand\ for\ essential\ items\ q\ in\ the\ affected\ area\ l\ during\ period\ t.$

Q_{plt}: $Total\ quantity\ of\ materials\ delivered\ from\ relief\ center\ p\ to\ the\ affected\ area\ l\ during\ period\ t.$

r_{lqt}: $The\ demand\ satisfaction\ rate\ for\ essential\ items\ q\ in\ the\ affected\ area\ l\ during\ period\ t.$

$\widehat{u_{lqt}}$: $The\ ideal\ demand\ satisfaction\ rate\ for\ essential\ items\ q\ in\ the\ affected\ area\ l\ during\ period\ t.$

$\widetilde{u_{lqt}}$: $The\ unmet\ demand\ rate\ for\ essential\ items\ q\ in\ the\ affected\ area\ l\ during\ period\ t.$

v_{plt}: $Binary\ variable\ equal\ to\ one\ if\ relief\ center\ p\ allocates\ the\ items\ to\ the\ affected\ area, otherwise\ it\ is\ zero.$

Objective functions and constraints:

$$\min(\sum_{i\in I}\sum_{j\in J}\sum_{m\in M} w_{js}x_{ijms}/D_{js}) + \sum_{j\in J}\sum_{k\in K}\sum_{m\in M} w_{ks}y_{jkms}/D_{ks}) \quad (1)$$

$$\min(\sum_{s\in S}\sum_{i\in I}\sum_{j\in J}\sum_{m\in M} A_{1ijm}t_{ijms}x_{ijms}) + (\sum_{s\in S}\sum_{j\in J}\sum_{k\in K}\sum_{m\in M} kA_{2jkm}t_{jkms}y_{jkms}) + (\sum_{s\in S}\sum_{j\in J}\sum_{k\in K}\sum_{m\in M} \gamma_k y_{jkms}) \quad (2)$$

$$\min(\sum_{s\in S}\sum_{i\in I}\sum_{j\in J}\sum_{m\in M} a_{1ijm}x_{ijms}) + (\sum_{s\in S}\sum_{j\in J}\sum_{k\in K}\sum_{m\in M} a_{2jkm}y_{jkms}) \quad (3)$$

$$\max\left(\sum_{s\in S}\sum_{k\in K}\sum_{j\in J}\sum_{m\in M} w_{ks}y_{jkm}/D_{ks}t_{jkms}\right) \tag{4}$$

$$min \sum_{p\in P}\sum_{l\in L}\sum_{t\in T} c_{plt}.v_{plt} + \sum_{p\in P}\sum_{l\in L}\sum_{q\in Q}\sum_{t\in T} c_{plqt}.d_{plqt} \tag{5}$$

$S.t$

$$\sum_{k\in k}\sum_{m\in M} y_{jkms} = \sum_{i\in I}\sum_{m\in M} x_{ijms} \tag{6}$$

$$\sum_{j\in J}\sum_{m\in M} y_{jkms} \le D_{ks} \tag{7}$$

$$\sum_{j\in J}\sum_{m\in M} y_{jkms} \ge \eta_{js}D_{js} \tag{8}$$

$$\sum_{p\in P} d_{plqt} \le D_{lqt} + \sum_{1}^{t-1}(D_{lqt} - \sum d_{plqt}) \quad \forall l \in L; q \in Q; t \in T \tag{9}$$

$$\sum_{p\in P} d_{plqt} \le s_{pqt} + \sum_{1}^{t-1}(s_{pqt} - \sum d_{plqt}) \quad \forall p \in P; q \in Q; t \in T \tag{10}$$

$$\sum_{p\in P}\sum_{l\in} d_{plqt} = \min\{\sum_{p\in P} s_{pqt} + \sum_{l}^{t-1}(s_{pqt} - \sum d_{plqt}), \sum_{l\in L} D_{lqt} + \sum_{1}^{t-1}(D_{lqt} - \sum_{p\in P} d_{plqt}) \quad \forall q \in Q; t \in T \tag{11}$$

$$\sum_{q\in Q} d_{plqt} \le Q_{plt} \quad \forall p \in P; l \in L; t \in T \tag{12}$$

$$l_q \le Q_{plt} \le u_q \quad \forall p \in P; l \in L; t \in T \tag{13}$$

$$\sum_{j\in J}\sum_{m\in M} x_{ijm} = Q_{is} \tag{14}$$

$$\sum_{i\in I}\sum_{m\in M} x_{ijms} \le D_{js} \tag{15}$$

$$\sum_{i\in I}\sum_{m\in M} x_{ijms} \ge \eta_{js}D_{js} \tag{16}$$

$$v_{plt} = \{0,1\};\ d_{plqt} \ge 0;\ y_{jkm} \ge 0;\ x_{ijm} \ge 0 \tag{17}$$

Constraint (1) minimizes the total weighted unmet demand rate of RDCs and ASAs for all periods. Constraint (2) minimizes the total potential environmental risks from transportation-related carbon emissions, waste, or disaster debris for all periods. Constraint (3) minimizes the total emergency costs for all periods. Constraint (4) describes the objective function of the problem as maximizing the total survivor satisfaction (SPS) for all periods in the entire disaster response decision-making system. Constraint (5) is the objective function of the problem that ensures minimizing the transportation cost, which consists of a fixed and unit transportation cost. Constraint (6) measures the equilibrium of the aid demand for each EDP in each period and implies that the aid received and distributed for each EDP in each period is equal. Constraints (7) and (8) specify the insufficient supply and the fairness principle in terms of each ASA in each period, respectively. Constraint (9) is a demand constraint whose goal is that the actual amount of material allocated to each affected area in each period is less than the demand in each period and the unmet demand in the previous period, i.e., the sum of the new demand. Constraint (10) is the supply constraint that can ensure that the amount of materials allocated to relief centers in each period does not exceed the amount of allocable materials. If there are remaining unallocated materials, they can be allocated in the next period. Constraint (11) is to maximize the demand satisfaction constraint, that is, if the supply of period t is greater than the demand, all the demands are satisfied. If the demand for period t is greater than the supply, all the supply is distributed. Constraint (12) implies that if a relief center decides to distribute materials to a damaged location in a given period, the corresponding transportation costs must be paid, that is, transportation capacity constraints are in place. Constraint (13) guarantees the maximum and minimum total amount of materials delivered. Constraint (14) guarantees that the sum of actual transported relief is equal to the inventory for each RDC in each period, which indicates that all available relief in each period is delivered to the EDPs. Constraint (15) formulates the unmet demand supply cases and shows that not all demands for EDPs can be fully satisfied in each period. Constraint (16) shows that all survivors located in each EDP can receive relief items in each period and measures the fairness principle. Constraint (17) specifies the types of model variables.

Model Uncertainty Approach

The main decisions in this case of the problem are to estimate the demands and determine their start time. Therefore, we consider a binary variable Z_i and a variable y_it for each demand. For $1 \leq c \leq C$, the value of Z_i is equal to one if the demand is met and zero otherwise. For $1 \leq t \leq T$ and $1 \leq i \leq I$, the value of y_{it} is equal to one if the demand for each set of items i is met in period t. Otherwise, its value is zero. Since each demand can only occur once in the planning horizon H, we have:

$$Z_i = \sum_{t=1}^{T} y_{it}\,, \qquad 1 \leq i \leq I;\ 1 \leq t \leq T;\ i = 1, \dots, I;\ t = 1, \dots, T \tag{18}$$

Constraint (18) allows the variable Z_i to act as a continuous variable. Since in Constraint (18) the independent variables are either zero or one, if we calculate their sum together, a value greater than or equal to zero is obtained. Now, if a demand is satisfied in period k, we can calculate y_{ik} through the continuous variable (19).

$$y_{ik} = \sum_{t=1}^{k} y_{ik}\,, \quad 1 \leq i \leq I;\ 1 \leq t \leq T;\ i = 1, \dots, I;\ t = 1, \dots, T \tag{19}$$

In order to estimate the demand for the provision of relief items, public donations are also needed. For this purpose, we consider the variable N_{it} as relief aid during period t for demand i. If the demand is not met during the period, its value is considered to be zero. The total demand amount should not exceed the potential demand amount. Because in case of exceeding, we will face a surplus of items, which may not have enough space for storage due to capacity limitations.

$$y_{it} N_{it} \leq N_{it}^{U}, \qquad 1 \leq i \leq I;\ 1 \leq t \leq T;\ i = 1, \dots, I;\ t = 1, \dots, T \tag{20}$$

In addition, the supply (transfer) of the amount of relief items received is carried out based on each of the demands met in each given period through the total items. This constraint is shown as an unstable Constraint in Constraint (21). Constraint (22) is the stable counterpart of Constraint (21). Therefore, we insert Constraint (22) in place of Constraint (21) in the problem. w_{it} is the consumption coefficient of relief items that need to be provided (its unit of measurement is percentage).

$$\sum_{i=1}^{I} w_{it} N_{it} \geq S_t\,, \quad 1 \leq i \leq I; 1 \leq t \leq T; i = 1, \dots, I; t = 1, \dots, T \tag{21}$$

$$\sum_{i=1}^{I} w_{it} N_{it} \geq \tilde{S}_t - \hat{S}_t \quad 1 \leq i \leq I; 1 \leq t \leq T; i = 1, \dots, I; t = 1, \dots, T \tag{22}$$

Problem Solving Method

The epsilon constraint method has been used to solve the proposed model. In the epsilon constraint method, one of the different objective functions is selected and the other objective functions are converted into constraints by considering an upper bound, and the problem is converted into a single-objective linear programming model and solved in the usual linear programming method. One of the exact methods for obtaining Pareto optimal solutions is the use of the epsilon constraint method, which was first presented by Aljedan. The main advantage of this method over other multi-objective optimization methods is its application to non-convex solution spaces, because methods such as weighted combination of objectives lose their effectiveness in non-convex space. The computational time of an algorithm is an important characteristic of any algorithm for its evaluation. Since one of the main weaknesses of algorithms based on exact search, including the epsilon method, is the high computational time constraint, it is obvious that the use of a metaheuristic algorithm will significantly reduce the computational time. One of the modified versions of the epsilon constraint method is the framework presented by Izadi et al. (2025), and Abolghasemian et al. (2020) have recommended its use due to its two major advantages. One of the advantages of this method is the reduction of the search space to find non-dominant points. Another advantage of this method is its shorter execution time compared to the original method. According to this method, we first solve the single-objective optimization problem for each objective. Then we determine the step length. Then we generate the set of suitable points and finally solve the single-objective optimization and estimate the Pareto frontier.

In this method, we always optimize one of the objectives, provided that we define the highest acceptable limit for the other objectives within the constraints. For a two-objective problem, we will have the mathematical representation according to Constraint 23:

$$\begin{aligned} &\min f_1(x) \\ &s.t \\ &f_2(x) \leq \varepsilon_2 \\ &x \in s \end{aligned} \tag{23}$$

By changing the values on the right side of the new ε constraints, the Pareto edge of the problem will be obtained.

4) Research findings

This section consists of two parts, the first part is related to the results of solving the model of distribution of relief items in crisis situations to show that the proposed model has the ability to be implemented in the real world. Therefore, the validity of the proposed model requires receiving answers from this section. The second part includes solving the multi-objective, multi-period and multi-product problem of distribution of relief items in a case study in Tehran. In addition, the results of sensitivity analysis on some parameters of each model have been carried out separately to measure the sensitivity of the objective function on them.

4-1) Practical results of the relief distribution model to check the validity of the model

In this section, the computational results of the proposed model are shown. GAMS software has been used to implement the model. To solve the problem according to Table 2, five numerical examples have been considered. Based on these examples, the model parameters are adjusted accordingly.

Table 2. Model parameter settings

Number	Q_{is}	D_{js}	η_{js}	η_{ks}	a_{1ijm}	a_{2jkm}	A_{1ijm}	A_{2jkm}	t_{ijms}	t_{jkms}	γ_k
1	60	110	0.3	0.3	2	2	1.5	1.5	2.5	2.5	0.4
2	70	110	0.3	0.3	2	2	1.5	1.5	2.5	2.5	0.6
3	65	110	0.3	0.3	2	2	1.5	1.5	2.5	2.5	0.6
4	60	115	0.3	0.3	2	2	1.5	1.5	2.5	2.5	0.6
5	60	80	0.3	0.3	2	2	1.5	1.5	2.5	2.5	0.6

Considering that this research considers the decision-making perspective through mathematical modeling for the supply chain, all the results in different decision-making modes for the crisis response stage are shown in Table 3. The computational results show that the proposed supply chain plan can achieve the optimal post-disaster relief distribution plan for all cases in a reasonable time (about 30 seconds). Therefore, the effectiveness and feasibility of the model and methods are confirmed. Secondly, the comparison of the obtained results shows that the proposed planning model significantly reduces the total unmet demand rate through the function F_1, the total potential environmental risks through the function F_2, and the total emergency costs through the function F_3. Also, the total satisfaction of the survivors is maximized through the function f. The results of the model implementation are shown in Table 3.

Table 3. Computational results under different decision-making scenarios

Sample	Objectives	Period S_3	S_2	S_1	Average
First	F_1	0.89	1.5	2.25	1.55
	F_2	708	482	557	582.3
	F_3	625	562	4.9	532
	F_4	0.78	1.5	3.5	1.93
	F_5	625	562	409	532
	f	0.325	0.421	0.307	0.351
Second	F_1	0.78	1.5	3.5	1.93
	F_2	725	475	571	590.3
	F_3	687	576	399	554
	F_4	0.78	1.5	3.5	1.93
	F_5	725	475	571	590.3
	f	0.425	0.668	0.456	1.549
Third	F_1	0.62	1.25	3.12	1.663
	F_2	710	395	578	561
	F_3	650	542	647	613
	F_4	0.62	1.25	3.12	1.663
	F_5	710	395	578	561
	f	0.442	0.561	0.478	0.493
Fourth	F_1	0.89	1.5	2.25	1.54
	F_2	708	482	557	582.3
	F_3	625	562	409	532
	F_4	0.89	1.5	2.25	1.54
	F_5	708	482	557	582.3
	f	0.325	0.421	0.307	0.351
Fifth	F_1	0.79	2.5	2.25	1.846
	F_2	628	548	446	540.666
	F_3	589	562	586	579
	F_4	0.79	2.5	2.25	1.846
	F_5	628	548	446	540.666
	f	0.235	0.568	0.469	0.424

According to the results obtained, increasing the amount of stocks has favorable effects on achieving social sustainability in relief distribution through increasing the satisfaction rate through the function f, while this increase imposes unfavorable effects on environmental and economic sustainability performance through the function F_2. However, following the increase in aid demand, the rate of total unmet demand, total potential environmental risks, and total emergency costs increase significantly. For this purpose, in Table 4, the values of $x_{ijms}$and $y_{jkms}$are shown for the accuracy of the above results.

Table 4. Optimal value of decision variables of the model

Sample number	x_{ijm} m_3	m_2	m_1	y_{jkm} m_3	m_2	m_1	F_1	F_2	F_3	F_4	F_5
First	2406	1250	1500	1479	1478	1506	60	0.351	582.3	0.781	532
Second	2650	1356	1645	2006	1639	1752	70	1.549	590.3	0.664	554
Third	2550	1152	1789	2147	1258	1896	65	0.493	613	0.748	561
Fourth	2478	1189	1678	2314	1164	1647	60	0.351	582.3	0.856	532
Fifth	2618	1236	1479	2569	1479	1563	60	0.424	540.666	0.569	579

Application Results of Multi-Objective, Multi-Period, Multi-Product Relief Distribution Model

This section shows the computational results of the proposed model. GAMS software was used to implement the model. In this research, the problem of allocating four types of essential goods (including water; food; medicine and equipment; clothing and blankets) to 7 affected neighborhoods in District 1 of Tehran, which are supported through two special support bases and a multi-purpose support base belonging to crisis management, which are located in Sohanek and Babaei neighborhoods. These locations have been determined and selected based on the crisis management requirements of Tehran province. The transportation costs and materials that can be supplied from each of the rescue centers to the affected areas are shown in Tables 5 and 6. Also, the fixed and variable costs from each relief center to the affected neighborhoods are shown in Table 7.

Table 5. Transportation costs from relief centers to the affected areas

Relief Centers	Neighborhood	Period				
		First	Second	Third	Fourth	Fifth
Special Crisis Management Support Base	Jamalabad	700	700	160	60	900
	Darabad	600	630	140	50	810
	Omidvar	200	560	120	800	720
	Kamraniyeh	900	490	100	720	630
	Aghaei	100	420	900	640	540
	Aghdasiyeh	800	350	810	560	450
	Pasdaran	300	600	720	480	400
Multipurpose Support Base	Jamalabad	600	540	630	400	360
	Darabad	900	480	540	300	320
	Omidvar	400	420	450	270	280
	Kamraniyeh	1200	360	90	240	240
	Aghaei	300	540	80	210	200
	Aghdasiyeh	700	450	70	180	260
	Pasdaran	300	90	60	150	320

Table 6. Material supply needs in relief centers (in thousands)

Relief Center	Relief Items	Period				
		First	Second	Third	Fourth	Fifth
Special Crisis Management Support Base	Water	1.8	2.4	2.2	3.3	11
	Food	3	3.3	3.4	8	17
	Medicine and Medical Equipment	4.8	3.4	2.8	5.8	11
	Clothing and Blankets	9563	2380	3440	4870	5830
Multipurpose Support Base	Water	7	2	6.3	10.8	20
	Food	4.5	4	3.6	10.8	13.5
	Medicine and Medical Equipment	2.9	3.2	4.5	7.5	8
	Clothing and Blankets	1952	3010	4240	6260	4252

Table 7. Fixed and variable costs of sending essential goods from relief centers to affected areas

Relief Center	Selected areas of Tehran Region 1						
	Jamalabad	Darabad	Omidvar	Kamraniyeh	Aghaei	Aghdasieh	Pasdaran
Special Support Base	[600 And 14000]	[300 And 7500]	[100 And 15000]	[500 And 12000]	[400 And 11000]	[350 And 9000]	[300 And 7000]
Multipurpose Support Base	[450 And 11000]	[450 And 11000]	[200 And 5000]	[150 And 3500]	[350 And 8000]	[150 And 4500]	[150 And 3500]

By running the model, the optimal value of the variable for allocating relief items from the relief center to the affected areas is determined. Based on this, we find out from which relief center each area receives essential items. In Table 8, the value of the variable v_{plt} which determines the allocation of relief items from relief center p to the affected area, is shown.

Table 8. Allocation of items from relief centers to affected areas

Period	Relief Center	Selected areas of Tehran Region 1						
		Jamalabad	Darabad	Omidvar	Kamraniyeh	Aghaei	Aghdasieh	Pasdaran
First	Special Support Base	0	1	1	0	1	1	1
	Multipurpose Support Base	1	1	0	1	1	0	0
Second	Special Support Base	1	1	0	1	0	1	1
	Multipurpose Support Base	1	0	1	1	1	1	0
Third	Special Support Base	0	0	1	1	1	1	0
	Multipurpose Support Base	1	1	0	0	0	0	1
Fourth	Special Support Base	0	1	0	1	1	1	1
	Multipurpose Support Base	1	0	1	0	1	1	0
Fifth	Special Support Base	1	1	0	1	0	1	1
	Multipurpose Support Base	1	0	1	1	1	1	0

According to the existing literature, four types of essential goods during an earthquake, including water; food; medicine and medical equipment; clothing and blankets, have been considered based on the Austrian standard (Hemmati et. Al 2025 ; Wang et. Al 2023). According to Table 8, the allocation of relief items to each area from relief centers has been specified. As it has been specified, all areas receive relief items. Some areas receive essential items from both relief centers, and due to the failure to meet the demand by one relief base, part of the demand must be met by the other base. In Table 9, it is specified which items are sent to the regions from each relief center in each period. According to Table 8, the allocation of relief items to each area from relief centers has been specified. As it has been specified, all areas receive relief items. Some areas receive essential items from both relief centers, and due to the failure to meet the demand by one relief base, part of the demand must be met by the other base. In Table 9, it is specified which items are sent to the regions from each relief center in each period. According to Table 8, the allocation of relief items to each area from relief centers has been specified. As it has been specified, all areas receive relief items. Some areas receive essential items from both relief centers, and due to the failure to meet the demand by one relief base, part of the demand must be met by the other base. In Table 9, it is specified which items are sent to the regions from each relief center in each period. According to Table 8, the allocation of relief items to each area from relief centers has been specified. As it has been specified, all areas receive relief items. Some areas receive essential items from both relief centers, and due to the failure to meet the demand by one relief base, part of the demand must be met by the other base. In Table 9, it is specified which items are sent to the regions from each relief center in each period.

Table 9. Distribution of types of relief items to each area

Affected Areas	Relief Items	Period First	Second	Third	Fourth	Fifth
Jamalabad	Water	2.1	6.9	6.9	12.5	3.7
	Food	10	34	34	61	21
	Medicine and Medical Equipment	690	1180	1960	1180	1180
	Clothing and Blankets	710	4150	1960	1180	1180
Darabad	Water	3.7	2.1	690	10	10
	Food	21	10	3.7	12	12
	Medicine and Medical Equipment	1180	4110	22	3470	3470
	Clothing and Blankets	1180	3470	1120	3450	3450
Amidvar	Water	14.7	2.1	2.9	12.5	3.7
	Food	72	10	2	61	21
	Medicine and Medical Equipment	4110	3450	12.5	1990	1180
	Clothing and Blankets	4090	4150	740	1980	1180
Kamraniyeh	Water	6.9	12.5	690	10	6.9
	Food	34	61	3.7	12	34
	Medicine and Medical Equipment	1960	1180	22	3407	1960
	Clothing and Blankets	1960	1180	1120	3450	1906
Aghayee	Water	12.5	690	12.5	690	2.9
	Food	61	3.7	61	3.7	2.3
	Medicine and Medical Equipment	3420	4090	1180	22	12.5
	Clothing and Blankets	3450	4110	1180	1120	740
Aghdasieh	Water	2.9	12.5	14.7	2.1	690
	Food	2.3	61	72	10	3.7
	Medicine and Medical Equipment	12.5	1990	4110	3450	22
	Clothing and Blankets	740	1980	4090	4150	1120
Pasdaran	Water	690	10	6.9	12.5	6.9
	Food	3.7	12	34	61	34
	Medicine and Medical Equipment	22	3470	1960	1180	1960
	Clothing and Blankets	1120	3450	1960	1180	1960

Also, the problem is defined based on two scenarios to realize the innovation of fair distribution of items among survivors. These two scenarios define the state that if an earthquake of magnitude 4 to 5 occurs or if an earthquake of magnitude 6 to 7 occurs, what items should be distributed among survivors in each area. By doing this, we ensure that during an earthquake, items are distributed in proportion to the intensity of the event. In Table 10, the amount of each item allocated to each area in each scenario is shown.

Table 10. Distribution of types of relief items to each area

Affected Areas	Relief Items	Scenario	
		Scenario One	Scenario Two
Jamalabad	Water	1	1
	Food	0	1
	Medicine and Medical Equipment	1	1
	Clothing and Blankets	1	1
Darabad	Water	1	0
	Food	0	1
	Medicine and Medical Equipment	0	1
	Clothing and Blankets	0	1
Amidvar	Water	1	1
	Food	0	1
	Medicine and Medical Equipment	1	0
	Clothing and Blankets	1	0
Kamraniyeh	Water	1	0
	Food	1	1
	Medicine and Medical Equipment	0	0
	Clothing and Blankets	0	1
Aghayee	Water	1	0
	Food	0	1
	Medicine and Medical Equipment	1	1
	Clothing and Blankets	1	1
Aghdasieh	Water	1	1
	Food	0	1
	Medicine and Medical Equipment	0	0
	Clothing and Blankets	1	1
Pasdaran	Water	0	١
	Food	1	0
	Medicine and Medical Equipment	1	0
	Clothing and Blankets	1	1

According to the results of Table 10, if relief items are allocated to the affected area in each scenario, it takes the value of one and otherwise it takes the value of zero.

Sensitivity Analysis

Given that the epsilon constraint method has been introduced to solve a mathematical problem, the values of the objective functions have been calculated for different values of epsilon and are shown in Table 11. The deterministic state of this model has been solved using GAMS software and CPLEX tool. In this table, different values of epsilon are defined and the objective functions have been solved with them. As is clear from the table, the values of the objective function do not show a significant change with increasing epsilon up to a certain value, but from a certain point onwards (for example, the first objective function), an increase in the epsilon value shows a significant increase in the values of the objective functions. These changes in the objective functions have shown different slopes. Based on the results obtained, for testing different values of epsilon, the feasible region and the improvement vector of the objective functions have been created. According to the results obtained, the level of significant changes of epsilon between 50 and 900 has been determined as the improvement vector. Determining this range indicates that if the epsilon value is considered to be less than 50 and greater than 900, the answer to the problem will fall outside the feasible region.

Therefore, the value of epsilon for searching for the local optimal solution for the first objective function is 500. Because, at this point the optimal solution for the first objective function occurs. The optimal situation for the second objective function occurs at epsilon 150. The optimal situation for the third objective function occurs at epsilon 600. The optimal situation for the fourth objective function occurs at epsilon 150. The optimal situation for the fifth objective function occurs at epsilon 600. Therefore, the optimal response range is between epsilon 150 and 500. Table 11 shows the results of solving the model with a step length of 50 for epsilon.

Table 11. Results of changing epsilon

Transportation Cost	Survivor Satisfaction	Total Emergency Costs	Percentage of Environmental Hazards	Unmet Demand	Epsilon
570	0.72	57	0.71	512	50
550	0.74	55	0.74	563	100
620	0.78	62	0.70	382	150
570	0.72	57	0.75	450	200
680	0.73	68	0.78	430	250
750	0.72.5	75	0.75	413	300
580	0.71	58	0.75	398	350
940	0.72	94	0.75	365	400
860	0.73	86	0.74	348	450
580	0.72.5	58	0.75	307	500
620	0.71	62	0.71	480	550
480	0.71	48	0.76	512	600
720	0.72	72	0.76	563	650
980	0.73	98	0.82	450	700
780	0.71	78	0.73	460	750
810	0.71	81	0.83	413	800
820	0.72	82	0.75	510	850
700	0.73	70	0.86	398	900
480	0.78	48	0.70	307	Optimal value

5) Conclusion and suggestions

In this paper, a mathematical programming model for the distribution of relief items is presented based on the design of a multi-objective, multi-period model for fair distribution. Therefore, this paper aims to achieve the goals of providing an optimization model for the distribution of livelihood packages in critical situations to deal with the crisis. For this purpose, a multi-objective and multi-level humanitarian supply chain is developed for the fair distribution of livelihood packages to deal with the crisis. Since research on the allocation of emergency materials usually considers one to two indicators, this paper examines five dimensions of humanitarian logistics indicators, which are: access cost, transportation cost, unmet demand rate in each period and the gap between the demand filling rate and the ideal demand satisfaction rate in the entire period, and environmental hazards. In addition, instead of using single-affected-area single-relief distribution networks or single-period or two-period distribution modes, this paper builds a model for allocating essential materials including water, food, medicine, equipment, and clothing and blankets from multiple relief centers to different affected areas, which is able to have a fair behavior in distributing items among the areas. Because, in this case, the planning for the affected areas is more consistent with the real situation. The model proposed in this paper is suitable for large-scale local (not national) sudden natural disasters that occur in urban areas (with a certain number of resident populations). Compared with earthquakes that are focused on, it cannot be directly applied to hurricanes or other low-impact and scattered disasters. Finally, a sensitivity analysis on the value of epsilon is performed to find the local optimal solution for the objective functions. The optimal values of the first objective function are obtained at epsilon 500. The optimal state for the second objective function is observed at epsilon 150. The optimal state for the third objective function is set at epsilon 600. Also, the optimal state for the fourth objective function is calculated at epsilon 150. Finally, the optimal state for the fifth objective function is also determined at epsilon 600. Therefore, the range of optimal responses is determined between epsilon 150 and 500. For further research, it is suggested to design a multi-period model for routing relief vehicles for a fair distribution of items. Considering a priority for each item using multi-criteria decision making to prioritize items and applying it in the mathematical model. Using data envelopment analysis models to calculate efficiency scores and rank factors.

References

Abolghasemian, M., Kanai, A. G., & Daneshmandmehr, M. (2020). A two-phase simulation-based optimization of hauling system in open-pit mine. Iranian journal of management studies, 13(4), 705-732. https://doi.org/10.22059/ijms.2020.294809.673898

Aghajani, M., Torabi, S. A., & Heydari, J. (2020). A novel option contract integrated with supplier selection and inventory prepositioning for humanitarian relief supply chains. Socio-Economic Planning Sciences, 71, 100780. https://doi.org/10.1016/j.seps.2019.100780

Boonmee, C., Arimura, M., & Asada, T. (2017). Facility location optimization model for emergency humanitarian logistics. International Journal of Disaster Risk Reduction, 24, 485-498. https://doi.org/10.1016/j.ijdrr.2017.01.017

Cao, C., Liu, Y., Tang, O., & Gao, X. (2021). A fuzzy bi-level optimization model for multi-period post-disaster relief distribution in sustainable humanitarian supply chains. International Journal of Production Economics, 235, 108081. https://doi.org/10.1016/j.ijpe.2021.108081

Ghahremani-Nahr, J., Nozari, H., & Szmelter-Jarosz, A. (2024). Designing a humanitarian relief logistics network considering the cost of deprivation using a robust-fuzzy-probabilistic planning method. Journal of International Humanitarian Action, 9(1), 19. https://doi.org/10.1186/s41018-024-00163-8

Hemmati, A., Motevalli, S. H., Pourghader Chobar, A., Akhlaghpour, A., & Nazari, L. (2025). Analyzing customer sentiment with AI to improve the smart supply chain. Engineering Management and Soft Computing, 11(1), 306-286. https://doi.org/10.22091/jemsc.2025.3654.1260

Izadi, E., Nikbakht, M., Feylizadeh, M., & Shahin, A. (2025). Ranking of criteria affecting humanitarian supply chain services based on blockchain platforms using multi-criteria decision-making methods. Engineering Management and Soft Computing, 10(2), 143-160. https://doi.org/10.22091/jemsc.2025.11552.1215

Jahangiri, S., Abolghasemian, M., Ghasemi, P., & Chobar, A. P. (2023). Simulation-based optimisation: analysis of the emergency department resources under COVID-19 conditions. International journal of industrial and systems engineering, 43(1), 1-19. https://doi.org/10.1504/IJISE.2023.128399

Kanoun, I., Chabchoub, H., & Aouni, B. (2010). Goal programming model for fire and emergency service facilities site selection. INFOR: Information Systems and Operational Research, 48(3), 143-153. https://doi.org/10.3138/infor.48.3.143

Maharjan, R., & Hanaoka, S. (2020). A credibility-based multi-objective temporary logistics hub location-allocation model for relief supply and distribution under uncertainty. Socio-Economic Planning Sciences, 70, 100727. https://doi.org/10.1016/j.seps.2019.07.003

Mamashli, Z., Bozorgi-Amiri, A., Dadashpour, I., Nayeri, S., & Heydari, J. (2021). A heuristic-based multi-choice goal programming for the stochastic sustainable-resilient routing-allocation problem in relief logistics. Neural Computing and Applications, 1-27. https://doi.org/10.1007/s00521-021-06074-8

Mansoori, S., Bozorgi-Amiri, A., & Pishvaee, M. S. (2020). A robust multi-objective humanitarian relief chain network design for earthquake response, with evacuation assumption under uncertainties. Neural Computing and Applications, 32(7), 2183-2203. https://doi.org/10.1007/s00521-019-04193-x

Narimani, R., Motamedi, M., & Amoozad khalili, H. (2023). Applying a Mathematical Model for the Distribution of Earthquake Relief Items to the Affected Areas of Tehran. Disaster Prevention and Management Knowledge. 13(2), 184-203. http://dx.doi.org/10.32598/DMKP.13.2.747.1

Niavand, M., Adibi, M. A., & Pourghader Chobar, A. (2024). Selection of green supplier by multi-moora combination method and two-stage clustering. Engineering Management and Soft Computing, 10(1), 14-49. https://doi.org/10.22091/jemsc.2024.10977.1181

Ozbay, E., Çavuş, Ö, & Kara, B. Y. (2019). Shelter site location under multi-hazard scenarios. Computers & Operations Research, 106, 102-118. https://doi.org/10.1016/j.cor.2019.02.008

Peng, D., Ye, C., & Wan, M. (2022). A multi-objective improved novel discrete particle swarm optimization for emergency resource center location problem. Engineering Applications of Artificial Intelligence, 111, 104725. https://doi.org/10.1016/j.engappai.2022.104725

Praneetpholkrang, P., & Huynh, V. N. (2020, February). Shelter Site Selection and Allocation Model for Efficient Response to Humanitarian Relief Logistics. In International Conference on Dynamics in Logistics (pp. 309-318). Springer, Cham. https://doi.org/10.1007/978-3-030-44783-0_30

Rezaei Kallaj, M., Abolghasemian, M., Moradi Pirbalouti, S., Sabk Ara, M., & Pourghader Chobar, A. (2021). Vehicle Routing Problem in Relief Supply under a Crisis Condition considering Blood Types. Mathematical Problems in Engineering, 2021. https://doi.org/10.1155/2021/7217182

Roh, S. Y., Shin, Y. R., & Seo, Y. J. (2018). The Pre-positioned warehouse location selection for international humanitarian relief logistics. The Asian Journal of Shipping and Logistics, 34(4), 297-307. https://doi.org/10.1016/j.ajsl.2018.12.003

Sabouhi, F., Bozorgi-Amiri, A., & Vaez, P. (2020). Stochastic optimization for transportation planning in disaster relief under disruption and uncertainty. Kybernetes. https://doi.org/10.1108/K-10-2020-0632

Shao-hong, Y., Jia-yang, N., Tai-long, C., Qiu-tong, L., Cen, Y., Jia-qing, C. & Jie, L. (2022). Location algorithm of transfer stations based on density peak and outlier detection. Applied Intelligence, 1-13. https://doi.org/10.1007/s10489-022-03206-y

Temiz, S., Kazanç, H. C., Soysal, M., & Çimen, M. (2025). A probabilistic bi-objective model for a humanitarian location-routing problem under uncertain demand and road closure. International Transactions in Operational Research, 32(2), 590-625. https://doi.org/10.1111/itor.13475

Wang, B. C., Qian, Q. Y., Gao, J. J., Tan, Z. Y., & Zhou, Y. (2021). The optimization of warehouse location and resources distribution for emergency rescue under uncertainty. Advanced Engineering Informatics, 48, 101278. https://doi.org/10.1016/j.aei.2021.101278