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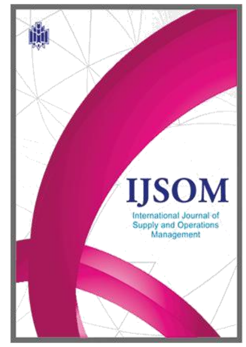

Incorporating Sustainability in Temporary Shelter Distribution for Disaster Response by the LP-based NSGA-II

Hossein Shakibaei [a], Saba Seifi [b] and Reza Tavakkoli-Moghaddam [a*]

[a] *School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran*
[b] *School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran*

Abstract

This paper introduces a comprehensive response mechanism designed to distribute temporary shelters after significant disasters effectively. The primary goal of this system is to overcome challenges posed by coordination, logistics, and resource allocation constraints to optimize relief operations following a catastrophe. The model utilizes a Linear Programming (LP) metric and a Non-dominated Sorting Genetic Algorithm (NSGA-II) as a well-known multi-objective evolutionary algorithm for advanced optimization. By leveraging these methodologies, the model validates its effectiveness while considering multiple objective functions and incorporating sustainability using a response perspective. The findings of the study verify the model's success in enhancing post-disaster shelter distribution and an overall responsive approach in various dimensional scenarios. The proposed integrated system can substantially contribute to the recovery of the impacted regions by streamlining coordination and improving the efficiency of relief operations in a more organized way. It provides valuable insights for decision-makers, practitioners, and researchers involved in disaster management. Finally, a conclusion and further research are provided.

Keywords: Post-Disaster; Integrated Model; Temporary Shelters; Sustainability; Meta-heuristics.

1. Introduction

A "disaster" is an unforeseen event causing harm, destruction, ecological disruption, human suffering, and deterioration of health and services, warranting an extraordinary response from outside the affected area (Najafi et al., 2013; Wang et al., 2016). Natural disasters such as earthquakes, hurricanes, tornadoes, volcanic eruptions, wildfires, floods, blizzards, and drought and man-made disturbances (e.g., terrorism, chemical spills, and nuclear mishaps) may fall under the disaster category (Ramezanian & Behboodi, 2017). In the 21st century, natural disasters pose significant challenges. For instance, a 5.9 magnitude earthquake hit Iran's northwest city of Khoy, causing at least three fatalities and injuring over 816 people while damaging buildings and infrastructure in the area.[1] Another example is that on 12 November 2017, a powerful 7.3 magnitude earthquake struck the Iran-Iraq border near Halabja. It resulted in at least 630 deaths and 8100 injuries, and was the deadliest quake of 2017.[2] Furthermore, poverty escalates as a result of displacement

[1] https://www.aljazeera.com/news/2023/1/29/deadly-earthquake-hits-khoy-iran
[2] https://en.wikipedia.org/wiki/2017_Iran%E2%80%93Iraq_earthquake#:~:text=Casualties%20and%20damage,-The%20province%20of&text=More%20than%20half%20of%20the,than%207%2C000%20others%20were%20injured.

*Corresponding author email address: tavakoli@ut.ac.ir
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caused by disasters, particularly in developing and low-income nations. Considering the increasing frequency and severity of disasters, there is a growing demand for effective management strategies in the realm of disaster management (Modgil et al., 2022).

Before disaster management strategies are activated, it is essential to employ a risk management approach to identify, assess, and mitigate potential risks that could disrupt humanitarian supply chain operations. This proactive approach enhances the resilience of the supply chain across all phases of disaster management: prevention, preparedness, response, and recovery (Cruz et al., 2004; Inan et al., 2023; Lindell & Perry, 2012). Fuzzy computations, Failure Modes and Effects Analysis (FMEA), and heatmap risk matrix are among the popular quantitative tools used in the risk management process (Bozorgi Amiri et al., 2020; Shakibaei, Seifi, et al., 2024). By employing these methods, organizations can better understand and manage the risks they face, ultimately enhancing their preparedness and response capabilities in disaster situations. After disasters, the initial response provides crucial services for affected people and communities to save lives and lay the foundation for long-term recovery. Humanitarian aid is primarily aimed at helping those in need to preserve lives, and it may involve logistical support (Paciarotti et al., 2021) or material allocation (Acar & Kaya, 2022). Emergency relief is often provided until institutions can step in to offer long-term assistance. Common forms of humanitarian aid involve responding to disasters through food and agriculture support, medical support, shelter distribution, and clean water provision.

Each year, the number of stakeholders affected by natural disasters who need aid increases. Humanitarian groups are facing greater pressure to improve their performance due to the rising frequency and severity of these disasters. On the other side, unstable humanitarian aid supply chains are susceptible to political influence and often ineffective as a result of insufficient planning and coordination among organizations (Fathalikhani et al., 2018). They lack an adequate logistics infrastructure and are unsure about where their relief assistance is coming from, and have unclear objectives (Xu et al., 2024). Coordination between various can decrease casualties, enhance information quality, and facilitate the movement and distribution of supplies in the impacted areas (Liang et al., 2021; Liu & Xie, 2016; Roblek et al., 2022). The fundamental characteristics of the supply chain for aid organizations are uncertainty and the unpredictability of emergencies. The humanitarian supply chain is unique and distinct with urgency, unpredictability, and coordination issues (Sabouhi et al., 2021). For sustainability, organizations need generative data to optimize operations, cut costs, and boost transparency. However, getting accurate and timely data in complex, dynamic environments is a big challenge, impacting performance and accountability (Shakibaei, Farhadi-Ramin, et al., 2024). Goli et al. (2023) integrate Circular Economy (CE) principles into the supply chain to further promote sustainability.

The primary goal is to create a cost-effective integrated system for multiple aspects following a major disaster, such as shelter distribution, improving post-disaster quality of life, and timely information delivery to professionals and affected individuals. This approach ensures seamless information flow among relevant parties, utilizing resources efficiently through specialized applications and devices, and establishing program connections. Limited research has been conducted in this field, leaving some unanswered questions as follows:

- How does the proposed model address the environmental impacts of helicopter or truck shelter distribution?
- How does it compare with existing models on sustainability indicators (cost, resources, resilience, equity)?
- How to improve post-disaster shelter distribution for better life quality and cost reduction?
- How can the proposed model integrate sustainability practices like recycling and reducing shelter materials?

A comprehensive approach for post-disaster temporary shelter distribution was developed and verified across different scenarios. Given the model's inherent complexity of the NP-hard class, the Non-dominated Sorting Genetic Algorithm (NSGA-II) was utilized. The model aimed to achieve four objectives: minimizing prevention and response phase costs, reducing maximum service time, and enhancing route reliability. Notably, the results demonstrated significant success in optimizing the route reliability objective. This implies that the model's allocation strategy and optimization algorithm are particularly effective in ensuring the consistent and reliable delivery of shelters to disaster-affected areas.

The combination of Linear Programming (LP) and the NSGA-II presents a novel methodology for optimizing disaster relief logistics. Unlike traditional models that tend to focus on a single objective, such as minimizing transportation costs or response time, our approach takes a more holistic view by addressing multiple, often conflicting objectives, including CO_2 emissions and response time. The LP-based metric ensures that the optimization process is structured, efficient, and suitable for real-time application in disaster scenarios, where rapid decisions are crucial. Additionally, the integration of the NSGA-II allows the model to generate a diverse set of Pareto-optimal solutions, offering decision-makers a broader range of trade-offs between key objectives rather than forcing a single, potentially suboptimal choice. This innovative methodology enhances the overall effectiveness of shelter distribution in disaster management and contributes to the sustainability of relief operations by minimizing their environmental impact.

The remainder of the text is structured as follows: Section 2 reviews existing literature on humanitarian supply chains from the early stages of risk emersion until post-disaster response solutions. Section 3 provides a clear description of the problem. In Section 4, the suggested approach is presented. Section 5 introduces the solution methods used to achieve the results. Section 6 illustrates the application of the proposed model to a simulated disastrous situation. Section 7 evaluates the validity and verifiability of the model through different-sized instances. Section 8 analyzes the sensitivity of the proposed method. In Section 9, valuable managerial insights are offered to the decision-makers. The paper concludes with a comprehensive summary and recommendations for future studies in Section 9.

2. Literature Review

The literature review is divided into three subsections: Section 2.1 focuses on disaster preparedness and response, Section 2.2 covers coordination and integration models, and Section 2.3 examines solution methods.

2.1 Disaster preparedness and response

In the last two decades, disaster preparedness gained significant attention from academics and practitioners. This led to various frameworks and approaches for strategically organizing humanitarian operations before crises (Seraji et al., 2022). Researchers have extensively studied the Humanitarian Logistics (HLs) region, focusing on the major logistical challenge for aid organizations: the extensive catastrophe scope and limited road network. Pyakurel et al. (2019) developed the contraflow problem, which optimizes the pathways during evacuation operations, to address these difficulties. Prioritization based on resource limitations is frequently necessary for emergency relief route optimization. To solve this problem, Zhu et al. (2019) proposed an emergency routing model for moving catastrophe victims with different levels of injury, considering capacity limits, to reduce operational costs and psychological suffering. Sharma et al. (2019) created a model for situating temporary blood banks in catastrophe situations so that hospitals can receive supplies with the shortest possible reaction times. In a recent study, De Vries and Van Wassenhove (2020) highlighted the underutilization of existing models in real humanitarian operations due to high operational uncertainty and expensive route optimization technologies. They recommend proposing practical models that can handle uncertainty effectively rather than relying on rigorous but costly and seldom used accurate models.

Optimizing emergency shelter prepositioning is vital for disaster preparedness. Bayram et al. (2015) proposed a Mixed-Integer Non-Linear Programming (MINLP) model to decide shelter locations, numbers, and capacities, thus minimizing evacuation time and post-disaster casualties. Paul and MacDonald (2016) proposed a stochastic model that considered several variables, including casualty estimates, transportation time, demographic characteristics, and demand clusters to develop the capacity given a probable disaster risk. Erbeyoğlu and Bilge (2020) recently suggested a strategy to create a pre-disaster relief network by positioning storage and distribution hubs to maximize service sufficiency and fairness at various demand points.

2.2 Coordination and integration models

The overall effectiveness of HLs is enhanced by coordinating the activities of many independent agencies. Zokaee et al. (2016) suggested a three-level relief distribution model that integrated suppliers, distribution centers, and demand locations to reduce the overall expenses of the entire relief chain. An integrated evacuation and distribution model that jointly optimizes vehicle scheduling and routing was proposed by Sabouhi et al. (2019). The objective was to distribute relief supplies and transport residents to shelters efficiently, considering limited vehicle capacity and split delivery options. Dubey et al. (2022) examined how information sharing, supply chain visibility, and blockchain technology can foster trust and collaboration among humanitarian actors amidst the growing use of technologies in decision-making.

2.3 Sustainability in humanitarian supply chains

Sustainability factors challenge humanitarian supply chains. Anjomshoae et al. (2023) explored the theoretical developments in measuring the sustainable performance of humanitarian supply chains. Cao et al. (2021) proposed a fuzzy tri-objective bi-level integer programming model that aims to minimize the unmet demand rate, potential environmental risks, and emergency costs at the upper level of the decision hierarchy while maximizing survivors' perceived satisfaction at the lower level. Laguna-Salvadó et al. (2019) provided a multi-objective master planning

Decision Support System (DSS) to manage these sustainable HSCs effectively by incorporating sustainability dimensions into their management. Shakibaei et al. (2024) contributed to this field by developing a multi-objective model to minimize social dissatisfaction, economic costs, and environmental damage in the face of disasters. Incorporating sustainability improves the entire supply chain performance.

2.4 Solution methods

Dealing with HLs models is a major computational challenge due to their size and multiple variables. The efficiency of solving such models by exact solvers (e.g., CPLEX and LINGO) is significantly impacted by the problem size. Li et al. (2012) developed a bi-level model and used the lagrangian function to address a stochastic two-stage humanitarian planning problem. A heuristic linear search strategy was created because the Lagrangian dual problem was concave. Tofighi et al. (2016) developed a fuzzy multi-objective model for disaster assistance by using a differential evolution technique. Despite achieving an optimality gap of 1.89% relative to the ideal solution, the approach's drawback is its dependence on trial-and-error parameter selection, making real-world application potentially time-consuming.

Researchers have created many heuristics and meta-heuristics to address the complexity of complicated real-world problems (Faghih-Roohi et al., 2016; Paul et al., 2019; Rezaei Somarin et al., 2018). Saeidian et al. (2016) considered metropolitan areas' resilience during an earthquake catastrophe. They proposed two algorithms, namely the Genetic Algorithm (GA) and Bee Algorithm (BA), to tackle the optimization challenge of selecting ideal relief center locations. Rath and Gutjahr (2014) proposed a mathematical heuristic for solving a three-objective warehouse location-routing problem in disaster relief. The method used an adaptive-constraint algorithm, generating constraints on demand by a Variable Neighborhood Search (VNS) algorithm and storing them in a constraint pool. Using queuing theory, Memari et al. (2018) suggested a fuzzy dynamic location-allocation model for disaster response. The model was solved and validated using the augmented-constraint approach and the NSGA-II. Talebi et al. (2022) improved ambulance routing as an Emergency Medical Service (EMS) in a dynamic natural disaster to assist and serve patients at least time and cost by employing the NSGA-II and a tailored Bees Algorithm (MOBA). In advancing pure NSGA-II, Long et al. (2016), Gholizadeh et al. (2020) and Delgoshaei et al. (2022) demonstrated that despite slower solving speed, hybridizing the NSGA-II with other methods in the LP class significantly boosted the quality of solutions. Stochastic multi-objective optimization has been employed for complex disaster relief network designs to balance logistics and resource allocation (Ghasemi et al., 2022).

3. Problem Description

Humanitarian organizations deploy trucks and helicopters to deliver temporary shelters to disaster-hit areas. The operation involves diverse truck warehouses and helicopter hangers. There are two clusters of affected areas: Cluster 1 with both good and damaged road access, where shelters can be delivered by both ground and air modes, and Cluster 2 with broken roads, where shelters are solely transported by air. Each cluster prioritizes points based on route reliability. However, breakdowns in ground vehicles lead to delays and system disruptions during shelter distribution.

Several researchers studied post-disaster temporary shelter distribution using different methods and models (Khamseh & Saatchi, 2021). One approach proposed a bi-objective model using the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the NSGA-II to consider the cost, service time, and demand uncertainty with heterogeneous vehicles. A two-stage stochastic programming model aimed to minimize total cost under demand uncertainty using Sample Average Approximation (SAA) and VNS. These studies offer valuable insights for decision-makers.

This paper presents an integrated model for distributing temporary shelters after a disaster. The model uses a planning approach and includes various vehicles like trucks and helicopters strategically placed in designated locations. It considers damaged and undamaged paths in its design and incorporates four spatial objective functions. The objectives aim to minimize prevention and response phase costs, reduce maximum service time, and maximize route reliability. The multi-objective model has been solved using the LP metric method followed by a meta-heuristic algorithm to address different scenarios. To address complex real-world decision-making problems effectively, models rely on simplifying assumptions that preserve essential system properties while reducing complexity. The following assumptions lead to a highly effective mathematical model:

1- Limit on vehicles; various types used to transport shelters to affected areas.
2- Clear starting points for all vehicles; each vehicle belongs to a specific warehouse.
3- All vehicles must be utilized during disasters.

4- Each damaged point is served by a single vehicle.
5- Warehouse stock sufficient to meet affected areas' needs.
6- Known locations and distances of affected areas from warehouses.
7- Demand at each affected point is known.
8- Vehicles return to their starting locations after the operation.
9- Damaged points are divided into two clusters, prioritized based on reliability factors.
10- Unrepairable breakdown leads to vehicle replacement.
11- Known breakdown times under different scenarios.
12- Delivery completion ensures service and prevents shortages. Disabled vehicles follow their schedules without performing duties.

In brief, this paper introduces an integrated model for distributing post-disaster temporary shelters, showcasing the following innovations and superiorities:

- Proposing an integrated model for temporary shelter distribution considering the costs of the prevention phase and the response phase as two separate objective functions.
- Incorporating sustainability in economic and environmental aspects, including the cost of facility, transportation, unmet demand, and carbon emissions.
- Developing an LP-based NSGA-II hybridization.

4. Proposed Model

This model aims to achieve four main goals, each represented by a separate objective function. The first function focuses on minimizing prevention phase costs, while the second aims to minimize response phase costs, encompassing fixed facility costs, transportation expenses, unmet demand costs, and carbon dioxide emissions from vehicles. The third objective function seeks to minimize the maximum service time, and the fourth aims to maximize route reliability. The model also considers the possibility of vehicle breakdown during ground assistance. Moreover, the second objective function incorporates sustainability considerations by targeting the reduction of total system costs and environmental impacts. Table 1 presents the notations utilized in the proposed mathematical model.

Table 1. Notations of the proposed mathematical model

Sets:	
$v^{'}$	Set of land vehicles
$v^{''}$	Set of aerial vehicles
ℓ	Set of the impacted areas with a passable road
$\ell^{'}$	Set of the impacted areas with a damaged road
d	Set of the ground vehicle depots
$d^{'}$	Set of the helicopter hangars
V	Set of vehicles
S	Set of scenarios
N	Number of all nodes
$n_{v^{'}}$	Number of trucks
$n_{v^{''}}$	Number of helicopters
n_{ℓ}	Number of impacted areas with a passable road
$n_{\ell^{'}}$	Number of impacted areas with a damaged road
n_d	Number of truck depots
$n_{d^{'}}$	Number of helicopter hangars
Parameters:	
χ_v	Capacity of vehicle v
Dem_i	Demand for shelters for node i (impacted area)
t_{vij}	Travel time from node i to j for vehicle v
r_{ij}	Permanent value of node i to j based on the reliability index
u_{vi}	Auxiliary and sequential variable that shows the number of nodes being visited with vehicle v in sub-tour elimination constraints
T_{iv}	Arrival time of vehicle v to node i
θ_{ij}	Traffic time of a vehicle traveling from node i to node j

Table 1. Notations of the proposed mathematical model (*Continued*)

Fx_v	Fixed cost of vehicle v
Fc	Unit cost of unmet demand
Ft_{vij}	Unit transportation cost of travel vehicle v from nodes i to j
Fco_v	Penalty cost of the transfer of CO2 produced by each vehicle v
Mco	Maximum budget amount of CO2 emissions
α_i	Unit cost of retrofitting impacted areas
η_i	Severity of the vulnerability of area i
ψ	Standard index for vulnerability control
Variables:	
k_i	1 if impacted areas are selected for retrofitting; 0, otherwise
x_{vij}	1 if vehicle v travels from node i to node j; 0, otherwise
y_i^s	1 if the shelter is not delivered to impacted area j under scenario s; 0, otherwise

The following mathematical model is presented, incorporating the aforementioned sets, variables, and parameters:

$$Min \sum_{i\in J}\sum_{j\in J}\sum_{v\in V}\alpha_i k_i \tag{1}$$

$$Min \sum_{i\in J}\sum_{j\in J}\sum_{v\in V} Fx_v + \sum_{s}\sum_{i\in n_\ell \cup n_{\ell'}} Fc.Dem_i.y_i^s + \sum_{i\in J}\sum_{j\in J}\sum_{v\in V} Ft_{vij}.x_{vij} + \sum_{i\in J}\sum_{j\in J}\sum_{v\in V} Fco_v.x_{vij} \tag{2}$$

$$Min\left(Max \sum_{i\in J}\sum_{j\in J}\sum_{v\in V} t_{vij}x_{vij}\right) \tag{3}$$

$$Min\left(\sum_{i\in J}\sum_{j\in J}\sum_{v\in V} r_{ij}x_{vij}\right) \tag{4}$$

s.t.

$$\sum_{i\in J}\sum_{j\in J}\sum_{v\in V} Fco_v.x_{vij} \le Mco \tag{5}$$

$$\eta_i k_i \ge \psi, \forall i \tag{6}$$

$$\sum_{i\in n_\ell \cup f(v,i)} x_{vij} - \sum_{i\in n_\ell \cup f(v,i)} x_{vji} = 0\,, \forall j \in n_\ell, v \in n_{v'} \tag{7}$$

$$\sum_{i\in n_\ell \cup n_{\ell'} \cup f(v,i)} x_{vij} - \sum_{i\in n_\ell \cup n_{\ell'} \cup f(v,i)} x_{vji} = 0\,, \forall j \in n_\ell \cup n_{\ell'}\,, v \in n_{v'} \tag{8}$$

$$\sum_{i\in f(v,i)}\sum_{j\in n_\ell} x_{vij} = 1\,, \forall v \in n_{v'}\,, f(v,i) \tag{9}$$

$$\sum_{i\in f(v,i)}\sum_{j\in n_\ell \cup n_{\ell'}} x_{vij} = 1\,, \forall v \in n_{d'} \tag{10}$$

$$\sum_{i\in n_\ell}\sum_{j\in f(v,i)} x_{vij} = 1\,, \forall v \in n_{v'} \tag{11}$$

$$\sum_{i\in n_\ell\cup n_{\ell'}}\sum_{j\in f(v,i)} x_{vij} = 1\,,\forall v\in n_{d'} \tag{12}$$

$$\sum_{v\in n_{v'}}\sum_{j\in n_\ell} x_{vij} + \sum_{v\in n_{v''}}\sum_{j\in n_\ell\cup n_{\ell'}\cup f(v,i)} x_{vij} = 1\,,\forall i\in n_\ell \tag{13}$$

$$\sum_{v\in n_{v''}}\sum_{j\in n_\ell\cup n_{\ell'}\cup f(v,i)} x_{vij} = 1\,,\forall i\in n_{\ell'} \tag{14}$$

$$\sum_{j\in n_\ell\cup f(v,i)}\sum_{i\in n_\ell} x_{vij}.Dem_i \le \chi_v\,,\forall v\in n_d\cup n_{d'} \tag{15}$$

$$\sum_{j\in n_\ell\cup n_{\ell'}}\sum_{i\in n_\ell\cup n_{\ell'}} x_{vij}.Dem_i \le \chi_{v'}\,,\forall v\in n_{v''} \tag{16}$$

$$u_{vi} - u_{vj} + n_\ell x_{vij} \le n_\ell - 1\,,\forall v\in n_{v'}\,, i\in n, i\in n_\ell \tag{17}$$

$$u_{vi} - u_{vj} + n_{\ell'} x_{vij} \le n_{\ell'} - 1\,,\forall v\in n_{v''}\,, i\in n_\ell\cup n_{\ell'} \tag{18}$$

$$u_{vi} \le n_\ell\,,\forall v\in n_{v'}\,, i\in n_\ell \tag{19}$$

$$u_{v.f(v,i)} = 0\,,\forall v\in n_{v'}\,, i\in n_\ell \tag{20}$$

$$u_{vi} \le n_\ell\cup n_{\ell'}\,,\forall v\in n_{v''}\,, i\in n_\ell\cup n_{\ell'} \tag{21}$$

$$u_{v.f(v,i)} = 0\,,\forall v\in n_{v''}\,, i\in n_\ell\cup n_{\ell'} \tag{22}$$

$$\sum_{v} T_{iv} = 0\,,\forall f(v,i) \tag{23}$$

$$T_{iv} - \sum_{j\in n_\ell\cup n_{\ell''}} x_{vij}.(T_{iv}+\theta_{ij}) = 0\,,\forall i\in n_\ell\cup n_{\ell'} \tag{24}$$

$$bigM(1-y_i^s) \ge (T_{iv}+\phi_v^s)\,,\forall i\in n_\ell\cup n_{\ell'}\,, s\in S\,, v\in n_\ell \tag{25}$$

The proposed model encompasses a set of objective functions that aim to minimize various costs. The first objective function (Eq. 1) seeks to minimize the retrofitting costs of impacted areas, essentially reducing the expenses associated with improving these zones for better resilience against future disasters. The second objective function (Eq. 2) aims to minimize the total costs, which include the fixed costs of vehicles, the cost of unmet demand, transportation costs, and CO2 penalty costs, thereby ensuring an economically sustainable operation. The third objective objective (Eq. 3) is to minimize the maximum travel time for all vehicles across the network, which is vital for time-sensitive service. Additionally, the model strives to minimize the reliability index across chosen routes, prioritizing more critical delivery paths through Eq. 4. Within the constraints, Eq. 5 limits CO_2 emissions to adhere to environmental sustainability standards and Eq. 6 controls the vulnerability measure in each area. Vehicle capacity constraints (Eqs. 15 and 16) guarantee that the demand for shelters delivered does not exceed the vehicle's capacity, ensuring that the logistics are feasible and practical. The rest of the constraints are flow conservation constraints that ensure a balanced flow is maintained within the network. Lastly, This comprehensive model uses binary variables to represent decisions and continuous variables for quantities in a form of Mixed-Integer programming (MIP).

5. Solution Methodology

The current research is primarily descriptive regarding applied purpose, quantitative, and tools. It utilizes library studies and mathematical modeling to develop a precise mathematical model for assessing the distribution of temporary shelters after a disaster. The model is solved using GAMS software. This research uses the LP metric method to solve the proposed model, and the approaches to validate the results under the NSGA-II were investigated.

In mentioned approach, the LP-metric plays a critical role in addressing specific aspects of the optimization process, particularly where linear constraints and objective functions are involved. It is well-suited for optimizing a set of linear relationships, making it ideal for problems such as transportation logistics and resource allocation, where the relationships between variables (e.g., transport capacity, shelter locations, and resource availability) can be expressed in linear terms. Using LP, we can efficiently determine optimal routes and resource distributions that minimize costs or maximize efficiency while adhering to operational constraints. However, disaster response scenarios often involve competing, non-linear objectives, such as balancing the reduction in response time with environmental concerns like CO_2 emissions. This is where the NSGA-II comes into play. The NSGA-II is a multi-objective optimization technique capable of managing these conflicting objectives by generating a set of Pareto-optimal solutions (Wang et al., 2021). While LP ensures that individual aspects of the logistics, such as routing and resource allocation, are optimized under a set of constraints, the NSGA-II evaluates and resolves trade-offs between multiple objectives, offering a diverse set of solutions that reflect the best compromises among the competing goals. The synergy between the NSGA-II and LP allows the model to optimize both the logistics of disaster response and sustainability metrics simultaneously, providing decision-makers with actionable solutions that consider both operational and environmental factors.

5.1. LP metric method

The LP metric method is a popular and robust method for solving multi-objective models. It starts by solving bi-objective sub-problems models and seeks to find solutions with higher quality (Delgoshaei et al., 2022). In our case, specifically designed for minimizing objective functions, it can be summarized as follows:

$$Z_{total} = \frac{w_1.(Z_1 - \mathrm{Z}_1^{min})}{\mathrm{Z}_1^{max} - \mathrm{Z}_1^{min}} + \frac{w_2.(Z_2 - \mathrm{Z}_2^{min})}{\mathrm{Z}_2^{max} - \mathrm{Z}_2^{min}} \tag{26}$$

where w_i is the weight of the i-th objective function, and Z_i^{min} and Z_i^{max} represent the ideal and anti-ideal solutions of the i-th objective function, respectively.

5.2. NSGA-II

Multi-objective Optimization Problems (MOPs) are based on the concept of Pareto dominance, which emphasizes research satisfying all objectives, which means there are two or more objectives that need to be improved at the same time. The Pareto-dominance concept evaluates how good a solution is by comparing it with all the other solutions based on all the objectives. We say that a solution x is better than another solution y (written as $x \prec y$) if and only if x has a lower or equal value than y for every objective ($f_i(x) \leq f_i(y)$) for $i = 1, 2, \ldots, n$), and x has a strictly lower value than y for at least one objective (there is an i in $\{1, \ldots, n\}$ such that $f_i(x) \leq f_i(y)$) (Ojha et al., 2019). This way of defining Pareto-dominance implies the possibility of several non-dominated solutions, and a MOP aims to find all these solutions, which are called the Pareto set.

GAs are evolutionary optimization algorithms based on mechanisms of genetics. Multi-objective GAs attempt to solve MOPs based on the concept of Pareto dominance with powerful optimization capabilities (Yuan et al., 2021). One of the popular methods for solving the MOPs is the NSGA-II metaheuristic algorithm, which is a non-dominated sorting genetic algorithm that can handle non-convex and non-smooth multi-objective optimization problems. The NSGA-II is a population-based algorithm that uses evolutionary operators, such as selection, crossover, and mutation, to generate and improve solutions. It also uses a ranking method to evaluate the solutions according to their dominance and diversity and a crowding distance measure to maintain a diverse and well-distributed set of solutions. The NSGA-II has successfully been applied to various contexts of MOPs (Mengyue & Keping, 2020). Also, it has successfully been combined with other methods (e.g., fuzzy inference systems) for optimizing post-disaster volunteer assignments (Rabiei et al., 2023).

5.3. Comparison with Non-preemptive Goal Programming

Non-preemptive Goal Programming (NGP) is a traditional approach for solving multi-objective optimization problems, particularly when the decision-maker aims to achieve a set of predefined goals without prioritizing one over another. In NGP, conflicting objectives are treated as soft constraints, and the goal is to minimize the deviation from these targets while satisfying the problem's constraints. While NGP can be effective in handling simple multi-objective problems, it presents certain limitations when applied to complex disaster relief logistics, where multiple objectives (e.g., minimizing response time, transportation cost, and CO_2 emissions) are involved.

One of the main challenges of using NGP in disaster relief logistics is its assumption of linearity and the necessity to define precise goal values for each objective. However, these goals may only sometimes be clear or fixed in real-world scenarios, especially in dynamic environments like disaster response, where objectives may shift based on changing conditions (e.g., available resources, urgency, or environmental considerations). In contrast, the LP-metric-based NSGA-II methodology offers a more flexible and robust approach by combining LP with a genetic algorithm. LP efficiently optimizes specific operational aspects (e.g., routing and resource allocation. At the same time, the NSGA-II generates a set of Pareto-optimal solutions to handle the trade-offs between conflicting objectives. Unlike NGP, where a predefined goal must be met for each objective, the LP-NSGA-II framework does not require rigid goal-setting and allows for the exploration of a range of possible solutions, offering a more comprehensive understanding of the trade-offs (Ransikarbum & Mason, 2022).

Furthermore, the LP-metric approach is better suited for problems where objectives are not simply linear deviations from a target but rather represent complex, multi-dimensional conflicts (e.g., the simultaneous need to minimize environmental impact and maximize response efficiency). The NSGA-II, being a population-based evolutionary algorithm, can explore this space more thoroughly, providing decision-makers with a variety of solutions that balance competing objectives in ways that NGP struggles to capture effectively. The LP-metric-based NSGA-II approach is also more adaptable to real-time changes in the disaster environment, as it continuously evaluates new solutions. In contrast, NGP typically requires recalibration of goal values after each decision cycle. While NGP can provide useful insights in static, well-defined optimization problems, the LP-metric-based NSGA-II methodology offers greater flexibility, adaptability, and scalability for disaster relief logistics, particularly when handling complex, conflicting objectives and dynamic, uncertain environments.

5.4. LP-metric-based NSGA-II method

In this study, we use the Pareto analysis to develop the NSGA-II for multi-objective optimization problems. This algorithm is a widely used meta-heuristic algorithm that generates non-dominated solutions, achieving a balance across different objectives. The method involves sorting the initial population based on overcoming conditions, calculating crowding distance, and then performing selection with binary selection for generating new children. The process is repeated until the desired generation or optimal condition is reached. This multi-objective genetic algorithm avoids issues caused by weighting in other approaches, providing a set of effective solutions instead of a single solution. It prioritizes moving toward the optimal solution following the LP metric method through a pairwise Pareto analysis. It allows for the definition of optimal conditions using a cost function without relying on Kahn and Tucker's conditions, such as pre-solution weighting methods. This is because the LP metric method can solve the proposed bi-objective problem as a single-objective MIP model (Pasandideh et al., 2015).

The summary of this algorithm's procedure is shown in Figure 1.

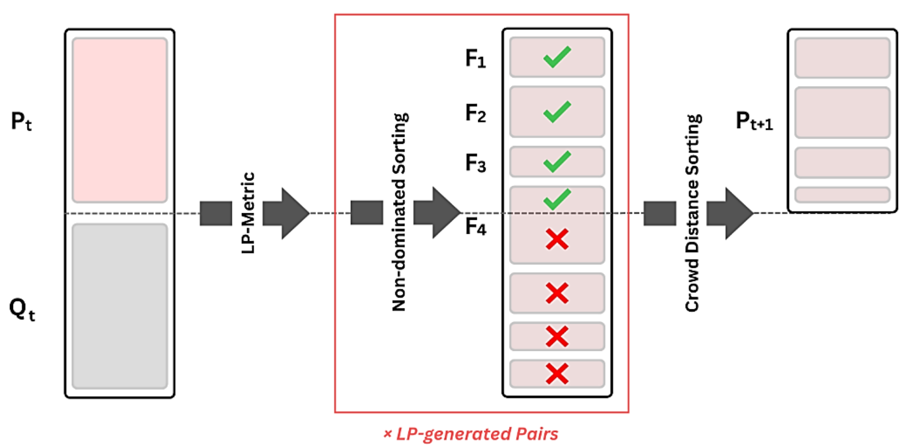

Figure 1. Schematic summary of the LP-based NSGA-II procedure.

The first step is to create a combined population R_t with a size of $2N$, which consists of the current dominating set P_t and the new generation Q_t. After reducing the four-objective problem down to a bi-objective problem using an iterative LP metric method for pairing purposes, the population R_t is ranked based on the non-domination and forms a non-dominant set F that is the union of F_1, F_2, ..., and F_k. In other words, the LP metric is implemented within the non-dominated solution construction, which results in a larger pool of solutions. The elitism approach is preserved since R_t contains all the solutions from the previous and current populations. To select the exact number of population members, the non-dominant set is ordered by the crowding distance from high to low, and then the best solutions are picked as the parent population for the next generation.

6. Case Study

The model is applied to a simulated case study inspired by typical real-world conditions faced in humanitarian operations. The case study builds upon the context and scope introduced by Gharib et al. (2022) by quantifying notations in a way that represents a disastrous situation that is worth solving. The values are as detailed as follows:

Table 2. Values of the sets.

Notation	Values
υ'	{Truck1, Truck2, Truck3}
υ''	{Helicopter1, Helicopter2}
ℓ	{Area1, Area2, Area3}
ℓ'	{Area4, Area5}
d	{Depot1}
d'	{Hangar1}
V	{Truck1, Truck2, Truck3, Helicopter1, Helicopter2}
S	{Scenario1, Scenario2}
N	8
$n_{\upsilon'}$	3
$n_{\upsilon''}$	2
n_{ℓ}	3
$n_{\ell'}$	2
n_d	1
$n_{d'}$	1

Table 3. Values of the parameters.

Notation	Values
χ_υ	Truck1: 100, Truck2: 150, Helicopter1: 50, Helicopter2: 60
Dem_i	Area1: 80, Area2: 90, Area3: 100, Area4: 70, Area5: 60
$t_{\upsilon ij}$	Random values with an average of 1.5 hour
r_{ij}	0.8
$T_{i\upsilon}$	An integer ranging from 0 up to 48 referring to the 48-hour Service Level Agreement (SLA)
θ_{ij}	Random values with an average of 0.5 hours
Fx_υ	Truck1: 1000, Truck2: 1500, Helicopter1: 2000, Helicopter2: 2500
Fc	500
$Ft_{\upsilon ij}$	Random values with an average of 100 Cost Units (CU)
Fco_υ	Truck1: 50, Truck2: 75, Helicopter1: 100, Helicopter2: 125
Mco	10000
α_i	Area1: 200, Area2: 250, Area3: 300, Area4: 350, Area5: 400
η_i	Area1: 0.8, Area2: 0.9, Area3: 1.0, Area4: 0.7, Area5: 0.6
ψ	0.5

Capacities are set to reflect typical load limits for trucks and helicopters used in disaster logistics. For example, trucks commonly used in relief efforts have capacities ranging from 100 to 150 units, while more limited helicopters range from 50 to 60 (Chowdhury et al., 2017). Demand values for each impacted area are based on average requirements for emergency shelters, considering factors like population density and severity of impact (Apte, 2010). Travel times are estimated based on average speeds and distances between nodes, considering potential delays due to road conditions or air traffic (Yi & Kumar, 2007). These costs are derived from operational expenses reported in disaster logistics case studies, such as vehicle maintenance, fuel, and driver wages (Balcik & Beamon, 2008). Penalty costs for CO2 emissions are included to reflect the increasing emphasis on environmental sustainability in logistics planning. The values are based on carbon pricing models used in the logistics industry (Dekker et al., 2012). The severity values assigned to each area are based on vulnerability indices used in risk assessments, considering factors like exposure, sensitivity, and adaptive capacity (Birkmann, 2007). The chosen value ensures that retrofitting efforts are prioritized for areas with the highest vulnerability, supporting targeted interventions (Cutter et al., 2012). The values can be tailored to specific conditions, ultimately enhancing the practicality of the model.

7. Model Validation & Verification

Validation and verification are crucial steps in developing optimization models to ensure their accuracy and reliability (Hartley & Starr, 2010). Validation is the process of confirming that the model correctly represents the real-world scenario it is intended to model. It involves checking that the model addresses the right problem and provides accurate information about the system being modeled (Fonseca i Casas, 2023). Comparing the model's solutions with known solutions in the existing literature is the most promising way to validate the model (Roy & Oberkampf, 2011). The closeness of results further validates this LP-based metaheuristic in comparison with the pure metaheuristic utilized in the paperwork by Gharib et al. (2022). By this means, the validity of the model can be supported. Verification, on the other hand, focuses on ensuring that the model has been correctly implemented. This means checking that the mathematical formulations and algorithms are correctly coded and that there are no errors in the logic or execution of the model. Verification is about ensuring the model performs as intended (Sargent, 2015). One way to verify the model is to develop a set of test cases that cover a wide range of scenarios, including edge cases, and run these tests to ensure the model behaves as expected under different conditions (Baier & Katoen, 2008). Thus, verification is performed using what-if analysis on several size-based instances.

In single-objective problems, an optimal solution is chosen for the purpose of the problem, while in MOPs, we encounter a set of Pareto solutions, and the performance of the algorithms cannot be easily evaluated. Evaluation criteria are important since they can be used to examine the performance of algorithms (Attar et al., 2014; Piroozfard et al., 2018; Zarei & Rasti-Barzoki, 2018). The comparing criteria include Quality Metric criterion (QM), Spacing Metric criterion (SM), Diversification Metric (DM), CPU Time (CPUT), and Mean Ideal Distance (MID). A lower value of SM, MID, and CPUT criteria, and a higher percentage of QM and DM criteria indicate better the algorithm efficiency. In this study, we apply the CPUT criterion to assess the performance of the model.

7.1 Number of nodes sizing instances

Regarding the population initialization, the initial population was randomly generated. Three small, medium, and large-sized instances for 10, 20, and 30 nodes, respectively, are designed in a simulation environment. The total computing time taken in solving these three instances is recorded in Table 4. The time duration is calculated by placing a piece of code at the beginning and end of the main algorithm.

The verification results confirm the model's correct implementation and scalability. The objective functions and run times for small, medium, and large instances increase consistently and logically with the number of nodes, demonstrating the model's capability to manage varying problem sizes effectively.

Table 4. Performance of the proposed model based on the differently sized instances.

Problem No.	Problem description	Number of nodes (N)	Obj 1	Obj 2	Obj 3 (Hour)	Obj 4	Run Time (s)
1	Small size	10	20.123	200.456	1.234	0.68	1254
2	Medium size	20	30.789	300.123	2.567	0.72	1545
3	Large size	30	40.456	400.789	3.890	0.75	1679

7.2 Number of vehicle sizing instances

Five scenarios involving different numbers of trucks and helicopters were executed to validate further and solve the proposed model. The model included four objective functions: minimizing prevention phase costs, minimizing response phase costs, minimizing maximum service time, and maximizing route reliability. Table 5 presents the performance results of the proposed model for the various scenarios. According to this table, the prevention costs in the first objective function increased with the rise in the number of helicopters and trucks, indicating a logical outcome. Similarly, the second objective function's cost increased with a steeper slope from state 4 to state 5. However, the third objective function decreased in the time taken to assist in affected areas as the problem dimensions increased. In contrast, the fourth objective function demonstrated an improvement in route reliability. Figure 2 reflects the trends discussed, visually illustrating the relationships between the problem dimensions and the corresponding outcomes in each objective function. Increasing the number of helicopters and trucks in the system leads to higher costs; however, it also improves overall reliability and reduces response time to affected areas. As depicted in Figure 3, the execution time rises proportionally with the increased number of helicopters and trucks.

Table 5. Performance of the proposed model based on the different scenarios.

Problem No.	**Number of Trucks ($n_{v'}$)**	**Number of Helicopters ($n_{v''}$)**	**Obj 1**	**Obj 2**	**Obj 3 (Hour)**	**Obj 4**	**Run Time (s)**
1	5	3	25.331	253.628	4.328	0.67	1053
2	8	5	31.628	324.128	3.964	0.74	1127
3	12	10	37.526	382.204	3.125	0.79	1248
4	16	13	52.628	516.328	2.127	0.86	1365
5	21	17	75.288	754.263	1.395	0.93	1440

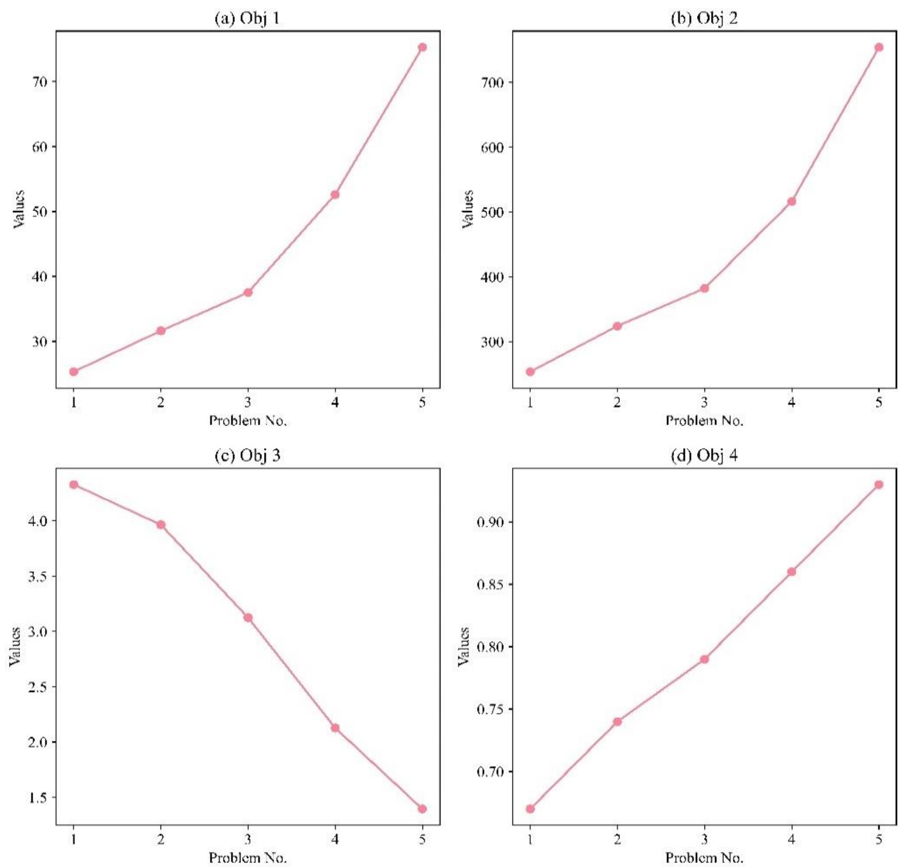

Figure 2. Performance of the four objective functions based on the different scenarios: a) First objective function, b) Second objective function, c) Third objective function, and d) Fourth objective function.

The results hint that increasing the number of helicopters and trucks leads to higher costs in the prevention and response phases. However, larger scenarios are associated with reduced service time and improved route reliability. Execution time increases with the scale of the problem, suggesting that larger scenarios require more computational resources and time to process.

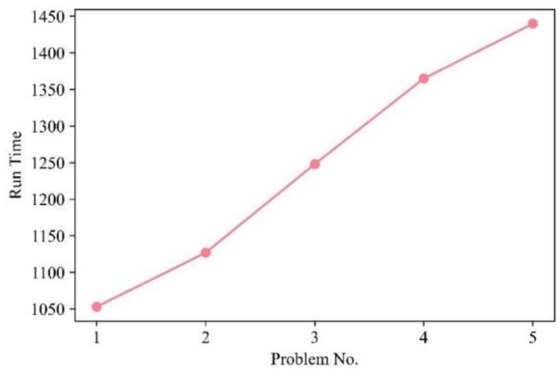

Figure 3. Execution time based on the different scenarios.

8. Sensitivity Analysis

8.1. Sensitivity Analysis of χ_v

A sensitivity analysis is conducted on the proposed model to examine the impact of various parameters. This type of analysis is commonly performed in optimization and modeling to assess the robustness and performance of a model under varying input conditions. The focus is on the vehicle's capacity (v), and the results are summarized in Table 6. It is observed that increasing the vehicle's capacity led to a decrease in objective function 2. Figure 4 plots the sensitivity of objective function 2 to the capacity of the vehicle. According to this figure, a rise in the capacity of vehicle v decreased objective function (2).

Table 6. Sensitivity analysis of χ_v.

Row	Parameter χ_v	Obj 2
1	15	286.325
2	20	271.65
3	25	225.49
4	30	193.74
5	35	145.39

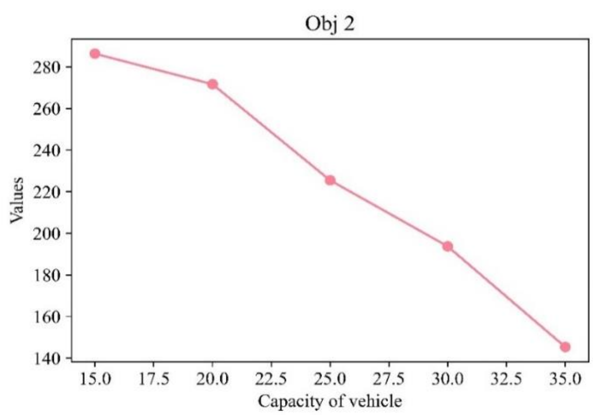

Figure 4. Sensitivity of the objective function 2 versus χ_v.

This information is crucial for decision-making and optimizing the proposed model, indicating that higher vehicle capacity may result in better outcomes in terms of response phase costs according to the specified objective function.

8.2. Sensitivity analysis of t_{vij}

Table 7 shows the sensitivity of the objective function (3) to the travel time from nodes i to j for vehicle v. It can be inferred that an increase in the travel time resulted in a corresponding rise in the value of objective function (3). Figure 5 plots the objective function (3) versus the travel time from nodes i to j for vehicle v. The plot shows that as the travel time increases, the objective function (3) also increases. In other words, the maximum service time is found to be higher when the travel time from nodes i to j for vehicle v is higher.

Table 7. Sensitivity analysis of t_{vij}.

Row	Parameter t_{vij}	Obj 3
1	0.5	2.368
2	1	2.846
3	1.5	3.749
4	2	4.547
5	2.5	6.589

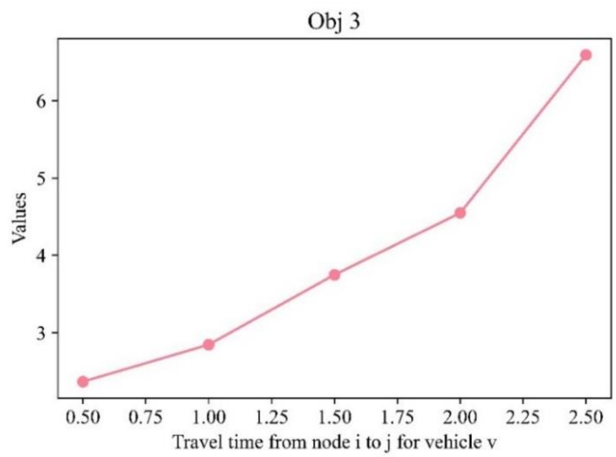

Figure 5. Sensitivity of the objective function 3 versus t_{vij}.

This visual representation confirms the positive correlation between travel time and the values of the objective function (3). This information is valuable for optimizing vehicle routes and service times in the context of service time optimization.

9. Conclusion and Future Study

This paper presented an integrated model for distributing temporary shelters after disasters, validated using different scenarios. Due to its NP-hard nature, a well-known multi-objective evolutionary algorithm, namely the NSGA-II, was employed to final Pareto-optimal solutions for four presented objective functions: minimizing prevention and response costs, reducing maximum service time, and maximizing route reliability. The novelty of our methodology lies in its ability to provide a range of optimal solutions that offer decision-makers flexibility in selecting the best trade-offs among competing objectives. This key feature distinguishes it from traditional optimization methods, such as NGP. The study revealed a logical correlation between prevention costs and the number of helicopters and trucks. As problem dimensions increased, time to assist decreased, and route reliability improved for the third and fourth objective functions. The research has significant implications for disaster management stakeholders in disaster-prone regions. The proposed model can be utilized by policymakers in affected countries and adapted for other types of disasters like forest fires. For future studies, an uncertainty approach is recommended to estimate demand levels effectively, and a machine learning approach can enhance the model's accuracy.

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