sustainability

Article

Designing the Distribution Network of Essential Items in the Critical Conditions of Earthquakes and COVID-19 Simultaneously

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Abstract: Current societies must make the necessary plans for effective responses and to reduce the destructive effects of disasters. For this reason, this research has developed a mathematical programming model under uncertainty for earthquake relief and response during COVID-19. In the presented model, the possibility of facility failure is considered according to the intensity of the earthquake and COVID-19 to increase reliability. The simultaneous occurrence of these disasters presents unique challenges in ensuring the timely delivery of essential supplies to affected regions. Distribution centers (DCs) are considered to be of two types: the first type is local DCs, which use public centers and are close to accident points. These types of centers are prone to failure because they use public facilities. Another type is the reliable DCs built outside the disrupted area, which have a very low probability of loss due to spending more money to build them. In addition, to consider the reliability capabilities, the new model has tried to provide a complete model for transportation planning by considering the multi-trip mode of vehicles. Moreover, this model considers distance restriction at the demand point for the first time because of COVID-19 during the earthquake. The proposed network design aims to offer effective solutions in promptly delivering essential items to affected areas, thereby enhancing disaster management strategies and minimizing the impact of these crises on vulnerable populations. Uncertainty is presented using the probability approach based on the modeling scenario and a case study from the city of Istanbul to illustrate the performance of the suggested model. Finally, the suggested mode is solved with an Lp-metric and goal programming (GP) approach. The results show that in this case, the proposed model shows that effective and efficient aid delivery is possible in terms of time and cost. Therefore, it can help crisis managers respond by providing the required budget and appropriate logistics planning.

Keywords: humanitarian supply chain; COVID-19 crisis; time window; multi-objective optimization; reliability

Citation: Abbasi, S.; Vlachos, I.; Rekabi, S.; Talooni, M. Designing the Distribution Network of Essential Items in the Critical Conditions of Earthquakes and COVID-19 Simultaneously. *Sustainability* **2023**, *15*, 15900. https://doi.org/10.3390/su152215900

Academic Editors: Irina Albastroiu Nastase, Mihaela Bucur, Oana Florina Virlanuta and Cristinel Vasiliu

Received: 11 August 2023
Revised: 4 November 2023
Accepted: 7 November 2023
Published: 13 November 2023

1. Introduction

Despite technological progress, sustainable development faces a significant obstacle in various countries due to natural disasters like earthquakes, floods, storms, avalanches, volcanic eruptions, and unnatural ones like war, terrorist attacks, political issues, immigration, and homelessness. The lack of preparation and ineffective response strategies to these calamities result in severe harm and losses to nations and their assets that might be impossible to recover [1–4]. Supply chain management goals include meeting demand, minimizing expenses and investment-related risks through well-known tools, and increasing competitive power in today's world [5,6]. Disasters are unforeseen and abrupt events that exceed a community's competence to manage and cause significant disruptions in that community. These occurrences have far-reaching economic, social, environmental, and political outcomes for society. However, some societies are significantly more prone to devastating incidents [7]; Turkey is a prime example. Turkey is a developing country and ranks 19th globally, with a Gross Domestic Product (GDP) of around USD 906 billion. Unfortunately, the COVID-19 pandemic has also impacted the economy, with the country sharing a 5.6 percent growth rate in 2022 amidst a challenging external environment and unconventional monetary policies [8].

Moreover, the country suffered two devastating earthquakes in February 2023, resulting in significant physical damage and direct losses estimated at USD 34.2 billion [9]. The region suffered considerable damage and destruction due to the disaster, with thousands of houses devastated and essential social amenities, such as roads and dams, damaged beyond repair. The death toll surpassed 86,000, with over 13,000 individuals still missing. Approximately 550,000 people were forced to flee their homes due to the disaster.

Turkey has suffered an estimated USD 34.2 in direct physical damages following two large earthquakes on February 6, equivalent to 4% of the country's 2021 GDP. The eventual recovery and reconstruction costs could be twice as high. It warns that GDP losses associated with economic disruptions will add to the cost of the disaster. Continued aftershocks are also likely to contribute to increased damage estimates over time. The earthquakes have left 1.25 million people temporarily homeless, with much of the damage occurring in 11 provinces in southern Turkey [9]. The earthquake also devastated the domestic supply chain (SC). According to the Natural Disaster Database, earthquakes in the 20th century were responsible for the deaths of over 1.8 million people, and in the years between 1990 and 2010, each event caused 2052 deaths [10,11]. The lack of preparedness in urban areas has increased vulnerability to devastating and terrifying earthquakes. Preventing these disasters may not be entirely possible, but appropriate planning can help communities be better prepared to face challenges [12–16].

To reduce further losses and damages caused by disasters, logistics and related planning will play a vital role in reducing the suffering of affected individuals. Humanitarian logistics is demonstrated as planning, implementing, and directing adequate transportation and keeping the flow of products, resources, and associated data from the point of origin to the place of utilization to reduce the pain and suffering of vulnerable people. Due to the risks and uncertainties related to any disaster, managing humanitarian logistics is very complex. Most researchers provide solutions to humanitarian logistics problems through modeling and optimization. Governments, the military, civil society, and humanitarian organizations are responsible for humanitarian and emergency actions [11,17]. Each of these organizations has different objectives and relief methods based on their organizational structure, which can lead to inefficiencies in relief efforts. Adequate and comprehensive logistics planning results in efficient relief efforts and reduces the suffering of those affected [18].

This paper provides an integer-mixed framework for disaster supply delivery and aid to COVID-19 earthquake victims in light of the significance of this issue. The framework includes a refugee network with a scenario-based approach and a relief goods SC in the case of an unanticipated disaster during the COVID-19 pandemic [19]. Four conflicting objectives are considered while determining the ideal network flow for the two chains: limiting the globalization of the coronavirus, overall logistical cost, and demand satisfaction in the evacuation and relief chains. Furthermore, this approach considers distance restriction between individuals at the required point for the first time. The following are the research inquiries:

- What could happen and what factors need to be considered when creating a distribution network for necessities in the event of COVID-19 and earthquakes occurring simultaneously?
- How can a distribution network be made more efficient to guarantee prompt and effective delivery of necessities when COVID-19 and earthquakes occur simultaneously?

The various sections of the article are constructed as follows: Section 2 reviews the previous studies, Section 3 explains the problem under consideration, and Section 4 illustrates the method used for solving the problem. Section 5 presents the case study and the obtained outcomes of the proposed model, and Section 6 compares the solution method. Section 7 presents the conclusions and future suggestions.

2. Literature Review

2.1. Related Work

Current emergency distribution networks vary in distribution level, horizon planning type, facility location performance, number of groups, mode of transportation, and infrastructure status. In crisis management, distribution networks should be planned and structured despite minimal knowledge. While relief distribution aims to provide emergency needs to the population in the shortest possible time and at the lowest possible cost, the flexibility to respond to dynamic demands may be even more vital. The difficulties in crisis distribution are caused by an absence of confidence regarding supply and demand, a lack of predictability about journey times owing to infrastructural obstacles, the channel of communication breaks, logistics issues, security concerns, and a lack of resources [20]. Previous research in this area can be divided into three categories: location-allocation, transportation, and a combination of location-allocation and transportation issues. Various other categorizations have been made after thoroughly reviewing the research in this area.

2.1.1. Location and Allocation

Facility location (FL) is one of the main issues in logistics network design and planning, in which decision-making regarding the site of facilities and the allocation of customers to these DCs takes place. FL in crisis management, which includes identifying suitable areas for shelters, hospitals, warehouses, DCs, evacuation sites, and other places, is essential for reducing human suffering. Studying FL issues in crisis management is vital to finding locations. FL can be determined based on two questions: which region should be chosen for location-allocation?

Equipment selection and when new facilities should be created or existing facilities should be rebuilt are the issues that Bonham and colleagues considered in their study of emergency equipment location before and after a disaster. Four deterministic, random, dynamic, and stable scenarios were examined to test the proposed model. Before a disaster, the location of shelters and relief warehouses was determined, and after a crisis, the location of DCs and medical facilities was determined. CS analyzed the types of disasters, decisions, objectives, constraints, and solution methods for all of these scenarios [21,22]. Cotes and Cantillo [23] illustrated a model for optimal FL to diminish logistics and deprivation costs. Important decisions were prepared, such as determining the amount of each product type necessary for servicing affected communities after a disaster. An exact solution approach was utilized to solve the problem. Ahmed et al. [24] suggested a novel humanitarian location-allocation-inventory model by focusing on preventing COVID-19 outbreaks with IoT-based technology in the response phase of disasters.

Haghi et al. [25] examined a multi-objective (MO) model for distributing goods and transferring casualties. To approach the actual situation, they considered some uncertainties and utilized a robust optimization method to address them. The epsilon-constraint approach was employed to solve the model. They also used an SC in Tehran to validate their model. Rahmani et al. [26] investigated a humanitarian SC model for dealing with risks in the aftermath of a disaster. They used backup facilities to improve model reliability. They developed the proposed model using a robust optimization approach under uncertain conditions. The probability of occurrence and severity of an incident were considered uncertainty parameters. A Lagrangian approach was utilized to solve the model. They also used SC to verify their model. Abbasi et al. [27] emphasized the need to employ IoT-based solutions to stop COVID-19 outbreaks during the crisis response phase in their unique location-allocation-inventory approach to humanitarian aid. To recommend medical treatments to COVID-19 patients and stop new illness epidemics, Abbasi et al. [28] developed a robust system that considered social isolation, resilience, expenses, and travel time.

Tirkolaee et al. [29] introduced a new multi-objective model to design a sustainable multi-product circular supply chain network during the COVID-19 outbreak. Ghasemi et al. [30] illustrated stochastic multi-objective mathematical programming for logistic distribution and evacuation planning during an earthquake. Conges et al. [31] suggested a new version of future crisis management cells, using virtual reality to provide a dynamic and modular crisis management cell linked to artificial intelligence.

2.1.2. Transportation

After establishing a logistics network, an emergency delivery plan must be created if transportation or distribution issues arise. Due to the number and variety of proposals, this subject is of utmost interest in emergency logistics research. Efforts made in logistics are more directly related to the unique difficulties of emergency shipping [21].

Usually, when disasters such as earthquakes occur, aid organizations face a shortage of resources to respond to demand from affected areas. By introducing this issue, Najafi et al. [32] suggested a robust optimization model to distribute limited resources efficiently. Their multi-objective model utilizes a multi-purpose transportation system for goods and evacuee transportation. The objectives of their model aimed to diminish the total weight of untreated casualties, unmet demands, and the number of vehicles used. Their proposed model considered uncertain elements such as demand for goods, the number of deaths, and supply. Maghfiroh et al. [33] studied a multi-state distribution model. They considered a three-level chain consisting of a supplier, a logistics operations area, and affected areas. The model considers various stages, including network and infrastructure conditions, facility access, and transportation methods. The first part of the Objective Function (OF) focuses on minimizing delivery time, while the second focuses on reducing total costs. In the context of a COVID-19 epidemic illness, Li et al. [34] considered a network of hub-and-spoke multimodal transportation for disaster assistance efforts. They started by building a mixed integer nonlinear programming model using multiple forms of transportation and various sorts of crisis alleviation. Minimizing costs and minimizing transit time were the two goals of the system they offered. They also modified the Grey Wolf Optimizer (GWO) method to address the NP-hardness of the issue under consideration. Safeer et al. [35] employed a classification-based review methodology to identify various cost functions and constraints for primary emergency operations in logistics. Haghgoo et al. [36] addressed both pre- and post-crisis stages in the humanitarian supply chain considering perishability.

2.1.3. Location and Transportation

To hasten the process of humanitarian aid transmission to those impacted by catastrophes, it is suggested that some practical features such as budget allocation, procurement, a flexible supply time horizon, and various vehicle fleet sizes be considered in this model, which is rarely addressed in flow network models. The design of the distribution network is a fundamental step in the SC. For this purpose, different decisions must be made at three strategic, tactical, and operational levels [37]. Location problems and transportation issues are the two significant steps in managing humanitarian distribution. By reviewing the literature in this field, it is also proven that location problems directly impact the efficiency of humanitarian distribution activities. The choice of warehouses and the required capacity of the centers directly affect the distribution decisions. As a result, the logical next step in the decision-making procedure is to tackle both of these obstacles from a combined viewpoint, which involves an examination of the reciprocal linkages between these two levels of making choices [21]. In the following, some research that includes these two problems in a combined form is examined. Tofighi et al. [12] presented a new scenario-based probabilistic-stochastic planning model for humanitarian logistics network design that can simultaneously deal with uncertainty and various goals of the decision problem. Table 1 shows some new works in this area.

Table 1. Literature summary.

Authors	**Objective Functions**			**Kind of Parameters**		**Number of Products**		**Decision Level**				**Time Window**	**Kind of Disaster**	**Case Study**	**Solution Method**
	Cost	**Time**	**Unmet Demand**	**Certain**	**Uncertain**	**Single**	**Multi**	**Location**	**Allocation**	**Transportation**	**Distribution**				
Tofighi et al. (2016) [12]	✓	✓			✓		✓	✓		✓			-	✓	Meta-Heuristic
Cotes and Cantillo (2019) [23]	✓			✓				✓					-		Exact
Yang and Wang (2020) [19]				✓		✓					✓	✓	COVID-19		Exact
Maghfiroh et al. (2020) [33]	✓	✓		✓			✓			✓	✓		-	✓	Heuristic
Shokr et al. (2021) [38]					✓			✓		✓		✓	-		Exact
Zokaee et al. (2021) [39]	✓				✓		✓	✓			✓		Earthquake	✓	Exact
Babaee-Tirkolaee et al. (2022) [29]	✓			✓			✓	✓			✓		COVID-19	✓	Meta-Heuristic
Hosseini-Motlagh et al. (2023) [40]	✓				✓	✓			✓				COVID-19	✓	Exact
Li et al. (2023) [41]	✓	✓		✓		✓				✓			COVID-19		Meta-Heuristic
Ehsani et al. (2023) [42]	✓	✓			✓		✓	✓	✓				COVID-19	✓	Exact
This Study	✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	Earthquake COVID-19	✓	Exact

2.2. Research Gap and Contributions

This paper designed the SC for humanitarian aid. This humanitarian relief supply chain design has several contradictory problems, but these problems should be solved using mathematical tools. Creating suitable camps to accommodate the victims is difficult in times of floods or earthquakes. This point is significant. We must pay attention to their relief, but the important thing is that in the era of COVID-19, gathering people may be dangerous; the gathering of several people in one relief camp is against health protocols. In the age of COVID-19, health organizations strictly recommend social distancing and hygiene protocols. The fundamental question arises: how should the crisis be managed if a flood and an earthquake occur during the COVID-19 pandemic? A practical example is the recent earthquake in Turkey. How should this SC design be structured?

In the event of an unforeseen catastrophe during the COVID-19 pandemic, the framework incorporates a relief goods SC and an evacuation network. The optimal network flow for the two chains was investigated by considering four competing objectives: demand satisfaction in the relief chain, demand satisfaction in the evacuation chain, total logistical cost, and preventing the spread of the coronavirus. The humanitarian products SC was divided into three tiers: suppliers, relief camps, and afflicted locations. The flight chain was divided into evacuated camps and impacted areas. The framework has been strengthened by considering many pathways between both places and the disruption of camps and trails owing to catastrophes.

Moreover, the multi-objective mixed-integer programming (MOMIP) issue was solved mathematically, and the results were compared with two methods. The mathematical framework was effectively evaluated during the catastrophe and produced real-life information. This is an urgent concept with several facets.

In general, the contributions of this study include:

- Considering reliable support DCs for affected population centres to improve reliability.
- Providing a bi-objective mathematical model to minimize the time spent transporting relief goods and related logistics costs is also considered.
- The uncertainties related to earthquake probability, earthquake magnitude, and the probability of DC destruction are considered using a scenario-based approach.
- Public facilities and establishments are considered DCs.
- Turkey has been used as a case study to describe the model's performance and the application of the described method.
- Considering distance restriction between people at the demand point.
- Reusing vehicles during the time horizon and in each period is considered.

3. Problem Statement

Our model includes the prominent SC members, consisting of a central warehouse, DCs, and affected areas. Figure 1 shows the levels of this SC. Each part of our SC has one or more relationships with the next part, and based on this, we have channels in our SC that we can accurately represent in the mathematical model. For example, each distributor has a relationship with all the central warehouses. Relief goods are sent through DCs, and each affected area has a relationship with all DCs. Two DCs are considered in the proposed model, the first of which can fail and use public facilities. The second type cannot fail and is more expensive to build. Suppose the affected areas are assigned to the first type of DC as the leading supplier. In that case, they must also be assigned to the second type of DC as a backup. However, suppose they are given to the second type of DC as the main DC. In that case, there is no need for a backup DC because these DCs have a very low probability of failure.

On the other hand, transportation constraints, such as vehicle capacity and the number of vehicles, were considered in the mathematical model. This study also considered the possibility of multi-trip states for carriages [43]. Since it is impossible to ensure the timely distribution of relief goods using a single mode of transportation, multimodal transportation is used in real-life situations during relief distribution. In this study, air and land transportation were also used. The goals of the proposed model were to minimize the time spent transporting relief goods, which is very important in crises, and to minimize the cost of building central warehouses.

Figure 1. The levels of this SC during both disasters.

3.1. Assumptions

- The capacity of distribution and backup centers is specified, but the capacity of central warehouses is considered unlimited.
- The uncertainties of the model, including the probability of an earthquake, the likelihood of failure of local DCs, and demand, were modeled using a probabilistic scenario-based approach.
- If the supply of goods through the main DC is not possible, goods will be supplied through backup centers.
- Goods have priority, reflected in the cost of a shortage of goods.
- Each vehicle can make multiple trips during the time horizon and in each period.
- Two methods of land and air transportation are used to transport goods.
- Vehicles are homogeneous in each transportation mode.
- The number and location of affected areas are identified.
- The possibility of shortages exists.
- The capacity of vehicles is specified.
- The distances between nodes are identified.
- Multiple periods are considered in the model.
- Multiple types of goods are considered in the model.

3.2. Sets

i	Set of warehouses during both earthquakes and COVID-19 disasters $i \in \{1,2,\ldots,I\}$;
g	Set of DCs during the both earthquakes and COVID-19 disasters $g \in \{1,2,\ldots,G\}$;
g'	Set of reliable DCs that can be used as a backup during both earthquakes and COVID-19 disasters $g\prime\epsilon\{1,2,\ldots,G'\}$;
o	Set of damaged points for earthquake and COVID-19 disasters $o \in \{1,2,\ldots,O\}$;
m	Set of vehicles $m \in \{1,2,\ldots,M\}$;
V_{im}	Set of vehicles of type m in the warehouse i ;
V_{gm}	Set of vehicles of type m in the DC $g \in G \cup G'$;
n_m	Set of number of trips of each vehicle type m in each period t $n \in \{1,2,\ldots,N\}$;
s	Set of scenarios $s \in \{1,2,\ldots,S\}$;
t	Set of time periods for earthquakes and COVID-19 disaster; $t \in \{1,2,\ldots,T\}$
l	Set of goods $l \in \{1,2,\ldots,L\}$;

3.3. Model Parameters

θ_i	Fixed cost of establishing a warehouse i;
θ_g	Fixed cost of establishing the DC $g \in G \cup G'$;
a_l	Size of the product, which includes the volume and weight of the product;
d_{olst}	The demand of good l in damaged point o in scenario s in period t during the earthquakes and COVID-19 disasters;
b_g	The capacity of DC $g \in G \cup G'$;
c_{igm}	The cost of each transportation unit from warehouse i to the DC $g \in G \cup G'$ by vehicle type m;
c_{gom}	The cost of each transportation unit from DC $g \in G \cup G'$ to the damaged point o by vehicle type m;

$time_{igm}$	Transfer time of products from the warehouse i to the DC $g \in G \cup G'$ by vehicle type m;
$time_{gom}$	Transfer time of products from the DC $g \in G \cup G'$ to the damaged point o by vehicle type m
p_s	Probability of scenarios during both earthquakes and COVID-19 disasters;
p_{gs}	Probability of destruction of the DC $g \in G$ under scenario s;
Φ_l	Shortage cost of products l during the two earthquakes and COVID-19 disasters;
q_m	The capacity of vehicle type m, which includes the volume and weight capacity of the vehicle;
α_{ig}	Distance from warehouse i to DC $g \in G \cup G'$;
α_{go}	Distance between the DC $g \in G \cup G'$ to the damaged point o;
md_o	Maximum allowable distance between people in damaged point o;
$diss_o$	Distance between people in damaged point o;
ψ	Large positive number;

3.4. Decision Variables

z_{ist}	If the central is selected in the scenario s in the period t is 1; otherwise, 0
zz_{gst}	If DC $g \in\ G \cup G'$ is selected in scenario s in period t is 1; otherwise, 0
y_{igst}	If DC $j \in J \cup J'$ is selected to the warehouse i in scenario s in period t is 1; otherwise, 0
x_{gost0}	If the damaged point o be assigned to the DC $g \in G$ in scenario s in the period t 1; otherwise, 0
x'_{gost0}	If the damaged point o is assigned to the DC $g \in G'$ as the leading supplier in scenario s in period t is 1; otherwise, 0
x_{gost1}	If damaged o is assigned to the DC $g \in G'$ as a backup supplier in scenario s in period t is 1; otherwise, 0
q_{iglst}^{mnv}	The quantity of product l that transfers from the central warehouse i to the DC $g \in G \cup G'$ by vehicle type m around $n \in N_m$ with vehicle $v \in V_{mi}$ in scenario s in period t;
$q_{iglst}^{\prime mnv}$	The quantity of the backup product l that is transported from the warehouse i to the DC $g \in G'$ by vehicle type m in round $n \in N_m$ and by vehicle $v \in V_{mi}$ in scenario s in period t;
q_{glost}^{mnv}	The quantity of the product l that is transported from the DC $g \in G \cup G'$ to the damaged point o by vehicle type m in round $n \in N_m$ and by Vehicle $v \in V_{mi}$ in scenario s in period t;
B_{olst}	Shortage amount of commodity l at incident point k in scenario s in period t;
w_{golst}^{mnv}	If the route $g \in G \cup G'$ is taken by vehicle type m in round $n \in N_m$ or with vehicle $v \in V_{mi}$ in scenario s in period t is 1; otherwise, 0
w_{iglst}^{mnv}	If the route i to $g \in G \cup G'$ is taken by vehicle type 'm at round $n \in N_m$ or by Vehicle $v \in V_{mi}$ in scenario s in period t is 1; otherwise, 0

3.5. Mathematical Model

The first OF (1) minimizes the total distribution time between central warehouses, DCs, and demand points during the two earthquakes and COVID-19 disasters. The second OF (2) minimizes the total cost, consisting of warehouse construction costs, unmet demand costs, and transportation costs of relief items from reliable and local DCs during the both earthquakes and COVID-19 disasters.

$$\begin{aligned} \min Z_1 = \sum_s p_s \Bigg(& \sum_i \sum_{g \in G \cup G'} \sum_l \sum_m \sum_t \sum_{n \in N_m} \sum_{v \in V_{mi}} time_{igm} w_{igls}^{mnv} \\ & + \sum_{g \in G \cup G'} \sum_o \sum_l \sum_m \sum_t \sum_{n \in N_m} \sum_{v \in V_{mi}} time_{gom} w_{golst}^{mnv} \Bigg) \end{aligned} \tag{1}$$

Constraint (3) is an equilibrium constraint for the DC inventories. Constraints (4) and (5) are demand constraints, indicating that relief items sent to each demand point cannot exceed the demand quantity. Constraint (6) guarantees that the backup warehouse will meet the required demand if the primary DC is destroyed. Constraint (7) calculates the shortage of relief items at demand points. Constraints (8) and (9) limit the maximum storage capacity of relief items at DCs. Constraints (10) and (11) indicate that each demand point is allocated to a reliable or local DC if a regional DC is chosen as the primary supplier, it must also be allocated to a dedicated DC as a backup. No backup warehouse is needed if a proper DC is selected as the primary supplier. Constraints (12) and (13) ensure that no relief items will be moved from that center if a DC is not reopened or not allocated. Constraints (14) and (15) guarantee that no relief items will be transported to the end of a demand point not allocated to a DC. Constraints (16) to (17) represent the maximum capacity of vehicles. Constraints (18) to (22) are used to determine if the route is traversed by a vehicle of type m or not. Constraint (23) illustrates the maximum allowable distance between people at the demand point. Constraints (24) and (25) represent the types of variables used.

$$\begin{aligned}\min Z_2 = \sum_s p_s \Bigg[& \sum_i \sum_t \theta_i z_{ist} + \sum_{g\in G\cup G'} \sum_t \theta_i zz_{gst} \\ & + \sum_o \sum_l \sum_t \Phi_l B_{olst} \\ & + \sum_{g\in G'} \left(\sum_i \sum_l \sum_m \sum_t \sum_{n\in N_m} \sum_{\nu\in V_{mg}} c_{igm} \alpha_{ig} q^{mnv}_{iglst} + \sum_o \sum_l \sum_m \sum_t \sum_{n\in N_m} \sum_{\nu\in V_{mg}} c_{gom} \alpha_{go} q^{mnv}_{golst} \right) \\ & + \sum_{g\in G} (1-p_{gs}) \left(\sum_i \sum_l \sum_m \sum_t \sum_{n\in N_m} \sum_{\nu\in V_{mg}} c_{igm} \alpha_{ig} q^{mnv}_{iglst} \right. \\ & \left. + \sum_o \sum_l \sum_m \sum_t \sum_{n\in N_m} \sum_{\nu\in V_{mg}} c_{gom} \alpha_{go} q^{mnv}_{golst} \right) \\ & + \left(\sum_{g'\in G'} \left(\sum_i \sum_l \sum_m \sum_t \sum_{n\in N_m} \sum_{\nu\in V_{mi}} c_{ig'm} \alpha_{ig} + \sum_o \sum_l \sum_m \sum_t \sum_{n\in N_m} \sum_{\nu\in V_{mg'}} c_{g'om} \alpha_{g'o} q^{mnv}_{g'olst} \right) \right) \Bigg] \end{aligned} \tag{2}$$

s.t

$$\begin{aligned} \sum_i \sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mi}} q^{mn\nu}_{iglst} + \sum_i \sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mi}} q'^{mn\nu}_{iglst} \\ = \sum_o \sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mg}} q^{mn\nu}_{golst} \end{aligned} \qquad \forall g \in G', l, s, t \tag{3}$$

$$\sum_i \sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mi}} q^{mn\nu}_{iglst} = \sum_o \sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mg}} q^{mn\nu}_{golst} \qquad \forall g \in G,\ l, s, t \tag{4}$$

$$\sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mg}} q^{mn\nu}_{golst} \le d_{olst}.x'_{gost0} \qquad \forall g \in G, o, l, s, t \tag{5}$$

$$\sum_i \sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mg}} q'^{mn\nu}_{iglst} \le \sum_o \sum_{g\in G} x_{\ gost0}.x_{g'ost1}.d_{olst}.p_{gs} \qquad \forall g \in G', l, s, t \tag{6}$$

$$B_{olst} = \max \left(0.d_{olst} - \sum_{g\in G\cup G'} \sum_m \sum_{n\in N_m} \sum_{V_{mg}} q^{mn\nu}_{golst} \right), \qquad \forall g \in G\ , l, s, t \tag{7}$$

$$\sum_i \sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mg}} \sum_l q^{mn\nu}_{iglst} + \sum_i \sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mi}} \sum_l q'^{mn\nu}_{iglst} = b_g \qquad \forall g \in G', s, t \tag{8}$$

$$\sum_i \sum_m \sum_{n\in N_m} \sum_{\nu\in V_{mi}} \sum_l q^{mn\nu}_{iglst} \le b_g \qquad \forall g \in G, s, t \tag{9}$$

$$\sum_{g\ \in G} x_{gost0} + \sum_{g\in g'} x'_{gost0} = 1 \qquad \forall o, s, t \tag{10}$$

$$\sum_{g\in G'} x_{gost1} = \sum_{g\in G} x_{gost0} \qquad \forall o\ , s, t \tag{11}$$

$$\sum_{g\in G\cup G'} y_{igst} \le \psi z_{ist} \qquad \forall\ i, s, t \tag{12}$$

$$\sum_I y_{igst} \le zz_{gst} \qquad \forall g \in G \cup G', s, t \tag{13}$$

$$q^{mn\nu}_{iglst} \le \psi y_{igst} \qquad \forall i, g \in G \cup G', l, s, t, m, n \in N_m, \nu\ \in V_{mi} \tag{14}$$

$$q'^{mn\nu}_{iglst} \le \psi y_{igst} \qquad \forall i, g \in G \cup G', l, s, t, m, n \in N_m, \nu \in V_{mi} \tag{15}$$

$$\sum_l a_l q^{mn\nu}_{iglst} \le q_m \qquad \forall i, g \in G \cup G', l, s, t, m, n \in N_m, \nu \in V_{mi} \tag{16}$$

$$\sum_l a_l q'^{mn\nu}_{iglst} \le q_m \qquad \forall i, g \in G \cup G', l, s, t, m, n \in N_m, \nu \in V_{mi} \tag{17}$$

$$\sum_l a_l q^{mn\nu}_{golst} \le q_m, \qquad \forall k, g \in G \cup G', l, s, t, m, n \in N_m, \nu \in V_{mi} \tag{18}$$

$$w^{mn\nu}_{golst} \le \psi q^{mn\nu}_{golst}, \qquad \forall k, g \in G \cup G', l, s, t, m, n\ \in N_m, \nu \in V_{mi} \tag{19}$$

$$w^{mn\nu}_{golst} \le q^{mn\nu}_{golst} \frac{1}{\psi} \qquad \forall k, g \in G \cup G', l, s, t, m, n\ \in N_m, \nu \in V_{mi} \tag{20}$$

$$w_{iglst}^{mnv} \leq \psi\, q_{iglst}^{mnv} \qquad \forall i, g \in G \cup G', l, s, t, m, n \ \in N_m, v \in V_{mi} \tag{21}$$

$$w_{iglst}^{mnv} \leq q_{iglst}^{mnv} \frac{1}{\psi} \qquad \forall i, g \in G \cup G', l, s, t, m, n \ \in N_m, v \in V_{mi} \tag{22}$$

$$diss_o . x'_{gost0} \leq md_o \qquad \forall g, o, s, t \tag{23}$$

$$x_{gost0}, x'_{gost0}, z_{ist}, zz_{gst}, y_{igst} \in \{0, 1\} \qquad \forall i, g \in G \cup G', l, s, t \tag{24}$$

$$q_{iglst}^{mnv}, q_{golst}^{mnv}, q'^{mnv}_{iglst}, B_{olst} \geq 0 \qquad \forall i, g \in G \cup G', o, l, s, t \tag{25}$$

3.6. Linearity

An optimization strategy for linearizing nonlinear functions is called "linearization according to auxiliary variable". The method entails adding an auxiliary variable and matching the auxiliary equality condition for each function's intermediate nonlinear factor. The product of two variables, one of which is continuous and the other binary, is represented by the auxiliary variable. Using this method, a nonlinear optimization issue may be converted into a linear one that can be solved more quickly.

The following are some essential details about linearization based on an auxiliary variable:

- In issues related to optimization, the method is used to linearize nonlinear functions.
- A matching auxiliary equality constraint and an auxiliary variable are introduced for each intermediate nonlinear component of the function [44].
- A nonlinear optimization problem can be made linear by using this strategy.
- Linearization based on an auxiliary variable is a commonly employed method in optimization.

The effective linearization method according to the auxiliary variable may be applied to tackle challenging optimization issues. It is extensively utilized in many disciplines, including as a tool for finance, engineering, and economics [44–47].

Due to the non-linearity of Constraints (7) and (8), we linearize them by introducing the following and associated variables and replacing them with the following constraints:

$t'_{gg'ost}$	Binary auxiliary variable for linearization
S^{+}_{olst}	Continuous auxiliary variable for linearization
S^{-}_{olst}	Continuous auxiliary variable for linearization
$_{olst}$	Binary auxiliary variable for linearization

$$t'_{gost} \leq \frac{1}{2}\left(x_{gost} + x'_{go1st}\right) \qquad \forall g \in G, g' \in G', o, s, t \tag{26}$$

$$t'_{g.g'.o.s.t} \leq \left(x_{gost} + x'_{go1st}\right) - 1 \qquad \forall g \in G, g' \in G', o, s, t \tag{27}$$

$$\sum_{i}\sum_{m}\sum_{n \in N_m}\sum_{v \in V_{mi}} q'^{mnv}_{iglst} \leq \sum_{k}\sum_{j \in J} t'_{gg'ost}.d_{kolst}.p_{gs} \qquad \forall g \in G', l, s, t \tag{28}$$

$$B_{olst} = S^{+}_{olst}, \qquad \forall o, s, l, t \tag{29}$$

$$S^{+}_{olst} - S^{-}_{olst} = d_{olst} - \sum_{g \in G \cup G'}\sum_{m}\sum_{n \in N_m}\sum_{v \in V_{mg}} q_{golst}^{mnv} \qquad \forall o, s, l, t \tag{30}$$

$$S^{+}_{olst} \leq \psi ._{olst} \qquad \forall o, s, l, t \tag{31}$$

$$S^{-}_{olst} \leq \psi .(1 - {}_{olst}) \qquad \forall o, s, l, t \tag{32}$$

4. Solution Methods

4.1. Goal Programming

A subset of multi-objective optimization, or multi-criteria decision analysis (MCDA), is goal programming (GP). Targets are defined for a collection of constraints, extending or generalizing linear programming. By translating several objectives into goals with present target values and weights, the technique may manage multiple objectives. Goal programming is utilized for three different kinds of analyses:

- Ascertain the resources needed to accomplish a desired set of goals.

- Assess the extent to which the objectives have been met in relation to the resources at hand.
- Offer the most fulfilling solution given the different resources available and the goals' relative importance.

Pre-emptive and lexicographic models are the two fundamental types of goal programming. Minimizing a deviation in a higher priority level is much more significant than any deviations in lower priority levels. In pre-emptive goal programming, the undesirable deviations are sorted into many priority levels. There is a definite priority ordering among the objectives in lexicographic goal programming [48].

One of the fundamental methods for creating paradigms in which the decision-maker (DM) tries to accomplish several objectives at once is general programming (GP). Like other approaches, GP may be expressed in mathematical models that are linear or nonlinear.

Achieving the level of desire set in a goal depends on the possibilities, resources, limitations, etc. In practice, the decision-maker may or may not achieve the level of desire set. In many cases, there may be differences between the desires, inclinations, and desires of the decision-maker and what can be achieved in practice. This rate of difference in ideal planning models is measured by a variable called the variables of deviation from the ideal. We display the variables deviating from the ideal with d_i^+ and d_i^-. For better information, seee below.

A goal's ability to be attained relies on available options, assets, constraints, etc. The decision-maker may or may not actually fulfil their degree of desire. In numerous instances, there could be discrepancies between the decision-maker's preferences, desires, goals, and what can be accomplished. A variable known as the factor of departure from the ideal is used to quantify this rate of variation in ideal planning systems. With d_i^+ and d_i^-, we show the variables that deviate from the ideal. See the material under for further details:

The states	**The variables deviating from the ideal**	**Description**
First	$d_i^+ = d_i^- = 0$	Full achievement of the goal
Second	$d_i^+ \neq 0, d_i^- = 0$	Overtaking of the goal.
Third	$d_i^+ = 0, d_i^- \neq 0$	Failure to achieve the goal
Fourth	$d_i^+ \neq 0, d_i^- \neq 0$	This is not possible

In this research, to implement the GP approach, the mathematical model is first solved as a single objective, and f_i^* is determined. Next, the number of negative deviations from each OF is calculated. Finally, the total deviations are minimized shows in Equations (33)–(35) [49].

$$MinZ_{GP} = d_1^- + d_2^-, \tag{33}$$

$$f_1^* = z_1 + d_1^- - d_1^+, \tag{34}$$

$$f_2^* = z_2 + d_2^- - d_2^+, \tag{35}$$

4.2. Lp-Metrics Approach

Lp spaces, function spaces that are defined by a natural generalization of the p-norm for finite-dimensional vector spaces, are a key component of the Lp-metrics strategy, a mathematical idea. Lebesgue spaces, often known as Lp spaces, are a crucial class of Banach spaces used in functional analysis and topological vector spaces.

The Lp-metric is a norm metric on Rn (or on Cn), defined by | |x − y| |p, where the Lp-norm | |. | |p is defined by | |x| |p = (n∑ i = 1|xi|p)1/p. The Lp-metric technique has a wide range of applications in measure and probability spaces, physics, statistics, economics, finance, engineering, and other fields, as well as in a variety of sciences such as physics, mathematics, and computer science [50].

The metric distance is used in Lp-metrics to compute the distance between the current and ideal outcomes. Xu and Cao [51] proposed Equation (36) to solve "the more, the better" difficulties using an anti-ideal method.

$$LP = \left\{ \sum_{j=1}^{k} w_j \left[\frac{f_j\left(x_j^*\right) - f_j(x)}{f_j\left(x_j^*\right) - f_j(\overline{x}_j)} \right]^p \right\}^{1/p} \tag{36}$$

The compatible Lp function is minimized to provide optimal solutions. Equation (36) can be used to determine the compatible Lp function as a normalized form for various objectives with different dimensions. p represents the importance of the decision-maker according to the relevant departure values while deciding. In this investigation, p was taken to be equal to 2. To find the best solution, each OF is independently solved using the appropriate restrictions ($f_j\left(x_j^*\right)$).

In other words, the maximum was changed into minimization when the reverse OFs were solved. We then used these numbers to minimize the Lp model based on these restrictions. The Equation (36) is finally completed to produce the ideal values and Lp deviations.

The importance of the j-the aim is indicated by the value of $\mathrm{w_j}$ ($\sum_\mathrm{j} \mathrm{w_j} = 1$), and a gradual-priority weighted technique is used to explore the whole solution space and find *Pareto-optimal* (*PO*) answers [52].

5. Case Study

An Mw 7.8 earthquake on 6 February 2023, at 04:17 TRT impacted northern and western Syria and southern and central Turkey. Gaziantep was 37 km to the west and north of the earthquake. The earthquake's highest Mercalli strength was XII at Antakya and the area surrounding the epicenter. At 13:24, a Mw 7.7 earthquake struck in its wake. The second earthquake had its epicentre 95 kilometres to the north of the first. There were tens of thousands of fatalities and extensive damage [53–55].

About 507,000 dwelling units were inside those seriously damaged and fallen structures, which highlights the enormity of the immediate housing requirements for those displaced by the earthquake. Millions of individuals now urgently required access to essentials, including shelter, food, clean water, and sanitation, due to the earthquake's escalation of the impacts of the continuing war in Syria. Turkey's two main fault zones constitute one of the most seismically active areas on the globe. An earthquake is one of the most harmful natural hazards [55–58].

Direct Relief and World Vision were among the organizations that provided disaster relief to those affected by the earthquake Figure 2 shows the location of the latest earthquake in Turkey, depicted schematically. Some information about the case is in Tables 2–7 and the results are in Tables 8 and 9.

Table 2. Characteristics of faults and research scenarios.

Earthquake Scenario	Scenario1	Scenario2	Scenario3	Scenario4
Fault	Location 1	Location 2	Location 3	Location 3
Length	68	74	32	20
Width	22	45	12	9
Severity of occurrence	3.5	8.5	60.1	7.1
Probability of occurrence	0.40	0.66	0.14	0.5

Table 3. Characteristics of relief goods.

Commodity	Volume (m^3)	Weight (kg)	Shortage Cost ($)	Discharge Time/Loading Time (Minutes)
Non-consumable	0.2	38	25	0.1
Consumable	0.17	5	77	0.03

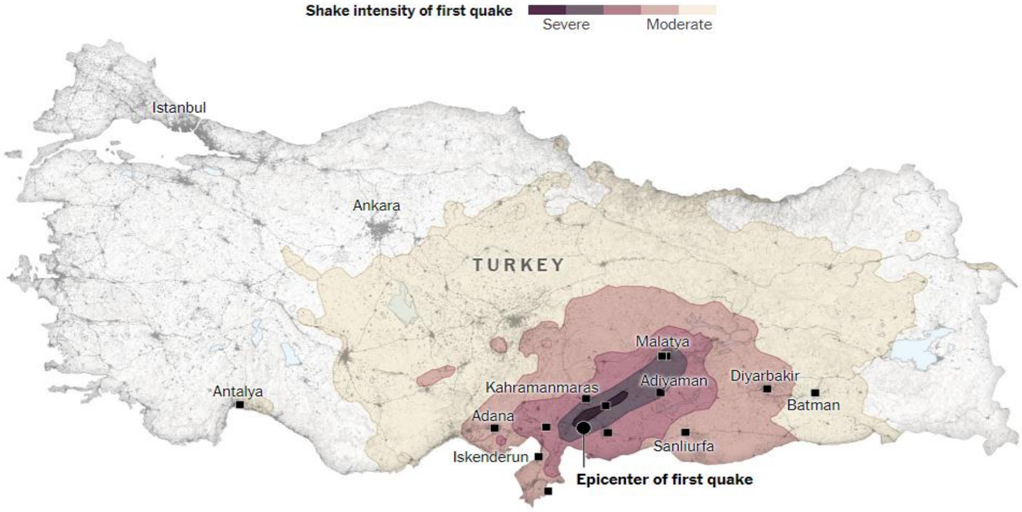

Figure 2. Schematic of the location of the recent earthquake in Turkey [59–61].

Table 4. Vehicle characteristics.

Vehicles	Weight Capacity (tons)	Volumetric Capacity (m^3)	Speed (km/h)	Cost ($)
Kind of one	1.2	30	100	8
Kind of two	5	61	70	3

Table 5. Facility specifications.

	Central Warehouse	Local DC	Backup DC
Capacity	2	5000	4000
Construction cost	1.1	0.20	0.8

Table 6. The percentage of destruction of the local DC.

Earthquake Scenario	Scenario1	Scenario2	Scenario3	Scenario4
District 15	22	17	21	15
District 16	30	10	15	12
District 18	40	20	30	15
District 19	30	10	20	16
District 20	60	40	56	39

Table 7. The amount of demand for incident points.

Damaged Points	Scenario1	Scenario2	Scenario3	Scenario4
1	3300	2088	7176	5621
2	5791	1122	6611	2011
3	4210	1081	8058	6344
4	1010	520	7622	5031
5	1329	850	5445	4310

Table 8. The pareto solutions for the GP method.

First OF	Second OF
1.75×10^{10}	7.62×10^{12}
2.13×10^{10}	5.40×10^{12}
3.55×10^{10}	4.30×10^{12}
3.92×10^{10}	3.20×10^{12}
4.90×10^{10}	2.00×10^{12}
5.80×10^{10}	2.09×10^{12}
6.80×10^{10}	1.01×10^{12}
8.81×10^{10}	1.00×10^{12}

Table 9. The pareto solutions for the Lp-metric method.

First OF	Second OF
1.33×10^{10}	9.62×10^{12}
2.10×10^{10}	8.20×10^{12}
4.15×10^{10}	7.30×10^{12}
5.98×10^{10}	6.27×10^{12}
7.10×10^{10}	4.03×10^{12}
7.89×10^{10}	4.09×10^{12}
8.82×10^{10}	2.81×10^{12}
9.82×10^{10}	1.99×10^{12}

The Lp-metric approach is one approach to finding Pareto-optimal answers to a multi-objective optimization issue. While dealing with issues that have several variables and restrictions, as well as when the objective functions are linear, it is very helpful.

The outcomes of the search demonstrate that Pareto solutions are investigated in a variety of domains, including multi-objective optimization, linear programming, vector optimization problems, and polynomial vector optimization issues. Different approaches to obtaining Pareto solutions have been proposed by researchers, including the conventional constraint technique and stochastic global optimization algorithms. Studies have also been conducted on proper Pareto solutions, a subset of Pareto solutions that satisfy extra requirements. The Pareto frontier for two OFs using the Lp-metric and GP techniques is shown in Figures 3 and 4. Table 9 shows the Pareto solutions for the Lp-metric method.

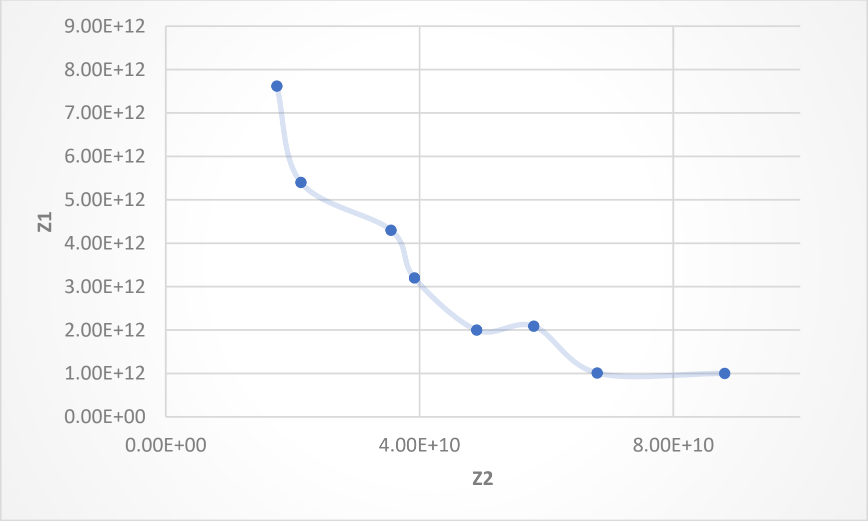

Figure 3. Pareto frontier of two OFs with the GP method.

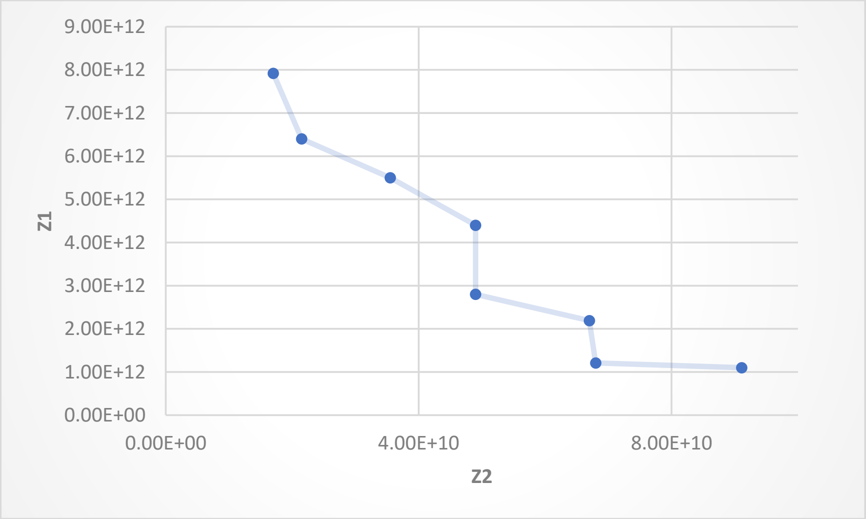

Figure 4. Pareto frontier of two OFs with the Lp-metric method.

Multi-objective optimization problems can have Pareto-optimal solutions found using the GP approach. The Pareto principle may be used to pinpoint the most crucial GP goals and limitations. In order to maximize a system's overall performance and produce the greatest results, GP focuses on a select few crucial factors.

Pareto solutions are those for multi-objective optimization problems where no alternative solution can enhance one goal without making at least one other objective worse. To put it another way, Pareto solutions are non-dominated solutions, meaning that no other option is superior across the board.

6. Comparing Solution Methods

The best result was achieved using Lingo software on a Core5 machine running at 21.2 GHz Intel. With the help of the Lp-metric and GP methodologies, the sample test issues are optimized in this part. Z represents the values acquired in the Lp-metric. The values acquired by the Lp-metric technique for the first and second goals are represented by a number of single objective (SO) values, f_1 and f_2, and a number of optimum multi-objective values are generated by contrasting these values independently. Z_{GP} in Table 10 displays the overall unfavourable deviation. After reviewing the calculation results, we compared the average values of the OFs using a variety of techniques. Figure 5 displays the pareto border.

Table 10. Using GP and Lp-metrics to achieve the results.

Number of Test Problem	**Size of Test Problem**	$Z_{GP}\left(f_1^*\right)$	$Z_{GP}\left(f_2^*\right)$	$Z_{LP}\left(f_1^*\right)$	$Z_{GP}\left(f_2^*\right)$	**CPU Time (for GP.)**	**CPU Time (for Lp.)**
P_1	Small	8.27631×10^5	54,640.18	8.2893×10^{10}	45,483.172	14.8	12.4
P_2	Small	4.27232×10^6	158,069	2.11×10^{11}	115,527.3	15.1	12.5
P_3	Medium	2.56632×10^8	190,281.2	4.13×10^{11}	226,506.2	17.4	13.7
P_4	Medium	4.32509×10^7	617,904.7	5.14×10^{11}	281,904.7	18	15
P_5	Medium	5.70672×10^7	785,247	6.79×10^{11}	372,507.2	23	20

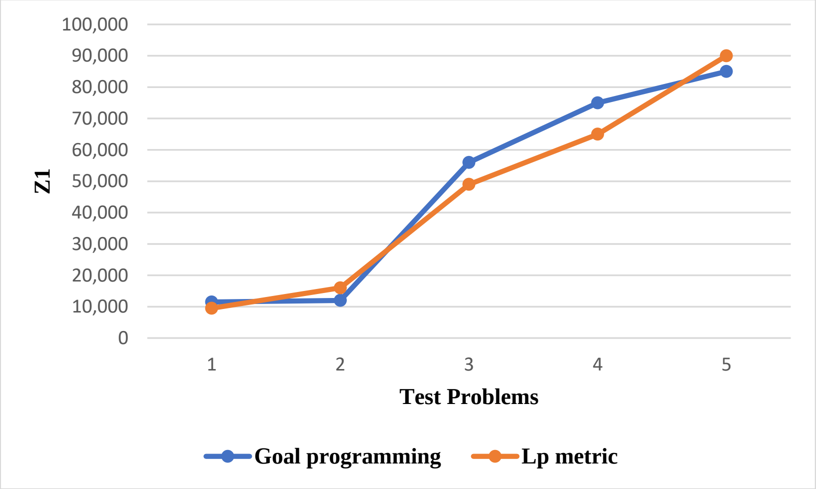

Figure 5. First OF is compared between the two methods.

Figure 6 illustrates how different methods give different values to the same goals for different problems. Problems with larger dimensions show more differences in goal values.

All of the problems have a much longer solution time when using the GP method, as shown in Figure 7. In this problem, equality constraints are a major cause of complexity as they increase the number of variables. A simple additive weighting (SAW) method was implemented to determine the best method.

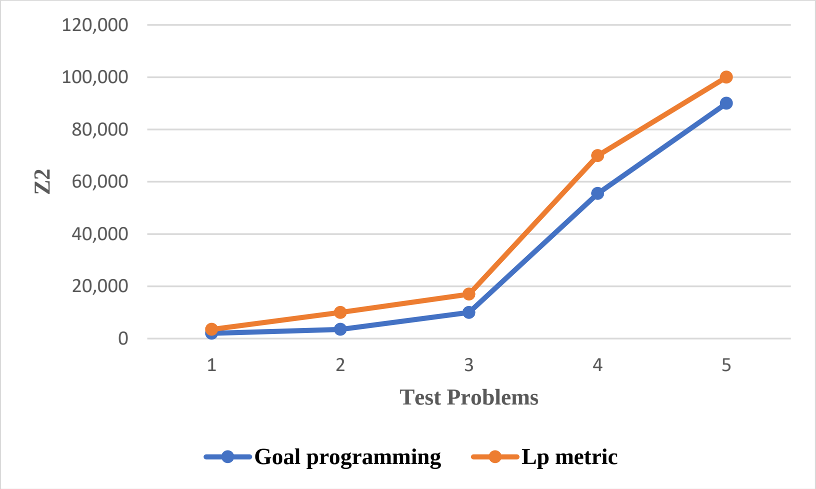

Figure 6. Comparing the two methods for second OF.

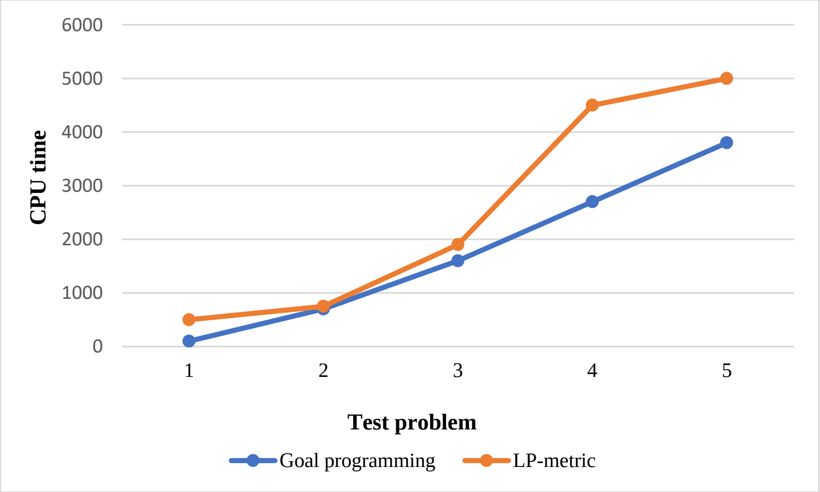

Figure 7. An analysis of the CPU time for the different methods.

In Table 11, each method is ranked according to its weight. It represents the optimal average values across different issues in the table. The solution time hurts weight determination because the goals are presented in their maximized state. Thus, it is an effective way to gain weight. After reviewing the solution methods, the Lp-metric method was found to have the best performance. Therefore, parameter analysis should be performed using the Lp-metric approach.

Table 11. Ranking the solutions methods.

Methods	SAW Criteria	Ranking
Lp-metric	0.441206	1
GP	0.371205	2

7. Sensitivity Analysis

In this section, we performed sensitivity analysis on several parameters to validate the proposed model. This sensitivity analysis aims to investigate the impact of parameter changes on the optimal solution. Only the desired parameter changes for sensitivity analysis, while the other parameters are considered constant. This study selects essential problem parameters such as demand for relief items, cost of transportation, and probability of local DC failure for sensitivity analysis.

7.1. Demand

For the demand parameter, different coefficients were considered, while other parameters were assumed to be constant. The amount of change in each OF concerning the shift in demand parameter is shown below.

In Figures 8 and 9, both OFs increase with increased demand. The second OF related to costs seems logical to grow with increased demand due to transportation costs and, in the case of demand satisfaction failure, the cost of shortages that arise. Also, an increase in demand in the first OF may result in more vehicles or round trips for each vehicle, increasing distribution time for both factors.

7.2. Transportation Cost

According to Figure 10, an increase in the transportation cost parameter leads to an increase in the value of the second OF, representing the total cost. However, according to our research, changing the transportation cost parameter does not affect the first OF.

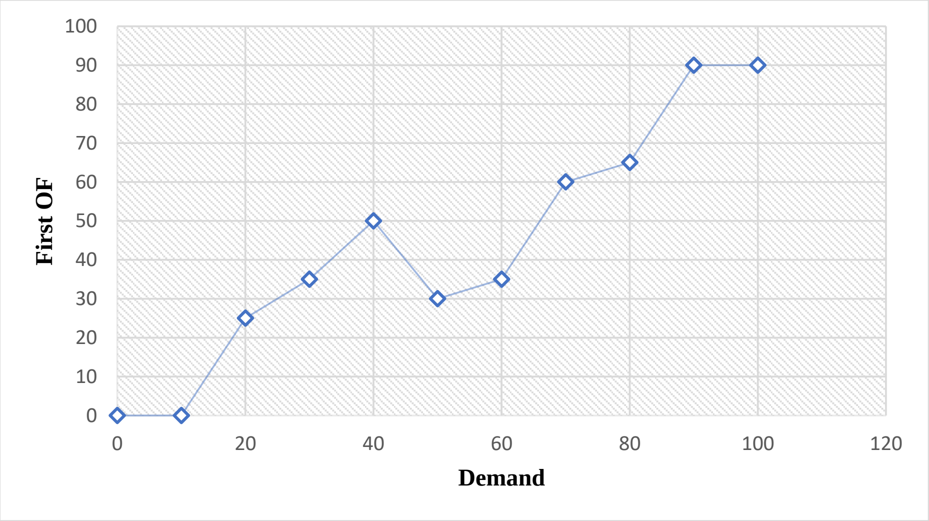

Figure 8. Variations of the first OF respect to demand fluctuation.

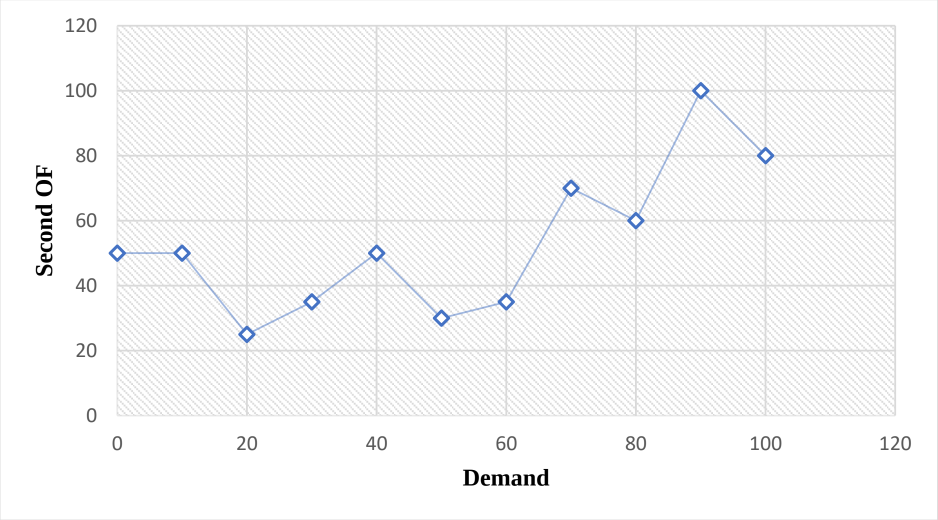

Figure 9. Variations of the second OF according to demand fluctuation.

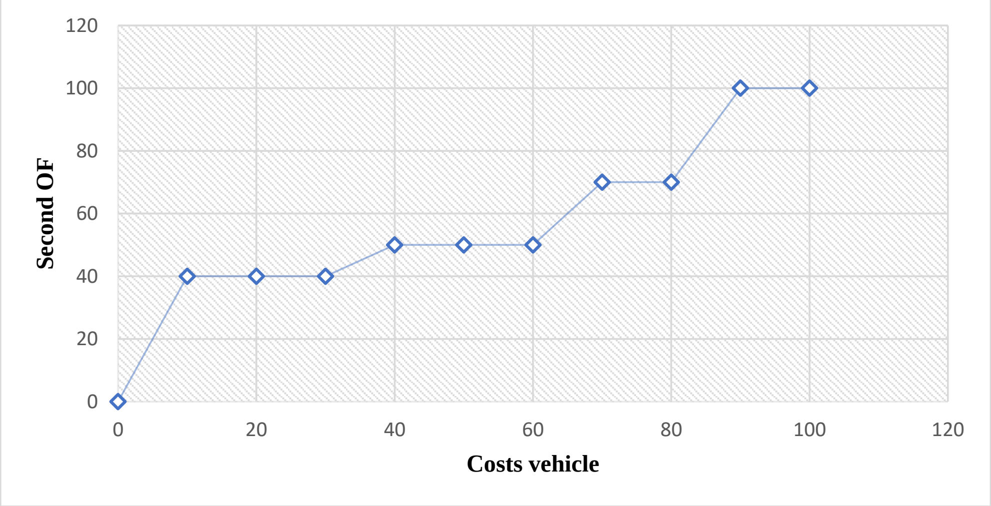

Figure 10. Changes of the second OF concerning the mean cost of the vehicle parameter.

7.3. Failure Rate Percentage

The amount of change in each OF concerning the difference in the local DCs failure rate percentage is shown below.

As seen in Figure 11, an increase in the local DCs' failure rate percentage leads to a decrease in the second OF related to the associated costs. With an increase in the probability of failure for local DCs, non-reliable centers will not be built, and only reliable DCs will be constructed, resulting in reduced costs. On the other hand, as seen in Figure 11, the increase in the local DCs' failure rate percentage leads to a rise in the first OF, which represents the time required to transport relief items. This seems logical due to the long distances between reliable DCs and the incident locations compared to local DCs.

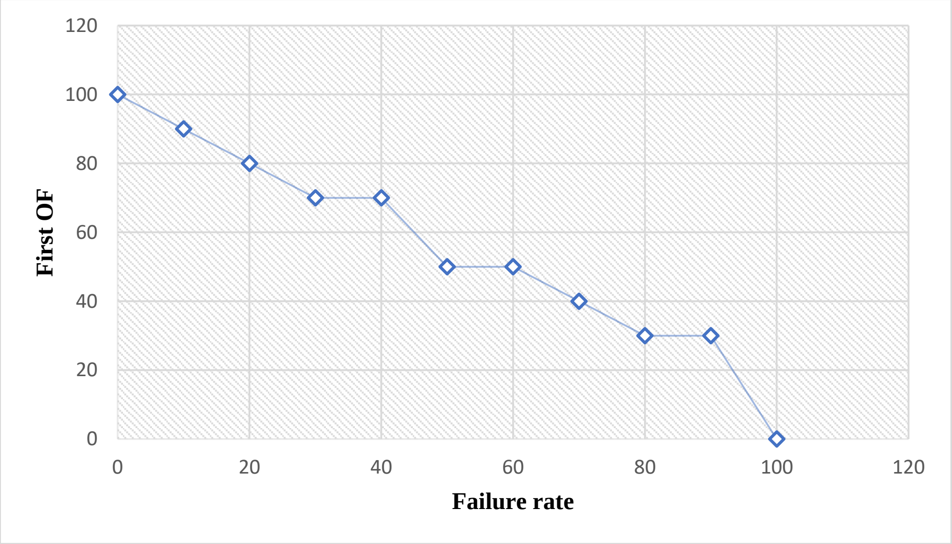

Figure 11. Changes of the first OF according to the failure of local DCs.

7.4. Maximum Allowable Distance between People

Figure 12 shows that an increase in the demand point *k* parameter's maximum permitted distance between individuals causes the value of the second OF, which represents the overall cost, to grow. Additionally, fewer people were impacted by COVID-19. Our research indicates that altering this parameter has no effect on the first OF.

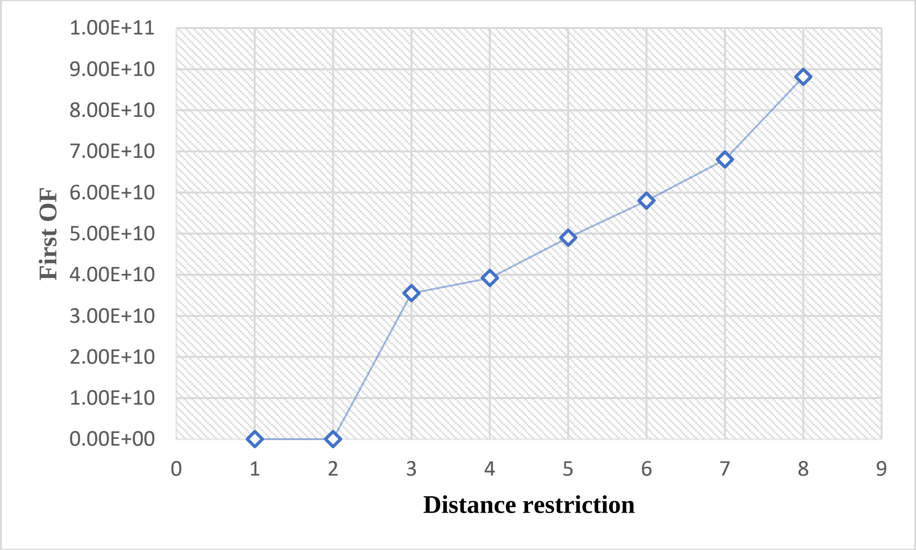

Figure 12. Changes of the first OF considering distance restriction between people at demand point.

8. Managerial Insights

The supervisor can think about the following aspects to offer perceptions or recommendations from a management viewpoint to assist the government to swiftly establishing suitable disaster relief arrangements:

1. In the event of a crisis, it is essential to give first priority to the distribution of resources like labour, supplies, and tools. The author can make recommendations for creating a system for allocating resources that takes into account things like population density, the extent of the damage, and the urgent needs of impacted communities. As a result, resources may be distributed by the government where they are most needed.
2. Effective inter-stakeholder collaboration is crucial to disaster management. The management might suggest a strong communication system that facilitates real-time information exchange between governmental institutions, relief groups, and communities that were impacted. Coordination, decision-making, and the efficient use of resources may all benefit from this.
3. The manager can stress how crucial it is for local government officials and non-governmental organizations (NGOs) to work together on disaster assistance. These organizations frequently possess important information about the surroundings, available resources, and impacted areas. Government agencies can better understand local conditions and enable more specialized assistance efforts by forming partnerships.
4. The manager might emphasize the importance of making data-driven decisions while managing a crisis. The government can learn about the level of damage, population relocation, and resource needs by utilizing technologies like satellite photography, remote sensing, and data analytics. Better decision-making, resource planning, and efficient allocation may all be aided by this data-driven strategy.
5. Regulatory roadblocks and ineffective bureaucracy can impede aid operations in times of crisis. By reducing paperwork, simplifying procedures, and using effective approval mechanisms, the author can recommend streamlining administrative operations. This can hasten relief efforts and guarantee that impacted populations receive aid on time.
6. Finally, management should emphasize how crucial it is to make investments in catastrophe preparedness measures. The government may reduce the effect of future catastrophes by investing in early warning systems, holding exercises, and proactively creating disaster response plans. When comparable situations develop, having a long-term outlook on disaster management can assist in expeditiously and suitably arranging resources.

The author may add to the body of knowledge on issue modeling and optimization methods by taking into account various management viewpoints and making observations or recommendations. This will give a comprehensive approach to disaster relief plans.

9. Conclusions and Future Suggestion

Crises and disasters are unpredictable and leave irreparable human and financial damage. All efforts in logistics planning and other activities aim to reduce suffering and provide better relief to affected people. In the proposed mathematical model, considering unforeseen factors results in more effective relief efforts. The research results ensure that the level of satisfaction with meeting the needs of affected individuals is at its highest. In the event of severe earthquakes and the destruction of existing infrastructure, the conditions for the relief chain are maintained. The proposed MOMIP mathematical model examined the costs incurred during relief operations and aimed to minimize these costs. One of these measures is considering the possibility of vehicles needing to travel again during relief operations, which reduces transportation costs over the entire period. From a management perspective, the model's results can be used to allocate appropriate budgets to deal with significant incidents. Considering the conflicting objectives, the results led to the maximum estimation of demands arising from the incident in the shortest possible time and with an appropriate budget in the proposed CS. Given the dual objective of the model, it can be concluded that the model is beneficial for relief efforts. GP and Lp-metric methods have been suggested to solve the model. These methods are the best for solving multi-objective problems (MOPs) and have been used to solve the proposed model in this research, and Lp-metric outperformed the GP approach in this study. As such, for sensitivity analysis, the GP approach was conducted. According to the results, by considering the maximum allowable distance between people, the total cost increased, but it decreased affected people during COVID-19. Moreover, by increasing demand, total cost, and delivery time increased.

Due to the high solution time of large test problems, it is suggested to use a metaheuristic method for solving them in large dimensions. In addition, the routing problem has not been addressed in this study, and considering the routing problem and the reliability of the routes can be used in future research. Moreover, predicting demand with machine learning algorithms can be helpful in future research to control demand fluctuation. Furthermore, using Industry 4.0 technology, such as blockchain, can enhance the deployment of humanitarian SC due to its ability to control demand data.

Author Contributions: Conceptualization S.A.; methodology S.A.; software S.A.; validation S.A. and S.R.; formal analysis S.A., I.V. and S.R.; investigation S.A. and S.R.; resources, S.A., M.T. and I.V.; writing—original draft preparation, S.A.; writing—review and editing, S.A. and M.T.; visualisation, S.R.; supervision, I.V.; project administration, S.A. and I.V.; funding acquisition, M.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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