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Optimizing Distribution Center Locations for Disaster Relief: A Multi-Objective Model and Case Study in Istanbul

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ABSTRACT

Effective distribution center location planning is crucial in disaster management, as it significantly influences the transportation, storage, and delivery of relief supplies to affected areas. This study uses a novel multi-objective mathematical programming model to optimize the concurrent selection of main distribution centers (MDCs) and local distribution centers (LDCs). The model addresses six key objectives: minimizing distances between demand points, LDCs, and MDCs; determining optimal numbers of LDCs and MDCs; reducing unsatisfied demand; improving citizens' accessibility to LDCs; and evaluating the suitability of selected centers for humanitarian operations. A goal programming approach is used to solve the model effectively. The model's applicability and efficacy are demonstrated through a case study in Istanbul, a region prone to seismic activity, with detailed sensitivity analyses validating its performance. By tackling the complexities of distribution center location planning in disaster management, this study enhances the efficiency and resilience of humanitarian logistics, ensuring the timely and effective delivery of relief supplies during crises.

Keywords: *disaster relief operations, humanitarian logistics, Istanbul earthquake, location, multiple-objective optimization*

1. INTRODUCTION

Natural disasters have inflicted substantial harm on human populations in recent years, resulting in significant fatalities and widespread devastation worldwide. The staggering records indicate that since 2010, there have been nearly 7,000 disasters, causing approximately 600,00 deaths, and affecting nearly 2 billion people, with predicted economic consequences exceeding US$ 2 trillion (www.emdat.be). Among the most prevalent natural disasters are floods, earthquakes, storms and landslides. The escalating frequency and impact of these disasters have prompted a growing focus from academics and researchers on this critical topic, seeking to aid vulnerable communities in disaster prevention and recovery.

Effective disaster management entails a holistic approach, involving coordinated efforts before, during and after disasters to mitigate their destructive effects and restore normalcy in affected societies (Galindo and Batta, 2013). The field of disaster management revolves around identifying strategies to reduce and combat the risks associated with these calamitous events (Haddow *et al.*, 2013). An optimal logistics strategy should involve organizing resources and relief supplies, identifying and establishing distribution centers and planning the distribution of these items (Das *et al.*, 2021). Scholars commonly classify disaster management into distinct stages, including mitigation, preparedness, response, and recovery (Altay and Green, 2006). Mitigation and preparedness, the pre-disaster stages, aim to minimize the physical, economic and social impacts by pre-positioning relief supplies, devising response plans, and strengthening building codes. The post-disaster stages encompass response efforts, such as search and rescue operations, relief supply distribution, and the provision of financial assistance to victims (Natural Hazards Research and Applications Information Center, 2005, Sections 2–4). Notably, disaster response operations in the post-disaster stage include the establishment of facilities in affected areas to deliver relief goods to the population (Noham and Tzur, 2018).

In the realm of disaster management, facility location models play a pivotal role in determining the optimal placement of warehouses, distribution centers, medical facilities, and shelters, as well as designing efficient distribution strategies for pre- and post-disaster operations (Boonmee *et al.*, 2017). Among the critical challenges within this domain is the design of a well-structured distribution network to facilitate the seamless delivery of relief goods through distribution centers (DCs).

In humanitarian logistics, distribution centers are typically categorized as Main Distribution Centers (MDCs) and Local Distribution Centers (LDCs). MDCs serve as stable facilities for storing, handling or arranging relief supplies, while LDCs are temporary centers established within the disaster zone, responsible for directly delivering relief supplies to the victims. MDCs are often considered the main coordination points for relief supplies, while LDCs act as the final delivery points for goods to the affected population.

While existing literature has predominantly focused on the location selection problem of LDCs, recognizing the critical significance of last-mile distribution from LDCs to beneficiaries, the inclusion of MDCs in studies has been relatively limited. Furthermore, the number of research works presenting mathematical models that simultaneously consider both MDCs and LDCs is scarce, creating a gap in the broader disaster location literature. Existing multiple-objective models have also been limited in terms of the number of objectives considered (Tavana *et al*., 2017; Cao *et al*., 2021).

This study seeks to address these critical gaps by introducing a novel multi-objective mathematical model that enables the simultaneous determination of MDC and LDC locations. The proposed model encompasses six key objectives, aiming (1) to minimize the total weighted distance among opened MDCs, LDCs, and demand points, (2) to maximize the total performance scores of the opened DCs, (3) to minimize the total unsatisfied demand, (4) to minize the number of opened LDCs, (5) to minize the number of opened MDCs, and finally, (6) to minimize victims' walking distance to assigned LDCs. Details of the literature review specifically conducted for objectives and mathematical models used for the targetted problem is presented in Section 2 while the details of the objectives are explanined in Section 3.

In this respect our research question can be stated as follows: How does the novel multi-objective mathematical model, designed to simultaneously determine the locations of MDCs and LDCs, perform in optimizing disaster management strategies in the context of urban centers, considering the specific case study of Istanbul.

The significance of addressing this research question is underscored by the immense challenges posed by disaster management, particularly in the context of urban centers vulnerable to catastrophic events. As one of the world's largest cities and at risk of a devastating earthquake, Istanbul serves as a pertinent real-life application for the proposed model. With a population exceeding 15 million and an estimated impact on 1-3 million people and 40-60 thousand buildings, the importance of preparedness and response planning cannot be overstated, making Istanbul an ideal case study for validation.

To test and calibrate the performance of the proposed model, comprehensive sensitivity analyses are conducted to optimize crucial parameters such as the minimum percentage of covered demand at each demand point, average allowed walking distance, minimum acceptable performance of LDCs and MDCs, and minimum required capacity usage. These analyses contribute to setting optimal parameter values, ensuring robust and reliable results for real-world applications.

This study makes a significant innovative contribution by developing a multi-objective mathematical model that simultaneously optimizes the locations of both MDCs and LDCs, thereby addressing a critical gap in the disaster management literature. Its application in Istanbul offers valuable insights, illustrating the model's effectiveness in urban disaster scenarios. Moreover, the incorporation of sensitivity analysis for parameter optimization enhances the adaptability of the model across diverse contexts. Given that Turkey is a high-risk earthquake zone, this research holds particular importance. The proposed model equips decision-makers with the ability to assess distribution center alternatives based on a comprehensive array of criteria, including those not explicitly incorporated into the model, thereby providing a flexible and essential tool for optimizing disaster management strategies.

The paper is organized as follows: Section 2 presents a literature review that is used to derive the the six objectives used in the study. In Section 3, the proposed methodology is introduced. Section 4 showcases the application in Istanbul. Section 5 offers practical and managerial insights based on the application results. Finally, Section 6 concludes the paper, emphasizing the significant contributions and potential applications of the proposed model.

2. HOW THE SIX OBJECTIVES ARE DERIVED

In this section, we provide an anwer how the six objectives used in the study are derived based on the literature review. For this, we present a summary of the humanitarian logistics literature with a particular focus on the location selection of DCs in terms of DC types. To find out the objectives used in the literature, we analyzed 57 relevant papers using ScienceDirect and Scopus databases, utilizing keywords such as "disaster location," "disaster response," "disaster relief," "disaster management," and "humanitarian logistics." Papers that specifically addressed the facility location problem were selected after the keyword search. Appendix 1 and 2 provide a list of the papers and the objectives used for the location problem of MDCs and LDCs, respectively. Additionally, **Table 1** summarizes the papers in terms of the objectives they employ.

Table 1 Objectives used in DC location studies in humanitarian logistics

Objective	Number of Papers	LDC	MDC
Time/distance to LDCs or beneficiaries	34	X	X
Demand coverage	33	X	X
Transportation cost	31	X	X
Investment cost	17	X	X
Beneficiaries' travel cost	9	X	
Accessibility/ availability	8	X	X
Storing/operating cost	6	X	X
Equity	5	X	
Unused inventory cost	5	X	
Psychological/ uncovered demand cost	3	X	
Total potential environmental risk	2	X	X
Security	2	X	
Reliability	2	X	
Socio-economic development level	2		X
Procurement cost	2	X	
Infrastructure	1		X
Storage environment	1		X
Management	1		X

The literature review reveals various objectives used in mathematical models for locating MDCs:

- "Cost" is the most prevalent objective for MDC location selection. It encompasses investment, maintenance or storage cost, and operational or transportation cost in certain proposed models (e.g., Tofighi *et al*., 2016; Tavana *et al*., 2017; Vahdani *et al*., 2018; Rahmani *et al*., 2018; Camacho-Vallejo *et al*., 2015; Timperio *et al*., 2017).
- Objectives related to "time/distance to LDCs or beneficiaries," such as "proximity to beneficiaries" and "LDC access time," are employed by various researchers and they are second most commonly utilized criteria. (Ahmadi *et al*., 2015; Tofighi *et al*., 2016; Camacho-Vallejo *et al*., 2015; Vahdani *et al*., 2018)."Demand coverage" is also one of the most commonly utilized criterion for MDC location selection (e.g., Afshar and Haghani, 2012; Salmeron and Apte, 2009; Camacho-Vallejo *et al*., 2015; Verma and Gaukler, 2015; Ahmadi *et al*., 2015; Salman and Yucel, 2015; Serrato-Garcia *et al*., 2016).
- "Accessibility" is considered in some models (e.g., Salman and Yucel, 2015; Brito Jr. *et al*., 2020; Verma and Gaukler, 2015; Vahdani *et al*., 2018; Noham and Tzur, 2018).
- "Infrastructure," "hygiene of the storage environment," and "management" are considered in a single study by Brito Jr. *et al*. (2020). "Infrastructure" is also adopted by Leeuw and Mok (2018), considering it as the distance of a DC from ports and airports. However, since this article does not contain a mathematical model, it is not included in **Table 1**.
- "Socio-economic development level" is a criterion employed only by Ahmadi *et al*. (2015) and Timperio *et al*. (2017).
- "Total potential environmental risk" identifies two criteria concerning sustainable distribution systems by Cao *et al*. (2021) and locationg DCs outside of identified hot zones by Timperio *et al*. (2017).

Turning to the literature review for LDC locating mathematical models, we find the following highlights:

- "Time/distance to LDCs or beneficiaries" and "demand coverage" are the two most favored objectives for LDCs.
- Different cost types, such as "transportation cost," "investment cost," "uncovered demand cost," "operating cost," "unused inventory cost," and "procurement cost," are used in locating LDCs. Transportation cost is the most commonly used cost type, while "psychological/uncovered demand cost" and "unused inventory cost" are among the least preferred criteria in the literature, each adopted by only a few studies.
- Transportation time between LDC and MDC is considered separately by some researchers (Vitoriano *et al*., 2011; Cao *et al*., 2018; Tavana *et al*., 2017; Maharjan and Hanaoka, 2018).
- "Equity" is an objective adopted solely in papers focusing on LDCs (e.g. Florez *et al*., 2015; Rancourt *et al*., 2015; Condeixa *et al*., 2017; Hasani and Mokhtari, 2018).
- "Efficacy" seeks to reduce distribution time for each demand point while accounting for the arrival of relief goods. Kobayashi et al. (2019) propose "efficacy" as a measure of how effectively distribution time is utilized in relief efforts by comparing it with equity and efficiency metrics.
- "Safety & security" is considered by Vitoriano *et al*. (2011) and Cavdur *et al*. (2016).
- "Environmental effects" is only employed by Boostani *et al*. (2020).

Table 1 demonstrates the wide array of criteria used in disaster DC location studies. The most commonly adopted criteria are "demand coverage," "time/distance to LDCs or beneficiaries," "transportation cost," "investment cost," and "beneficiaries' travel cost." Notably, the criteria for MDC and LDC differ due to their distinct purposes, as explained earlier.

The proposed model in this study integrates three of the top four criteria from the literature for DC location selection: "total distance to beneficiaries," "demand coverage," and "investment cost." Furthermore, an objective is added to minimize average walking distance among demand points and their assigned LDC, akin to the concept of beneficiaries' travel cost, which is the sixth most preferred criterion in the literature. Additionally, an objective is included to evaluate the suitability/operational efficiency of a location for MDC and LDC, aiming to maximize the performance scores of the selected/opened DCs. These scores can be assessed based on various criteria, which might not be set as specific objectives in the model, such as office and warehouse facilities, cost, infrastructure, and security (Yılmaz and Kabak, 2020). To the best of our knowledge, this is the first study to consider the conformity of DC criteria in mathematical models for location selection.

Furthermore, equity, a common objective in the literature, is incorporated into the proposed model as constraints. While often overlooked in the literature, the importance of warehouse facilities criteria is acknowledged in the constraints, considering its crucial impact on relief operations and ensuring the delivery of healthy goods in real-life scenarios. Lastly, the proximity of MDCs to airports and seaports is also added as constraints to enable the supply chain to utilize different transportation modes, thus enhancing the accessibility of MDCs to suppliers.

This paper employs a multi-objective approach to address the complexities of humanitarian logistics. The objectives are specifically designed to optimize the distribution of relief supplies, enhance accessibility, reduce unsatisfied demand, ensure the model's cost-effectiveness and evaluate the operational efficiencies of DCs for relief efforts such as preserving relief supplies. By integrating all six objectives, this paper adopts a holistic approach to relief operations, with each objective addressing distinct facets of disaster management. This comprehensive strategy significantly enhances the overall efficiency and effectiveness of relief efforts.

The model effectively balances trade-offs among the objectives, recognizing that conflicts may arise—such as the conflict between minimizing costs and maximizing accessibility. By considering all objectives, decision-makers can navigate these trade-offs more effectively and make informed choices. Furthermore, the model's adaptability to complex scenarios is critical, as disasters often present unforeseen challenges. The multi-objective framework provides the necessary flexibility to respond to varying conditions and requirements in real time. Additionally, the diverse objectives reflect the needs of various stakeholders, including affected populations and local governments, thereby enhancing stakeholder engagement. This consideration fosters collaboration and support among these groups. By optimizing multiple objectives, the model not only contributes to immediate response efforts but also builds resilience in disaster management and preparedness. In summary, these objectives are essential for developing a well-rounded, efficient, and effective disaster management strategy. Their comprehensive consideration facilitates improved decision-making and enhances outcomes during crisis situations.

The details and specific formulations of the proposed model are provided in the following section. The model's comprehensive integration of various objectives and criteria reflects its potential for robust and efficient disaster management decision-making.

3. PROPOSED METHODOLOGY

This study aims to address the location selection of disaster response MDCs and LDCs in a single model. Given the multiple-objective nature of the examined problem, a multiple-objective mixed-integer program is developed, incorporating the following six objectives:

1. ***Minimizing the weighted distance among demand points, MDCs, and LDCs***: This objective primarily focuses on reducing the average distance traveled by relief supplies from the source to the demand points. It basicly optimizes relief supply distribution and holds critical importance in delivering relief items efficiently, making it the most preferred objective in the literature. It is crucial for facilitating the efficient transportation and delivery of relief supplies, as it directly influences the speed and effectiveness of response efforts.
2. ***Maximizing the performance scores of the opened distribution centers***: In real-life scenarios, DC alternatives conform to required criteria, such as warehouse and office facilities, based on their specific characteristics and conditions. Evaluating DC performance scores becomes crucial for assessing alternatives according to specified criteria, especially in complex disaster environments. Assessing the suitability of distribution centers helps ensuring that selected locations can effectively support humanitarian operations and prevent perishing foods. By employing Multi-Criteria Decision Making (MCDM) or Multi-Attribute Decision Making (MADM) methods, this objective aims to maximize the convenience of relief operations, ensuring products are delivered to disaster victims without deterioration. Moreover, it allows for the consideration of both qualitative and quantitative criteria and the separate evaluation of LDCs and MDCs. The proposed model uses the results from Yılmaz and Kabak (2020), where an MCDM model using an integrated Interval Type-2 Fuzzy Analytic Hierarchy Process (AHP) and Interval Type-2 Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach was developed to specify the performance of DC criteria.
3. ***Minimizing the total unsatisfied demand:*** Minimizing unsatisfied demand is crucial for ensuring that all affected individuals receive the assistance they need, thus improving overall disaster response outcomes. The demand at a demand point or region is contingent on factors such as the magnitude of the disaster, building damage ratio, topography of the region, and the number of buildings and people. The IMM-JICA report (2002) provides estimates for different Istanbul earthquake scenarios, forecasting the demand population by taking 100%, 50%, and 10% of the population in heavily, moderately, and partially damaged buildings, respectively. This study adopts this assumption to estimate the demand.
4. ***Minimizing the number of opened LDCs:*** This objective aims to reduce the investment cost of opened LDCs. While the model focuses on overall optimization, it can minimize only one type of DC, and in this case, it can specifically reduce the number of LDCs. This approach acknowledges that there are usually many more LDCs in the disaster relief chain compared to MDCs. As MDCs and LDCs have distinct missions and features, it is essential to consider the existence of two different types and missions of DCs and avoid solely focusing on reducing the total number of DCs without considering their unique roles.
5. ***Minimizing the number of opened MDCs:*** Similar to the fourth objective, this objective aims to minimize the investment cost of opened MDCs. It recognizes the difference in numbers between MDCs and LDCs in the disaster relief chain and specifically focuses on reducing the number of MDCs. By minimizing the number of opened distribution centers (both MDCs and and LDCs), the objectives help control costs while maintaining effective logistics.
6. ***Minimizing the average walking distance between demand points and their assigned LDC:*** In the proposed model, disaster victims are assumed to reach LDCs on foot. Therefore, minimizing the average walking distance of victims to access relief aids is of utmost importance. This objective addresses the specific average distance between assigned LDCs and the served/satisfied individuals, acknowledging the chaotic and challenging conditions during post-disaster scenarios. This objective ensures that affected populations can easily access necessary aid and enables the model to enhance overall accessibility.

It is important to emphasize that these objectives are not necessarily conflicting; rather, they are complementary and synergistic in nature. While some objectives focus on minimizing costs, such as investment cost for opened LDCs and MDCs, others concentrate on maximizing the performance scores of selected DCs to enhance the efficiency of disaster relief operations. Additionally, objectives such as minimizing total unsatisfied demand and average walking distance between demand points and their assigned LDCs are driven by the central aim of ensuring that aid reaches affected populations promptly and effectively.

Moreover, the consideration of both qualitative and quantitative criteria in the objectives contributes to a comprehensive and balanced decision-making process. By taking into account multiple attributes, the proposed model enables a thorough evaluation of DC alternatives, facilitating better-informed decisions for disaster management.

The simultaneous optimization of these objectives accounts for the interplay between different criteria and operational requirements, promoting a more holistic approach to disaster response planning. By working in harmony, these objectives collectively aim to improve the overall efficiency, effectiveness, and responsiveness of the distribution network, ultimately benefitting disaster-affected communities.

In conclusion, the integration of these diverse objectives within the proposed model ensures that disaster response MDCs and LDCs are selected in a manner that not only optimizes various criteria but also addresses the unique challenges of disaster scenarios. By recognizing the complementary nature of these objectives, the model provides a comprehensive and robust tool for decision-makers, offering an optimal and balanced solution for disaster management.

3.1 Proposed Mathematical Model

The proposed multiple-objective integer programming model is presented in this sub-section. The sets, parameters, and decision variables of the model are given below:

Sets:

- K Set of demand points, indexed by k
- J Set of candidate Local Distribution Center (LDC), indexed by j
- I Set of candidate Main Distribution Center (MDC), indexed by i

Parameters:

- l_k Product demand of demand point k, $k \in K$
- s_j Capacity of LDC j, $j \in J$
- c_i Capacity of MDC i, $i \in I$
- d_{jk} Distance between LDC j and demand point k, $j \in J$, $k \in K$
- b_{ij} Distance between MDC i and LDC j, $i \in I, j \in J$
- w_i Performance score of MDC i, $i \in I$
- w_j Performance score of LDC j, $j \in J$
- f_i^m Warehouse facilities performance score of MDC i, $i \in I$
- f_j^l Warehouse facilities performance score of LDC j, $j \in J$
- α Minimum satisfied demand rate at every demand point k
- h_i Distance between MDC i and assigned airport, $i \in I$
- f_i Distance between MDC i and assigned seaport, $i \in I$
- λ Minimum acceptable warehouse facilities priority (weight) for MDC i, $i \in I$
- μ Minimum acceptable warehouse facilities priority (weight) for LDC j, $j \in J$
- P Maximum acceptable distance between MDC i and assigned airport, $i \in I$
- R Maximum acceptable distance between MDC i and assigned port, $i \in I$
- maw Maximum average distance between demand point k and assigned LDC j, $j \in J, k \in K$
- mw Maximum acceptable distance between demand point k and assigned LDC j, $j \in J, k \in K$
- L Minimum required capacity usage rate for opening LDC j, $j \in J$
- M Minimum required capacity usage rate for opening MDC i, $i \in I$

The decision variables are defined as follows. The binary variables x_i and y_j indicate whether a candidate MDC i and LDC j is opened or not, respectively. Variable t_{jk} denotes the quantity shipped from LDC j to demand point k. Similarly, a_{ij} denotes the quantity shipped from MDC i to LDC j.

Decision Variables:

$$x_i : \begin{cases} 1; & if\ MDC\ i \text{ is opened} \\ 0; & \text{otherwise} \end{cases} \qquad i \in I$$

$$y_j : \begin{cases} 1; & if\ LDC\ j \text{ is opened} \\ 0; & \text{otherwise} \end{cases} \qquad j \in J$$

t_{jk}: Satisfied demand amount of point k by $LDC\ j$

a_{ij}: The transferred amount of product from MDC i to LDC j

The proposed model based on the above notation is given below.

$$\text{Min } Z_1 = \sum_j \sum_k d_{jk} t_{jk} + \sum_i \sum_j b_{ij} a_{ij} \tag{1}$$
$$\text{Max } Z_2 = \sum_i w_i x_i + \sum_j w_j y_j \tag{2}$$
$$\text{Min } Z_3 = \sum_k (l_k - \sum_j t_{jk}) \tag{3}$$
$$\text{Min } Z_4 = \sum_j y_j \tag{4}$$
$$\text{Min } Z_5 = \sum_i x_i \tag{5}$$
$$\text{Min } Z_6 = \sum_j \sum_k d_{jk} t_{jk} \,/ \sum_j \sum_k \alpha\, l_k \tag{6}$$

Subject to:

$$\sum_k t_{jk} \le s_j y_j \ , \quad \forall j \tag{7}$$
$$\sum_j t_{ij} \le c_i x_i \ , \quad \forall i \tag{8}$$
$$\sum_i a_{ij} = \sum_k t_{jk} \ , \quad \forall j \tag{9}$$
$$\sum_j t_{jk} \ge \alpha\, l_k, \quad \forall k \tag{10}$$
$$\sum_{i | f_i^m \ge \lambda} x_i \ge \sum_i x_i / 2 \tag{11}$$
$$\sum_{j | f_j^l \ge \mu} y_j \ge \sum_j y_j / 2 \tag{12}$$
$$\sum_{i | h_i \le P} x_i \ge 1 \tag{13}$$
$$\sum_{i | f_i \le R} x_i \ge 1 \tag{14}$$
$$\sum_j \sum_k d_{jk} t_{jk} \le maw \sum_j \sum_k t_{jk} \tag{15}$$
$$t_{jk} = 0 \quad for\ d_{jk} > mw \tag{16}$$
$$\sum_i a_{ij} \ge L s_j y_j \ , \quad \forall j \tag{17}$$
$$\sum_j a_{ij} \ge M c_i x_i \ , \quad \forall i \tag{18}$$
$$a_{ij}, t_{jk}, d^+, d^- \ge 0, \ x_i, y_j \in 0{,}1 \tag{19}$$

The objective functions of the proposed model are given by Eq.(1)-(6). The first objective function (Eq. 1) represents the minimization of total weighted distance among opened MDCs, LDCs, and demand points. The second objective given in Eq. (2) maximizes the total performance scores (priorities) of the opened DCs. In other words, this objective enables the selection of more appropriate DCs based on preferred criteria by the DM and increases the efficiency of humanitarian logistics operations. The objective function (Eq. 3) aims to minimize total uncovered demand. The objective functions given in Eq. (4) and Eq. (5) minimize the total number of opened LDC and MDC, respectively. The objective function (Eq. 6) aims to minimize the total walking distance of the victims from their demand point to the assigned LDC.

Eq. (7) and (8) are the capacity constraints of LDCs and MDCs, respectively. Eq. (9) guarantees that no commodity abides in LDCs. Eq. (10) is the equity constraint and ensures that the demand of every demand point will be satisfied at least at a specified minimum satisfied demand rate (α). With this constraint, it is ensured that there is not much difference between the points in the distribution of the products. For instance, if α equals to 0.6, the model will satisfy 60 % of the demand at every demand point. It might also be satisfied at higher rates at some demand points, but not lower. Herewith the decision maker will be able to prevent any discrimination in supply among demand points. Eq. (11) and (12) represent that at least half of the opened MDCs and LDCs have a warehouse facilities performance score above the determined level by the DM. Warehouse facility performance is defined in terms of suitability for operations such as loading, unloading, storage area for relief supplies, storage area for vehicles, and other properties such as floor capacity, loading bays, floodlights, place, and number of doors, healthy environment to prevent perishing relief goods, etc. Detailed information on mentioned criterion can be found in Celik and Gumus (2016) and Roh *et al.* (2015). Since MDCs and LDCs have different missions and infrastructure requirements, two different constraints are added for LDCs and MDCs for warehouse facilities performance scores (f_i^m and f_j^l) that are different from the performance score of DCs (w_i and w_j). The former is related to only warehousing facilities while the latter includes all relevant criteria defined by the DM. Eq. (11) and (12) enable DM to select at least half of the DCs that meet the warehouse facilities performance score at desired level, thus helps to increase the efficiency of relief operations.

Leeuw and Mok (2018) emphasizes the importance of an DC infrastructure by focusing its distance to airports and seaports. Considering that MDCs are critical points that relief supplies can be transferred from both national and international suppliers, this study adopts similar logic and Eq. (13) and (14) make sure that at least one opened MDC is within the maximum acceptable distance (P and R) to the assigned airport, and seaport supply point, respectively. These constraints enable the selection of MDCs that are convenient for different transportation modes. Thus, relief supplies can be delivered to MDCs simultaneously and quickly with different ways. Eq. (15) expresses that victims' average walking distance to their assigned LDC is lower than a specific value determined by DM (maw). Although this constraint is similar to sixth objective, this constraint is added to prevent the model from obtaining a compromised solution with a long walking distance that DM cannot accept. Eq. (16) prevents the assignment of a demand point to an LDC that is more distant than the maximum acceptable distance (mw). By this constraint, a victim will not need to walk more than the given threshold.

Eq. (17) and (18) impose the minimum capacity usage rate for opened LDCs and MDCs, respectively. These constraints enable DM to open DCs that can cover their opening cost. Eq. (19) defines the nature of the decision variables of the model.

3.2 Solving the Proposed Model: A Goal Programming Approach

Goal programming minimizes the deviation between the goals and their achievement levels and aims to transform multiple objectives into a single one (Taha, 2003). It is one of the most preferred techniques for decision-making problems with multiple conflicting objectives. Additionally, goal programming problems can be solved easily by non-complex solution procedures (Sen and Nandi, 2012). That's why, in this study, a goal programming approach is used to solve the proposed multiple-objective programming model.

The goal programming formulation with m goals is given below.

$$Min\ Z = \sum_i^m (d_i^+ + d_i^-) \tag{20}$$

$$f_i(\mathbf{x}) - d_i^+ + d_i^- = f_i^* \qquad i = 1, \dots, m \tag{21}$$

$$\mathbf{x} \in \mathbf{X} \tag{22}$$

$$\mathbf{x}, d^+, d^- \geq 0 \tag{23}$$

The objective function contains primarily the deviational variables (d_i^+, d_i^-) that represent each goal. $\mathbf{x} = (x_1, x_2, \dots, x_n)$ are the decision variables. $f_i(\mathbf{x})$ represents the function for goal *i* and f_i^* is target achievement level of goal *i*. In Eq. (22) the feasible region for the problem excluding the achievement of the goals is defined.

One of the most important disadvantages of this approach is the subjectivity for setting the achievement levels of the goals and aspiration levels (Hughes and Grawoig, 1973). A suboptimal solution might be computed if the goals are set too low. It is required to make weights and objective values homogeneous. Additionally, the decision maker may not have the information required by this method. To overcome these disadvantages, in this study, the goals are determined by solving the mathematical program for each objective independently.

The goal programming approach is applied with the following steps:

Step 1. Solve the model for each of the objectives $Z_1, Z_2, \dots, Z_6$ independently.

Step 2. Determine the optimum solutions obtained in Step 1 ($Z_1^*, Z_2^*, \dots, Z_6^*$) as goals.

Step 3. Formulate and solve the goal-programming model. Additionally, since the results in Step 2 have different unit of measures, they are normalized in the goal programming model with Eq. (24) and (25). Denominator express the range of the maximum and minimum solution. Numerator denotes positive and negative deviation of the solution from the optimal one for the maximization and minimization objectives respectively.

$$\mathbf{Min}\ \sum \boldsymbol{d_i^+}/\Delta_i \quad \text{for maximization objectives} \tag{24}$$

$$\mathbf{Min}\ \sum \boldsymbol{d_i^-}/\Delta_i \quad \text{for minimization objectives} \tag{25}$$

Step 4. The solution of the model is called a compromised (harmonized) solution that is obtained as a result of minimizing the undesired deviational variables in the form of an achievement function. As a result, a solution that is close to the desired goals is found.

4. APPLICATION: THE CASE OF ISTANBUL

Istanbul, with a population of over 15 million, stands as one of the most populated cities in the world. Located near an active fault zone in the Marmara Sea, approximately 20 km south of the city, it carries an extremely high seismic hazard risk (Le Pichon *et al*., 2001). In 1999, an earthquake with a magnitude of 7.4 struck close to Istanbul, resulting in 20,000 fatalities, 50,000 injuries, and an economic loss of 6.2 billion USD (Salman and Yucel, 2015; Erdik and Durukal, 2008). Based on estimates, a potential earthquake in Istanbul may impact more than 3 million people, leaving at least half of them homeless and heavily damaging over 60,000 buildings. In preparation for such a disaster and its aftermath, the selection of MDC and LDC locations becomes crucial.

In 2002, the Japan International Cooperation Agency (JICA) and Istanbul Metropolitan Municipality collaborated on a disaster prevention and mitigation plan for Istanbul (IMM-JICA, 2002). The report included four earthquake scenarios for the city, with the worst-case scenario, Model C, depicting a magnitude of 7.7 on the Richter scale (See **Figure 1**).

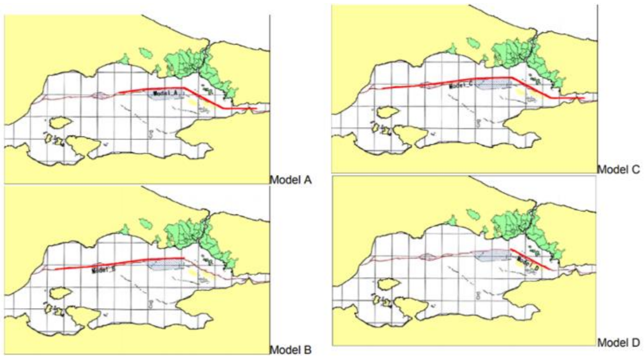

Figure 1 Earthquake scenarios for Istanbul (IMM-JICA Report,7-1)

IMM-JICA report (2002) states that because of the size of broken fault segments, damage and affected people geographically within the city will be different in the scenarios. The ratio of the heavily damaged buildings depending on Model C is given in **Figure 2**. The dark red area denotes the heavily damaged region while the blue and white colors depict the areas that are not affected by the related earthquake scenario.

For this application, the data from Model C is utilized, and demand points along with their demand levels, MDC candidates, and LDC candidates are determined accordingly.

4.1 Candidate Locations

Candidate LDC and MDC locations for the Istanbul case are carefully selected through a combination of the Istanbul Disaster Response Plan (IDRP) (https://istanbul.afad.gov.tr) and expert consultations. Face-to-face meetings were conducted with three experts from AFAD (Disaster and Emergency Management Presidency of the Ministry of Interior, Turkey), who possess specialized knowledge in earthquake DC locations, to gain valuable insights into the determination of DC candidate locations.

Regarding LDCs, the initial selection process, following the IDRP guidelines, involves identifying public buildings like stadiums and schools as potential candidates. Subsequently, based on expert recommendations, culture center facilities of municipalities are added to the list of candidates. Moreover, experts suggest the inclusion of shopping centers due to their suitability for humanitarian aid operations, equipped with convenient features such as roof and rack systems, ample parking space, and ease of vehicle operations. Consequently, a total of 181 LDC alternatives are determined.

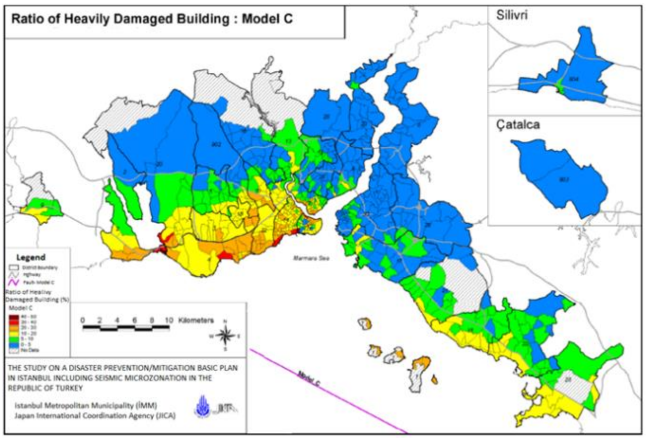

Figure 2 Ratio of heavily damaged buildings for Scenario earthquakes of Istanbul (IMM-JICA Report,7-1).

As for MDCs, the IDRP provides five initial alternatives, which are considered in the first place. Additionally, to ensure comprehensive coverage, warehouses of commercial cargo companies operating in Istanbul are included as MDC candidate points. These selections take into account various criteria, such as capacity, building structure, equipment, and equipment suitability. As a result, the list comprises 27 MDC alternatives, thoroughly evaluated for their compatibility with the disaster response requirements.

4.2 Assumptions and Data Collection

The IDRP outlines crucial timeframes for disaster response operations. It assumes that the service group responsible for in-kind donations and warehouse management will be assembled within 12 hours of the disaster occurrence. Additionally, MDCs and LDCs are expected to be activated within 3 days (72 hours) after the disaster, following the determination of the victims' demand. However, due to the inherent uncertainty in post-earthquake conditions, there may be challenges and unforeseen circumstances that need to be addressed in real-time.

To facilitate smooth transportation and response operations, the Priority Road List, determined in the IDRP, plays a pivotal role in ensuring that essential roads are given priority for opening and usage. Periodic reinforcement works are carried out for critical transportation points, such as bridges and viaducts, to enhance their structural integrity and resilience in disaster scenarios. It is also assumed that the roads connecting the opened DCs and demand points will be added to the priority road list to avoid disruptions during the product transfer process.

For the application, data from 751 neighborhoods in Istanbul is utilized, with 482 neighborhoods on the European side and 269 on the Anatolian side. However, the Adalar district, consisting of five islands in the Marmara Sea (known as the Princes' Islands), is excluded from the dataset as its needs are addressed through a separate transportation plan. Additionally, neighborhoods located more than 13 km away from any candidate LDC are not included in this application, and separate plans will be made to accommodate their needs.

The estimation of parameters for the application is as follows:

Demand: The IMM-JICA report (2002) provides estimates for the victim population based on the damage level of buildings. Similar to Görmez *et al*. (2011), the demand in each district is calculated considering the population and the severity of building damage. Different percentages of population are considered for heavily (100%), moderately (50%), and partially (%10) damaged buildings, respectively. The demand amounts are determined based on the estimated number of victims in each neighborhood.

In 2020, to update the probable earthquake loss in Istanbul, Bogazici University and Istanbul Metropolitan Municipality published the "District Possible Earthquake Loss Estimate Booklets" (https://depremzemin.ibb.istanbul) for 39 districts and their neighborhoods. These booklets include an analysis of injuries, loss of life, building damage, and infrastructure damage in a possible earthquake if Model C Scenario in the IMM-JICA report occurs. This updated information is used to predict the demand.

DC Capacities: It is assumed that all candidate DCs have capacity constraints in line with real-life scenarios. The capacity of all MDC and LDC candidates is derived from the land area data obtained from the General Directorate of Land Registry and Cadastre Parcel Query Application (https://parselsorgu.tkgm.gov.tr).

Distances: The parameters h_i, f_i, which represent the distances among demand points (neighborhoods) and DC alternatives, are obtained through Google Maps.

Performance Scores: The results of the MCDM model proposed by Yılmaz and Kabak (2020) are used for the parameters w_i, w_j, f_i^m, f_j^l. This MCDM model specifies weights of the related DC criteria using AHP and prioritizes alternative DCs with the Interval Type-2 Fuzzy TOPSIS approach. For further details, refer to Yılmaz and Kabak (2020).

The remaining parameters, α, λ, μ, P, R, maw, mw, L, and M, will be determined by the decision-maker (DM) based on their specific preferences and requirements for the disaster response scenario. These parameters play a crucial role in shaping the model's outcomes, and their optimization ensures a robust and tailored decision-making process for disaster response planning. Scenario and sensitivity analyses are conducted in the next section to support the DM to set the values of these parameters (α, λ, μ, P, R, L, M, and maw).

Based on the above-given parameters, the goal programming model is formulated as follows.

$$Min\, Z = d_1^+ + d_2^- + d_3^+ + d_4^+ + d_5^+ + d_6^+ \quad (24)$$
$$\textstyle\sum_j \sum_k d_{jk} t_{jk} + \sum_i \sum_j b_{ij} a_{ij} - d_1^+ = Z_1^* \quad (25)$$
$$\textstyle\sum_i w_i x_i + \sum_j w_j y_j + d_2^- = Z_2^* \quad (26)$$
$$\textstyle\sum_k (l_k - \sum_j t_{jk}) - d_3^+ = Z_3^* \quad (27)$$
$$\textstyle\sum_j y_j - d_4^+ = Z_4^* \quad (28)$$
$$\textstyle\sum_i x_i - d_5^+ = Z_5^* \quad (29)$$
$$\left(\textstyle\sum_j \sum_k d_{jk} t_{jk} \,/\, \sum_j \sum_k \alpha . l_k\right) - d_6^+ = Z_6^* \quad (30)$$

Constraints that are given in Eq (7)-(19)

$$a_{ij}, t_{jk},\ d^+, d^- \geq 0,\ x_i, y_j \in \{0,1\} \quad (31)$$

In this model, $Z_1^*, Z_2^*, \dots, Z_6^*$ are the optimal values of models solved with objective functions $Z_1, Z_2, \dots, Z_6$, respectively.

4.3 Sensitivity Analysis for Setting Parameters

To ensure the robustness and effectiveness of the proposed mathematical model, a sensitivity analysis is conducted to determine the optimal values of the parameters. The goal is to examine how changes in specific parameters affect the results and identify critical threshold levels.

Table 2 The scenario analyses

ID	Investigated parameter	Parameter Interval	Parameter Values	Significant Objective Functions*
1	Maximum average walking distance (maw)	3-5 km	3, 4, 5	Z_1, Z_3, Z_4, Z_5
2	Minimum acceptable warehouse facilities performance score for MDC (λ)	0.55 – 0.7	0.55, 0.57, 0.6, 0.63, 0.65, 0.67, 0.7	Z_1, Z_5
3	Minimum acceptable warehouse facilities performance score for LDC (μ)	0.21-0.6796	0.21, 0.26, 0.49, 0.6, 0.627, 0.67, 0.6796	Z_2, Z_3, Z_4
4	Maximum acceptable distance between MDC *i* and assigned airport (P)	7-36 km	7, 8, 11.5, 17.8, 25.6, 31, 36	Z_5, Z_6
5	Maximum acceptable distance between MDC *i* and assigned port (R)	7-30 km	7, 10, 13, 18.7, 21, 24, 30	Z_4
6	Minimum required capacity usage rate for opening MDC (M)	0-0.8	0, 0.2, 0.4, 0.5, 0.6, 0.7, 0.8	Z_1, Z_3
7	Minimum required capacity usage rate for opening LDC (L)	0-0.3	0, 0.1, 0.2, 0.3	Z_4

*Z_1: Average product transportation distance
Z_2: Average DC performance score
Z_3: Total uncovered demand
Z_4: Number of opened LDCs
Z_5: Number of opened MDCs
Z_6: Average walking distance

For each analysis, a parameter is selected for investigation, and an interval for its value is defined. Several points within the interval are then chosen for evaluation. Additionally, since the "minimum covered demand rate at every demand point (α)" interacts significantly with other parameters, the analysis is performed for various α values. The interval for α is set as 70% - 100% for all analyses, covering α values of 70%, 80%, 90%, and 100%. Subsequently, the model is solved using the related objective functions. The complete list of all the analyses is presented in **Table 2**.

For example, in Scenario 1, the "Maximum average walking distance (maw)" parameter is investigated, and its interval is defined as 3-5 km. The analysis is conducted for *maw* values of 3, 4, and 5 km. As there are four α values considered, a total of 12 runs are performed to cover all combinations. These analyses are repeated for all six objective functions. If the results for an objective function in a specific scenario do not provide significant information, they are not presented. For instance, in Scenario 1, only the results for $Z_1, Z_3, Z_4,$ and Z_5 are considered to derive conclusions since they are the significant objective functions for this particular scenario. The last column of **Table 2** presents the noteworthy objective functions for each scenario.

Finally, the results from the sensitivity analyses are consolidated to interpret the findings and comment on critical thresholds. This allows the decision-maker to understand how changes in the parameters impact the outcomes and make informed decisions in disaster response planning.

The GAMS software with the CPLEX solver, running on a laptop with an Intel Core i5 @ 1.6 GHz processor, is employed to solve the models. The computation time for each run is approximately 3 minutes.

4.3.1 Scenario 1: Maximum Average Walking Distance (maw)

In this sensitivity analysis, we investigated the impact of the maximum average walking distance (*maw*) on the feasibility and performance of the proposed model. The initial analysis indicated that the model becomes infeasible when *maw* is less than 3 km. Considering that an average walking distance of more than 5 km would require victims to walk for over an hour under inhumane conditions, we tested *maw* values of 3 km, 4 km, and 5 km.

Figure 3a presents the results for the objective function "the number of opened MDC" under different *maw* values. It is evident that to ensure the coverage of all demands, the average walking distance must be set to at least 4 km. When *maw* is 3 km, the model yields a feasible solution only when α is less than or equal to 80%. The number of opened MDCs shows limited sensitivity to changes in α within the range of 80-100% when *maw* is 4 km. Moreover, the model exhibits insensitivity to α changes when *maw* is 5 km.

Notably, the lowest number of opened MDCs is observed when *maw* is 3 km. This outcome occurs because, in contrast to *maw* values of 4 km and 5 km, the model solely focuses on covering the minimum demand dictated by the α constraint to achieve feasibility. Consequently, the total covered demand decreases, leading to a reduction in the number of opened MDCs compared to higher *maw* values, as shown in **Figure 3c**.

Figure 3b presents the results when the objective function is set as "the number of opened LDCs." Similar to the previous analysis, *maw* must be at least 4 km to cover all demands. As *maw* decreases, the model tends to increase the number of opened LDCs to cover demand greater than α. Moreover, the model reduces the number of opened MDCs to decrease the average product transportation distance.

The results for the objective function "Total covered demand" are displayed in **Figure 3c**. Total covered demand is insensitive to changes when α = 90%, 100%, and *maw* = 4 km and 5 km. The results of the objective "the average product transportation distance" are shown in **Figure 3d.** Interestingly, choosing *maw* = 3 km and *maw* = 4 km with α = 70% and 80% results in the same average product transportation distance.

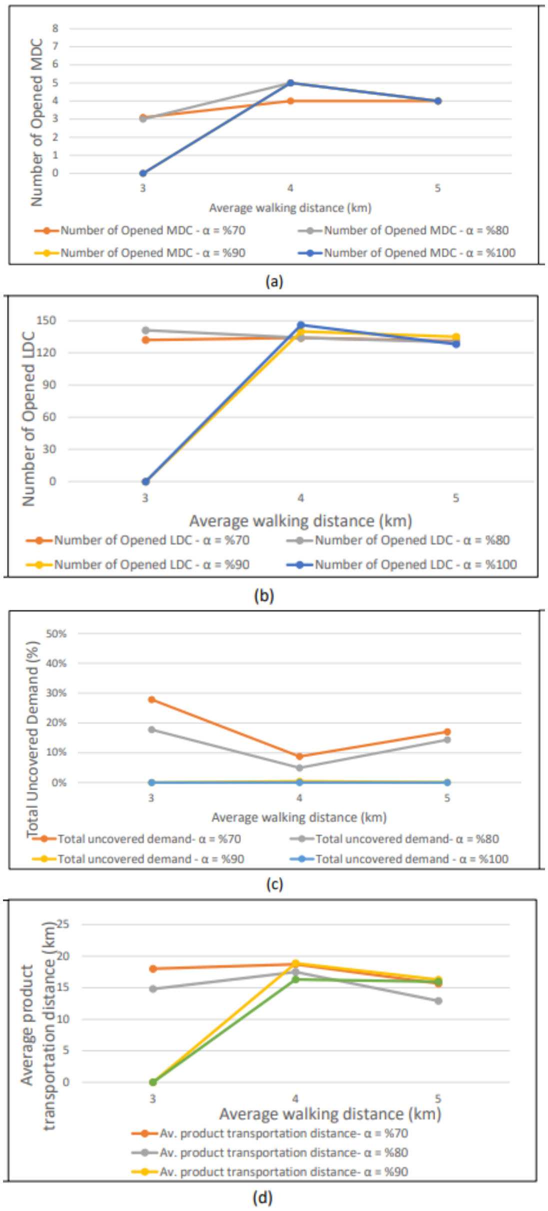

Figure 3 The result of Scenario 1 with objective function
a) Number of opened MDCs
b) Number of opened LDCs
c)Total uncovered demand
d) Average product transportation distance

Based on the comprehensive analyses in Scenario 1, we recommend selecting *maw* = 5 km. Increasing *maw* from 4 km to 5 km leads to significant improvements in the objective functions, making *maw* = 5 km the preferred choice to effectively cover all demand while optimizing disaster response operations.

4.3.2 Scenario 2: Minimum Acceptable Warehouse Facilities Performance Score for MDC (λ)

In this sensitivity analysis, we examined the impact of the minimum acceptable warehouse facilities performance score for MDCs (λ) on the feasibility and performance of the proposed mathematical model. The parameter analysis interval for λ was set as 0.55-0.7, considering the performance scores of the candidate MDCs.

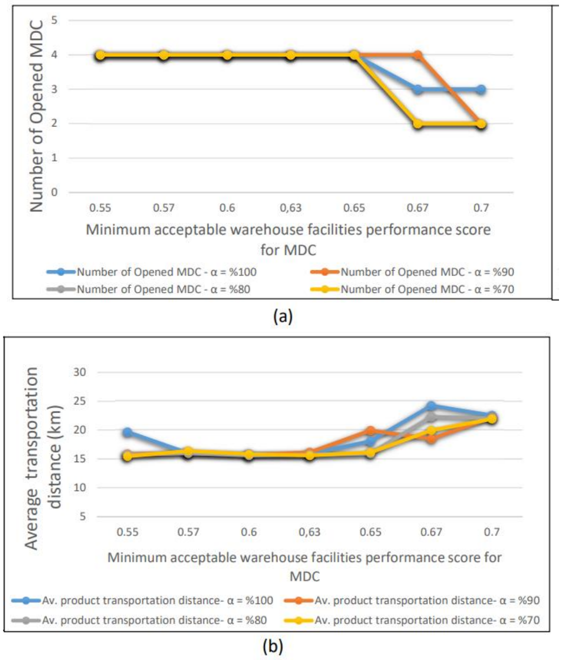

Figure 4 The result of Scenario 2 with objective function
a) Number of opened MDCs
b) Average product transportation distance

Figure 4a illustrates the results for the objective function "the number of opened MDCs." The analysis reveals that the change in λ between 0.55 and 0.65 has little impact on the number of opened MDCs. The decrease in the number of opened MDCs only occurs when the examined parameter increases above 0.67. This is because higher values of λ force the model to select DCs with higher performance scores, which are fewer in number.

In **Figure 4b**, we present the results for the objective function "average product transportation distance." The analysis demonstrates that the variation of the examined parameter between 0.55-0.63 has minimal effect on the average product transportation distance. However, a critical point emerges when increasing this parameter to 0.67, similar to the impact on the number of opened MDCs.

As a result of the comprehensive analyses in Scenario 2, we recommend setting the minimum acceptable warehouse facilities performance score for MDCs as 0.63 when aiming to cover all demand. However, if the DM aims to cover at least 70-80% and 90% of the demand at every demand point, then the related parameter should be set as 0.67 and 0.7, respectively. These values strike a balance between warehouse performance and the number of opened MDCs, optimizing the disaster response process while ensuring that the selected MDCs meet the required performance standards.

4.3.3 Scenario 3: Minimum Acceptable Warehouse Facilities Performance Score for LDC (μ)

In this analysis, we investigated effect of parameter µ on the feasibility and performance of the proposed mathematical model. The parameter analysis interval for µ was set as 0.21-0.6796, considering the performance scores of the candidate LDCs.

Figure 5a illustrates the results for the objective function "the number of opened LDCs" with respect to changes in μ. The analysis indicates that the parameter is not sensitive to changes between 0.21-0.627. However, a strong sensitivity arises when μ increases above 0.627. This is because, at higher µ values, the model is compelled to select LDCs with higher performance scores, which are fewer in number. The most sensitive point is when μ reaches 0.6796, resulting in a 35% decrease in the number of opened LDCs. However, this decrease also leads to reductions in the total covered demand and the average DC performance score.

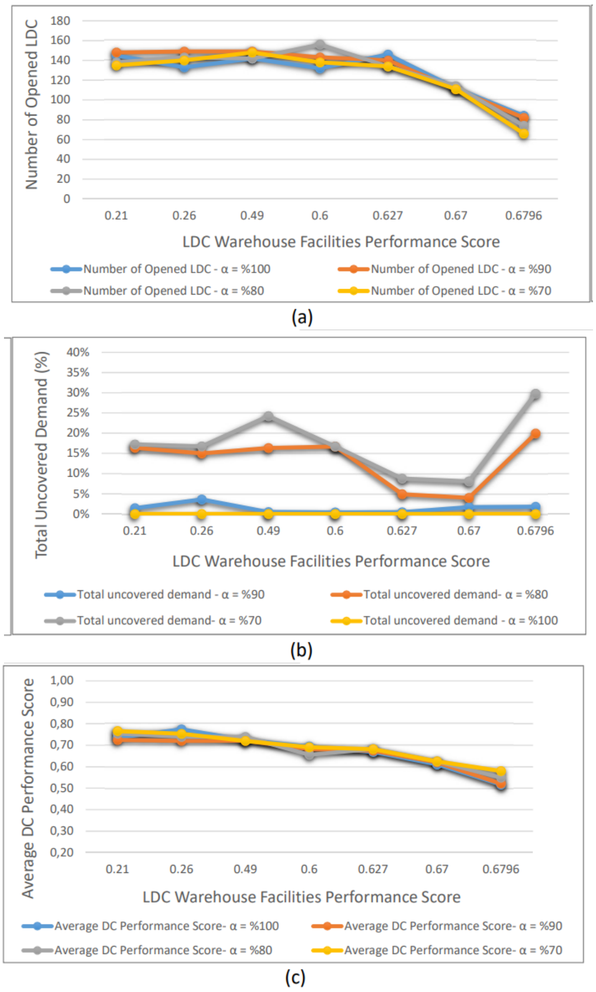

Figure 5 The result of Scenario 3 with objective function
a) Number of opened LDCs
b) Total uncovered demand
c) Average DC performance score

Figure 5b shows the effect of the change in µ on the average DC performance score. The analysis reveals that the model is not sensitive to μ changes between 0.21-0.49. However, an increase above 0.49 leads to a decrease in the average DC performance score, with the most significant sensitivity observed when μ reaches 0.6796. This decrease occurs because the model is compelled to select LDCs with a low total performance score but with higher μ.

As a result, we recommend setting μ as 0.67 as a balanced choice. However, it is crucial to note that this parameter is highly sensitive to the number of opened LDCs. Additionally, altering the number of opened LDCs impacts the average product transportation distance and average DC performance score depending on the value of α. Therefore, DMs should carefully decide on the value of μ based on their specific priorities, as it exhibits high sensitivity to different objectives and can significantly influence the overall disaster response strategy.

4.3.4 Scenario 4: Maximum Acceptable Distance between MDC and Assigned Airport (P)

In this analysis, we explored parameter P where interval for P was set as 7-36 km, considering the distances between MDCs and their corresponding airports.

Figure 6a illustrates the results for the objective function "the number of opened MDCs" with respect to changes in P. The analysis reveals that the number of opened MDCs is one more than in other cases when P is set to 7 or 8 km, with α = 100%. This occurs because candidate MDCs within this distance range have lower capacities compared to other MDCs, requiring the model to open an additional MDC to cover all demand adequately. Conversely, when α = 70% and P = 36 km, the number of LDCs decreases, and the number of MDCs increases by 2. However, the examined parameter shows low sensitivity to other changes.

Additionally**, Figure 6b** demonstrates that the average walking distance of a victim increases significantly, especially when α = 70% and P is set to 7 and 17.8 km, respectively.

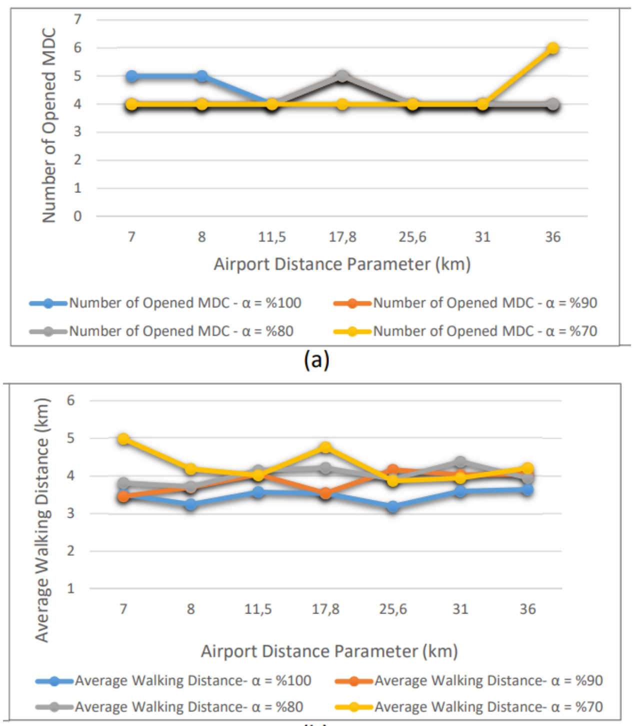

Figure 6 The result of Scenario 4 with objective function
a) Number of opened LDCs
b) Average walking distance

Based on the results, we recommend setting P as 11.5 km when α = 100% and 8 km for α = 70%, 80%, and 90%. These values strike a balance between the number of opened MDCs, the number of LDCs, and the average walking distance of victims, thereby ensuring an efficient and effective disaster response operation.

4.3.5 Scenario 5: Maximum Acceptable Distance between MDC and Assigned Port (R)

In this analysis, the parameter R is examined. The parameter analysis interval for R was set as 7-30 km, considering the distances between MDCs and their corresponding ports.

Figure 7 illustrates the results for the objective function "the number of opened LDCs" with respect to changes in R. The analysis revealed that when α = 100% and 90%, the number of opened LDCs increases as R changes within the range of 7-10 km. The model showed low sensitivity to changes in R between 10-21 km. However, beyond this range, at R = 24 and 30 km, the number of opened LDCs becomes highly sensitive.

Based on the results, we recommend setting parameter R as 13 km to ensure the coverage of 80-100% of the demand at every demand point. For a coverage target of 70% of the demand, the parameter R should be preferred at 10 km. These choices strike a balance between the number of opened LDCs and the distance to the assigned port, optimizing the disaster response efficiency while meeting specific coverage objectives.

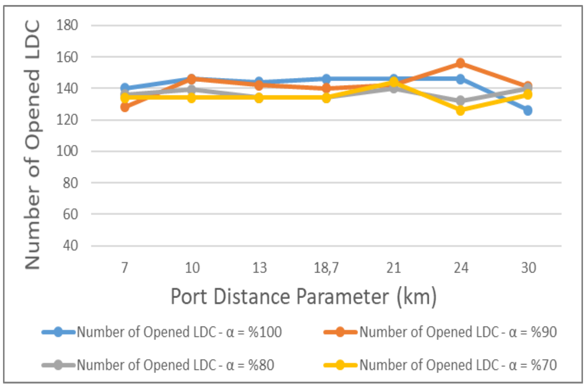

Figure 7 The result of Scenario 5 with objective function Number of opened LDCs

4.3.6 Scenario 6: Minimum Required Capacity Usage Rate for Opening MDC (M)

In this scenario, the parameter M is explored. The parameter analysis interval was set between 0 and 80%, as the proposed model couldn't find feasible solutions when M $\geq$ 80%.

Figure 8a displays the results for the objective function "the number of opened MDCs" with varying M values. Notably, when M = 60%, the average product transport distance increases when α = 70%, 80%, and 90%. The sensitivity is particularly pronounced at α = 90%. If the desired M value is set to 60% or 80%, the average product transport distance increases by approximately 10 km due to the reduced number of opened MDCs. However, parameter changes beyond these specific values can be considered insensitive in terms of average product transportation distance.

Figure 8b demonstrates the change in M concerning total covered demand and the minimum satisfied demand rate at every demand point. The analysis revealed that M is not sensitive to changes in terms of total covered demand when α = 90-100%. However, it shows moderate sensitivity when M is increased to 70% with α = 80%. Thus, we recommend setting the minimum required capacity usage rate for opening an MDC at 50% when the desired coverage level is α = 90%, and M = 60% for other demand ratios. These choices optimize the utilization of MDC capacities while ensuring effective disaster response operations.

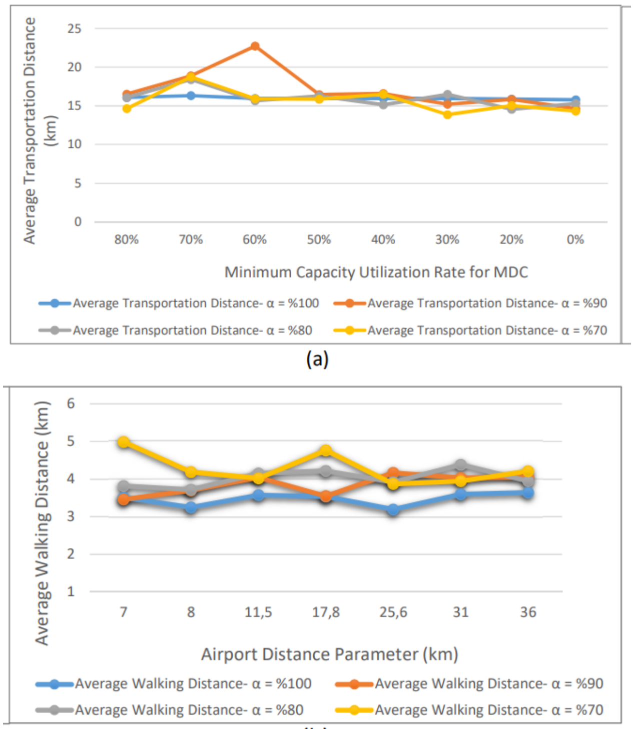

Figure 8 The result of Scenario 6 with objective function
a) Average product transportation distance
b) Total uncovered demand

4.3.7 Scenario 7: Minimum Required Capacity Usage Rate for Opening LDC (L)

In this scenario, parameter L, is examined. The parameter analysis interval was set between 0 and 30%, as the proposed model could not find feasible solutions when $L \geq 30\%$.

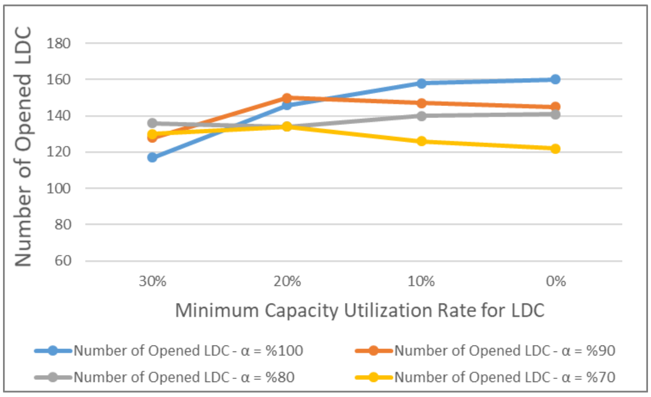

Figure 9 The result of Scenario 7 with objective function number of Opened LDC

Figure 9 shows the impact of L on the number of opened LDCs and the coverage level α. When L is $\leq$ 20%, the model opens as many LDCs as possible to reduce the average walking distance (maw) for efficient relief operations. However, this parameter becomes highly sensitive when it is increased to 30% and α = 90% and 100%. In such cases, the number of opened LDCs remains approximately the same for α = 70% and 80% since the model prioritizes reducing the total covered demand to optimize the solution. For the remaining scenarios, the parameter change is considered insensitive.

Based on the results, we recommend setting the minimum required capacity usage rate for opening an LDC at 30%. This choice will ensure an appropriate balance between the number of opened LDCs and the coverage level, leading to an efficient and effective disaster response system.

4.4 Results of the Sensitivity Analysis

Based on the comprehensive sensitivity analysis conducted in this section, we summarize the results from two perspectives: suggested values of the parameter and the objective functions. The critical points for the parameters in the proposed model are summurized as follows:

Demand Coverage: Sensitivity analysis indicates that selecting α = 100% does not significantly adversely affect the objectives. Considering the humanitarian responsibilities and ethical implications, this paper covers all demand to establish an disaster response system in Istanbul case.

Average Walking Distance (*maw*): The model requires at least 4 km for total demand coverage; however, establishing the parameter at 5 km yields more optimal solutions for the objectives. Consequently, the average walking distance for victims should be limited to a maximum of 5 km, which corresponds to a reasonable duration for walking.

Table 3 Solution of Istanbul application for suggested parameters.

Analyzed Value	Model Solution
Total weighted distance /	115,041,200 product.km
Average product transportation distance	26.37 km
Total DC performance value	66.457
Average DC performance value	0.639
Total uncovered demand	0
Covered demand rate	100%
The number of opened MDC	4 (MDC 1, 2, 19, 20)
The number of opened LDC	100
Average walking distance	3.886 km

Minimum Acceptable Warehouse Facilities Performance Scores: At least half of the opened MDCs and LDCs should have warehouse facility performance scores exceeding 0.63 and 0.67, respectively. Increasing this performance threshold for LDCs significantly reduces the number of opened LDCs. However, this adjustment adversely affect the average performance score of the DCs. Similarly, increasing the performance threshold for MDCs significantly raises the avarage transportation distance for relief supplies.

Minimum Required Capacity Usage Rate for MDC and LDC: The minimum required capacity usage rate for opening an MDC and LDC should be set at 60% and 30%, respectively. It is the upper limit for this LDC parameter to obtain a feasible solution.

Maximum Acceptable Distance to Assigned Port: The maximum acceptable distance between an opened MDC and its assigned port should be limited to 13 km. Decreasing the value of this parameter increases the number of opened MDCs.

Maximum Acceptable Distance to Assigned Airport: The maximum acceptable distance between an opened MDC and its assigned airport should be limited to 11.5 km. This limitaiton optimally balances the objectives related to the number of opened LDCs and average walking distance for affected individuals.

When the proposed mathematical model is executed with the above-given parameters, the results presented in **Table 3** are obtained. The optimal locations for opened LDCs and MDCs are illustrated in **Figure 10**, demonstrating an effective distribution of relief resources in response to potential disasters in the Istanbul area.

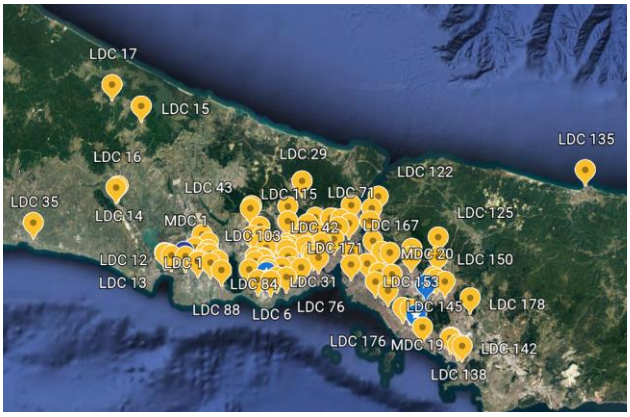

Figure 10 Opened DCs for Istanbul application with the suggested parameters.

Upon analyzing the model solution using the suggested parameters, the following observations related to the objectives are made:

MDC and LDC Numbers: As anticipated based on the sensitivity analysis results, four MDCs are opened to ensure full coverage of all demands with an average walking distance (*maw*) of 5 km. The LDC number is 100, which aligns with the higher value chosen for the parameter μ.

Average Walking Distance: Despite setting *maw* to 5 km, the average walking distance is calculated as 3.886 km. This indicates that only a small percentage of victims need to travel around 5 km to reach the nearest LDCs, which are strategically located near densely populated areas.

Average Product Transportation Distance: Due to the reduction in the number of DCs compared to the sensitivity analysis, the average product transportation distance is slightly higher. This is expected as the focus was on optimizing the DCs to achieve full demand coverage while minimizing the total number of DCs.

Average DC Performance Score: The average DC performance score is determined as 0.639, which closely matches the warehouse facilities' performance scores of the selected DCs. This indicates that the chosen DCs have adequate warehouse facilities' performance to efficiently handle and distribute relief resources.

Overall, the model solution with the suggested parameters demonstrates an effective disaster response plan with a balanced distribution of MDCs and LDCs. The optimization process aims to cover the maximum demand while minimizing the number of DCs and optimizing walking distances for the affected population. The results indicate that the proposed disaster response plan can efficiently handle potential disasters in the Istanbul area.

5. MANAGERIAL INSIGHTS

Based on the results the following insights for managers and DMs on the field can be derived:

1. Optimal Resource Allocation: The proposed model provides DMs with an effective tool for optimizing resource allocation during disaster response planning. By selecting suitable locations for MDCs and LDCs based on multiple objectives, managers can ensure that aid materials are efficiently distributed to affected areas. The sensitivity analyses shed light on critical parameter values, enabling managers to make informed decisions and prioritize objectives based on the specific needs of the disaster scenario.
2. Prioritizing Accessibility and Coverage: The sensitivity analysis highlights the significance of distance and coverage-related criteria in disaster relief logistics. Managers can use this information to prioritize the objective functions accordingly. By focusing on reducing average walking distances for victims while maintaining adequate coverage, disaster response efforts can be more efficient and effective, leading to quicker aid delivery and improved outcomes for affected communities.
3. Flexibility in Decision-Making: The sensitivity analyses demonstrate that certain parameters have varying degrees of impact on the model's results. This finding emphasizes the importance of flexibility in decision-making. Managers can adjust the parameter values based on their specific priorities and stakeholder requirements. By customizing the model to suit different scenarios and disaster types, DMs can tailor their response strategies to the unique challenges posed by each situation.
4. Addressing Uncertainties: While the proposed model provides a robust framework for location selection, uncertainties are inherent in disaster situations. Future studies incorporating fuzzy mathematical models or other uncertainty-handling techniques can be explored to account for fluctuations in demand and other parameters. This approach will enhance the model's resilience and enable managers to adapt their strategies dynamically in rapidly changing disaster scenarios.
5. Integration of Infrastructure Considerations: In future iterations of the model, incorporating infrastructure considerations, such as bridges and tunnels that may affect accessibility after a disaster, can further enhance its practicality. By factoring in the potential impact of

damaged DCs and roads, decision-makers can better prepare for post-disaster challenges and ensure continuity in aid distribution.

6. Learning from Behavioral Studies: Behavioral studies analyzing beneficiary actions in chaotic disaster situations can provide valuable insights into human response patterns. Integrating these findings into the model can enhance its accuracy and effectiveness, leading to more informed decision-making during disaster response planning.

In conclusion, the proposed model offers a valuable decision support tool for disaster response planning at the tactical level. By leveraging sensitivity analyses and customizing parameter values, managers can optimize resource allocation, prioritize objectives, and adapt their strategies to diverse disaster scenarios. Continued research and integration of infrastructure considerations and behavioral insights will further refine the model's practicality and enhance disaster relief logistics, ultimately improving aid delivery and outcomes for affected communities.

6. CONCLUSIONS AND FUTURE STUDIES

In this paper, we addressed the crucial task of selecting suitable locations for MDCs and LDCs to facilitate efficient transportation of aid materials in the event of a potential earthquake. We introduced a multi-objective mixed-integer mathematical model and successfully solved it using a goal programming approach. To demonstrate the practical application of the model, we conducted a real-case study for Istanbul, a city vulnerable to high-magnitude earthquakes. Extensive sensitivity analyses were performed to determine the appropriate values for the model parameters, which can be adapted to other application areas with necessary updates.

One notable aspect of the sensitivity analyses is the importance of objective functions. Although all objectives were initially considered equally important in the multiple-objective model, certain objectives exhibited more significant impacts on the results than others. For instance, the number of opened LDCs (Z_4) had a substantial effect on four out of seven parameters, while average product transportation distance (Z_1) and total uncovered demand (Z_3) affected three parameters each. This finding aligns with previous research in the literature, where distance and coverage-related criteria were commonly preferred as primary objective functions.

It is essential to emphasize that our proposed DC site selection model serves at the tactical level specifically for distributing disaster relief products within a city. Therefore, it is not suitable for determining locations for permanent warehouses nationwide or international distribution centers for humanitarian aid organizations. Furthermore, in scenarios involving floods or tsunamis, the potential abandonment of certain neighborhoods must be taken into account when identifying demand points.

For future studies, it would be beneficial to develop a fuzzy mathematical model to handle uncertainties in demand and other parameters, which are typically subject to decision-makers' judgments. Various methods, such as extensions of fuzzy sets, can be explored to compare the obtained results. Additionally, incorporating the consideration of damaged DCs and roads after a disaster (Salman and Yucel, 2015) and network restoration (Rojas Trejos *et al.*, 2023) would further enhance the model's practicality. Behavioral studies could also be conducted to understand the beneficiaries' actions in chaotic disaster situations (Gutjahr and Dzubur, 2016), contributing to a more comprehensive disaster response strategy.

In conclusion, our proposed model offers valuable insights for disaster response planning at the tactical level, specifically for city-based distribution of aid during various types of disasters. Sensitivity analyses serve as a powerful decision support tool for parameter selection, and decision-makers can prioritize objectives based on stakeholder priorities. As we continue to refine and expand our approach, we hope to contribute further to the field of disaster relief logistics and optimize the allocation of resources for better preparedness and response in critical situations.

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REFERENCES

Abounacer, R., Rekik, M. & Renaud, J. (2014). An Exact Solution Approach for Multi-Objective Location-Transportation Problem for Disaster Response, *Computers and Operations Research,* 41, pp. 83-93.

Afshar, A., Haghani, A. (2012). Modeling Integrated Supply Chain Logistics in Real-Time Large-Scale Disaster Relief Operations. *Socio-Economic Plannning Science 46*, pp. 327–338. https://doi.org/10.1016/j.seps.2011.12.003

Ahmadi, M., Seifi, A. & Tootooni, B. (2015). A Humanitarian Logistics Model for Disaster Relief Operation Considering Network Failure and Standard Relief Time: A Case Study on San Francisco District, *Transportation Research Part E: Logistics and Transportation Review, 75*, pp. 145–163. doi: 10.1016/j.tre.2015.01.008.

Akgün, İ., Gümüşbuğa, F. & Tansel, B. (2015). Risk Based Facility Location by Using Fault Tree Analysis in Disaster Management, *Omega, 52*, pp. 168–179. doi: 10.1016/j.omega.2014.04.003.

Altay, N. & Green, W. G. (2006). OR/MS Research in Disaster Operations Management', *European Journal of Operational Research, 175(1)*, pp. 475–493. doi: 10.1016/j.ejor.2005.05.016.

Balcik, B., Beamon, B.M. & Smilowitz, K. (2008). Last Mile Distribution in Humanitarian Relief, J*ournal of Intelligent Transportation Systems: Technology, Planning, and Operations,12(2)*, pp. 51-63,

Baskaya, S., Ertem, M.A. & Duran, S. (2017). Pre-Positioning of Relief Items in Humanitarian Logistics Considering Lateral Transhipment Opportunities, *Socio-Economic Planning Sciences, 57*, pp. 50-60.

Bell, M.G.H., Fonzone, A. & Polyzoni, C. (2014). Depot Location in Degradable Transport Networks, *Transportation Research Part B, 66*, pp. 148-161.

Boonmee, C., Arimura, M. &Asada, T. (2017). Facility Location Optimization Model for Emergency Humanitarian Logistics. *International Journal of Disaster Risk Reduction, 24,* pp. 485–498. https://doi.org/10.1016/j.ijdrr.2017.01.017

Boostani, A., Jolai, F. & Bozorgi-Amiri, A. (2020). Designing a Sustainable Humanitarian Relief Logistics Model in Pre- and Postdisaster Management, International *Journal of Sustainable Transportation*, 15(8), pp. 604-620. doi: 10.1080/15568318.2020.1773975

Brito, Jr I., Leiras, A. & Yoshizaki, H.T.Y. (2020). A Multi-Criteria Stochastic Programming Approach for Pre-Positioning Disaster Relief Supplies in Brazil, *Production*, 30. doi: 10.1590/0103-6513.20200042.

Camacho-Vallejo, J.-F., González-Rodríguez, E., Almaguer, F.-J. & González-Ramírez, R.G. (2015). A Bi-Level Optimization Model for Aid Distribution After the Occurrence of a Disaster. *Journal of. Cleaner Production 105*, 134–145.

Cao, C., Li, C., Yang, Q., Liu, Y. & Qu, T. (2018). A Novel Multi-Objective Programming Model of Relief Distribution for Sustainable Disaster Supply Chain in Large-Scale Natural Disasters, *Journal of Cleaner Production, 174*, pp. 1422-1435.

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. https://doi.org/10.1016/j.ijpe.2021.108081*

Cavdur, F., Kose-Kucuk, M. and Sebatli, A. (2016). Allocation of Temporary Disaster Response Facilities Under Demand Uncertainty: An Earthquake Case Study, *International Journal of Disaster Risk Reduction, 19*, pp. 159-166.

Celik, E. & Gumus, T.A. (2016). An Outranking Approach Based on Interval Type-2 Fuzzy Sets to Evaluate Preparedness and Response Ability of Non-Governmental Humanitarian Relief Organizations, *Computers and Industrial Engineering, 101*, pp. 21-34.

Chang, M.S., Tseng, Y.L. & Chen, J.W. (2007). A Scenario Planning Approach for the Flood Emergency Logistics Preparation Problem Under Uncertainty, *Transportation Research Part E*, 43, pp. 737-754.

Condeixa, L.D., Leiras, A., Oliveira, F. & de Brito, I. (2017). Disaster Relief Supply Pre-Positioning Optimization: A Risk Analysis Via Shortage Mitigation, *International Journal of Disaster Risk Reduction*, 25, pp. 238-247 https://doi.org/10.1016/j.ijdrr.2017. 09.007

Das, K., Lashkari, R. S. & Khan, A. R. (2021). A Humanitarian Logistics-Based Planning for Rescue and Relief Operation After a Devastating Fire Accident, *Operations and Supply Chain Management*, 14(1), pp. 51 – 61.

Elçi, O. & Noyan, N. (2018). A Chance-Constrained Two-Stage Stochastic Programming Model for Humanitarian Relief Network Design, *Transportation Research Part B, 108*, pp. 55-83.

Erdik, M. & Durukal, E. (2008). Earthquake Risk and its Mitigation in Istanbul, *Natural Hazards, 44*, pp. 181-197.

Ervural, B. & Kabak, O. (2019). A Cumulative Belief Degree Approach for Group Decision-Making Problems with Heterogeneous Information, *Expert Systems*,36(6), doi: 10. 1111/exsy.12458 Fikar, C., Gronalt, M. & Hirsch, P. (2016).

Fikar, C., Gronalt, M. & Hirsch, P. (2016). A Decision Support System for Coordinated Disaster Relief Distribution, *Expert Systems with Applications, 57*, pp. 104-116, doi: 10.1016/j.eswa.2016.03. 039https://doi.org/10.1016/j.eswa.2016.03.039.

Florez, J.V., Lauras, M., Okongwu, U. & Dupont, L. (2015). A Decision Support System for Robust Humanitarian Facility Location, *Engineering Applications of Artificial Intelligence, 46*, pp. 326-335.

Galindo, G. & Batta, R. (2013). Prepositioning of Supplies in Preparation for a Hurricane under Potential Destruction of Prepositioned Supplies, *Socioeconomics Planning Science, 47*, pp. 20-37, doi: 10.1016/j.seps.2012.11.002

Görmez, N., Köksalan, M. & Salman, F. S. (2011). Locating Disaster Response Facilities in Istanbul, *Journal of the Operational Research Society, 62*, pp. 1239–1252. doi: 10.1057/jors.2010.67.

Gutjahr, W.J. & Dzubur, N. (2016). Bi-Objective Bilevel Optimization of Distribution Center Locations Considering User Equilibria, *Transportation Research Part E, 85*, pp. 1-22.

Haddow, G., Bullock, J. & Coppola, D. P. (2013). *Introduction to Emergency Management*. Elsevier.

Hasani, A. & Mokhtari, H. (2018). Redesign Strategies of a Comprehensive Robust Relief Network for Disaster Management, *Socio-Economic Planning Sciences*, https:// doi.org/10.1016/j.seps.2018.01.003

Hughes, A.J. & Grawoig, D. E. (1973). *Linear Programming: An Emphasis on Decision Making.* London: Addison-Wesley Publishing Company Inc . pp. 300-316 039https://doi.org/10.1016/j.eswa.2016.03.039

IMM-JICA Report (2002). Istanbul Metropolitan Municipality-Japan International Coorperation Agency, *the Study on a Disaster Prevention / Mitigation Basic Plan in Istanbul including Seismic Microzonation in the Republic of Turkey* http://www.ibb.gov.tr/trTR/SubSites/DepremSite/Publishing images/JICA_ENG.pdf

Khanchehzarrin, S., Panah, M. G., Mahdavi-Amiri, N. & Shiripour, S. (2022) A Bi-Level Multi-Objective Location-Routing Optimization Model for Disaster Relief Operations Considering Public Donations, *Socio-Economic Planning Sciences*, 80, https://doi.org/10.1016/j.seps.2021.101165.

Kobayashi,T., Khojasteh, Y. & Kainuma, Y. (2019). Analysis of Multi-objective Decision Problems in Humanitarian Supply Chains, *Operations and Supply Chain Management,* 12(2), pp. 60 – 67

Kokaji, K. & Kainuma, Y. (2018). Development of a Disaster Relief Logistics Model Minimizing the Range of Delivery Time, *Operations and Supply Chain Management*, 11(2), pp. 66 - 72.

Le Pichon, X., Sengor, A.M.C., Demirbag, E., Rangin, C., Imren, C., Armijo, R., Gorur, N., Cagatay, N., Mercier de Lepinay, B., Meyer, B., Saatcilar, R. & Tok, B. (2001). The Active Main Marmara Fault, *Earth and Planetary Science Letters, 192*(4), pp. 595-616.

Leeuw, S., Mok, W. Y. (2016) An Empirical Analysis of Humanitarian Warehouse Locations, *Journal of Operations and Supply Chain Management*, 9 (1), pp. 55 – 76.

Li, B., Hernandez, I., Milburn, A.B. & Ramirez-Marquez, J.E. (2018). Integrating Uncertain Usergenerated Demand Data When Locating Facilities for Disaster Response Commodity Distribution, *Socio-Economic Planning Sciences*, 62, pp. 84-103, doi: 10.1016/j.seps.2017.09.003

Lusiantoro, L., Mara, S. T. W., & Rifai, A. C. (2022) A Locational Analysis Model of the COVID-19 Vaccine Distribution, *Operations and Supply Chain Management,* 15(2), pp. 240 - 250.

Maharjan, R. & Hanaoka, S. (2018). A Multi-Actor Multi-Objective Optimization Approach for Locating Temporary Logistics Hubs During Disaster Response, *Journal of Humanitarian Logistics and Supply Chain Management*, 8(1), pp. 2-21.

Naji-Azimi, Z., Renaud, J., Ruiz, A. & Salari, M. (2012). A Covering Tour Approach to the Location of Satellite Distribution Centers to Supply Humanitarian Aid, *European Journal of Operational Research, 222*, pp. 5986-605, doi: 10.1016/j.ejor.2012.05.001

Natural Hazards Research and Applications Information Center, (2005). *Holistic Disaster Recovery*. Public Entity Risk Institute, Boulder, CO.

Noham, R. & Tzur, M. (2018). Designing Humanitarian Supply Chains by Incorporating Actual Postdisaster Decisions, *European Journal of Operational Research, 265,* pp. 1064-1077, doi: 10. 1016/j.ejor.2017.08.042https://doi.org/10.1016/j.ejor.2017.0 8.042.

Paul, N.R., Lunday, B.J. & Nurre, S.G. (2017). A Multiobjective, Maximal Conditional Covering Location Problem Applied to the Relocation of Hierarchical Emergency Response Facilities, *Omega, 66*, pp. 147-158.

Rahmani, D., Zandi, A., Peyghaleh, E. & Siamakmanesh, N. (2018). A Robust Model for a Humanitarian Relief Network with Backup Covering Under Disruptions: A Real World Application. *Int. J. Disaster Risk Reduct. 28,* pp. 56–68. https://doi.org/10.1016/j.ijdrr.2018.02.021

Rancourt, M.-E., Cordeau, J.-F., Laporte, G. & Watkins, B. (2015). Tactical Network Planning for Food Aid Distribution in Kenya, Computers and Operations Research,56, pp. 68-83, doi: 10.1016/j. cor.2014.10.018https://doi.org/10.1016/j.cor.2014.10.018.

Rath, S. & Gutjahr, W. J. (2014). A Math-Heuristic for the Warehouse Location–Routing Problem in Disaster Relief, *Computers and Operations Research, 42,* pp. 25-39, doi: 10.1016/j.cor.2011.07.016

Rekik M., Ruiz A., Renaud J. & Berkoune, D. (2011). A Decision Support System for Distribution Network Design for Disaster Response. *Working Paper CIRRELT-2011-036,* Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation.

Rennemo, S.J., Ro, K.F., Hvattum, L.M. & Tirado, G. (2014). A Three-Stage Stochastic Facility Routing Model for Disaster Response Planning, *Transportation Research Part E: Logistics and Transportation Review, 62*, pp. 116-135.

Rivera-Royero, D., Galindo, G. & Yie-Pinedo, R. (2016), A Dynamic Model for Disaster Response Considering Prioritized Demand Points, S*ocioeconomics Planning Science*, *55*, pp. 59-75, doi: 10.1016/j.seps.2016.07.001https://doi.org/10.1016/j.seps.20 16.07.001.

Rodriguez, R.M., Martinez, L. & Herrera, F. (2011), Hesitant Fuzzy Linguistic Term Sets for Decision Making, *IEEE Transactions on Fuzzy Systems*, *20*(1), pp. 109-119.

Roh, S., Jang, H., Han, C., (2013), Warehouse Location Decision Factors in Humanitarian Relief Logistics. *Asian J. Shipp. Logist*., 29, pp. 103–120. https://doi.org/10.1016/j.ajsl.2013.05.006

Roh, S., Pettit, S., Harris, I. & Beresford, A. (2015), the Pre-Positioning of Warehouses at Regional and Local Levels for a Humanitarian Relief Organisation, *International Journal of Production Economics*, *170*, pp. 616-628, doi: 10.1016/j.ijpe.2015.01.015https://doi.org/10.1016/j.ijpe. 2015.01.015.

Rojas Trejos, C. A., Meisel, J. D., & Adarme Jaimes, W. (2023). Humanitarian Aid Distribution Logistics with Accessibility Constraints: A Systematic Literature Review. *Journal of Humanitarian Logistics and Supply Chain Management*, 13(1), pp. 26-41.

Rottkemper, B., Fischer, K. & Blecken, A. (2012), A Transshipment Model for Distribution and Inventory Relocation Under Uncertainty in Humanitarian Operations, *Socio-Economic Planning Sciences, 46* (1), pp. 98-109.

Salman, F. S. & Yücel, E. (2015). Emergency Facility Location Under Random Network Damage: Insights from the Istanbul Case, *Computers & Operations Research*, 62, pp. 266-281. doi: 10.1016/j.cor.2014.07.015.

Salmeron, J. &Apte, A. (2010). Stochastic Optimization for Natural Disaster Asset Prepositioning, *Production and Operations Management, 19* (5), pp. 561-574.

Sen, N. & Nandi, M. (2012). Goal Programming, its Application in Management Sectors– Special Attention into Plantation Management: A Review, *International Journal of Scientific and Research Publications*, 2(9).

Serrato-Garcia, M. A., Mora-Vargas, J. & Murillo, R. T. (2016). Multi Objective Optimization for Humanitarian Logistics Operations Through the Use of Mobile Technologies, *Journal of Humanitarian Logistics and Supply Chain Management*, 6 (3), pp. 399-418. doi: 10.1108/JHLSCM-01-2015-0002

Shaw, L., Das, S. K. & Roy, S. K. (2022) Location-Allocation Problem for Resource Distribution Under Uncertainty in Disaster Relief Operations, *Socio-Economic Planning Sciences*, 82, https://doi.org/10.1016/j.seps.2022.101232.

Sheu, J.B. & Pan, C. (2014). A Method for Designing Centralized Emergency Supply Network to Respond to Large-Scale Natural Disasters, *Transportation Research Part B: Methodological, 67*, pp. 284-305, doi: 10.1016/j.trb.2014.05.011.

Shu, J., Lv, W.& Na, W. (2021) Humanitarian Relief Supply Network Design: Expander Graph Based Approach and a Case Study of 2013 Flood in Northeast China, *Transportation Research Part E*, 146. https://doi.org/10.1016/j.tre.2020.102178

Taha, H. (1996). *Operations Research: An Introduction* (6th Edition), Pearson College Div, ISBN 10: 0132729156 ISBN 13: 9780132729154.

Tavana, M., Abtahi, A.-R., Di Caprio, D., Hashemi, R.& Yousefi-Zenouz, R. (2017). An Integrated Location-Inventory-Routing Humanitarian Supply Chain Network with Pre- and Post-Disaster Management Considerations. S*ocioecon. Plann. Sci*. https://doi.org/10.1016/j.seps.2017.12.004

Timperio, G., Panchal, G. B., Samvedi, A., Goh, M. & De Souza, R. (2017). Decision Support Framework for Location Selection and Disaster Relief Network Design. *Journal of Humanitarian Logistics and Supply Chain Management*, 7(3), pp. 222-245. doi: 10.1108/JHLSCM -11-2016-0040.

Tofighi, S., Torabi, S. A. & Mansouri, S. A. (2016). Humanitarian Logistics Network Design Under Mixed Uncertainty, *European Journal of Operational Research, 250(1)*, pp. 239–250. doi: 10.1016/j.ejor.2015.08.059.

Vahdani, B., Veysmoradi, D., Noori, F. & Mansour, F. (2018). Two-Stage Multi-Objective Location-Routing-Inventory Model for Humanitarian Logistics Network Design Under Uncertainty. *Int. J. Disaster Risk Reduct., 27, pp.* 290–306. https://doi.org/10.1016/j.ijdrr.2017.10.015

Verma, A. & Gaukler, G. M. (2015). Pre-Positioning Disaster Response Facilities at Safe Locations: An Evaluation of Deterministic and Stochastic Modeling Approaches, *Computers & Operations Research*, pp. 1–13. doi: 10.1016/j.cor.2014.10.006.

Vitoriano, B., Ortuño, M.T., Tirado, G. & Montero, J. (2011). A Multi-Criteria Optimization Model for Humanitarian Aid Distribution. *J. Glob. Optim. 51*, pp. 89–208. https://doi.org/10.1007/s10898-010-9603-z

Widener, M.J. & Horner, M.W. (2011). A Hierarchical Approach to Modeling Hurricane Disaster Relief Goods Distribution, *Journal of Transport Geography, 19(*4), pp. 821-828.

Yılmaz, H. & Kabak, Ö. (2020). Prioritizing Distribution Centers in Humanitarian Logistics Using Type-2 Fuzzy MCDM Approach. *Journal of Enterprise Information Management*, 33(5), pp. 1199-1232.

Zhang, J., Dong, M. & Chen, F.F. (2013). A Bottleneck Steiner Tree Based Multi-Objective Location Model and Intelligent Optimization of Emergency Logistics Systems, *Robotics and Computer Integrated Manufacturing, 29*, pp. 48-55.

Zhong, S., Cheng, R., Jiang, Y., Wang, Z., Larsen, A. & Nielsen, O. A. (2020) Risk-Averse Optimization of Disaster Relief Facility Location and Vehicle Routing Under Stochastic Demand, *Transportation Research Part E: Logistics and Transportation Review*, 141, pp. 366-5545.

Url-1 < *https://public.emdat.be/*>, accessed 20.12.2020.

Url-2 <https://istanbul.afad.gov.tr/tamp-istanbul/>, accessed 14.07.2020.

Url-3 *<https://depremzemin.ibb.istanbul/guncelcalismalarimiz/#olasi-deprem-kayip-tahmnler-le-ktapiklari/>*, accessed 05.07.2020.

Url-4 <https://parselsorgu.tkgm.gov.tr>. accessed 14.07.2020

APPENDIX 1: OBJECTIVES FOR MDC LOCATION PROBLEM

Objective	**Brito Jr. *et al.*(2016)**	**Ahmadi *et al.*(2015)**	**Salman and Yucel (2015)**	**Tofighi *et al.*(2016)**	**Afshar and Haghani (2012)**	**Salmeron and Apte**	**Camacho-Vallejo *et al.*(2015)**	**Verma and Gaukler**	**Rahmani *et al.*(2018)**	**Tavana *et al.*(2017)**	**Noham and Tzur (2018)**	**Vahdani *et al.*(2018)**	**Cao *et al.*(2021)**	**Timperio *et al.*(2017)**	**Serrato-Garcia *et al.*(2016)**
Investment cost		x							x	x		x			
Storing/operating cost	x									x		x		x	x
Transportation cost	x			x			x	x		x		x	x	x	x
Accessibility/availability	x		x					x			x	x		x	
Time/distance to LDCs or beneficiaries		x		x			x					x			
Infrastructure	x														
Storage environment	x														
Demand coverage		x	x		x	x	x	x					x	x	x
Management	x														
Socioeconomical development level		x												x	
Total potential environmental risk													x	x	

APPENDIX 2: OBJECTIVES FOR LDC LOCATION PROBLEM

	Widener and Horner (2011)	Rath and Gutjhar (2014)	Vitoriano *et al.*(2011)	Rennemo *et al.*(2014)	Rottkemper *et al.*(2012)	Florez *et al.*(2015)	Ahmadi *et al.*(2015)	Rancourt *et al.*(2015)	Bell *et al.*(2014)	Tofighi *et al.*(2016)	Afshar and Haghani (2012)	Akgün *et al.*(2015)	Rivera-Royero *et al.*(2016)	Zhang *et al.*(2013)	Naji-Azimi *et al.*(2012)	Rekik *et al.*(2011)	Sheu and Pan (2014)	Cavdur *et al.*(2016)	Abounacer *et al.*(2014)	Gutjahr and Dzubur (2016)	Chang *et al.*(2007)	Balcik *et al.*(2008)	Görmez *et al.*(2011)	Paul *et al.*(2017)	Elçi and Noyan (2018)	Fikar *et al.*(2016)	Cao *et al.*(2018)	Rahmani *et al.*(2018)	Tavana *et al.*(2017)	Nohan and Tzur (2018)	Condeixa *et al.*(2017)	Li *et al.*(2018)	Baskaya *et al.*(2017)	Hasani and Mokhtari (2018)	Shu *et al.*(2021)	Zhong *et al.*(2020)	Boostani *et al.*(2020)	Cao *et al.*(2021)	Shaw *et al.*(2022)	Khanchehzarrin *et al.*(2022)	Maharjan and Hanaoka (2018)	Serrato-Garcia *et al.*(2016)	Kokaji and Kainuma (2018)	Das *et al.* (2021)	Lusiantoro et al. (2022)
Transportation cost between LDC and beneficiaries	x							x				x																x	x					x			x	x			x				
Time/distance to LDCs/ beneficiaries	x								x	x		x		x	x	x	x	x	x	x	x		x		x	x	x	x	x	x	x	x	x			x			x	x			x	x	x
Investment cost		x				x	x	x		x										x	x			x	x			x						x	x				x	x	x				
Transportation cost among MDCs and LDCs		x	x	x	x	x		x		x			x				x				x	x			x			x	x		x							x	x		x	x		x	
Time between LDC and MDC			x																								x		x	x															
Demand Coverage		x			x	x		x		x	x		x			x		x	x	x		x	x	x	x		x	x		x	x	x	x	x			x	x	x		x				x
Psychological/ uncovered demand cos																	x						x						x													x			

APPENDIX 2: OBJECTIVES FOR LDC LOCATION PROBLEM (CON'T)

	Widener and Horner (2011)	Rath and Gutjhar (2014)	Vitoriano *et al.*(2011)	Rennemo *et al.*(2014)	Rottkemper *et al.*(2012)	Florez *et al.*(2015)	Ahmadi *et al.*(2015)	Rancourt *et al.*(2015)	Bell *et al.*(2014)	Tofighi *et al.*(2016)	Afshar and Haghani (2012)	Akgün *et al.*(2015)	Rivera-Royero *et al.*(2016)	Zhang *et al.*(2013)	Naji-Azimi *et al.*(2012)
Equity		x				x		x							
Reliability			x						x						
Accessibility/ availability															
Security			x												
Unused inventory cost									x						
Storing/operating cost															
Procurement cost															
Negative environmental effect															

	Rekik *et al.*(2011)	Sheu and Pan (2014)	Cavdur *et al.*(2016)	Abounacer *et al.*(2014)	Gutjahr and Dzubur (2016)	Chang *et al.*(2007)	Balcik *et al.*(2008)	Görmez *et al.*(2011)	Paul *et al.*(2017)	Elçi and Noyan (2018)	Fikar *et al.*(2016)	Cao *et al.*(2018)	Rahmani *et al.*(2018)	Tavana *et al.*(2017)	Nohan and Tzur (2018)
Equity															
Reliability															
Accessibility/ availability			x												x
Security			x												
Unused inventory cost										x				x	
Storing/operating cost											x				
Procurement cost															
Negative environmental effect															

	Condeixa *et al.*(2017)	Li *et al.*(2018)	Baskaya *et al.*(2017)	Hasani and Mokhtari (2018)	Shu *et al.*(2021)	Zhong *et al.*(2020)	Boostani *et al.*(2020)	Cao *et al.*(2021)	Shaw *et al.*(2022)	Khanchehzarrin *et al.*(2022)	Maharjan and Hanaoka (2018)	Serrato-Garcia *et al.*(2016)	Kokaji and Kainuma (2018)	Das *et al.* (2021)	Lusiantoro et al. (2022)
Equity	x			x											
Reliability															
Accessibility/ availability				x											
Security															
Unused inventory cost		x												x	
Storing/operating cost		x								x		x			
Procurement cost										x				x	
Negative environmental effect							x								

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