A Comparative Study of Multiple Objectives for Disaster Relief Logistics

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Abstract. Disaster relief logistics is a critical part of humanitarian emergency operations. In this study, we develop integer programming models with a focus on the pre-disaster location selection for depots in which relief items would be stored and the post-disaster distribution of relief items to demand locations. The goal is to determine the optimal depot locations and depot-demand node allocations by minimizing the total transportation cost of delivering relief items. We incorporate performance measures that represent the efficiency, efficacy, and equity of the decisions in our models in terms of total transportation cost, total waiting time, and percent of unmet demand, respectively. We consider the uncertainties that would affect the decisions made in terms of demand and transportation times in our case study by analyzing the results under various scenarios. We provide observations regarding the performance of different objectives under different scenarios for demand and transportation network conditions.

Keywords: Disaster management · Humanitarian relief logistics · Location selection · Integer programming · Multi-objective programming · Demand and distance uncertainty

1 Introduction

One of the most important challenges that humanity faces are dealing with disasters. According to the International Federation of Red Cross and Red Crescent Societies (IFRC), a disaster is “a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community’s or society’s ability to cope using its own resources” (IFRC 2019). Disasters can have natural or human-made causes. Natural disasters include floods, hurricanes, earthquakes, and cyclones, whereas human-made disasters include wars, famines, and epidemics, all of which are relevant threats for the world population today. It is extremely important to be prepared for disasters to alleviate the problems during disaster relief operations. As one of the most frequently observed natural disasters, earthquakes are experienced in various locations that cause significant damage and a great number of casualties. For example, more than 165,000 people died as a result of the Indian Ocean earthquake that triggered tsunamis and hit Indonesia in 2004 and more than 222,000 people died in the 2010 earthquake in Haiti, which is considered the worst

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earthquake encountered by the United Nations (UN) (de la Torre et al. 2012). Even with the advanced seismic technology, it is extremely difficult to determine where and when the earthquake will attack early enough to take precautions.

In Turkey, Istanbul, being a densely populated mega-city with a population of 15+ million, is facing a great risk as it is in the highly active North Anatolian Fault Zone (NAFZ). It has been reported by geoscientists that an earthquake of magnitude 7 or greater is expected to originate in the eastern Marmara Sea, twenty kilometers south of Istanbul, where there has not been an earthquake since 1776 (Weston 2017). Such an earthquake could devastate the region, and many people would need shelter, food, water, and medical care. To prevent further damage to people in the aftermath of such an earthquake, required relief items must be delivered timely to the affected population, and the success of these logistics operations relies on the level of preparedness. In this study, we focus on the pre-disaster location selection for depots in which relief items would be stored and the post-disaster distribution of relief items to demand locations.

Disaster operations management (DOM) deals with activities before, during, and after the disasters aiming mainly to minimize casualties and costs. DOM is commonly described in four phases in the literature: mitigation, preparedness, response, and recovery (Altay and Green 2006). Mitigation and preparedness are pre-disaster phases in which the goal is to reduce the possible impacts of a disaster and prepare a community to respond effectively when a disaster occurs. Response and recovery are post-disaster phases in which the affected people are helped by the government and non-governmental organizations (NGOs) immediately using the available resources and the stabilization efforts continue to support the community until returning to a state of normalcy. This study aims to determine the best depot locations in the preparedness phase and the best possible depot assignments to demand locations in the response and recovery phase of a disaster.

Research in disaster relief logistics deals with decisions regarding the numbers, capacities, and locations of depots to store emergency relief items and shelters to protect the affected population as well as the transportation of items to those in need. The challenges in disaster relief operations are mainly due to destabilized infrastructure, limited time and capacity to distribute relief materials, and uncertain demand (de la Torre et al. 2012). As the frequency and scale of disasters increase, efficient and accountable use of scarce resources has become crucial in relief operations and the quality of decisions made in disaster relief logistics can be measured in terms of efficiency, efficacy, and equity (Beamon and Balcik 2008; Huang et al. 2012). In this study, we incorporate performance measures that represent the efficiency, efficacy, and equity of the decisions in our model in terms of total transportation cost, total waiting time, and percent of unmet demand, respectively.

As disasters occur at uncertain times and locations, the post-disaster demand and transportation conditions are also uncertain. In modeling systems with such uncertainties involved, one must take into account a range of possible scenarios to provide more applicable solutions. Therefore, we consider the uncertainties that would affect the decisions made in terms of demand and transportation times in our case study by analyzing the results under various scenarios.

2 Literature Review

The increase in the number and impact of disasters in the recent decades necessitated the smart use of scarce resources, which, in essence, is a common goal in operations research and management sciences (OR/MS). Therefore, the OR/MS community has been increasingly studying disaster management issues and developing quantitative methods to support humanitarian operations. Altay and Green (2006) review the OR/MS studies in DOM from 1980 to 2004 and report that, of the 109 papers, 44% address mitigation, 21.1% address preparedness, 23.9% address response, and 11% address recovery in the disaster lifecycle. Galindo and Batta (2013) also review the OR/MS literature in DOM from 2005 to 2010 and show that, of the 155 papers, 23.9% are in mitigation, 28.4% are in preparedness, 33.5% are in response, only 3.2% are in recovery, and 11% are in multiple stages, similar to this study where we deal with both pre-disaster and post-disaster decisions. This shows that more research needs to focus on, especially recovery operations, including relief distribution.

A review of 83 papers in relief distribution networks with an OR component from 1990 to 2013 by Anaya-Arenas et al. (2012) shows that only 8 of these papers study both location and transportation problems. Our study deals with both depot location selection and transportation problems, contributing to this less studied area of research. This review article also points out the need to design more sophisticated but realistic models that are capable of supporting crisis managers.

One realistic assumption regarding disaster management, in general, is that there are multiple perspectives (of NGOs, government organizations, or affected population); hence, multiple objective functions. Boonmee et al. (2017) review the optimization models for facility location problems in humanitarian logistics, specifically the models in four categories: deterministic, dynamic, stochastic, and robust. Minimizing response time, risk, cost (in terms of distance, time, facility fixed costs, or operating costs), unsatisfied demand are found to be the main objectives in the emergency humanitarian logistics literature. To support integrated disaster stage management, developing new objective functions by integrating the facility location problem with other problems such as routing, evacuation, inventory, resource allocation, and relief distribution problems is suggested.

Several humanitarian logistics studies adopt multiple objective functions. Gutjahr and Nolz (2016) provide a review on multi-criteria optimization in humanitarian OR and classify criteria in three categories: efficiency (cost), effectiveness (time, coverage, travel distance, reliability, and security), and equity (fairness). As an example in relief logistics, Tzeng et al. (2007) propose a multi-objective relief distribution model with three objectives: minimizing the total cost and the total travel time for efficiency and maximizing the minimal satisfaction for fairness. In another study, Huang et al. (2015) assume three objective functions of lifesaving utility, delay cost, and fairness with a rolling horizon approach to update information in their convex quadratic network flow problem. Zhan et al. (2014) propose a multi-objective, multi-supplier, multi-affected area, multi-relief, and multi-vehicle relief allocation problem based on disaster scenario information updates to coordinate efficiency and equity. Gralla et al. (2014) study the trade-offs among multiple objectives in an immediate humanitarian aid delivery after an earthquake scenario by surveying 18 expert humanitarian logisticians. They identify the amount of cargo delivered to be the most important and the cost to be the least important objective, compared to the prioritization of aid by commodity type, the prioritization of aid by delivery location, and the delivery speed. Ransikarbum and Mason (2016) develop a multi-objective network optimization model that integrates supply distribution and network restoration decisions. This model maximizes the minimum percent of satisfying demand, minimizes the total unsatisfied demand, and minimizes the total network restoration and transportation costs as a weighted objective function subject to capacity, resource, and budget constraints. Ferrer et al. (2018) develop a compromise programming model for multi-criteria optimization in humanitarian last mile distribution for a single commodity using a convoy of vehicles with the criteria of time, cost, equity, priority, security, and reliability. This model is illustrated using a case based on the 2010 Pakistan floods, and a detailed vehicle schedule is produced. To ensure equity in humanitarian relief distribution, Gutjahr and Fischer (2018) propose extending the deprivation cost objective, that quantifies human suffering due to the lack of resources or services, by a term proportional to the Gini inequity index. The frequency of deliveries of a single commodity with recurring demand is decided. The model is illustrated using the 2015 Nepal earthquake, and it is argued that a high level of equity can be obtained at the expense of a slight increase in deprivation cost.

There are also studies using two-stage stochastic models in humanitarian operations such as emergency relief distribution (Barbarosoglu and Arda 2004, Rawls and Turnquist 2010) and facility location (Mete and Zabinsky 2010). Gonçalves et al. (2013) also propose a two-stage linear stochastic optimization model for humanitarian aid supply operations of the World Food Program (WFP) in Ethiopia. The first stage of this model includes supply and prepositioning stock decisions, and the second stage includes distribution flows from an origin to a destination. They show that incorporating uncertainty in model parameters such as demand, transportation cost, and accessibility improve the cost-effectiveness of the food aid distribution operations. Noyan et al. (2015) develop a two-stage stochastic programming model to design the last mile relief network. The model determines the locations and capacities of distribution points, assigns demand locations to distribution points, and allocates supplies with a hybrid allocation policy and criteria of accessibility and equity. The model also considers the uncertain demand and transportation network conditions.

According to the aforementioned classifications in the disaster relief logistics literature, our study proposes a deterministic model for both the pre- and post-disaster stages where demand and transportation time uncertainties are included by considering various scenarios.

3 Methodology

The disaster relief logistics models proposed in this study are integer programming models with the objectives of minimizing costs (in terms of total distance and transportation cost), total waiting time, and maximum percent of unmet demand. The assumptions of the proposed model are as follows:

1. There is enough storage capacity at the depots to meet the total demand.
2. Only a specific number of locations can be chosen out of the total number of available depot locations.

3. Each depot can send relief aid to a specific number of demand nodes based on the number of available vehicles for that depot.
4. The unit transportation cost is a constant that does not depend on the depot-demand node pair.
5. Loading time and unloading time for a truck are assumed to be equal.
6. There is enough number of trucks available at time zero, such that all demand can be loaded starting at the same time and delivered immediately.

The notation used in the model is defined as follows.

Sets:

$\boldsymbol{S}$: a set of alternative depot nodes, $i = 1, 2, \ldots, S$
$\boldsymbol{D}$: a set of demand nodes, $j = 1, 2, \ldots, D$
$\boldsymbol{K_i}$: set of available vehicles (trucks) at depot i, $k = 1, 2, \ldots, Nv_i$

Parameters:

cap_i: The capacity of depot i in number of pallets
dem_j: Demand of node j in number of pallets
d_{ij}: Distance between depot i and demand node j in kilometers
t_{ij}: Total transportation cost per pallet from depot i to demand node j in dollars (the per pallet cost based on the sum of fuel cost, f_{ij}, distribution cost, $Dist_{ij}$, and worker cost, Wr_i)
$Accu_{ij}$: Accumulated waiting time in minutes (the sum of loading time, unloading time, and the time needed to reach demand nodes)
MD: Maximum number of depots that can be opened
Nv_{i}: Number of vehicles available at each depot at time zero
$vcap$: Capacity of a truck in a number of pallets

Decision variables:

x_{ij}: Number of pallets delivered from depot i to demand node j

$$w_{ij} = \begin{cases} 1, & depot\ i\ serves\ node\ j \\ 0, & otherwise \end{cases}$$

$$y_i = \begin{cases} 1, & if\ depot\ location\ i\ is\ selected \\ 0, & otherwise \end{cases}$$

The mathematical models for the depot location selection problem with two different objective functions are called Model 1 and Model 2 and are formulated as follows.

Models 1 and 2:

$$\text{Minimize } Z_1 = \sum_{i \in \mathrm{S}} \sum_{j \in \mathrm{D}} \left(x_{ij} d_{ij}\right) \tag{1}$$

$$\text{Minimize } Z_2 = \sum_{i \in \mathrm{S}} \sum_{j \in \mathrm{D}} \left(x_{ij} t_{ij}\right) \tag{2}$$

Subject to:

$$\sum\nolimits_{j \in \mathrm{D}} x_{ij} \leq Cap_i \times y_i \quad \forall i \in S \tag{3}$$

$$\sum\nolimits_{i \in \mathrm{S}} x_{ij} \geq dem_j \quad \forall j \in D \tag{4}$$

$$\sum\nolimits_{i \in \mathrm{S}} y_i \leq MD \tag{5}$$

$$x_{ij} \geq 0, \text{integer} \quad \forall i \in S, \forall j \in D \tag{6}$$

$$y_i \in \{0, 1\} \quad \forall i \in S \tag{7}$$

The objective function Z_1 in (1) minimizes the total distance between the demand nodes and the depot locations selected. The objective function Z_2 in (2) minimizes the total transportation cost that consists of fuel cost, distribution cost, and worker cost. Constraint (3) ensures that the storage capacity of depots is not exceeded while (4) ensures the amount of relief materials will satisfy the demand for each node. Constraint (5) controls the number of selected depot locations with the maximum number required. Constraint (6) and (7) are the non-negativity and binary constraints for the x_{ij} and y_i variables, respectively.

The mathematical models for the response stage problems in which depots are allocated to demand nodes are given as Models 3 and 4 below.

Model 3:

$$\text{Minimize } Z_3 = \sum\nolimits_{i \in \mathrm{S}} \sum\nolimits_{j \in \mathrm{D}} \left(x_{ij} Accu_{ij} \right) \tag{8}$$

Subject to: (3)–(7)

$$\sum\nolimits_{j \in \mathrm{D}} x_{ij} \leq vcap \times Nv_i \quad \forall i \in S \tag{9}$$

$$x_{ij} \leq vcap \times w_{ij} \quad \forall i \in S, \forall j \in D \tag{10}$$

$$\sum\nolimits_{j \in \mathrm{D}} w_{ij} \leq Nv_i \times y_i \quad \forall i \in S \tag{11}$$

$$w_{ij} \in \{0, 1\} \quad \forall i \in S, \forall j \in D \tag{12}$$

The objective function Z_3 in (8) minimizes the total accumulated waiting time for the demand nodes to receive relief items. In addition to constraints (3)–(7), constraint (9) limits delivered pallets with the number of vehicles. Constraint (10) ensures the number of delivered pallets is at most as much as the capacity of vehicles for each trip. Constraint (11) limits the number of demand nodes that can be served by a depot with the number of available vehicles at that depot. Constraint (12) defines the binary w_{ij} variables.

Model 4:

$$\text{Minimize} \quad Z_4 \tag{13}$$

Subject to: (3), (5)–(7), (9)–(12)

$$Z_4 \geq \frac{dem_j - \sum_{i \in S} x_{ij}}{dem_j} \qquad \forall j \in D \tag{14}$$

$$\sum_{i \in S} x_{ij} \leq dem_j \qquad \forall j \in D \tag{15}$$

The objective function Z_4 in (13) minimizes the maximum percent of unmet demand defined by constraint (14). To allow for unmet demand, constraint (4) is modified as constraint (15).

The disaster relief logistics optimization models defined above are related to decision making in the preparedness stage and the response stage. These decisions are based on different performance metrics, which requires a multi-objective decision-making approach.

3.1 Multi-objective Optimization

In multi-objective optimization problems, there is usually a trade-off between various objectives. Different studies have offered many approaches to model the trade-off between multiple objective functions from the decision maker's perspective. According to Chiandussi et al. (2012), *a priori* preference articulation assume that the decision maker can pre-order the objectives before searching for the solution. The Global Criterion Method (GCM) is one of the *a priori* preference articulation methods. The target of GCM is to know how close the model is to the ideal solution (or the vector of optimal solutions for every objective function separately, while achieving all of the objective functions at the same point). We apply the GCM to determine the best set of objective function weights using the following equation.

$$L(x) = \sum_{f=1}^{F} c_f \left(\frac{Z_f(x) - Z_f^*}{Z_f^*} \right) \tag{16}$$

Where F is the number of objectives, c_f is the weight of objective function f, $Z_f(x)$ is the function value at solution x, Z_f^* is the ideal function value, and $L(x)$ is the closeness percentage. This approach is also called compromise programming. A second methodology, linear combination of weights or the weighted sum method, is an *a posteriori* preference articulation according to Chiandussi et al. (2012). We determine the objective function weights that provide the minimum closeness measure based on the GCM and use those weights when minimizing the weighted sum of objectives as $\min \sum_{f=1}^{F} c_f Z_f(x)$.

4 Case Study and Computational Results

This case study is based on a sample network shown in Fig. 1 below. In this network, there are 12 demand nodes (blue nodes) and 7 alternative depot locations (orange triangular nodes), and 2 collection points (black squares). The collection points will be used when the direct access from depots to demand nodes is limited because of the disaster impact. In those scenarios, the relief items will be sent from depots to the available collection point and then sent to the demand nodes, which is reflected in the models as increased distances to be traveled. At most 4 depot locations can be selected out of 7 to open depots at ($MD = 4$). The capacity of each depot is 600 pallets ($cap_i = 600, \forall i \in S$).

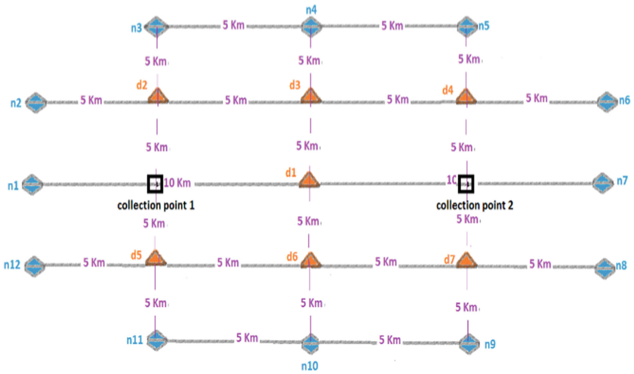

Fig. 1. The sample disaster relief logistics network

The vehicles used for transportation are trucks with a capacity of 160 pallets ($vcap = 160$). Average truck speed is assumed to be 45 km/hr. The total loading and unloading time is assumed to be 40 min. It is assumed that 5 workers and 5 vehicles are available at each depot ($Nv_i = 5$). Since the number of vehicles available at each depot is 5, and we assume that each vehicle is sent to one demand node, each depot can serve at most 5 distinct demand nodes.

Fuel cost, f_{ij}, is the product of distances and the unit transportation cost of $2.5 per km. Distribution cost, $Dist_{ij}$, is related to shipping taxes, truck driver cost, and maintenance cost, that depend on distances traveled. We assume that there are three levels of distribution costs (low, medium, and high) depending on the location of depots, as shown in Table 1. Worker cost Wr_i is equal to the product of the number of workers at a depot and the wage of each worker for that depot, which also depends on the type of depot classified as Grade A, B, or C.

The relief items are stored on pallets at depots. As an international collaborative project of NGOs, the Sphere Handbook provides universal minimum humanitarian standards, such as 2100 calories and 2.5–3 L of water per person per day (The Sphere Project 2018). The assumptions regarding the demand for relief items are made based on these standards. The types of items that should be stored on a pallet are determined based on Tzeng et al. (2007), and the quantities of items per pallet are determined to provide relief aid for four people. The value or cost of items on a pallet is estimated by an online

Table 1. Distribution and worker costs for depots

	Depots (i)	Distribution Cost ($Dist_{ij}$) ($)		Depots (i)	Worker Cost (Wr_{2i}) ($)
Low	1	120	Grade A	4, 7	40
Medium	2, 3, 4	140	Grade B	2, 5	30
High	5, 6, 7	160	Grade C	1, 3, 6	20

search for these types of relief aid items. The number of items of each type and their costs are shown in Table 2.

Table 2. Pallet contents

Relief Materials	Amount	Volume (cm^3)	Volume (unit)	Price ($)
Sleeping bag	4	12375	1	7.5
Tent	1	27300	2.21	50
Box of mineral water	1	28080	2.27	18
Rice (5 kg)	2	5225	0.42	10
Box of instant noodles	1	21199	1.71	12
Box of dry food	2	18468	1.49	15
Box of canned food	2	3532	0.29	36

In this study, we consider the demand and distances to be random parameters. We use a set of scenarios, Ω, to represent uncertainty regarding demand and distance in the model. The probability of each scenario is $P^s, s \in \Omega$, where $P^s \in [0, 1]$ and $\sum_{s\in\Omega} P^s = 1$. As shown in Table 3, we define three demand scenarios: high demand scenario with 30% probability, medium demand scenario with 45% probability, and low demand scenario with 25% probability. A set of demand values are generated from the Uniform distribution between 100 and 150 pallets for the medium demand case. Then, 125% of the medium demand is taken as the high demand case, and 75% of the medium demand is taken as the low demand case. The total random demand values for each demand scenario are shown in Table 3.

The other random factor is the condition of the transportation network. We define three distance scenarios as shown in Table 3: normal transportation conditions scenario with 40% probability, limited accessibility of demand nodes with 35% probability (direct transportation is not possible, collection point 1 must be used), and highly affected transportation network scenario with 25% probability (direct transportation or using collection point 1 is not possible, collection point 2 must be used). Therefore, S1 is the

Table 3. Scenario probabilities

		Demand		
		Low (25%)	Medium (45%)	High (30%)
	Total demand (pallets)	987	1312	1647
Distances	Direct transportation (40%)	10% S1	18% S2	12% S3
	Limited accessibility (collection point 1) (35%)	8.75% S4	15.75% S5	10.5% S6
	Highly affected network (collection point 2) (25%)	6.25% S7	11.25% S8	7.5% S9

best-case scenario in terms of low demand and short distances to be traveled, whereas S9 is the worst-case scenario with high demand and long distances to be travelled.

The case study problem is solved for Model 1–4 under scenarios S1–S9. First, Model 1–4 are individually solved for each scenario and Z_f^* are obtained. The weights of objective functions are determined to be $c_2 = 0.1$ and $c_1 = c_3 = c_4 = 0.3$ having the lowest closeness percentage according to the GCM from Eq. (16) and these are used in the linear combination of weights to find $Z_{weighted}^*$. The results are obtained using GAMS 24.6.1 software with CPLEX 12.6.3 solver on a computer with 1.50 GHz CPU AMD processor and 4 GB RAM. We provide the optimal objective function values in Table 4 and optimal depot locations in Table 5.

Table 4. Optimal objective values for each demand-distance scenario

Scenario	Z_1^*	Z_2^*	Z_3^*	Z_4^* (%)	σ_{Z_4} (%)	$Z_{weighted}^*$
S1	**5,599**	**249,220**	**47,385**	6.7	0.372	**44,135**
S2	7,442	335,830	62,987	6.2	0.202	57,728
S3	9,347	427,823	79,077	24.8	11.862	72,571
S4	16,139	267,410	61,305	**3.5**	0.458	53,624
S5	21,462	362,660	81,503	5.7	2.136	68,078
S6	26,937	465,210	102,308	24.8	11.929	86,678
S7	16,108	267,330	61,259	**3.5**	0.458	50,429
S8	21,405	362,520	81,421	5.7	1.548	68,024
S9	26,872	465,040	102,210	24.8	12.340	86,615

Our observations based on these results are as follows:

1. Given a certain distance scenario, Z_1^*, Z_2^*, and Z_3^* values decrease as the demand decreases. These objective function values are at their lowest level (best value) for

Table 5. Optimal depot locations for each demand-distance scenario

Scenario	Model 1	Model 2	Model 3	Model 4
S1	2, 4, 5, 7	1, 3	2, 4, 5, 7	1, 3, 6
S2	2, 4, 5, 7	1, 3, 6	2, 4, 5, 7	1, 2, 3, 6
S3	2, 4, 5, 7	1, 3, 6	2, 4, 5, 7	1, 3, 4, 6
S4	2, 5	1, 3	1, 2, 5	1, 3, 6
S5	1, 2, 5	1, 3, 6	1, 2, 5	1, 3, 5, 6
S6	1, 2, 5	1, 3, 6	1, 2, 5	1, 2, 3, 6
S7	4, 7	1, 3	1, 4, 7	1, 3, 6
S8	1, 4, 7	1, 3, 6	1, 4, 7	1, 3, 4, 6
S9	1, 4, 7	1, 3, 6	1, 4, 7	1, 3, 4, 6

the low demand scenarios (S1, S4, S7) and their highest level (worst value) for the medium demand scenarios (S2, S5, S8). They have slightly lower values for the high demand scenarios (S3, S6, S9) than for the medium demand scenarios.

2. The Z_4^* values are the same in S3, S6, S9, where the demand is high. So, no matter what the distance scenario is, the best possible maximum percent of unmet demand is 24.8% for this case study. The Z_4^* values for S4 and S7 are equal, the Z_4^* values of S5 and S8 are equal, as well.
3. We can also see from the results of Model 4 that the equity of percent of unmet demand gets worse as the demand gets higher. The standard deviations of percent of unmet demand among demand nodes, σ_{Z_4}, (provided in Table 4) are significantly higher in S3, S6, and S9 than other scenarios.
4. It is clear from the results that the first model can also present the optimal values not just for Z_1^* also, it gives the optimal values for Z_3^*.
5. The $Z_{weighted}^*$ value increases as the demand gets higher, given any distance scenario. It also increases in the second and third distance scenarios compared to the normal traffic conditions scenario.
6. In all the models, depot location decisions do not change significantly depending on the level of demand. There are exceptions only in the form of selecting a subset of the depots when the demand is lower, such as in S4 and S7 for Model 1 and S1, S4, and S7 in Model 2.
7. Depot location decisions in Model 1, Model 3, and Model 4 change as the matrices of distance, total transportation cost, and total accumulated waiting time are changed, i.e., as the distances change. We can see this behavior for Model 1: In S4 and S7, two depot locations are selected as opposed to four locations in S1. Also, in S5 (or S6) and S8 (or S9), three depot locations are selected as opposed to four locations in S2 (or S3). Model 3 results also show a similar pattern. However, Model 2 depot location decisions are not affected by the changing distances, and this is because the objective function cost coefficients are proportionally increasing as the distances increase. Therefore, the optimal solutions for S4 and S7 are the same for Model 2, and the optimal solution for S1 is slightly different in terms of only a few x_{ij}^* values.

8. Considering the limitation that at most 4 depot locations can be chosen, Model 1 and Model 3 choose 4 depots only in the direct transportation scenarios, but Model 4 chooses 4 depots in all but the low demand scenarios to ensure equity in terms of percent of unmet demand.

5 Discussion and Conclusion

In this comparative study of multiple objectives for disaster relief logistics, we develop models to determine depot locations and plan the distribution of relief items to demand nodes in a region affected by a disaster such as an earthquake. We consider multiple scenarios for uncertain demand and uncertain transportation network conditions. Based on the comparison of results for different objective functions and different scenarios, we identify the characteristics of the decisions made in each case. We observe that given a certain distance scenario, total distance (Z_1^*), total transportation cost (Z_2^*), and accumulated waiting time (Z_3^*) values decrease with demand. Depot location decisions in Model 1, Model 3, and Model 4 change as the distances change; however, they are not affected in Model 2 since cost coefficients are proportionally increasing with the distances. Also, the equity of percent of unmet demand (Z_4^*) gets worse as demand rises.

As a future research direction, the assumption that there are enough vehicles to deliver relief aid can be modified such that not all the demanded pallets can be loaded starting at time zero. In this case, either additional vehicles must wait, or the initial vehicles must be waited to return from the demand nodes after delivery, which would make Model 3 (minimizing the accumulated waiting time) more realistic. Considering the uncertainties in time-related parameters at the time of a disaster, this humanitarian aid distribution problem can be studied using stochastic modeling to improve the applicability of solutions. Another future research direction would be the application of the proposed models based on real data for a central region of a city such as Istanbul where the population that can be affected by a disaster is dense.

Uncertainty in demand and transportation network conditions necessitates consideration of different scenarios for disaster relief logistics. This scenario-based comparative study of multiple objectives provides valuable information regarding the performance of relief distribution decisions in various cases, and such studies can provide decision makers different perspectives and options to improve disaster relief operations and help reduce the losses due to disasters.

References

Altay N, Green WG (2006) OR/MS research in disaster operations management. Eur J Oper Res 175(1):475–493

Anaya-Arenas AM, Ruiz A, Renaud J (2012) Relief distribution networks: a systematic review. Ann Oper Res 223(1):53–79

Barbarosoglu G, Arda Y (2004) A two-stage stochastic programming framework for transportation planning in disaster response. J Oper Res Soc 55(1):43–53

Beamon BM, Balcik B (2008) Performance measurement in humanitarian relief chains. Int J Public Sect Manag 21(1):4–25

Boonmee C, Arimura M, Asada T (2017) Facility location optimization model for emergency humanitarian logistics. Int J Disaster Risk Reduct 24:485–498

Chiandussi G, Codegone M, Ferrero S, Varesio FE (2012) Comparison of multi-objective optimization methodologies for engineering applications. Comput Math Appl 63(5):912–942

de la Torre LE, Dolinskaya IS, Smilowitz KR (2012) Disaster relief routing: integrating research and practice. Socio-Econ Plan Sci 46(1):88–97

Ferrer JM, Martin-Campo FJ, Ortuño MT, Pedraza-Matinez AJ, Tirado G, Vitoriano B (2018) Multi-criteria optimization for last mile distribution of disaster relief aid: test cases and applications. Eur J Oper Res 269:501–515

Galindo G, Batta R (2013) Review of recent developments in OR/MS research in disaster operations management. Eur J Oper Res 230(2):201–211

Gonçalves P, Leiras A, Chawaguta B, Yoshizaki H (2013) Stochastic optimization for humanitarian aid supply and distribution of World Food Programme (WFP) in Ethiopia. In: 24th annual conference of the production and operations management society, pp 1–10

Gralla E, Goentzel J, Fine C (2014) Assessing trade-offs among multiple objectives for humanitarian aid delivery using expert preferences. Prod Oper Manag 23(6):978–989

Gutjahr WJ, Nolz PC (2016) Multicriteria optimization in humanitarian aid. Eur J Oper Res 252:351–366

Gutjahr WJ, Fischer S (2018) Equity and deprivation costs in humanitarian logistics. Eur J Oper Res 270(1):185–197

Huang K, Jiang Y, Yuan Y, Zhao L (2015) Modeling multiple humanitarian objectives in emergency response to large-scale disasters. Transp Res Part E Logist Transp Rev 75:1–17

Huang M, Smilowitz K, Balcik B (2012) Models for relief routing: equity, efficiency and efficacy. Transp Res Part E Logist Transp Rev 48:2–18

International Federation of Red Cross and Red Crescent Societies (2019). https://www.ifrc.org/en/what-we-do/disaster-management/about-disasters/what-is-a-disaster/. Accessed 1 Apr 2019

Mete HO, Zabinsky ZB (2010) Stochastic optimization of medical supply location and distribution in disaster management. Int J Prod Econ 126(1):76–84

Noyan N, Balcik B, Atakan S (2015) A stochastic optimization model for designing last mile relief networks. Transp Sci 50(3):1092–1113

Ransikarbum K, Mason SJ (2016) Multiple-objective analysis of integrated relief supply and network restoration in humanitarian logistics operations. Int J Prod Res 54(1):49–68

Rawls CG, Turnquist MA (2010) Pre-positioning of emergency supplies for disaster response. Transp Res Part B Methodol 44(4):521–534

The Sphere Project (2018) The sphere project: humanitarian charter and minimum standards in disaster response, 4th edn. The Sphere Project, Geneva, Switzerland

Tzeng GH, Cheng HJ, Huang TD (2007) Multi-objective optimal planning for designing relief delivery systems. Transp Res Part E Logist Transp Rev 43:673–686

Weston P (2017) Massive earthquake could hit Istanbul at any moment with just SECONDS warning, say scientists. http://www.dailymail.co.uk/sciencetech/article-4513880/Istanbul-overdue-potentially-devastating-earthquake.html. Accessed 1 Apr 2019

Zhan S, Liu N, Ye Y (2014) Coordinating efficiency and equity in disaster relief logistics via information updates. Int J Syst Sci 45(8):1607–1621