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Optimization of Humanitarian Relief Item Distribution with Emphasis on Operational Costs and Vehicle Breakdown Time under Crisis Conditions

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ABSTRACT

The distribution of relief items during crises is widely recognized as a critical challenge in humanitarian logistics and disaster management. In such contexts, time and operational costs emerge as two pivotal factors determining the success of relief operations. Relief vehicles play a vital role in the rapid and effective delivery of essential supplies to affected areas. However, vehicle breakdowns can significantly delay distribution and escalate operational expenses. Consequently, optimizing the distribution of relief items—particularly by addressing operational costs and vehicle breakdown time under crisis conditions—requires focused investigation. This study proposes a mathematical model for the location-routing problem in humanitarian organizations, developed under uncertainty and designed to simultaneously manage cost efficiency and vehicle reliability. Humanitarian organizations confronting disasters face multifaceted challenges, including demand volatility, dynamic geographic conditions, and resource constraints. The objective of this research is to optimize the distribution process of essential items through a multi-objective model that concurrently determines optimal depot locations and efficient distribution routes by controlling both cost and time-related performance metrics. The weighted sum method is employed to solve the proposed model. Results indicate that the model effectively identifies the shortest routes, minimizes logistical costs, and enables optimal allocation of vehicles to destinations based on vehicle type. Finally, Pareto-optimal solutions are generated, and a sensitivity analysis is conducted on the time-based connectivity coefficient between routes. Findings demonstrate that the proposed model substantially enhances the efficiency and effectiveness of humanitarian logistics operations. Model validation is performed through a real-world case study, and the results are benchmarked against existing operational plans, revealing superior performance of the proposed approach. Across comparisons of different objective functions, the number of non-dominated solutions ranges from 15 to 86, with evident convergence. The highest number of non-dominated solutions (86) is obtained when comparing the first and fourth objective functions, indicating superior solution quality and convergence relative to other scenarios. Overall, this study provides decision-makers with a scientific, data-driven tool to formulate more effective disaster response strategies through cost reduction and optimal resource utilization.

KEYWORDS: Facility location, vehicle routing, humanitarian logistics, cost control, vehicle breakdown time

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1. Introduction

The distribution of relief items under crisis conditions represents one of the most critical challenges in crisis management and humanitarian logistics. When natural disasters or human-induced crises occur, the need for rapid and effective response to the needs of affected populations becomes paramount. Relief vehicles, as the primary means of transporting essential supplies, play a vital role in accelerating this process. However, two key factors that can significantly influence the efficiency of these operations are operational costs and vehicle breakdown times. In crisis situations, the distribution of relief items demands both speed and high efficiency to address the immediate needs of victims (Ghahremani-Nahr et al., 2024). Nevertheless, two major challenges persist in this domain: operational costs and vehicle breakdown times. Operational costs—encompassing fuel, maintenance, and repair expenses—can directly impact the financial resources of humanitarian organizations. Conversely, vehicle downtime may lead to delays in the delivery of essential supplies, thereby exacerbating damages and losses in affected areas. Disasters are often unpredictable and result in substantial human casualties, financial losses, and widespread social and environmental harm (Wang et al., 2021). A prominent example is the 2019 outbreak of COVID-19, which triggered severe global consequences (Jahangiri et al., 2021). Statistics further indicate that natural disasters such as earthquakes and floods rank among the most frequent catastrophes, leaving thousands of casualties in their wake. Under such circumstances, humanitarian logistics plays a pivotal role in the movement, storage, and equitable distribution of relief items (Jahangiri et al., 2021). Given resource constraints, fairness in allocation becomes essential to ensure that all regions receive assistance commensurate with their demand levels (Yofrido & Harjana, 2019; Anaya-Arenas et al., 2018).

Natural and human-induced disasters—including earthquakes and floods—continue to occur with increasing intensity, imposing severe consequences on communities. Within this context, humanitarian supply chains, as a specialized form of supply chain systems, play a vital role in mitigating the impacts of such crises. Their objective is to preserve human life, alleviate suffering, and restore communities to self-sufficiency (Jahangiri et al., 2021). According to the World Health Organization (WHO), crises cause extensive mortality, destruction, and environmental disruption, necessitating transregional assistance (Yang et al., 2022). Annually, more than 500 crises claim approximately 75,000 lives and affect over 200 million individuals. The surge in demand under such conditions often exceeds available resources, thereby complicating relief management and planning processes (Peng et al., 2022). The success of relief operations is inherently dependent on supply chain efficiency. However, performance evaluation in this domain has received limited attention; only 45% of humanitarian organizations engage in such assessments, and merely 20% implement them on a continuous basis (Giedelmann-López et al., 2022). This is despite evidence that performance measurement can enhance the effectiveness of relief operations and improve organizational accountability (Wei et al., 2020; Mamashli et al., 2021).

Given the significance of the aforementioned issues, this study addresses a location-routing problem within a humanitarian context, incorporating fairness-oriented objective functions to ensure equitable assistance—first, to affected locations, and second, through optimized dispatch and distribution via transportation assets during crisis response in a designated region. To this end, appropriate locations for relief item distribution are determined using defined objective functions. Subsequently, to enable effective disaster response, decisions regarding facility provisioning are made through vehicle deployment along optimal routes. Furthermore, in the event of vehicle breakdowns during relief operations, timely dispatch of maintenance crews ensures controlled repair durations and service intervals, thereby mitigating downtime. Accordingly, this research seeks to develop a mathematical optimization model capable of optimizing relief item distribution while accounting for operational costs and vehicle breakdown times. By employing this model, distribution routes can be determined to minimize costs while simultaneously managing vehicle failure durations. This research has the potential to enhance the efficiency of humanitarian logistics, accelerate service delivery to affected areas, and ultimately contribute to saving lives and reducing financial losses.

Therefore, this study aims to address the following research question: *How can mathematical models and optimization algorithms be leveraged to optimize the distribution of relief items such that operational costs are minimized and vehicle breakdown times are effectively managed under crisis conditions?* The findings may contribute to improving the efficiency of humanitarian logistics and increasing the speed of crisis response, ultimately leading to enhanced life-saving capabilities and reduced economic damages.

The remainder of this paper is organized as follows. Section 2 presents a literature review of prior research. Section 3 delineates the mathematical modeling framework alongside the metaheuristic solution approach. Section 4 demonstrates the application of the proposed model through a case study conducted within the Ouyaz Industrial Group. Finally, Section 5 offers a comprehensive conclusion together with recommendations for future research avenues.

2. Literature Review

Two-echelon distribution systems are recognized as a critical variant of the location-routing problem (LRP) and have been extensively investigated in operations research literature. In such systems, goods are transported from primary depots to intermediate facilities (first echelon) and subsequently delivered to final destinations (second echelon). Numerous studies have contributed diverse modeling approaches to this domain. For instance, Yu et al. (2020) proposed a multi-objective two-echelon LRP (2E-LRP) model solved via the non-dominated sorting genetic algorithm II (NSGA-II) for waste collection applications. Wei et al. (2020) developed a hybrid ant colony optimization framework specifically designed for post-disaster humanitarian logistics. Cheng et al. (2021) focused on multi-period disaster debris clearance using a two-echelon structure and employed a genetic algorithm for solution generation. Wang et al. (2021) introduced a multi-period two-echelon location-routing problem (MP-2ELRP) model integrating k-means clustering with particle swarm optimization (PSO). Gandra et al. (2021) incorporated two-dimensional loading constraints into the 2E-LRP formulation, while Fallahtafti et al. (2021) developed a multi-objective model for cash-in-transit logistics. Additional contributions include Cao et al. (2021), who addressed sustainable humanitarian supply chains under uncertainty using fuzzy bi-level programming; Mohamed et al. (2022), who examined stochastic multi-period capacitated variants; Du et al. (2022), who integrated carbon emission considerations into joint delivery systems; and Heidari et al. (2022), who proposed green closed- and open-loop routing frameworks solved via NSGA-II and multi-objective grey wolf optimizer (MOGWO) algorithms.

Alongside LRP research, the vehicle routing problem (VRP) has attracted substantial scholarly attention. Studies such as Hasanpour Jesri et al. (2022) and Nozari et al. (2022) have developed diverse mathematical formulations and heuristic/metaheuristic solution approaches tailored to crisis conditions, demand uncertainty, and resource constraints. These contributions demonstrate the adaptability of VRP frameworks to complex humanitarian contexts where rapid response and resource optimization are paramount.

Contemporary literature indicates that hybridizing exact methods with metaheuristic algorithms in LRP and VRP contexts can effectively optimize costs, delivery times, resource allocation, and uncertainty management under both routine and crisis conditions (Narimani et al., 2024). Ghahremani-Nahr et al. (2024) specifically investigated deprivation costs in humanitarian logistics to optimize resource allocation and minimize response delays during disasters. Their findings revealed that as uncertainty levels increase—corresponding to higher casualty counts and escalated demand for relief items at disaster sites—costs associated with supply provisioning and casualty transportation rise substantially. Furthermore, sensitivity analysis demonstrated that elevated deprivation costs incentivize the model to increase dispatched quantities to fully satisfy demand, thereby prioritizing human welfare over pure cost minimization.

Existing research demonstrates that LRP and VRP models possess considerable potential for optimizing relief item distribution. The present study contributes a multi-period location-routing model under uncertainty conditions specifically designed for humanitarian supply chains. Uncertainty modeling holds particular significance in this domain, as it has been frequently overlooked in prior humanitarian logistics research despite its critical relevance to real-world operations. Moreover, vehicle breakdown time—a pivotal factor influencing system efficiency—has not been comprehensively addressed in extant literature; most studies concentrate predominantly on cost minimization and delivery time optimization while neglecting operational disruptions caused by mechanical failures. This research systematically investigates the impact of vehicle breakdown durations on distribution system performance and proposes that future models should explicitly incorporate breakdown time as a key decision variable within optimization frameworks.

Despite recent advancements in relief distribution optimization, the majority of studies have focused on minimizing direct transportation costs, selecting optimal facility locations, and designing efficient routes under crisis scenarios. Some research has addressed demand uncertainty management and enhanced coordination within humanitarian supply chains. However, the dimension of vehicle failure and incapacitation—which can critically influence operational costs and induce significant delays in relief delivery—has not been directly integrated into location-routing models. Recent studies on fleet management and predictive maintenance demonstrate that unexpected vehicle breakdowns not only impose repair and replacement costs but also substantially increase response times and reduce the operational efficiency of relief missions. Nevertheless, the simultaneous integration of operational costs and reliability indicators within relief distribution models under uncertainty conditions—particularly through a cost-control lens—remains absent in contemporary literature.

Consequently, a distinct research gap is evident: existing models capture only partial aspects of humanitarian supply chain operational realities while overlooking the latent effects of vehicle breakdowns on both cost structures and response timeliness. The present research endeavors to bridge this gap by developing an optimization model that explicitly incorporates vehicle breakdown time alongside distribution costs and analyzes its cascading effects on relief operations. This approach represents a novel step toward enhancing the efficiency and effectiveness of humanitarian supply chain systems through more realistic operational modeling.

3. Research Methodology

This study presents a mathematical optimization model designed to determine precise routing strategies for relief vehicles within humanitarian supply chains during crisis response operations. The proposed model incorporates multiple innovations aimed at minimizing aggregate operational expenditures—including facility breakdown costs, fixed costs associated with shelter establishment, transportation costs for relief commodities, and service delivery expenses—while simultaneously minimizing the total evacuation time required to transfer victims from all affected areas to designated shelters.

Furthermore, the model functions as a multi-objective framework for the equitable allocation of essential relief items to all impacted destinations through diversified origin coverage. This approach systematically reduces both allocation costs and the number of feasible routing alternatives required to fulfill demand across the network. Specifically, the model achieves fairness in resource distribution by ensuring that every affected destination receives assistance via the shortest feasible route, thereby minimizing allocation expenditures while upholding distributive justice principles in humanitarian operations.

The proposed formulation constitutes a multi-objective integer linear programming (MOILP) model characterized by four distinct objective functions oriented toward route cost minimization and path length optimization. The designed supply chain network encompasses multiple cities serving as demand points, a heterogeneous fleet of relief vehicles, and predefined emergency routes. Within this structure, relief commodities are transported by vehicles from designated origin cities to disaster-affected locations via optimally selected pathways that minimize transfer costs.

According to the model specifications, relief delivery operations are executed using a single vehicle type selected to simultaneously minimize operational expenditure and repair duration. A noteworthy feature of the routing mechanism is that a single city (destination) may be serviced by multiple vehicles to ensure demand satisfaction and operational redundancy. Additionally, the model explicitly accounts for vehicle breakdown durations as a critical operational parameter, integrating maintenance time requirements directly into the optimization framework to enhance realism and practical applicability.

To resolve the inherent trade-offs among competing objectives, the multi-objective model is transformed into a single-objective linear programming formulation through the epsilon-constraint method. This technique preserves one objective as the primary optimization target while converting the remaining objectives into constraint conditions bounded by predetermined threshold values (ε), thereby enabling computationally tractable solution generation while maintaining decision-maker preferences.

This section delineates all structural components of the developed deterministic mathematical model for humanitarian supply chain operations, including decision variables, input parameters, objective functions, and operational constraints. The model is specifically engineered to address integrated vehicle routing and relief station location decisions while explicitly incorporating facility breakdown durations and uncertainty considerations into the optimization framework.

For empirical validation, the proposed model is implemented within a case study context involving five affected cities (destinations) serviced by relief vehicles operating as supply origins. Two distinct scenarios are examined: one employing four relief vehicles and another utilizing nine relief vehicles. This comparative analysis enables assessment of fleet size impacts on operational performance metrics including cost efficiency, service coverage, response time, and system resilience under breakdown conditions. The dual-scenario approach facilitates robust evaluation of the model's scalability and adaptability across varying resource availability levels typical of real-world humanitarian operations.

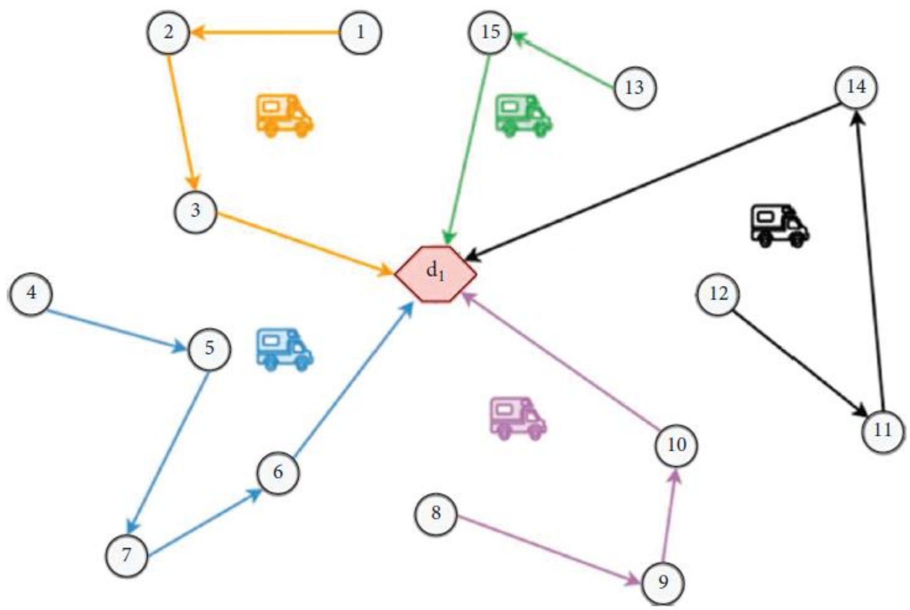

Figure 1. Overall Mechanism of the Humanitarian Supply Chain

Notation

Sets and Indices

- K: Total number of relief vehicles
- N: Number of beneficiaries (demand points)
- L: Number of maintenance crews/technicians
- k: Index for feasible routes ($k = 1,2, \dots, K$)
- i: Index for all possible origins/supply nodes
- j: Index for all possible destinations/demand nodes

Cost Parameters

- c_{ij}: Operational cost of traversing route from node $i$to node j
- c'_{ij}: Service cost incurred along route from node $i$to node j
- F_k: Fixed cost of establishing route $k$to serve a destination
- C_{ik}: Cost of establishing connectivity between origin $i$and route k
- C_{km}: Cost of establishing connectivity between routes $k$and m
- C_{mj}: Cost of establishing connectivity between route $m$and destination j
- γ_i: Maximum allowable cost for establishing connectivity between center $i$and an existing route

Time Parameters

- t_{ij}: Travel time required to move from node $i$to node j
- e_i: Earliest feasible arrival time at node i
- l_i: Latest permissible arrival time at node i
- f_i: Repair duration required for a vehicle breakdown at node i
- r_k: Maximum allowable travel time for vehicle $k$along its assigned route
- β: Maximum permissible time interval for establishing connectivity between origin $i$and destination j

Demand and Capacity Parameters

- m_i: Demand quantity at node i
- q_k: Capacity of relief vehicle k

Spatial and Reliability Parameters

- d_{ik}: Spatial distance between origin $i$and route k
- d_{km}: Spatial distance between routes $k$and m
- d_{mj}: Spatial distance between route $m$and destination j
- cr_i: Frequency of vehicle breakdowns at node i

Model Coefficients

- α: Connectivity coefficient between routes, reflecting the synergistic effect of inter-route coordination to enhance network robustness

Decision Variables

- W_{ij}: Flow volume established between origin–destination pair (i, j)
- v_{ijkm}: Binary variable indicating whether origin–destination pair $(i, j)$is served via routes $k$and m:

$$v_{ijkm} = \begin{cases} 1 & \text{if } C_{ik} + \alpha C_{km} + C_{mj} \leq \gamma_i \\ 0 & \text{otherwise} \end{cases}$$

(Definition 1)

This notation framework underpins the multi-objective integer linear programming model designed to optimize humanitarian logistics operations by simultaneously addressing cost efficiency, service equity, route reliability, and responsiveness under uncertainty. The explicit incorporation of breakdown frequency (cr_i) and repair duration (f_i) enables the model to account for vehicle reliability as a critical determinant of operational continuity in crisis response scenarios.

Decision Variables

The decision variables in this study are classified into two categories: continuous variables and binary integer variables. This classification reflects the hybrid nature of the optimization problem, which simultaneously addresses timing continuity and discrete routing decisions under operational uncertainty.

Continuous Variables

- T_i: Arrival time at node i, representing the temporal instant when a relief vehicle reaches demand point i. This variable enables precise scheduling within time windows defined by earliest (e_i) and latest (l_i) permissible arrival constraints.
- w_i: Waiting time for vehicle repair at node i. This variable holds particular significance as it explicitly incorporates facility breakdown risk into the optimization framework. By modeling waiting duration as a decision variable rather than a fixed parameter, the model captures the dynamic interplay between mechanical failures and operational continuity, thereby enhancing realism in crisis response planning (Ghahremani-Nahr et al., 2024).

Binary Variables

- x_{ijk}: Equals 1 if relief vehicle $k$traverses the route from node $i$to node j; 0 otherwise. This variable defines the primary routing structure of the humanitarian logistics network.
- x_{ijkl}: Equals 1 if vehicle $k$requires maintenance intervention while traveling from node $i$to node $j$with technician $l$dispatched; 0 otherwise. This variable explicitly models breakdown events and their operational consequences within the routing decisions.
- x_{ijkm}: Equals 1 if flow between origin–destination pair $(i, j)$is routed through intermediate paths $k$and m; 0 otherwise. This variable facilitates multi-echelon connectivity assessment in complex network topologies.
- Y_k: Equals 1 if route $k$is activated within the solution; 0 otherwise. This variable controls infrastructure activation costs associated with route establishment.
- Z_{km}: Equals 1 if routes $k$and $m$are simultaneously utilized to serve interconnected demand points; 0 otherwise. This variable captures synergistic routing opportunities that enhance network resilience.
- Ve_{lkm}: Equals 1 if maintenance technician $l$is assigned to support operations along routes $k$and m; 0 otherwise. This variable integrates fleet maintenance resources directly into the distribution planning process.

Objective Functions

The proposed model employs a multi-objective integer linear programming framework with four distinct objective functions designed to balance cost efficiency, temporal performance, infrastructure utilization, and operational resilience. Although initially conceptualized as a bi-objective problem, the formulation expands to four objectives to comprehensively address humanitarian logistics complexities.

Objective Function (1): Minimization of Total Routing and Service Costs

$$\min \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{K} (c_{ij} x_{ijk} + c'_{ij} x_{ijkl})$$

This function minimizes aggregate operational expenditures, comprising both standard transportation costs (c_{ij}) and supplementary service costs (c'_{ij}) incurred during breakdown events. By integrating breakdown-related expenses directly into the cost structure, the model acknowledges that mechanical failures impose not only time penalties but also financial burdens through emergency repairs and service disruptions (Wang et al., 2021).

Objective Function (2): Minimization of Cumulative Vehicle Repair Time

$$\min \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{K} w_i \cdot cr_i \cdot x_{ijk}$$

This function minimizes the total waiting duration attributable to vehicle breakdowns across the network. The term cr_i(breakdown frequency at node i) weights the waiting time $w_i$to reflect location-specific reliability risks. Minimizing this aggregate metric reduces the probability of prolonged service interruptions and enhances system responsiveness during critical relief operations (Giedelmann-López et al., 2022). Critically, this objective operationalizes vehicle reliability as a quantifiable performance dimension rather than an assumed constant.

Objective Function (3): Minimization of Fixed Route Establishment Costs

$$\min \sum_{k=1}^{K} F_k Y_k$$

This function minimizes infrastructure activation expenditures required to establish operational routes within the humanitarian network. The parameter $F_k$represents sunk costs associated with route preparation, including security assessments, road clearance, and communication setup. This objective ensures fiscal responsibility in resource-constrained disaster environments where capital expenditures must be justified against operational benefits (Narimani et al., 2024).

Objective Function (4): Minimization of Route Count for Path Efficiency

$$\min \sum_{k=1}^{K} Y_k$$

This function minimizes the total number of active routes to promote path simplicity and operational focus. By reducing route proliferation, the model enhances managerial controllability, decreases coordination complexity, and facilitates faster decision-making during rapidly evolving crisis scenarios. This objective indirectly promotes the selection of shortest feasible paths while maintaining demand coverage requirements (Anaya-Arenas et al., 2018).

Multi-Objective Resolution Approach

To address the inherent trade-offs among these competing objectives, the epsilon-constraint method is employed to transform the multi-objective formulation into a single-objective linear program amenable to exact solution techniques. Specifically, Objective Function (2) is converted into a hard constraint with an upper bound $\bar{f}$:

$$\sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{K} w_i \cdot cr_i \cdot x_{ijk} \leq \bar{f}$$

This constraint guarantees that the cumulative repair time across all vehicles and routes does not exceed a predetermined threshold $\bar{f}$, which may be calibrated based on crisis severity and acceptable service degradation levels. The remaining objectives are either prioritized hierarchically or combined through weighted aggregation depending on decision-maker preferences. This approach preserves solution tractability while maintaining explicit control over reliability performance—a critical advantage over purely cost-driven models that neglect breakdown consequences (Wei et al., 2020).
The integrated modeling framework thus advances humanitarian logistics optimization by simultaneously addressing four dimensions of operational excellence: economic efficiency (Objective 1), temporal reliability (Objective 2), infrastructure prudence (Objective 3), and network simplicity (Objective 4). The explicit incorporation of waiting time $w_i$as both a decision variable and objective component represents a methodological innovation that bridges the gap between theoretical routing models and the mechanical realities of field operations in disaster zones.

Constraints

(5) $\sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{K} x_{ijk} \leq K$
(6) $\sum_{j=1}^{N} x_{0jk} = 1 i = 0; k = 1, \ldots, K$
(7) $\sum_{i=1}^{N} x_{i0k} = 1 i = 0; k = 1, \ldots, K$
(8) $\sum_{k=1}^{K} \sum_{j=0}^{N} x_{ijk} = 1 j \neq i$
(9) $\sum_{k=1}^{K} \sum_{i=0}^{N} x_{ijk} = 1 i \neq j$
(10) $\sum_{k=1}^{K} \sum_{j=0}^{N} x_{ijk}(t_{ij} + f_i + w_i) \leq r_k j \neq i$
(11) $T_0 = w_0 = f_0 = 0$
(12) $e_i \leq (T_i + w_i) \leq l_i$
(13) $\forall i, j, k, m \ x_{ijkm} \leq Y_k$
(14) $\forall i, j, k, m \ x_{ijkm} \leq Y_m$
(15) $\sum_{k=1}^{K} \sum_{m=0}^{M} V_{ijkm} x_{ijk} \geq 1 \forall i, j$
(16) $\sum_{k=1}^{K} \sum_{m=0}^{M} Ve_{lkm} x_{ijk} \geq 1 \forall k$
(17) $VR_{ij}^1 = \{k \mid d_{ik} + d_{kj} \leq \beta\}$
(18) $VR_{ij}^2 = \{(k, m) \mid (k < m), (k, m \notin VR_{ij}^1), d_{ik} + \alpha d_{km} \leq \beta$
or

$$VR_{ij}^2 = \{(k, m) \mid (k < m), (k, m \notin VR_{ij}^1), d_{im} + \alpha d_{mk} \leq \beta$$

(19) $\forall k, m \ k < m \ Z_{km} \leq Y_k$
(20) $\forall k, m \ k < m \ Z_{km} \leq Y_m$
(21) $\forall i, j, k, m \ x_{ijkm} \in \{0,1\}$
(22) $\forall k \ Y_k \in \{0,1\}$

(23) $\forall k, m\ k < m\ Z_{km} \in \{0,1\}$
(24) $Ve_{lkm} \in \{0,1\} \forall k, m\ k < m$

Equation (5) ensures that the selected routes must never exceed the number of vehicles. To achieve maximum coverage, inclusion of this constraint in the equation set is essential. Otherwise, part of the route will remain uncovered. Equation (6) ensures that the starting point of the relief route with vehicle $k$begins from node zero (origin). Also, equation (7) ensures that a round-trip path exists between two nodes. The set of equations (8) and (9) ensures that the selected routes from $i$to $j$start from origin zero. Additionally, it ensures that no route exists for starting from any node and ending at the same node. Equation (10) ensures that the sum of travel time between two nodes, vehicle repair time at each node, and waiting time to receive service for performing repairs does not exceed the maximum time that the vehicle is permitted to move along the route from $i$to j. Constraint (11) ensures that the total travel time between two nodes starting from the origin node, vehicle repair time at the origin node, and waiting time to receive repair service at the origin node equals zero. Considering $t_{ij} + f_i = T_i$, ultimately, constraint (12) ensures that the duration of movement, repair, and waiting time to receive vehicle repair services does not exceed the earliest and latest times. Constraints (13) and (14) indicate that if communication between cities (i, j)will be established through routes (m, k), these cities must be origins. Constraint (15) indicates the coverage condition for allocation. That is, according to Definition (1), if $C_{ik} + \alpha C_{km} + C_{mj} \leq \gamma_i$, then $V_{ijkm} = 1$; otherwise $V_{ijkm} = 0$. Constraint (16) indicates the coverage condition for each type of vehicle for vehicle allocation to each route. Constraint (17) indicates the first set of valid routes for each vehicle in the multi-route allocation model. Also, it indicates the second set of valid routes in the multi-route allocation model. Constraint (18) is an either-or constraint. Between the two constraints of the second set of valid routes, only one of them is always satisfied. For this purpose, by adding $M > 0$as a large positive number and y_1, y_2as binary variables, we formulate as follows and add constraints (25) to (28) to the above equation set.

(25) $VR_{ij}^2 = \{(k, m) \mid (k < m), (k, m \notin VR_{ij}^1), d_{ik} + \alpha d_{km} \leq \beta + My_1$
(26) $VR_{ij}^2 = \{(k, m) \mid (k < m), (k, m \notin VR_{ij}^1), d_{ik} + \alpha d_{km} \leq \beta + My_2$
(27) $y_1 + y_2 = 1$
(28) $y_1, y_2 \in \{0,1\}$

Constraints (19) and (20) indicate that routes $m$and $k$have been selected; therefore, communication is established between them and the cities. The remaining constraints (21) to (24) ensure that the values of the decision variables are zero or one.

The above equations are considered for application in conditions where individuals in 5 crisis-stricken cities require relief assistance. As shown in Figure 2, relief flow is established through bidirectional routes between every two cities. Considering the above equation set, we intend to determine the relief routes and the coverage of each city by vehicles on these routes.

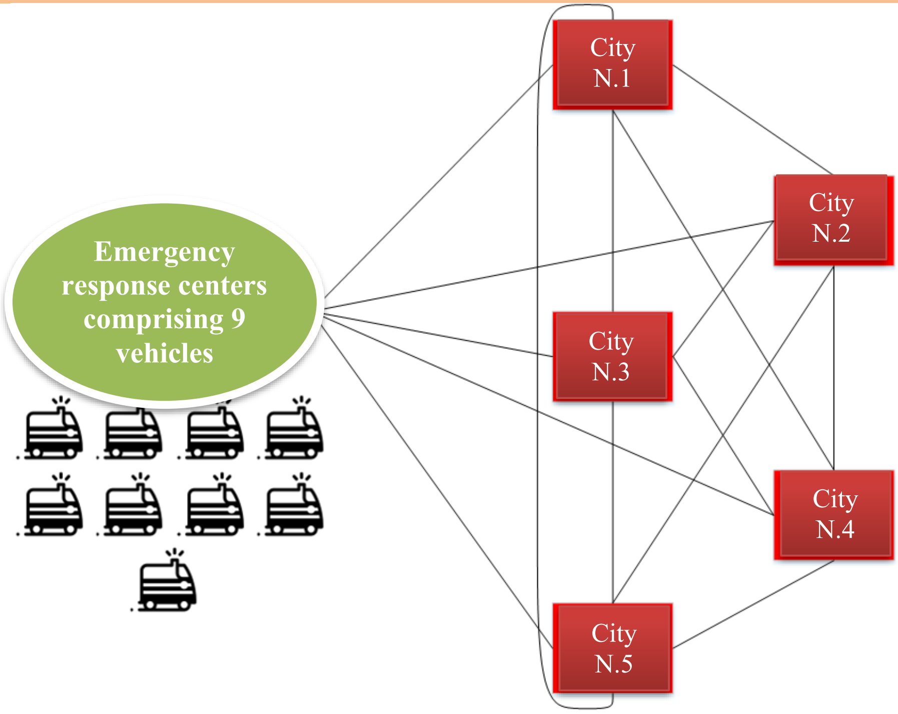

Figure 2. All Relief Routes to Affected Cities by Vehicles

3-2. Problem Solution Method: Weighted Sum Method

In this paper, the weighted sum method has been employed to solve the problem and obtain the optimal solution. This method is a multi-objective optimization technique in which multiple objectives exist and the best solution must be determined. According to this method, all multi-objective functions are combined into a single composite objective function using a weighted sum as expressed in the following equation, thereby transforming the problem into a single-objective formulation:

$$(29)\ f = w_1 f_1 + w_2 f_2 + w_3 f_3$$

An important issue in assigning the weight coefficient vector $w_1, \dots, w_n$ in the weighted sum method is that these weights are positive and their sum equals one. Furthermore, the optimal solution is highly dependent on the selected weight coefficients, and changing them alters the value of the composite objective function. Therefore, values must always be selected that do not deteriorate the value of the composite objective function (Rezaei et al., 2021).

4. Findings

4-1. Model Validation

This section addresses the validation of the proposed model. For this purpose, after defining dimensions for sample sizes of the model's sets, the model was implemented in the GAMS software environment. Following model execution, and in accordance with theorems proven by Abolghasemian et al. (2024), two properties—feasibility and boundedness of the mathematical model—were evaluated to justify validity. This is because it has been proven that a necessary and sufficient condition for mathematical model validity is that the model be both feasible and bounded. For model implementation, the size of the sets was first determined as presented in Table 2.

Table 2. Sets and Their Sizes

Sets	Sizes
K: Total number of relief vehicles	2
N: Number of beneficiaries	2
L: Number of maintenance technicians	2
k: Number of possible routes	2
i: All possible origins	1
j: Number of possible destinations	3

Table 3 presents the computational results obtained from model execution.

Table 3. Results of Model Feasibility and Boundedness

Result	**Computational Tool**	**Model Solution Time (seconds)**	**Boundedness**	**Feasibility**
Mathematical Model	CPLEX	0.059	Bounded	Feasible

Given the results in Table 3, and the confirmation of both boundedness and feasibility of the model, the validity of the model is concluded.

4-2. Experimental Results of Mathematical Model Solution

This section presents practical results obtained from the proposed model. The model was implemented using GAMS software. In this research, the allocation problem of four types of essential relief items (namely blankets, tents, food, and water) to seven affected neighborhoods in District 1 of Tehran—supported by two relief bases—has been considered. These locations were determined and selected based on the requirements of the Tehran Province Crisis Management Organization and are fixed. Transportation costs and available supplies from each rescue center to the affected areas are presented in Tables 4 and 5. Additionally, fixed and variable costs from each relief center to the affected neighborhoods are shown in Table 4.

Table 4. Transportation Costs from Relief Centers to Affected Areas

Relief Centers	**Neighborhood**	**Period**				
		First	Second	Third	Fourth	Fifth
Special Support Base of Crisis Management Organization	Jamalabad	700	700	160	60	900
	Darabad	600	630	140	50	810
	Omidvar	200	560	120	800	720
	Kamranieh	900	490	100	720	630
	Aghayi	100	420	900	640	540

Relief Centers	**Neighborhood**	**Period**				
	Ekbatanieh	800	350	810	560	450
	Pasdaran	300	600	720	480	400
Multi-purpose Support Base	Jamalabad	600	540	630	400	360
	Darabad	900	480	540	300	320
	Omidvar	400	420	450	270	280
	Kamranieh	1200	360	90	240	240
	Aghayi	300	540	80	210	200
	Ekbatanieh	700	450	70	180	260
	Pasdaran	300	90	60	150	320

Table 5. Supply Requirements of Items at Relief Centers (in thousands)

Relief Items	**Period**				
	First	Second	Third	Fourth	Fifth
Blanket	1.8	2.4	2.2	3.3	11
Tent	3	3.3	3.4	8	17
Food	4.8	3.4	2.8	5.8	11
Water	9563	2380	3440	4870	5830
Blanket	7	2	6.3	10.8	20
Tent	4.5	4	3.6	10.8	13.5
Food	2.9	3.2	4.5	7.5	8
Water	1952	3010	4240	6260	4252

Upon model execution, the optimal value of the relief item allocation variable from relief centers to affected areas is determined. Based on this, it becomes evident which center supplies essential items to each area. Table 6 specifies the allocation quantities of relief items from relief centers to affected areas, with the results displayed accordingly.

Table 6. Allocation of Items from Relief Centers to Affected Areas

Period	**Relief Center**	**Selected Neighborhoods of Tehran District 1**						
		Jamalabad	Darabad	Omidvar	Kamranieh	Aghayi	Ekbatanieh	Pasdaran
First	Special Support Base	0	1	1	0	1	1	1
	Multi-purpose Support Base	1	1	0	1	1	0	0
Second	Special Support Base	1	1	0	1	0	1	1
	Multi-purpose Support Base	1	0	1	1	1	1	0

Period	Relief Center	Selected Neighborhoods of Tehran District 1						
Third	Special Support Base	0	0	1	1	1	1	0
	Multi-purpose Support Base	1	1	0	0	0	0	1
Fourth	Special Support Base	0	1	0	1	1	1	1
	Multi-purpose Support Base	1	0	1	0	1	1	0
Fifth	Special Support Base	1	1	0	1	0	1	1
	Multi-purpose Support Base	1	0	1	1	1	1	0

Based on existing literature, four essential relief items during earthquake occurrences—namely blankets, tents, food, and water—have been considered (Danshvar et al., 2023; Wang et al., 2023). According to Table 6, the allocation pattern specifying how each neighborhood receives relief assistance from relief centers has been determined. As evident from the table, all neighborhoods receive relief items. Certain neighborhoods obtain essential supplies from both relief centers, which is necessitated by the inability of a single relief base to fully satisfy demand, thereby requiring partial fulfillment by the alternative base. Table 7 specifies which types of relief items are dispatched from each relief center to the affected areas during each period.

Table 7. Distribution of Relief Item Types to Each Affected Neighborhood

Affected Neighborhoods	Relief Items	Period				
		First	Second	Third	Fourth	Fifth
Jamalabad	Blanket	2.1	6.9	6.9	12.5	3.7
	Tent	10	34	34	61	21
	Food	690	1180	1960	1180	1180
	Water	710	4150	1960	1180	1180
Darabad	Blanket	3.7	2.1	690	10	10
	Tent	21	10	3.7	12	12
	Food	1180	4110	22	3470	3470
	Water	1180	3470	1120	3450	3450
Omidvar	Blanket	14.7	2.1	2.9	12.5	3.7
	Tent	72	10	2.3	61	21
	Food	4110	3450	12.5	1990	1180
	Water	4090	4150	740	1980	1180
Kamranieh	Blanket	6.9	12.5	690	10	6.9
	Tent	34	61	3.7	12	34
	Food	1960	1180	22	3470	1960

Affected Neighborhoods	Relief Items	Period				
	Water	1960	1180	1120	3450	1960
Aghayi	Blanket	12.5	690	12.5	690	2.9
	Tent	61	3.7	61	3.7	2.3
	Food	3420	4090	1180	22	12.5
	Water	3450	4110	1180	1120	740
Ekbatanieh	Blanket	2.9	12.5	14.7	2.1	690
	Tent	2.3	61	72	10	3.7
	Food	12.5	1990	4110	3450	22
	Water	740	1980	4090	4150	1120
Pasdaran	Blanket	690	10	6.9	12.5	6.9
	Tent	3.7	12	34	61	34
	Food	22	3470	1960	1180	1960
	Water	1120	3450	1960	1180	1960

Since the multi-objective problem in this study is solved using the weighted sum method, the optimal value of the objective function depends on the weight coefficients assigned to each objective function. Given that the composite objective function in the weighted sum formulation takes the form $w_1 f_1 + w_2 f_2 + w_3 f_3$with the constraint that the sum of weights equals one ($\sum w_i = 1$), various weight combinations were examined as presented in Table 8.

Table 8. Objective Function Values Under Different Weight Configurations

Row	w_1	w_2	w_3	Objective Function Value
1	$1/3$	$1/3$	$1/3$	35,996.988
2	$1/6$	$1/6$	$2/3$	57,969.729
3	$2/3$	$1/6$	$1/6$	76,014.309
4	$1/6$	$2/3$	$1/6$	92,482.238

Based on the obtained results for the objective function, it is observed that the composite objective function value is highly sensitive to the assigned weights. For instance, as the weight of the second objective function decreases, the composite objective function value increases, demonstrating an inverse relationship between the weight allocation and the resulting objective value.

Furthermore, the problem has been defined under two scenarios to achieve the innovation of equitable distribution of relief items among survivors. These scenarios represent conditions where either an earthquake of magnitude 4–5 on the Richter scale occurs or an earthquake of magnitude 6–7 occurs, specifying which items should be distributed to survivors in each neighborhood accordingly. This approach ensures that relief items commensurate with the earthquake's intensity are distributed during the event. Table 9 presents the allocation quantity of each item to each neighborhood under both scenarios.

Table 9. Distribution of Relief Item Types to Each Affected Neighborhood Under Two Scenarios

Affected Neighborhoods	Relief Items	Scenario	
		Scenario 1 (Magnitude 4–5)	Scenario 2 (Magnitude 6–7)
Jamalabad	Blanket	1	1
	Tent	0	1
	Food	1	1
	Water	1	1
Darabad	Blanket	1	0
	Tent	0	1
	Food	0	1
	Water	0	1
Omidvar	Blanket	1	1
	Tent	0	1
	Food	1	0
	Water	1	0
Kamranieh	Blanket	1	0
	Tent	1	1
	Food	0	0
	Water	0	1
Aghayi	Blanket	1	0
	Tent	0	1
	Food	1	1
	Water	1	1
Ekbatanieh	Blanket	1	1
	Tent	0	1
	Food	0	0
	Water	1	1
Pasdaran	Blanket	0	1
	Tent	1	0
	Food	1	0
	Water	1	1

According to the results in Table 9, a value of one indicates that a relief item is allocated to the affected neighborhood under the respective scenario, whereas a value of zero indicates no allocation. This binary representation enables rapid decision-making during crisis response by predefining item distribution protocols aligned with disaster severity levels.

4-3. Pareto Solutions

Figures 3 through 8 present the non-dominated solutions obtained for the considered multi-objective problem. Based on the generated frontier, convergence of the solutions is evident. Figure 3 displays the solutions in comparison between the first and second objective functions. In this case, 15 non-dominated solutions have been generated for the problem. Similarly, Figure 4 illustrates the solutions in comparison between the first and third objective functions, yielding 19 non-dominated solutions. Furthermore, Figure 5 presents the solutions in comparison between the first and fourth objective functions, resulting in 86 non-dominated solutions for the problem.
Figures 6 through 8 depict the non-dominated solutions in pairwise comparisons among the remaining objective functions. According to each considered case, the number of non-dominated solutions equals 24, 27, and 35 respectively. In these cases, the obtained solutions demonstrate acceptable convergence properties. The quality of solutions in the comparison between the first and fourth objective functions is superior to all other considered cases.

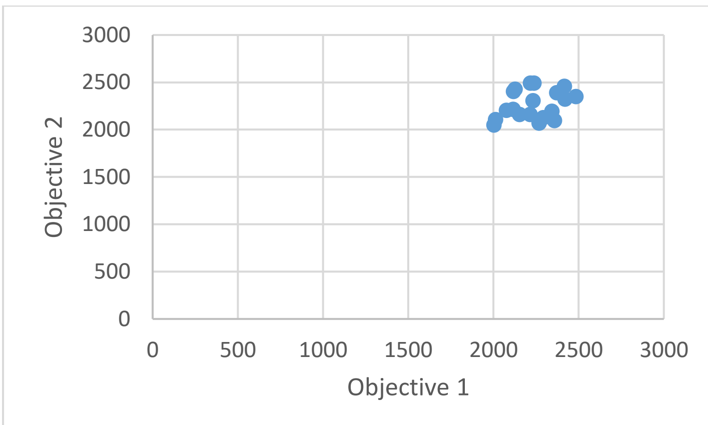

Figure 3. Non-dominated points comparing the first and second objective functions

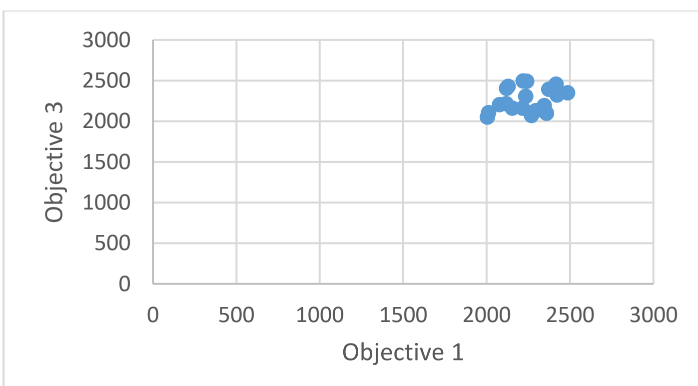

Figure 4. Non-dominated points comparing the first and third objective functions

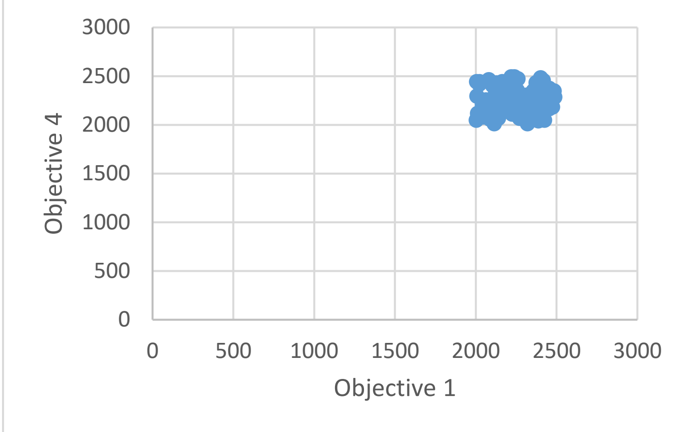

Figure 5. Non-dominated points comparing the first and fourth objective functions

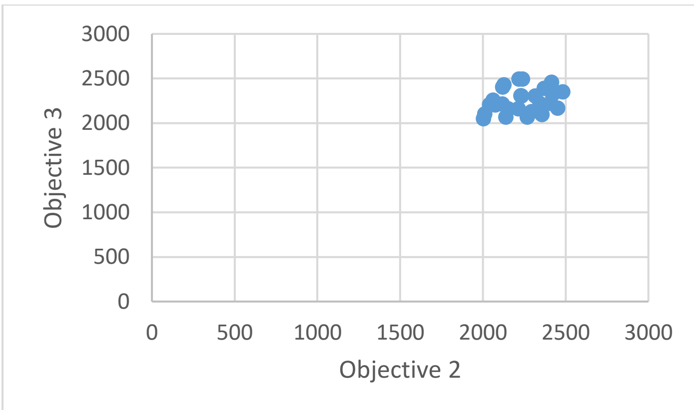

Figure 6. Non-dominated points comparing the second and third objective functions

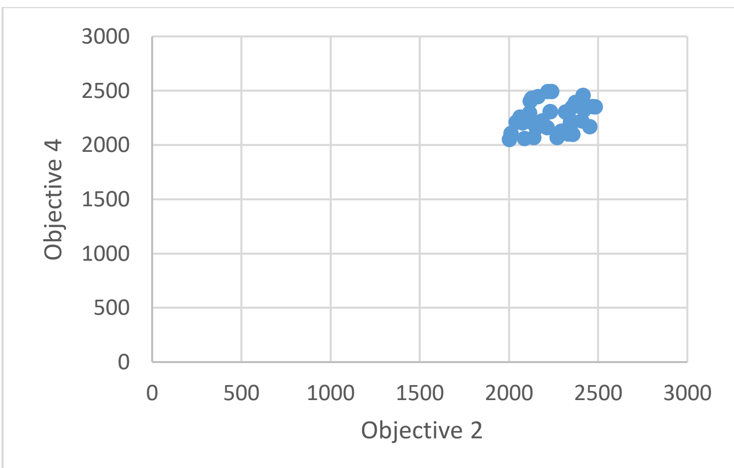

Figure 7. Non-dominated points comparing the second and fourth objective functions

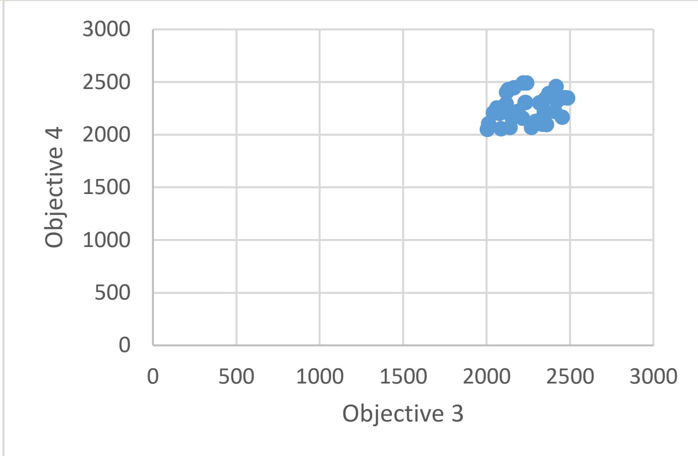

Figure 8. Non-dominated points comparing the third and fourth objective functions

4-4. Sensitivity Analysis

This section examines the effect of modifying a single parameter on the objective function of the proposed allocation problem. Specifically, the sensitivity of an influential parameter on the values of the objective functions is evaluated. For this purpose, the value of parameter βin Constraint (8)—defined as the temporal connectivity coefficient between routes that controls the maximum permissible time distance for establishing connectivity between an origin $i$and destination j—is incremented by one unit. That is, $\beta + 1$replaces βin the constraint formulation.
Given that this modification does not expand the feasible region—meaning the feasible region either remains unchanged or contracts—the optimal objective function value cannot improve (i.e., decrease in a minimization context). Table 10 presents the allocation costs of relief operations under the baseline scenario.

Table 10. Relief Allocation Costs

City	Route D-3-1	Route D-4-3-2	Route D-3	Route D-4	Route D-3-5
City 1	378	—	—	—	—
City 2	—	491	—	—	—
City 3	—	—	135	—	—
City 4	—	—	—	266	—
City 5	—	—	—	—	299

According to Table 10, the total cost of the shortest-path allocation—obtained by summing the costs across all feasible routes—equals 1,569 monetary units under the modified $\beta + 1$condition. Following this parameter adjustment, the objective function value deteriorates relative to the baseline scenario. Consequently, the shortest-path allocation cost increases from 1,492 monetary units to 1,569 monetary units.
This sensitivity analysis demonstrates that increasing the maximum allowable time-distance threshold βparadoxically elevates total operational costs in this humanitarian logistics context. The counterintuitive result stems from the expanded solution space introducing less efficient route combinations that, while temporally permissible under the relaxed constraint, incur higher

transportation and service expenditures. This finding underscores the critical importance of calibrating temporal constraints in humanitarian routing models to balance responsiveness with cost efficiency—a consideration particularly relevant for crisis managers operating under severe resource limitations (Ghahremani-Nahr et al., 2024; Wang et al., 2021).

5. Conclusion

This study proposes a multi-objective optimization model for allocating optimal routes to relief vehicles with the aim of enhancing humanitarian logistics operations and controlling operational expenditures. The objective functions encompass minimization of total costs and vehicle repair durations. The epsilon-constraint method has been employed to solve the mathematical model, capable of identifying both dominated and non-dominated solutions without subjective judgment. Application of the model within a case study context for optimal route allocation in crisis response demonstrates that the obtained results outperform conventional operational plans. Furthermore, an integer programming model has been developed for the allocation of essential relief items to diverse destinations, effectively reducing both allocation costs and the number of feasible routing alternatives.

The results indicate that the shortest feasible routes have been successfully identified for essential item distribution, with the total allocation cost calculated at 1,492 monetary units. Comparative analysis across different objective function pairs yielded between 15 and 86 non-dominated solutions, with observable convergence characteristics. The highest number of non-dominated solutions (86) corresponds to the comparison between the first and fourth objective functions, demonstrating superior solution quality and convergence relative to other configurations.

Given that the enhancement of information management and communication systems has been identified as a critical factor for successful implementation of humanitarian supply chains during crisis response, it is recommended that responsible organizations disseminate accurate information from the earliest moments of disaster occurrence. Such transparency would enable spontaneous volunteer organizations and civil society institutions to complement official efforts in procuring and distributing relief items. Route allocation decisions for facility deployment during disasters are typically made based on decision-makers' experience or ad hoc judgments; consequently, the proposed model not only improves both the efficiency and effectiveness of humanitarian relief logistics but also provides actionable guidance for route allocation decision-making within humanitarian logistics contexts. The findings of this study will prove valuable for designing appropriate strategic responses to future disasters.

For future research directions, it is recommended to develop a robust optimization model that explicitly incorporates uncertainty considerations within a multi-covering location framework to enhance resilience under volatile disaster conditions.

References

Abolghasemian, M., Bigdeli, H., & Shamami, N. (2024). Locating routing problem (LRP) of distribution of priority support items to ground forces in war conditions. *Engineering Management and Soft Computing*, *10*(1), 262–292.

Abolghasemian, M., Ghane Kanafi, A., & Daneshmandmehr, M. (2020). A two-phase simulation-based optimization of hauling system in open-pit mine. *Interdisciplinary Journal of Management Studies*, *13*(4), 705–732.

Anaya-Arenas, A. M., Ruiz, A., & Renaud, J. (2018). Importance of fairness in humanitarian relief distribution. *Production Planning & Control*, *29*(14), 1145–1157.

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

Cheng, C., Zhu, R., Costa, A. M., Thompson, R. G., & Huang, X. (2021). Multi-period two-echelon location routing problem for disaster waste clean-up. *Transportmetrica A: Transport Science*, *17*(4), 568–598.

Du, J., Wang, X., Wu, X., Zhou, F., & Zhou, L. (2022). Multi-objective optimization for two-echelon joint delivery location routing problem considering carbon emission under online shopping. *Transportation Letters*, *16*(3), 321–339.

Fallahtafti, A., Ardjmand, E., Young, W. A., II, & Weckman, G. R. (2021). A multi-objective two-echelon location-routing problem for cash logistics: A metaheuristic approach. *Applied Soft Computing*, *111*, 107685.

Gandra, V. M. S., Çalık, H., Wauters, T., Toffolo, T. A., Carvalho, M. A. M., & Vanden Berghe, G. (2021). The impact of loading restrictions on the two-echelon location routing problem. *Computers & Industrial Engineering*, *160*, 107609.

Ghahremani-Nahr, J., Nozari, H., & Szmelter-Jarosz, A. (2024). Designing a humanitarian relief logistics network considering the cost of deprivation using a robust-fuzzy-probabilistic planning method. *Journal of International Humanitarian Action*, *9*(1), Article 19.

Giedelmann-López, N., Guerrero, W. J., & Solano-Charris, E. L. (2022). System dynamics approach for food inventory policy assessment in a humanitarian supply chain. *International Journal of Disaster Risk Reduction*, *81*, 103286.

Hasanpour Jesri, Z., Eshghi, K., Rafiee, M., & Van Woensel, T. (2022). The multi-depot traveling purchaser problem with shared resources. *Sustainability*, *14*(16), 10190.

Heidari, A., Imani, D. M., Khalilzadeh, M., & Sarbazvatan, M. (2022). Green two-echelon closed and open location-routing problem: Application of NSGA-II and MOGWO metaheuristic approaches. *Environment, Development and Sustainability*, *25*, 5892–5928.

Jahangiri, S., Abolghasemian, M., Ghasemi, P., & Pourghader Chobar, A. (2021). Simulation-based optimization: Analysis of the emergency department resources under COVID-19 conditions. *International Journal of Industrial and Systems Engineering*, *39*(4), 431–452.

Jahangiri, S., Abolghasemian, M., Pourghader Chobar, A., Nadaffard, A., & Mottaghi, V. (2021). Ranking of key resources in the humanitarian supply chain in the emergency department of Iranian hospital: A real case study in COVID-19 conditions. *Journal of Applied Research on Industrial Engineering*, *8*(Special Issue), 1–10. https://doi.org/10.22105/jarie.2021.275255.1263

Mamashli, Z., Bozorgi-Amiri, A., Dadashpour, I., Nayeri, S., & Heydari, J. (2021). A heuristic-based multi-choice goal programming for the stochastic sustainable-resilient routing-allocation problem in relief logistics. *Neural Computing and Applications*, *34*, 10457–10483.

Mohamed, I. B., Klibi, W., Sadykov, R., Şen, H., & Vanderbeck, F. (2022). The two-echelon stochastic multi-period capacitated location-routing problem. *European Journal of Operational Research*, *303*(3), 1169–1186.

Narimani, R., Motamedi, M., & Khalili, H. A. (2024). A mathematical programming model for the distribution of relief items in a humanitarian supply chain. *Emergency Management*, *13*(1), 51–69.

Nozari, H., Tavakkoli-Moghaddam, R., & Gharemani-Nahr, J. (2022). A neutrosophic fuzzy programming method to solve a multi-depot vehicle routing model under uncertainty during the COVID-19 pandemic. *International Journal of Engineering*, *35*(2), 360–371.

Peng, D., Ye, C., & Wan, M. (2022). A multi-objective improved novel discrete particle swarm optimization for emergency resource center location problem. *Engineering Applications of Artificial Intelligence*, *111*, 104725.

Rezaei Kallaj, M., Abolghasemian, M., Moradi Pirbalouti, S., Sabk Ara, M., & Pourghader Chobar, A. (2021). Vehicle routing problem in relief supply under a crisis condition considering blood types. *Mathematical Problems in Engineering*, *2021*, Article 7217182.

Wang, B., Qian, Q., Gao, J., Tan, Z., & Zhou, Y. (2021). The optimization of warehouse location and resources distribution for emergency rescue under uncertainty. *Advanced Engineering Informatics*, *48*, 101278.

Wang, Y., Sun, Y., Guan, X., Fan, J., Xu, M., & Wang, H. (2021). Two-echelon multi-period location routing problem with shared transportation resource. *Knowledge-Based Systems*, *226*, 107168.

Wei, X., Qiu, H., Wang, D., Duan, J., Wang, Y., & Cheng, T. C. E. (2020). An integrated location-routing problem with post-disaster relief distribution. *Computers & Industrial Engineering*, *147*, 106632.

Yang, S., Ni, J., Chen, T., Liu, Q., Yang, C., Chen, J., ... Li, J. (2022). Location algorithm of transfer stations based on density peak and outlier detection. *Applied Intelligence*, *52*, 17892–17904.

Yofrido, F. M., & Harjana, L. T. (2019). Social-fairness perception in natural disaster, learn from Lombok: A phenomenological report. *Indonesian Journal of Anesthesiology and Reanimation*, *1*(1), 1–7.

Yu, X., Zhou, Y., & Liu, X. (2020). The two-echelon multi-objective location routing problem inspired by realistic waste collection applications: The composable model and a metaheuristic algorithm. *Applied Soft Computing*, *94*, 106477.

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ETHICAL CONSIDERATION

Authenticity of the texts, honesty and fidelity has been observed.

CONFLICT OF INTEREST

Author/s confirmed no conflict of interest.