Simultaneous solution of location and routing problem in critical times with the help of mathematical modeling

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Abstract

Effective planning and execution of humanitarian aid logistics activities ensure that disaster-related losses are minimized. This study addresses a tactical-level pre-disaster humanitarian logistics problem where a decisionmaker decides on cross-dock locations by taking potential vehicle routes into account. A decision support model is proposed for the location selection and distribution operations in humanitarian logistics with explicit fuel consumption estimation. In the addressed problem, the demand amount of each node depends on probabilistic disaster scenarios. Probabilities of whether each arc/road is open or closed and heterogeneous vehicle fleet in terms of vehicle sizes are also respected. The model is formulated as probabilistic bi-objective mixed integer linear programming, whose objectives are minimization of the total cost (i.e., fuel cost, vehicle fixed cost, and fixed opening cost) and total travel time. To the best of our knowledge, the proposed decision support model is unique in terms of the features considered simultaneously. The application of this process deals with a case study and subsequent numerical analysis of a possible earthquake in Tehran. Throughout the paper, it has been proven that the proposed model has the potential to assist managers in preparing for a natural disaster. A solution approach based on the clustering method is also proposed to solve the larger problems of the problem. The effective application of this heuristic method is demonstrated by presenting it to real-scale problems.

Keywords*:* meta heuristic; location-routing problem; heuristic; heterogeneous vehicle

1. Introduction

Humanitarian logistics involve the set of activities to plan, implement, and control the flow of people to evacuate from a disaster area to safer places and the flow and storage of aid materials efficiently and cost-effectively (Boonmee et al., 2017; Oruc and Kara, 2018; Kawase and Iryo, 2023). Meeting the needs of the victims, such as medical assistance, shelter, water, food, sanitation, and hygiene products, as soon as possible is crucial to minimize losses caused by disasters (Mansoori et al., 2020; Burkhardt et al., 2023). However, due to the increasing amount of needs and victims who are scattered in different places during or immediately after a disaster, different resources (fleet, drivers, fuel, etc.) must be used effectively to help victims. Meeting demand with the fewest number of vehicles ensures that resources are available to fulfill any further unexpected requirements that may occur. Ensuring that the vehicles return to their initial points serves a similar purpose provided that vehicles have been distributed to their beginning locations due to the potential needs of these neighborhoods. Moreover, minimizing the fuel required for logistics activities contributes to the effective use of fuel resources, which can become scarce in the event of a disaster.

Allocation of scarce resources in an efficient manner is one of the main priorities of humanitarian organizations (van Wassenhove and Pedraza Martinez, 2012). Several constraints have to be handled in the processes such as complete or partial collapse of the road infrastructure or transport system (Cotes and Cantillo, 2019). Moreover, uncertainty in the problems (e.g., uncertain type, time and place of disasters, number of victims and, correspondingly, needs/demand, etc.) may further complicate the decision processes, increasing the problem difficulty (Tavana et al., 2018; Cotes and Cantillo, 2019; Bilir, 2023; Turkeš et al., 2023).

Distribution systems need to be capable of handling these challenges while trying to achieve the main goal, meeting at least the minimum/vital demands of disaster victims (Sabouhi et al., 2021).

There are two basic problems in the classical humanitarian system. The location selection problem is a strategic-level decision problem about facility location, while the vehicle routing problem (VRP) is an operational-level decision problem about vehicle routing. These problems can be considered separately or simultaneously, the location routing problem (LRP) integrates these two sets of decisions.

In summary, the LRP case addresses both decisions and makes location selection by respecting actual routing costs rather than direct distances of facility demand–location points pairs, which only allude to routing cost. Making these two decisions independently can lead to suboptimal planning outcomes, whereas simultaneously decision-making enables to improve delivery efficiency (Tordecilla et al., 2023). The LRP aims to determine facility locations among the potential alternatives and to construct vehicle routes for distribution. In humanitarian logistics cases, both facility location and routing decisions are significant for shortening delivery time and reducing costs (Nagy and Salhi, 2007; Moshref-Javadi and Lee, 2016).

This research addresses a pre-incident tactical relief logistics problem in which a manager (government, municipality, non-profit organization, etc.) decides on different center locations considering possible vehicle routes. Cross-dock locations refer to assembling areas for aid materials that will be delivered to disaster victims. The idea here is similar to that of assembling points for evacuation purposes. So, any available flat and containable area can be a potential cross-dock point. Accordingly, location and routing decisions need to be made simultaneously. Note that the routing decisions here correspond to the distribution of vital aid materials, and hence the pre-disaster plan is made so as to meet all of the potential vital needs of the victims. A decision planning is described for the presented problem, which deals with facility location selection and distribution operations in relief logistics with explicit estimation of fuel consumption under uncertain demand and road closure and heterogeneous vehicle fleet assumptions. The heterogeneous fleet may consist of several vehicles that differ in size, capacity or operating costs. The method is expressed as a probabilistic bi-objective mixed integer linear programming (BOMILP), whose objectives are to minimize the system cost - which includes vehicle costs, fuel consumption, fixed cost and vehicle utilization for relief operations. (eg, maintenance). rent, opportunity, etc and fixed opening cost (e.g. area reservation for transfer operations) - and total travel time. The model accounts for potential uncertainties in disaster victim demand and road closures due to road damage. Additionally, a solution approach utilizing a clustering algorithm has been suggested for addressing cases of larger scale, compared to those accommodated by the BOMILP model. The heuristic approach integrates the advantageous aspects of both a clustering algorithm and MIP-based heuristics to reduce the problem size and shorten the computation time. The effectiveness of these proposed techniques and the potential advantages derived from their implementation are demonstrated through numerical analyses conducted on a case study and a series of larger instances. From this point of view, the aim of this study is to develop a decision support model that simultaneously takes into account explicit fuel consumption estimation, heterogeneous fleet, and demand and road closure uncertainties in the context of pre-disaster humanitarian logistics. As far as is known, such an attempt for LRP has not been made yet.

The rest of the paper is structured as follows. The second section of the paper presents the relevant literature. Section 3 includes the problem definition for the addressed LRP in humanitarian logistics, presents the proposed model for the defined problem, and introduces the solution approach. Section 4 provides numerical analyses performed on a case study. Section 5 summarizes managerial insights. The concluding section presents general comments on the Study and future research directions.

2. Literature review

This section presents a literature review to reveal the contribution of the study. The addressed problem in this study lies primarily in the area of humanitarian logistics. Several problem types have been addressed in the field of humanitarian logistics, such as allocation problems (Natarajan and Swaminathan, 2017; Chang et al., 2023), network problems (Zhang et al., 2022), production routing- inventory problems (Zargary and Samouei, 2022), and assignment problems (Rabiei et al., 2023). This study proposes a quantitative decision model for an LRP in humanitarian logistics. A number of studies similarly addresses LRP variants for humanitarian and emergency logistics (see e.g., Ahmadi et al., 2015; Bozorgi-Amiri and Khorsi, 2016; Ghasemi et al., 2022; Wang et al., 2022). However, instead of focusing only on the problems of the humanitarian system, all LRP literature was randomly reviewed in order to gain a broader perspective, also studies in other fields can also be used in humanitarian logistics.

As observed from the literature review, various studies deal with LRP variants from different application areas such as disaster management (Beiki et al., 2020a; Zhong et al., 2020), environmental externalities management (Mohammadi et al., 2013; Delfani et al., 2020; Vakili et al., 2021; Alamatsaz et al., 2021; Araghi et al., 2021), or waste management (Delfani et al., 2020; Nikzamir and Baradaran, 2020; Saeidi-Mobarakeh et al., 2020; Delfani et al., 2021; Zhao et al., 2021). In addition to varying application areas, several problem aspects have been studied as well, such as inventory (e.g., Aghighi et al., 2021; Harati et al., 2021), allocation (e.g., Javid and Azad, 2010; Shiripour et al., 2015), or reverse flow management (e.g., Zhalechian et al., 2016). Researchers formulate and solve the addressed problems through different operations research approaches such as linear or nonlinear optimization techniques, multi-objective models, stochastic programming, or various heuristic algorithms (Panadero et al., 2023).

Rather than relying on rough numbers, several studies use explicit calculations while estimating fuel consumption amounts from freight transportation operations (e.g., Rafie-Majd et al., 2018; Li et al., 2021). Explicit calculation of energy consumption allows for estimating fuel cost and resulting emissions more accurately. The literature was also examined according to whether the vehicle fleet consisted of homogeneous (e.g., Vural et al., 2021; Aghighi et al., 2021; Wang et al., 2023) or heterogeneous vehicle fleet that comprises vehicles differing in terms of capacities (e.g., Delfani et al., 2021; Harati et al., 2021; Li et al., 2021; Hashemi et al. 2022; Khoshgehbari and Mirzapour Al-e-Hashem, 2023).

Demand is the most frequently tackled uncertainty dimension (see e.g., Zarandi et al., 2014; Marinakis et al., 2016; Pekel and Kara, 2019; Zhang et al., 2020; Martinez-Reyes et al., 2021; Tordecilla et al., 2021; Roosta et al. 2023). A few studies deal with uncertainty on road conditions and closures. For instance, Xu et al. (2016) present a model for 72-hour post-earthquake Abbreviations: BOMP, bi-objective mathematical programming; BOMILP, bi-objective mixed integer linear programming; BOMINLP, bi-objective mixed-integer non-linear programming; CCP, chance-constrained programming; EL, emergency logistics; F, fuel consumption; H, heterogeneous fleet; HL, humanitarian logistics; IP, integer programming; LAR, locationallocation- routing; LARI, location-allocation-routing-inventory; LR, location-routing; LRI, location-routing-inventory; MIP, mixed integer programming; MILP, mixed integer linear programming; MINLP, mixed integer nonlinear programming; MISP, mixed integer stochastic programming;MOFP,multi-objective fuzzy programming;MOMILP,multi-objectivemixed integer linear programming; MOMINLP, multi-objective mixed integer nonlinear programming; MOMIP, multi-objective mixed-integer programming; MONLM, multi-objective nonlinear model; MOP, multi-objective programming; NLIP, nonlinear integer programming; SILP, stochastic integer linear programming; SP, stochastic programming.

LRP that considers road condition uncertainty. The study places significant emphasis on road network reliability between points as a crucial performance measure. To accurately represent road reliability, a random fuzzy variable is adopted. Subsequently, an improved genetic algorithm is utilized to solve the model. The case study demonstrates the efficiency of the proposed model and algorithm. The aim in the study of Sabouhi et al. (2021) is to minimize the expected arrival times of relief vehicles to the affected areas, taking into account the possible destruction of roads due to disasters. The relief supplies required in each affected area and on disrupted routes are considered mas uncertain parameters. In the study, a two-stage stochastic programming model is proposed for the distribution of relief supplies from distribution centers to the affected areas. The model is applied to a case study to demonstrate its applicability. Zhang et al. (2021) proposed a model for a multi-objective LRP, which aims to tackle uncertainty in the transportation networks and the time-varying demands. The primary objective of the study is to develop a time-varying planning approach to effectively respond to emergency situations, particularly oil spills. To solve the model, the researchers devised a hybrid heuristic algorithm. Beiki et al. (2021) proposed a multi-objective mixed integer mathematical model for the location routing of a medical assistance problem considering route reliability. Considering several different routes, determining the reliability of each route according to the percentage of route failures increases the applicability and efficiency of the model. An epsilon constraint method is used to solve the model. The performance of the model is tested on different scenarios, and results demonstrate its efficiency in minimizing costs. De Veluz et al. (2023) proposed a model for the stochastic multi-objective pre-disaster LRP. The model uses a scenario-based approach to determine the minimum number of distribution centers and evacuation centers to minimize the evacuation and relief distribution time. To demonstrate the applicability of the model, a case study of typhoons in the Philippines was conducted. The purpose of this case study was the assessment of the probability of road closure after a typhoon. The probability of roads being destroyed or blocked by landslides, fallen trees, or flooding varies depending on the strength of the typhoon. A multi-objective particle swarm optimization approach is used to solve the developed mathematical model. The results are expected to contribute to the planning of decision-makers prior to a disaster.

The related literature review shows that this study contributes to the field of humanitarian logistics by formulating and solving an LRP with explicit fuel consumption estimation, heterogeneous fleet, and demand and road closure uncertainties under bi-objectives of cost and time. The applicability of the proposed decision support model and potential benefits obtained from its use have been demonstrated on an exemplar humanitarian logistics problem confronted in Tehran, Iran. Moreover, an alternative solution method utilizing a clustering algorithm for addressing large-scale cases has been proposed. The performance of the heuristic has been shown on larger problems. To the best of the authors' knowledge, this is the first attempt to address the LRP with the aforementioned features simultaneously.

3. Problem description, formulation, and solution approach

This section includes the problem definition for the LRP considered in humanitarian logistics, presents the proposed model for the defined problem, and introduces a solution methodology designed to efficiently tackle larger instances of the problem.

3.1. Formal problem description

This study addresses a tactical-level pre-disaster humanitarian logistics problem where cross-dock locations (available empty areas that can be reserved and could be utilized for transfer operations after a disaster) and potential routes are determined as a preparation prior to any potential disasters. The corresponding probabilistic LRP is defined on a graph that comprises a set of potential facilities (cross-dock nodes) $V_F = \{1,2, \ldots, C\}$, a set of demand nodes $V_C = \{1,2, \ldots, D\}$, and sets of capacitated vehicles K_n, located initially at each cross-dock points $n \in V_F$. The set of available arcs on the graph is denoted by $A = (i,j) : i \in V_F, j \in V_C \; or \; i \in V_C, j \in V_F \cup V_C$.

The problem involves two main decisions: (i) where to locate cross-dock facilities that will be employed to distribute aid materials to the locations of victims in case of an emergency or disaster and (ii) how to derive vehicle routes that form a distribution plan for meeting the minimum/vital demands of victims. The minimum/vital demands of the victims, which can be met by one or more cross-dock points, are not known in advance; however, occurrence probabilities of a predefined set of demand scenarios are pre-calculated based on several metrics such as population density, susceptibility to disasters, magnitude likelihoods of disasters, and so forth.

Due to unexpected circumstances, roads existing on the logistics network may become unavailable. Here, it is assumed that road closure probabilities, N_{ij} assigned to each arc $(i, j) \in A$, can be anticipated. According to the defined road closure probabilities, a tactical planning-level target is derived as constructing robust distribution plans, that is, the probability that the plans will be required to be altered in the operational planning phase due to road closures should be limited. In other words, the probability for each route that the route will be completed without any detour needs should meet a predefined target. In summary, the aim is to find a route for each vehicle that starts from and ends at its assigned parking, which satisfies a predefined condition on the minimum probability that no arcs in the route are going to be closed/disrupted, ɣ.

The problem has two objectives that need to be considered. The first objective minimizes the total cost comprising fuel cost, the vehicle fixed cost, and the fixed opening cost. The vehicle fixed cost is confronted once a vehicle is used for distribution operations and may comprise maintenance cost, rental cost, opportunity cost, and so forth. A fixed opening cost is assumed to be yielded for each selected cross-dock location in the resultant location routing plan, related to various costs such as renting an area, grading the field, or the opportunity cost of reserving the area for transfer operations. The second objective minimizes the total travel time of distribution operations. The cost minimization objective ensures sustaining the efficiency of the aid chain for the operations to be carried out, whereas the time minimization objective ensures meeting the needs of the disaster victims as soon as possible after the disaster occurs.

3.2. A probabilistic bi-objective mixed integer linear programming model

The introduced problem is first formulated as a probabilistic BOMILP model. Table 1 presents the notation table that shares information related to the sets, parameters, technical parameters, and variables required for the description of the proposed model.
The proposed model has two objective functions (1.1, 1.2) and 16 constraint sets (2, …,16). The mathematical model is as follows:

$$Minimize\ (Total\ Cost)$$

$$\sum_{i,j\in A}\sum_{n\in V_F}\sum_{m\in K_n}\sum_{s\in S}P_s\left[\lambda\left(y_{nm}\left(\frac{a_{ij}}{g_{ij}}\right)X_{ijnm}+\gamma\beta_{nm}a_{ij}g_{ij}^2X_{ijnm}+\gamma r\left(\mu_{nm}X_{ijnm}+F_{ijnms}\right)a_{ij}\right)\right]+l+\sum_{i\in VF}z_iY_i$$
$$+\sum_{i\in VF}\sum_{j\in VC:(i,j)\in A}\sum_{m\in Kn}X_{ijnm}\pi_{im}, \quad (1.1)$$

Table 1
Notation table

Symbol	Description
Sets	
V_F	*Set of potential cross-dock points {1,2, …, C}*
V_C	*Set of demand points {1,2, …, D}*
K_n	*Set of vehicles at each cross-dock point* $n \in V_F$ *{1,2, …, E}*
A	*Set of arcs,* $(i,j) \in V_F \cup V_C$: $i \in V_F$, $j \in V_C$ *or* $i \in V_C$, $j \in V_F \cup V_C$
S	*Set of scenarios,* $\{1,2,\dots,F\}$
Parameters	
d_{is}	Demand of point $i \in V_C$ under scenario $s \in S$ in kg
t_{ij}	Travel time from i to j, $(i,j) \in A$ in second
z_i	Fixed opening cost of cross-dock point, $i \in V_F$ in €
p_s	Probability of occurrence of the demand scenario, $s \in S$
b_{nm}	Capacity of vehicle $m \in K_n$ at cross-dock point $n \in V_C$ in kg
a_{ij}	Distance between i and j, $(i,j) \in A\ in\ km$
g_{ij}	Vehicle speed between i and j, $(i,j) \in A\ in\ {}^{m}/_{s}$
π_{im}	Fixed cost of using vehicle $m \in K_n$ from cross-dock point $i \in V_F$ in €
N_{ij}	Probability of road closure, $(i,j) \in A$, $[0-1)$
ɣ	Probability target that no arcs in each obtained route is going to be closed/disrupted, (0,1)
l	Fuel cost in €
Technical parameters	
y_{nm}	Technical parameter, $k_{nm}V_{nm}N_{nm}$
β_{nm}	Technical parameter, $0.5C_{nmd}A_{nm}\rho$ in kg
μ_{nm}	Technical parameter, curb weight of vehicle in kg
λ	Technical parameter, $\xi/\kappa\psi$
γ	Technical parameter, $1/(1000\ \eta n_{tf})$ in €/liter
r	Technical parameter, $\tau + \delta sin\varphi + \delta H_r cos\ \varphi$
Decision variables	
X_{ijnm}	Binary variable equals to 1 if vehicle $m \in K_n$ travels from cross-dock point $n \in V_F$, in arc $(i,j) \in A$, and 0 otherwise, {0,1}
Y_i	Binary variable equals to 1 if cross-dock points $i \in V_F$ opens and 0 otherwise, {0,1}
F_{ijnms}	Amount of load carried by vehicle $m \in K_n$ from cross-dock point $n \in V_F$, in arc $(i,j) \in A$ under scenario $s \in S$ in kg
Q_{inms}	Amount of load delivered by vehicle $m \in K_n$ from cross-dock point $n \in V_F$ to demand point $i \in V_C$, under scenario $s \in S$ in kg

$$Minimize\ (Total\ Travel\ Time)$$

$$\sum_{i\in V_F}\sum_{i,j\in A}\sum_{m\in K_n}X_{ijnm}\mathrm{t}_{ims}, \qquad (1,2)$$

subject to

$$\sum_{n\in VF}\sum_{m\in Kn} Q_{inms} = d_{is}, \ \forall i \in V_C, s \in S, \tag{2}$$

$$\sum_{j\in V_C:(i,j)\in A}\sum_{m\in Kn} F_{i\,jnms} \leq \sum_{m\in Kn} b_{nm}Y_i, \ \ \forall i \in V_F, s \in S, n = i, \tag{3}$$

$$\sum_{j\in V_F \cup V_C:(i,j)\in A}\sum_{m\in Kn} X_{ijnm} \leq 0 \ \forall i \in V_F, n \in V_F, n \neq i, \tag{4}$$

$$\sum_{j\in V_F \cup V_C:(i,j)\in A}\sum_{m\in Kn} X_{ijnm} \leq 0 \ \ \forall\, i \in V_F, n \in V_F, n \neq i, \tag{5}$$

$$\sum_{j\in V_F \cup V_C:(i,j)\in A} X_{ijnm} \leq Y_i, \ \forall i \in V_F, n \in V_F, n = i, m \in K_n, \tag{6}$$

$$\sum_{j\in V_F \cup V_C:(i,j)\in A} X_{ijnm} = \sum_{j\in V_F \cup V_C:(i,j)\in A} X_{ijnm}, \ \ \forall i \in V_C, n \in V_F, m \in K_n, \tag{7}$$

$$\sum_{j\in V_C:(i,j)\in A} X_{ijnm} = \sum_{j\in V_C:(j,i)\in A} X_{jinm}, \qquad \forall i \in V_F, n = i, m \in K_n, \tag{8}$$

$$\sum_{j\in V_F \cup V_C:(i,j)\in A} X_{ijnm} = 1, \ \forall i \in V_F \cup V_C, n \in V_F, m \in K_n, \tag{9}$$

$$\sum_{j\in V_F \cup V_C:(i,j)\in A} F_{i\,jnms} = \sum_{j\in V_F \cup V_C:(j,i)\in A} F_{i\,jnms} - Q_{inms} \ \forall i \in V_C, s \in S, n \in V_F, m \in K_n, \tag{10}$$

$$F_{i\,jnms} \leq X_{ijnm}b_{nm}, \qquad \forall s \in S, n \in V_F, m \in K_n, (i,j) \in A, \tag{11}$$

$$\prod_{(i,j)\in A}(1 - N_{ij}\, X_{ijnm}) \geq \gamma, \ \forall\, n \in V_F, m \in K_n, \tag{12}$$

$$X_{ijnm} \in \{0,1\}, \qquad \forall\,(i,j) \in A, n \in V_F, m \in K_n, s \in S, \tag{13}$$

$$Y_i \in \{0,1\}, \qquad \forall i \in V_F, \tag{14}$$

$$Y_i\, F_{i\,jnms} \geq 0, \qquad \forall\,(i,j) \in A, n \in V_F, m \in K_n, s \in S, \tag{15}$$

$$Q_{inms} \geq 0, \qquad \forall i \in V_F, n \in V_F, m \in K_n, s \in S. \tag{16}$$

The objective function (1.1) includes fuel cost, fixed opening cost (i.e., reserving the area for transfer operations), and vehicle fixed cost of employing a vehicle for distribution operations (i.e., maintenance, rental, opportunity, etc.). Here, fuel consumption amounts are estimated by the approach used by Barth et al. (2005). The objective function (1.2) calculates the total travel time of the distribution operation. Constraint (2) guarantees that the demand points are satisfied in all scenarios. The total amount of cargo sent from any point in the region with the limit (3) does not exceed the capacity of that point. With the help of constraints (4) and (5), vehicles return to the cross-dock points where they were initially located. Constraint (4) ensures that only the vehicles that belong to the particular cross-dock point leave the cross-dock point, preventing all other vehicles' departures. Constraint (5) similarly ensures that only the vehicles that belong to the particular cross-dock point arrive at the cross-dock point, preventing all other vehicles' arrivals. Constraint (6) prevent flow from unopened cross-dock points. Constraint set (3) and constraint set (11) include constraint set (6). However, constraint set (6) is used to tighten the formulation of the model and accelerate the convergence to the optimal solution. Flow conservation in the logistics network is ensured by constraints (7) and (8). Constraint (9) enables that each vehicle can visit each point at most once. The load of each vehicle in all scenarios can be tracked by constraint (10). Constraint (11) ensures that no cargo is transported on an arc that is not traversed by any vehicle. The minimum probability condition that no arcs in the route are going to be closed/disrupted is imposed by constraint (12). Constraints (13)–(16) represent the restrictions imposed on the decision variables.

3.3. Clustering-based solution approach

A solution method that employs a route-based myopic clustering idea has been proposed to implement the BOMILP model in particularly large-sized instances. The clustering approach in routing problems is traditionally based on partitioning the points to be visited into clusters according to certain characteristics and determining routes separately for each cluster before combining them (Erdo˘gan and Miller-Hooks, 2012; Sutrisno and Yang, 2023). Partitioning the points to be visited reduces the problem size and shortens the computation time. As a result, the BOMILP model can be used in any problem size since the size of subproblems (clusters) will be user-defined based on the computational availabilities.

The developed solution approach, which is based on the idea of solving large-sized problems by breaking them down into smaller parts, for the addressed problem can be summarized as follows:

• The clustering process starts with assigning one potential cross-dock point to each cluster. The process initially checks the travel times between potential cross-dock points. One cross-dock, the total distance (in terms of travel time) of which is the highest from selected cross-docks for other clusters, is selected as a starting node of a cluster to form initial routes with one node (depot, cross-dock, depot).
• Cross-docks are iteratively added to these routes. In each iteration, all remaining cross-dock points are checked for each arc (i,j) in each route whether traveling from i to j indirectly through the cross-dock increases the total travel time the least($\min_{ijn} (t_{in} + t_{nj} - t_{ij})$,where n represents candidate cross-docks, and (i,j) represents current arcs). The cross-dock point with minimum cost increase is added to the determined route, replacing the determined arc.
• To prevent too large clusters that would remain unsolvable with the BOMILP model, each cross-dock route within a cluster can be at most twice the average route length.
• Once cross-docks are clustered into routes, demand points are added to the routes using the same least-time-increase approach. The demand points here can be added to clusters subject to the total capacity of the cross-docks in the route. Note that there still will be a single milk run in each cluster, as the purpose is not to form routes but only is to form clusters.
• The problem is solved by addressing each cluster as a sub-problem in the BOMILP model.

Algorithm 1
Initialize parameters

Define number of clusters, $\mathbf{N_c}$
Define number of cross-dock points, $\mathbf{N_{cd}}$
Define number of demand points, $\mathbf{N_d}$
Define maximum route length
Define soft route length limit
Define soft route length violation penalty coefficient, **pen**
Define starting cross-docks set, **SN** involving the most distant $\mathbf{N_c}$ cross-dock nodes from each other
Insert depot to **SN**
For n = 1 to $\mathbf{N_{cd}}$
Insert to **SN** cross-dock node m satisfying $\max_{m} \sum t_{nm}$
Assume that there are $\mathbf{N_c}$ routes that start from depot visiting one cross-dock node from **SN** and return to depot
Iteratively insert other cross-docks that myopically increase the traveled time the least
For n = 1 to $\mathbf{N_{cd}}$ - $\mathbf{N_c}$
For sn = 1 to $\mathbf{N_c}$
If route sn reached to maximum route length, break
Let Z be the number of arcs in route sn
For z = 1 to Z (for each arc in route sn)
Let i, j be the starting and ending nodes of arc z
Calculate the travel time increase **tinc** = $\mathbf{t_{in}}$ + $\mathbf{t_{n\,j}}$ - $\mathbf{t_{i\,j}}$
If route length is reached to soft route length limit, multiply **tinc** with the penalty coefficient (**tinc** = **tinc * pen**)
If minimum **tinc**, record which cross-dock is added to which arc of which route
Add the latest recorded insertion plan
Iteratively insert demand nodes that myopically increase the traveled time the least
For n = 1 to $\mathbf{N_d}$
For sn = 1 to $\mathbf{N_c}$
If route sn reached to maximum demand capacity of its cross-docks, break
Let Z be the number of arcs in route sn
For $z = 1$ to Z (for each arc in route sn)
Let i, j be the starting and ending nodes of arc z
Calculate added the travel time increase **tinc** = $\mathbf{t_{in}}$ + $\mathbf{t_{n\,j}}$ - $\mathbf{t_{i\,j}}$
If minimum **tinc**, record which demand node is added to which arc of which route
Add the latest recorded insertion plan

4. Numerical analyses

This section presents the application of the proposed model to a humanitarian logistics problem based on real data obtained in Tehran, Iran. First, the case description is presented and then the numerical analysis is presented.

4.1. Base case data description

Many earthquakes have occurred throughout history because many fault lines pass through Iran. These earthquakes had destructive effects. Using the studies, nine locations out of 81 potential intersection point locations (V_F = {1,2,...,9}) are selected, which are expressed as empty areas in the kartal region. 20 neighborhoods (V_C= {1,2, …, 20}) in the region were considered as demand points. It is assumed that there is one vehicle at each cross-dock point for delivery operations: a small vehicle at F1, F4, F7. A medium vehicle in F2, F5, F8. And a large vehicle in F3, F6, F9 be available.

The demand values of the points have been determined by taking into account the "Earthquake Potential Loss Estimation Booklet". Using a table called "number of houses damaged by earthquake", four equally probable scenarios ($p_s = 0.25$, $s \in S, |S| = 4$) are designed according to the damage status of the buildings. In a possible Tehran earthquake with an instantaneous magnitude of 7.5. The damage conditions of the buildings are severe damage, severe damage, moderate damage and minor damage. Based on each scenario, the amount of demand (dis) for providing aid packages to 3.75 people (estimated in the study of Unal, 2011) has been calculated for each household. In addition, the weight of each aid package is considered to be 1 kg per person when calculating the demand values. The obtained figures are rounded after calculation.

The data regarding the distance among all cross-dock and demand points (a_{ij}) are arranged by considering the connection status between the roads because not all roads are interconnected. The speed parameter (g_{ij}) is uniformly random in a range of 50–90 km/h. Travel time (t_{ij}) was calculated using the distance and speed parameters.

The road closure probabilities in the network were calculated based on the map prepared by considering the estimated number of damaged buildings when an earthquake of Mw = 7.5 occurred in the district. Arbitrary road closure probability indicators are assigned to each node, according to the color of the area the node belongs to (i.e., 0 to the lightest color, which refers to no road closure, 0.04, 0.05, and 0.06 to the darker colors in line with the higher number of road closure expectations). Then, road closure probabilities are calculated for each arc ($\aleph_{ij}$) as average of road closure probability indicators of starting (i) and ending (j) nodes of the arc. The probability target that no arcs in each route of each vehicle are going to be closed/disrupted (Ɣ) is assumed to be 60%.

The initial fixed opening fee for each potential cross-dock point is $150. There is direct transport between the depot and berthing points. The costs of this direct shipment will be added to the initial opening cost if the cross-dock point is used. When calculating transportation costs here, cars assume 20 liters of fuel per 100 km at a fuel price of $1.57 per liter.

4.2. Base case solution

The probabilistic BOMILP comprises two objective functions, which can be solved by means of ∈-constraint method (Haimes, 1971). This section first introduces the solution approach, and then the results for the base case are presented. This approach has also been utilized in several studies involving multi-objective models within the realm of humanitarian logistics (Kimms and Maiwald, 2018; Oruc and Kara, 2018; Zhang and Chen, 2023).

4.2.1. ∈-constraint-based solution approach

The ∈-constraint method facilitates the generation of Pareto optimal solutions in multi-objective optimization problems. This approach involves treating each objective function iteratively as the primary focus while formulating the remaining objectives as inequality constraints (Kazanc et al., 2021; Curtis et al., 2023).

The base case is addressed through the solution of two ∈-constraint variants derived from the proposed model. In the first variant, the objective is to minimize the total cost, subject to the constraint on the maximum travel time ($\in_1$). Conversely, the second variant focuses on minimizing the total travel time required for delivery operations, with a constraint imposed on the maximum cost ($\in_2$).

Table 2
The summary results for the base case

KPIs	Total cost minimization[a]	Total travel time minimization[b]
Total fixed opening cost (€)	588.1	1001.2
Total vehicle cost (€)	189.9	284.3
Total fuel cost (€)	68.6	72.9
Total cost (€)	846.7	1358.4
Total travel time (seconds)	6954.1	5317.5
Opened cross-docks	F5, F6, F9	F1, F4, F5, F6, F9

[a] The optimal solution's computation time is approximately 17 minutes.
[b] The optimal solution's computation time is approximately two minutes.

Total cost minimization variant	Total travel time minimization variant
Minimize total cost (1.1):	*Minimize* total travel time (1.2):
S.t.	S.t.
Constraints (2)–(11), (13)–(16), and (17.3)	Constraints (2)–(11), (13)–(16), and (17.3)
The total travel time (1.2)$\leq \in_1$ (18)	The total cost (1.1)$\leq \in_2$ (19)

The probabilistic BOMILP model offers two variants: the total cost minimization variant incorporates the objective function (1.1) focused on minimizing the total cost, along with constraints (2)–(11), (13)–(16), (17.3), and (18). On the other hand, the total travel time minimization variant features the objective function (1.2) aimed at minimizing total time, along with the set of constraints (2)–(11), (13)–(16), (17.3), and (19).

The initial values of $\in 1$ and $\in 2$ can be established by assigning suitably large numerical values to them. Subsequently, the respective values can be updated at fixed intervals during a Pareto analysis. IBM ILOG CPLEX Optimization Studio 20.1 has been used to formulate and solve the problem.

4.2.2. Numerical results for the base case

Table 2 presents the summary results in terms of the defined Key Performance Indicators (KPIs). The results reveal that the type of objective function employed alters the location and routing decisions. The time minimization objective requires opening relatively more facilities to reduce travel times, though total cost increases due to fixed costs. The cost minimization objective ensures finding a delivery plan with a significantly reduced total cost. Table 3 presents the routes obtained in both scenarios.

According to the results, the desired probability target (Ɣ), which is set to 60%, is satisfied for all vehicle routes since the aggregate route non-closure probability for each route is higher than 0.6.

Note that the proposed BOMILP model can be easily adapted to respect additional scenario pending parameters and decisions. The sample model respects travel time, vehicle speed and road closure probability parameters and scenario-dependent routing decisions.

Table 3
Obtained routes for the base case

Objectives	Route #	Aggregate route non-closure probabilities	Delivery	plans							
Total cost minimization	Route1	0.76	F5	DP11	DP3	DP12	DP7	F5			
	Route2	0.63	F6	DP10	DP15	DP8	DP2	DP19	DP16	DP18	DP20	F6
	Route3	0.68	F9	DP17	DP5	DP9	DP4	DP14	DP6	DP13	DP1	F9
Total travel time minimization	Route4	0.91	F1	DP19	F1							
	Route5	0.91	F4	DP13	F4							
	Route6	0.76	F5	DP10	DP12	DP3	DP11	F5				
	Route7	0.66	F6	DP20	DP18	DP16	DP2	DP8	DP7	DP15	F6	
	Route8	0.71	F9	DP1	DP6	DP14	DP4	DP9	DP5	DP17	F9	

4.3. Pareto analysis between the total travel time and total cost objectives

The set of Pareto efficient solutions for the considered problem is obtained by using the ∈-constrained method. This subsection conducts a trade-off analysis between the objectives of total travel time and total cost. To achieve this, the value of ∈1, specified for the total travel time ∈-constraint, is varied within the range of 5400 to 7000 seconds, with intervals of 100 seconds.

Note that the Pareto efficient solutions obtained are mutually indifferent. Trade-offs exist among them, indicating that to enhance performance in terms of one dimension, compromises must be made in the other one. The results show the cost of decreasing total distribution duration incrementally. The decision-makers may set the ∈-constraints according to their resources and urgency assessments for aid distribution. Note that the lowest total cost and travel time values that could be obtained are €846.7 and 5317.5 seconds, respectively. The reason that delivery plans with relatively lower total travel times have higher total logistics costs is the fact that to reduce total travel time, more cross-dock points are required, resulting in higher opening costs.

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4.4. Analysis on the effects of different aggregate route non-closure probabilities

The constraint set (17.3) in the model allows to take route closure probabilities into account. In the base case, an optimal delivery plan is obtained by assuming the minimum probability that no arcs in the route are going to be closed/disrupted (Ɣ) as 0.6. In this section, delivery plans are obtained by considering three additional settings where Ɣ is set to 0.5, 0.7 and 0.8. Table 5 presents the summary results for different aggregate route non-closure probabilities.

Table 4
Summary results for different aggregate route non-closure probabilities

	Total cost minimization				Total travel time minimization			
KPIs	ɣ = 0.5[a]	ɣ = 0.6[a]	ɣ = 0.7[b]	ɣ = 0.8[c]	ɣ = 0.5[d]	ɣ = 0.6[d]	ɣ = 0.7[d]	ɣ = 0.8[e]
Total fixed opening cost (€)	588.1	588.1	763.2	1173.2	1001.2	1001.2	1176.3	1601.9
Total vehicle cost (€)	189.9	189.9	237.1	339.4	284.3	284.3	331.5	454.0

Total fuel cost (€)	68.6	68.6	72.8	72.8	98.9	72.9	72.9	74.4
Total cost (€)	846.7	846.7	1073.2	1611.5	1358.4	1358.4	1582.2	2152.6
Total travel time (seconds)	6954.1	6954.1	8050.2	12863	5317.5	5317.5	5685.9	7695.0
Opened cross-docks	F5, F6, F9	F5, F6, F9	F5, F6, F7, F9	F1, F2, F3, F5, F6, F7	F1, F4, F5, F6, F9	F1, F4, F5, F6, F9	F1, F4, F5, F6, F7, F9	F1, F2, F3, F4, F5, F6, F7, F9

[a]The optimal solution's computation time is approximately 17 minutes.
[b]The feasible solution that is obtained with a 2.81% optimality gap after 12 hours of computation time.
[c]The feasible solution that is obtained with a 3.2% optimality gap after 12 hours of computation time.
[d]The optimal solution's computation time is approximately 2 minutes.
[e]The feasible solution that is obtained with a 15.29% optimality gap after 12 hours of computation time.

4.5. The effects of respecting vehicle heterogeneity

In the base case, a heterogeneous vehicle fleet is employed, and it is assumed that in facilities, there are small, medium, and large vehicles with different vehicle capacities, costs, and fuel consumption rates. This subsection provides an analysis to compare the base case results with the results obtained under the assumption that all vehicles are medium-sized. Tables 5 and 6, respectively, present the KPI values and distribution plans under homogeneous and heterogeneous vehicles.

As can be observed from the results, the use of only medium-sized vehicles rather than a heterogeneous fleet for delivery operations increases the number of vehicles required for both objectives (see Table 6). This change causes delivery plan updates and an increase in the total cost and travel times. When the heterogeneous vehicle fleet is used under cost minimization, the model employs large, high-capacity vehicles in long routes in order to reduce travels to and from cross-dock points, and thus fixed opening, fixed vehicle, and fuel costs. The use of large vehicles provides an advantage also in the case of time minimization through saving time by visiting points close to each other in a single visit, while small vehicles can save fuel on short routes. Therefore, in both cases, the use of the heterogeneous vehicle fleet has the potential to provide advantages to the decision maker.

Table 5
Summary results for homogeneous and heterogeneous vehicles

	Total cost minimization		Total travel time minimization	
KPIs	Heterogeneous	Homogeneous[a]	Heterogeneous	Homogeneous[b]
Total fixed opening cost (€)	588.1	957.2	1001.2	1386.0
Total vehicle cost (€)	189.9	275.3	284.3	385.4
Total fuel cost (€)	68.6	57.4	72.9	59.6
Total cost (€)	846.7	1290.0	1358.4	1831.0
Total travel time (second)	6954.1	7230.8	5317.5	5508.8
Opened cross-docks	F5, F6, F9	F1, F2, F5, F6, F7	F1, F4, F5, F6, F9	F1, F2, F4, F5, F6, F7, F9

[a]The optimal solution's computation time is approximately 20 minutes.
[b]The optimal solution's computation time is approximately 2 minutes.

Table 6
Distribution plans under homogeneous and heterogeneous vehicles

Total cost minimization	Heterogeneous	Route 1	F5	DP11	DP3	DP12	DP7	F5				
		Route 2	F6	DP10	DP15	DP8	DP2	DP19	DP16	DP18	DP20	F6
		Route 3	F9	DP17	DP5	DP9	DP4	DP14	DP6	DP13	DP1	F9
	Homogeneous	Route 1	F1	DP19	F1							
		Route 2	F2	DP17	DP5	DP9	DP4	DP13	DP1	F2		
		Route 3	F5	DP11	DP10	DP15	DP7	F5				
		Route 4	F6	DP8	DP2	DP16	DP18	DP20	F6			
		Route 5	F7	DP6	DP14	DP3	DP12	F7				
Total travel time minimization	Heterogeneous	Route 1	F1	DP19	F1							
		Route 2	F4	DP13	F4							
		Route 3	F5	DP10	DP12	DP3	DP11	F5				
		Route 5	F6	DP20	DP18	DP16	DP2	DP8	DP7	DP15	F6	
		Route 6	F9	DP1	DP6	DP14	DP4	DP9	DP5	DP17	F9	
	Homogeneous	Route 1	F1	DP19	DP2	DP16	F1					
		Route 2	F2	DP9	DP5	DP4	DP1	F2				
		Route 3	F4	DP13	F4							
		Route 5	F5	DP11	DP10	F5						
		Route 6	F6	DP20	DP18	DP8	DP7	DP15	F6			
		Route 7	F7	DP12	DP3	DP14	DP6	F7				
		Route 8	F9	DP17	F9							

4.6. Decomposing location and routing decisions

The proposed model allows to make interdependent location and routing decisions simultaneously. In order to reveal the benefits of such simultaneous decision making, this section provides a comparison to a sequential decision-making approach, where location decisions are given first, then these decisions are fixed and routing decisions are given accordingly. In order to decide on the cross-dock locations, a direct distribution is assumed between cross-docks and demand points (i.e., departs from the cross-dock point, visits one customer, and returns back to the cross-dock point)

Table 7
The summary results for the simultaneous and sequential approaches under the cost minimization

KPIs	Simultaneous approach[a]	Sequential approach[b]
Total fixed opening cost (€)	588.1	788.4
Total vehicle cost (€)	189.9	229.2
Total fuel cost (€)	68.6	68.7
Total cost (€)	846.7	1086.4
Total travel time (seconds)	6954.1	7747.9
Opened cross-docks	F5, F6, F9	F4, F6, F7, F9

[a]The optimal solution's computation time is approximately 17 minutes.
[b]The optimal solution computation time is approximately 10 minutes.

in order to eliminate routing decisions. For this purpose, eight vehicles are assumed to exist at each cross-dock point, and constraints (20) and (21) were added to the model.

$$X_{ijnm} = X_{ijnm} \forall i \in V_F, j \in V_C, n = i, m \in K_n, (i,j) \in A, (j,i) \in A \qquad (20)$$

$$\sum_{i \in V_F} \sum_{j \in V_C:(i,j) \in A} X_{iji1} * b_{n1} \geq \sum_{i \in V_C} d_{is} \forall s \in S. \qquad (21)$$

Constraints (20) ensure that direct distribution occurs between cross-docks and demand points. Constraint (21) allows to have sufficient amount of vehicle capacity to satisfy demand at each scenario under direct distribution.

The sequential approach suggests to open F4, F6, F7, and F9. Then, these cross-dock points are fixed and the model is re-run by removing the constraints (20) and (21) for taking the routing decisions. As a result, a different delivery plan for the vehicles is obtained, compared to that of the base case. Table 7 presents the summary results for the comparison.

The results show that the use of the sequential approach results in a total cost increase of 28%, which reveals the benefit of optimizing location and routing decisions simultaneously. The comparison is further extended with a larger-sized instance. The new instance comprises 15 cross-docks and 36 demand points. The distance data are obtained from the Pollution-Routing Problem Instance Library (Pollution-Routing Problem, 2022) using UK50_01 instance. Similar to the base case, the speed parameter is uniformly random between 50 and 90 km/h, and travel time is calculated using the distance and speed parameters. The road closure probability for each arc is uniformly random between 0.04 and 0.06. The rest of the parameters are the same as the base case. Table 8 presents the summary results for the comparison.

The analysis on the larger-sized instance shows that similar outcomes were achieved, compared to the base case. The analysis also reveals the benefit of using the BOMILP model, the cost minimization objective.

Table 8
The summary results for the simultaneous and sequential approaches for the larger sized instance

KPIs	Total cost minimization		Total travel time minimization	
	Simultaneous approach[a]	Sequential approach[b]	Simultaneous approach[c]	Sequential approach[e]
Total fixed opening cost (€)	961.2	1174.4	1562.3	2192.0
Total vehicle cost (€)	324.7	364.1	482.1	549.5
Total fuel cost (€)	49.9	48.2	51.8	49.7
Total cost (€)	1336.0	1586.7	2096.2	2791.2
Total travel time (seconds)	5405.9	5367.2	3803.9	3805.8
Opened cross-docks	F3, F9, F11, F12, F15	F3, F4, F9, F10, F12, F15	F6, F7, F8, F9, F11, F12, F14, F15	F1, F3, F4, F6, F7, F8, F9, F11, F12, F14, F15

[a] The feasible solution that is obtained with a 0.87% optimality gap after 12 hours of computation time.
[b] The feasible solution that is obtained with a 0.78% optimality gap after 12 hours of computation time.
[c] The feasible solution that is obtained with a 8.27% optimality gap after 12 hours of computation time.
[d] The feasible solution that is obtained with a 7.39% optimality gap after 12 hours of computation time.

Table 9
The summary results for the clusteringbased solution approach

Total cost minimization[a]		
Larger problems	The BOMILP model	The clustering solution approach (€)
UK100_01	No solution found	2666.2
UK100_02	No solution found	2722.3
UK100_03	No solution found	2970.0
UK100_04	No solution found	2811.0
UK100_05	No solution found	3533.0

Abbreviation: BOMILP, bi-objective mixed integer linear programming.
[a]Both the optimization model and the clustering solution approach were executed for a duration of 12 hours

4.7. Performance of the clustering-based solution approach

This section examines the effectiveness of the approach, with a specific focus on evaluating costs in larger instances. The expanded instances consist of 20 cross-docks and 80 demand points, utilizing distance data sourced from the Pollution-Routing Problem Instance Library through the UK100_01-UK100_05 instance. The rest of the used parameters are the same as the base case.

In the clustering process, the 100 points are divided into three distinct clusters based on their mutual distances. Subsequently, the problem is addressed and solved independently for each cluster, resulting in specific outcomes. Table 9 provides a comprehensive summary of the results obtained through the clustering-based solution approach.

The results obtained underscore the effectiveness of the solution approach applied to the larger instances. Noteworthy is the better performance demonstrated by the solution approach, even in cases where the model fails to produce feasible solutions. This indicates that as the problem size increases, the solution approach proves to be more efficient and reliable, highlighting its effectiveness in addressing larger-sized problems.

5. Managerial insights

The analyses conducted using the proposed model for the LRP confronted in humanitarian logistics operations provide some valuable managerial insights to organizations operating in this critical field. The integration of location selection and routing decisions increases the complexity of the problem and the LRP is among the key decision problems that play a vital role in designing efficient humanitarian aid logistical activities. The proposed model for the addressed problem here takes the heterogeneous vehicle fleet, demand uncertainty, and road closures into account. The use of a comprehensive emission model proposed by Barth et al. (2005) allows us to estimate better fuel costs.

In order to ensure the efficacy of the aid chain during disaster relief operations, cost reduction, one of the objectives of the model, is important, as resources are most likely to be limited and require careful control while planning operations. However, merely focusing on cost reduction is inadequate to fulfill the fundamental goal of humanitarian aid activities, which is to minimize losses and maximize assistance to affected communities. Therefore, the proposed model incorporates an additional important objective, which is the minimization of total travel time. Adopting the two objective functions, the model allows to facilitate an assessment of trade-offs between the prominent KPIs, cost (resource usage) and time, in humanitarian logistics. While constructing a pre-disaster plan, the knowledge of such trade-offs may help the decision-makers to understand the requirements and potential results of a disaster case and invest and prepare accordingly. More specifically, the model provides information on the potential service time required for aid distribution, the number of cross-dock points to reserve, fleet size and structure to invest in, and how much extra resources are needed to decrease the service time.

The suggested heuristic holds the potential to empower decision-makers to address larger problems encountered in practical scenarios. Numerical analysis shows that the model cannot provide feasible solutions within acceptable solution times. Employing the clustering solution approach could offer a viable strategy for generating feasible delivery plans for the humanitarian logistics problem.

6. Conclusion

This study proposes a probabilistic BOMILP model for an LRP that can be confronted in predicate humanitarian logistics operations planning. The model respects total cost (i.e., the fixed opening cost of cross-docks, vehicle fixed cost, and fuel cost) and total travel time minimization objectives. The purpose of minimizing the travel time is crucial in ensuring that aid is sent to disaster victims as soon as possible to reduce the loss of life and provide for other urgent needs of the victims. The cost minimization objective is employed to ensure the economic sustainability of the resulting location and delivery plans. Efficient use of resources at the time of disaster is significant to meet the needs of a higher number of disaster victims and to sustain humanitarian operations for a longer time. The proposed model goes beyond cost reduction and considers critical factors such as demand uncertainty and road closures, aligning it more closely with real-life disaster relief operations. According to the research, this proposed decision planning method is novel in terms of structures that are considered simultaneously.

Numerical analyses show the added value and applicability of the proposed model under several problem settings. An examplar Pareto analysis is also provided to demonstrate how to estimate the additional resources needed to reduce aid distribution durations. The analysis for different desired aggregate road non-closure probabilities shows that reducing risk results in an increase in total cost and travel time. The analyses also reveal the potential advantages of having a heterogeneous vehicle fleet over a homogeneous one. Furthermore, numerical analyses are conducted to assess the performance of the heuristic to demonstrate that the proposed algorithm can generate promising solutions for instances of reasonable size.

It has been proven that the proposed model has the potential to support managers in preparing for an incident. By incorporating multiple objective functions and presenting a case study, this study offers valuable insights and lays the groundwork for future research to leverage new technologies and enhance the resilience of humanitarian aid supply chains. In future studies, new technologies such as drone and robot deliveries that make it feasible to reach unattainable regions can be addressed in new decision models. Also, other parameters that may potentially be uncertain in similar cases such as speed or unit costs can be respected. Routing decisions in the first echelon of the supply chain (among depots and cross-docks) can be tackled as well. As a final suggestion, operationallevel LRPs may be confronted in the post-disaster response phase of disaster management while executing the tactical pre-disaster plans can be addressed. Such problems may involve dynamic decisions of reallocating vehicles between cross-dock points, reuse or redirecting vehicles, or demand changes.

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