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RESEARCH ARTICLE

A stochastic location and allocation model for critical items to response large-scale emergencies: A case of Turkey

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ABSTRACT

This paper aims to decide on the number of facilities and their locations, procurement for pre and post-disaster, and allocation to mitigate the effects of large-scale emergencies. A two-stage stochastic mixed integer programming model is proposed that combines facility location- prepositioning, decisions on pre-stocking levels for emergency supplies, and allocation of located distribution centers (DCs) to affected locations and distribution of those supplies to several demand locations after large-scale emergencies with uncertainty in demand. Also, the use of the model is demonstrated through a case study for prepositioning of supplies in probable large-scale emergencies in the eastern and southeastern Anatolian sides of Turkey. The results provide a framework for relief organizations to determine the location and number of DCs in different settings, by using the proposed model considering the main parameters, as; capacity of facilities, probability of being affected for each demand points, severity of events, maximum distance between a demand point and distribution center.

1. Introduction

Large-scale emergency incidents, both natural, such as flood, earthquake, etc., and human made, such as terror (or bio-terror) attacks, can cause a big increment in demand for food, water, medical supplies or protective materials. In the early stage of post-emergencies, the demand for medical supplies and protective materials are the most vital components in reducing the number of injured people and casualties. In case of emergency, the initial supplies are needed to be delivered to the affected regions within 24 hours [1]. Sheu [2] indicates that efficient logistics play a significant role in relieving the impact of emergencies. To be able to deliver supplies on time, the locations of DCs play a critical role in humanitarian relief logistics management.

Prepositioning the DCs is a challenging task in emergency management system. Particularly, this paper addresses the location of facilities which is a critical strategic decision for suchlike systems. One of the most significant applications of location theory is the location of medical and protective supplies. Jia et al. [3, 4] introduce models and solution approaches to determine the facility location of medical supplies in response to large-scale emergencies.

Besides location decisions, capacities of supply providers are key decisions in emergency response management. However, comparatively limited research has been found on the topic of pre-positioning particular supplies [5]. The existing models usually do not consider uncertainty in demand. There has been a few works on pre- positioning first responders for large scale emergencies. Locating first-response commodities is different from locating and stocking supplies, where multiple commodities must be considered, the commodities may have different storage necessities and transportation conditions and costs [5].

In this paper, a mathematical model is proposed that combines facility location- prepositioning, decisions on pre-stocking levels for emergency supplies, and allocation of located DCs to affected locations and distribution of those supplies to several demand locations after large-scale emergencies; with uncertainty in demand and number of affected locations where high demand requirements occur. The proposed mathematical formulation is a two-stage stochastic mixed integer programming (SMIP) model,

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which is addressed as NP hard problems [6]. In many situations, parameters of the optimization problems cannot be known with certainty [5, 7, 8, 9, 10], in such cases stochastic programming (SP) methodologies are one of the strategies to apply. In two-stage stochastic programming, first-stage decisions are made in the existence of uncertainty for future scenarios. Second-stage decisions are made after the realization of the random parameters are known, and are dependent on the first-stage decisions [5, 11].

In our model, potential locations and severity of the uncertain large scale emergency events are represented via a set of discrete scenarios with probabilities. The first-stage decisions in the SP model involve the DCs' locations and allocation of the located DCs to affected regions, as well as the amount of stocking for multiple types of supplies (medical and protective). In the second-stage, recourse decisions are made including the distribution of available stocked and projected to be bought supplies, after large-scale emergencies occur, to reply particular scenario events.

In the next section, the literature on related topics is reviewed as emergency management, facility location and allocation, and prepositioning. In Section 3, the formulation of the proposed mathematical model is presented. We demonstrate the use of the model through a case study for pre positioning of supplies in probable large-scale emergencies in the eastern and southeastern Anatolian sides of Turkey. Data setup and results and analysis are presented in detail, in Section 4. Section 5 delivers conclusions and directions for future work.

2. Literature review

A survey on general insight to emergency management for operations research and management sciences is presented by Altay and Green [12]. Galindo and Batta [13] also present an extended literature review that covers the years between 2005 and 2010, inspired by Altay and Green's [12] paper. The optimization models in emergency logistics problems are reviewed in detail by Caunhye et al. [14]. In this paper, we present a literature review of the humanitarian relief logistics management taking into account disaster operations, as the facility location, prepositioning, and allocation problems, using deterministic and stochastic programming models.

The facility location problem is determined as one of the main operations of the preparedness in humanitarian relief operations. The early paper on facility location models for humanitarian relief operations are presented by Toregas et al. [15], Psaraftis et al. [16] and Iakovou et al. [17]. Jia et al. [3,4] and Huang et al. [18] presented only the location problem. Murali et al. [1] present locate-allocate heuristic for capacitated facility location to response large-scale emergencies under demand uncertainty. Shui et al. [19] present a mixed integer programming model in order to determine the locations and amounts of the emergency logistics DCs. Yushimito et al. [20] propose a heuristic algorithm based on Voronoi diagrams in order to solve the distribution center location problem.

As a preparation for an emergency, the prepositioning of supplies aims to minimize the response time, enhance emergency response capacity [21], and cover the maximum required inventory. The two-stage stochastic programming models are presented for prepositioning of relief inventory in Rawls and Turnquist [5, 22], Verma and Gaukler [23], Döyen et al. [24], Hong et al. [25], Salmerón and Apte [26], Lodree et al. [27], Campbell and Jones [28]. The relief routing [29] and disruption of network [30] is taken into consideration along with prepositioning.

Location and allocation models enable to decide where to open facilities and determine how to assign demand to facilities to increase the utilization of resources. Mitsakis et al. [31] present an optimal allocation model for emergency response to minimize maximum and average response time using existence resources. Chang et al. [32], Mete and Zabinsky [33,34], and Gunnec and Salman [35] propose two stage stochastic programming model for location and allocation of emergency relief source. Yi and Özdamar [36], Sheu [55], and Rawls and Turnquist [43] presented dynamic allocation model to optimize for preparedness and response activities. A genetic algorithm [56], particle swarm optimization algorithm [38], an epsilon constrained approach [45] are also proposed for location and allocation model for emergency response. The location-allocation plans often fail, because the uncertain and unusual nature of emergencies is not explicitly accounted [41, 57]. Stochastic programming is specified as a suitable optimization tool to plan the humanitarian relief logistics activities, because of reflecting uncertainty by probabilistic scenarios representing disasters and their outcomes [33]. Uncertainty is the nature of natural and man made disasters.

In summary, Table 1 categorizes facility location models according to the problem and data type that use deterministic or stochastic parameters. Firstly, most of the studies consider location but prepositioning. Secondly, most of the studies deal with either pre or post disaster procurements. Almost none of them take into account both procurement types. Bozorgi-Amiri et al. [38] is one of the studies that consider both procurement types. Lastly, approximately half of the studies solves problem with only deterministic parameters. In this study, we propose a two-stage stochastic optimization model to solve the location, prepositioning and allocation and post disaster procurement problem for critical items to be prepared in responding to large scale emergencies. The proposed model aims to support and improve the decisions made at strategic and operational levels for large-scale emergencies. The strategic decisions contain the location of DCs. The operational part

Table 1. Facility location problems and data type

Author	Objective	Location	Location/ Prepositioning	Location/ Allocation	Deterministic	Stochastic	
						Stochastic	Stochastic/Uncertain Parameters
Yi and Ozdamar [36]	Unsatisfied Demand Minimization	✓		✓	✓		
Yushimito and Ukkusuri [28]	Cost Minimization	✓	✓		✓		
Jia et al. [3]	Distance Minimization	✓				✓	Demand
Chang et al. [32]	Distance Minimization	✓		✓		✓	Demand
Jia et al. [4]	Coverage Minimization	✓			✓		
Günneç and Salman [35]	Time and Risk Minimization	✓		✓		✓	Demand
Mete and Zabinsky [33]	Cost and Time Minimization	✓		✓		✓	Demand and time
Balcik and Beamon [11]	Coverage Maximization	✓			✓		
Shui et al. [19]	Cost and Time Minimization	✓			✓		
Mete and Zabinsky [34]	Cost Minimization	✓		✓		✓	Demand time and supply
Rawls and Turnquist [5]	Cost Minimization	✓	✓			✓	Demand and link availability
Salmeron and Apte [26]	Unsatisfied Demand Minimization		✓	✓		✓	Demand and time
Huang et al. [18]	Coverage Maximization/Distance Minimization	✓			✓		
Han et al. [37]	Distance Minimization	✓			✓		
Verma and Gaukler [23]	Distance Minimization	✓	✓			✓	Distance
Campell and Jones [28]	Cost Minimization		✓		✓		
Duran et al. [21]	Time Minimization	✓	✓			✓	Demand/ Supply
Rawls and Turnquist [22]	Cost Minimization	✓	✓			✓	Demand and link availability
Bozorgi-Amiri et al. [38]	Cost Minimization	✓		✓		✓	Procuring cost, demand and inventory
Naji-Azimi et al. [39]	Distance Minimization				✓		
Döyen et al. [24]	Cost Minimization	✓	✓	✓		✓	Demand
Yushimito et al. [20]	Cost Minimization and Coverage Maximization	✓			✓		
Galindo and Batta [30]	Cost Minimization	✓	✓			✓	Demand
Murali et al. [1]	Coverage Maximization	✓				✓	Demand
Lin et al. [40]	Cost Minimization	✓		✓	✓		
Paul and Hariharan [41]	Cost Minimization	✓		✓	✓		
Afshar and Haghani [42]	Unsatisfied Demand Minimization	✓			✓		
Rawls and Turnquist [43]	Cost Minimization	✓		✓		✓	Demand and link availability
Hong et al. [25]	Cost Minimization	✓	✓			✓	Demand and transportation capacity
Lodree et al. [27]	Cost Minimization		✓			✓	Demand
Rath and Gutjahr [44]	Cost Minimization	✓			✓		
Abounacer et al. [45]	Unsatisfied Demand and Time Minimization	✓		✓	✓		
Sheu and Pan [46]	Distance, operational and physiological costs minimization	✓		✓	✓		
Verma and Gaukler [47]	Cost Minimization	✓	✓	✓	✓	✓	Earthquake damage and distances
Salman and Gül [48]	Time Minimization	✓		✓	✓		
Caunhye et al. [49]	Time Minimization	✓		✓	✓		
Renkli and Duran [50]	Distance Minimization		✓	✓		✓	Survivability of infrastructure
Rath et al. [51]	Coverage maximization and cost minimization			✓		✓	Route accessibility cost
Kılcı et al. [52]	Maximization of the minimum weight of open shelter areas	✓			✓		
Aydin [53]	Distance Minimization	✓		✓		✓	Failure of existing infrastructure
Tofighi et al. [54]	Distribution time and total cost minimization	✓	✓			✓	Demand, supply and network availability
Our Study	Cost Minimization	✓	✓	✓		✓	Demand

consists the prepositioning and allocation of critical items. The model also considers the penalty cost in the lack of critical items to satisfy demand (medical and protective).The paper basically contributes to emergency management literature. Additionally, the contributions of the paper on stochastic prepositioning and facility location and allocation literature are significant. Another contribution of the paper is to present a real world case study from the eastern and southeastern Anatolian sides of Turkey for response to any large scale emergency(s). It is a novel case study and unique for this region.

3. Two stage stochastic facility location-allocation model

In this section, we propose a capacitated facility location and allocation problem (CFLAP) formulation as a two-stage SP problem. As explained earlier, the objective is to minimize total cost of prepositioning, procurement, inventory holding, transportation and penalty cost of unsatisfied demand.

Now, CFLAP formulation is given as a two-stage SP problem, starting with the notation presented as follows.

Notation and mathematical formulation:
Sets:
$\mathrm{I_E}$: set of existing facility locations,
$\mathrm{I_P}$: set of possible facility locations,
I: set of all facility sites, $\mathrm{I} = \mathrm{I_E} \cup \mathrm{I_P}\ ,\ for\ \forall G, \forall NG$
$\mathrm{J_A}$: set of affected regions,
$\mathrm{J_N}$: set of non- affected (safe) regions,
J: set of all demand points, $\mathrm{J} = \mathrm{J_A} \cup \mathrm{J_N}\ \ for\ \forall G, \forall NG$
S: set of all possible scenarios,
K: set of commodities,
G: set of governmental organizations,
NG: set of non-governmental organizations,
Parameters:
f_i: fixed cost for facility $i \in \mathrm{I}, for\ \forall G, \forall NG$
cap_i: capacity of facility $i \in \mathrm{I}, for\ \forall G, \forall NG$
s: a possible future scenario and $s \in \mathrm{S}$
p_s: occurrence probability of scenario $s \in \mathrm{S}$
$r_j^s := 1$ if region $j \in \mathrm{J}$ is affected in scenario $s \in \mathrm{S}$, 0 otherwise
d_j^{ks}: demand of commodity $k \in K$ in scenario $s \in S$ for region $j \in \mathrm{J}$
c^k: procurement cost for each unit of commodity $k \in \mathrm{K}$
h^k: holding cost for each unit of commodity $k \in \mathrm{K}$
v^k: volume of each unit of commodity $k \in \mathrm{K}$
u^k: penalty cost for each unsatisfied unit of commodity $k \in \mathrm{K}$
dis_{ij}: distance between facility $i \in \mathrm{I}$ and region $j \in \mathrm{J}$
$maxdis$: maximum distance allowed to transport any commodity
md_j^k: minimum pre-disaster procurement percentage of demand for commodity $k \in \mathrm{K}$ in region $j \in \mathrm{J}$
t_{ij}: transportation cost of one unit of commodity $k \in \mathrm{K}$ from facility $i \in \mathrm{I}$ to region $j \in \mathrm{J}$

Decision variables:
$x_i := 1$ if facility $i \in \mathrm{I}$ is opened, 0 otherwise
$\beta_{ij} := 1$ if facility $i \in \mathrm{I}$ is assigned to region $j \in \mathrm{J}$, 0 otherwise
α_j^{ks}: unsatisfied demand from commodity $k \in \mathrm{K}$ at region $j \in \mathrm{J}$ in scenario $s \in \mathrm{S}$
y_{ij}^k: pre-disaster procurement from commodity $k \in \mathrm{K}$ at facility $i \in \mathrm{I}$ to be transported to region $j \in \mathrm{J}$
z_{ij}^{ks}: post-disaster procurement of commodity $k \in \mathrm{K}$ at facility $i \in \mathrm{I}$ to be transported to region $j \in \mathrm{J}$ in scenario $s \in \mathrm{S}$

In the scenario based formulation of CFLAP, each scenario denotes a different circumstance, the affected regions and non- affected regions with a different level of severity. Each scenario $s \in S$ occurs with a different probability,$\mathrm{p_s}$, and $\sum_{\mathrm{s \in S}} \mathrm{p_s} = 1$. In total, in case of independent affecting possibilities, we have $|\mathrm{S}| = 2^{|\mathrm{J}|}$ possible scenarios. Please note that our model does not necessitate any assumption on independence of each scenario. Furthermore, each unit of demand that is not satisfied by any of facility(s) cause a large penalty,$\mathrm{u}^k\ k \in \mathrm{K}$, cost. This penalty can be incurred due to casualties or finding an alternative source to treat disaster victims. There are some assumptions need to be highlighted such as all costs are known in advance i.e., fixed cost of locating facilities, holding cost, procurement cost, transportation cost, penalty cost of unsatisfied demand. Distance between facilities and affected regions are gathered from Google Maps [58]. Population of the affected regions is gathered from TUIK [59]. A maximum distance is assumed so that the maximum traveling distance between affected regions and the allocated facility cannot exceed a specific value. Also some limitations are need to be specified such as, if applicator has uncertainty in supply, time, cost etc. the modeler will need to redesign the mathematical model, and if there are larger number of nodes in the network the mathematical model will need to be solved via heuristics or metaheuristics solution approaches.

Here, the CFLAP is formulated as a two-stage stochastic programming problem. In the first stage, the location decisions are made before random large-scale emergencies occur. In the second stage, following the events, the affected region-facility assignments decisions are made for each affected region given that the particular regions are affected and facilities are located. The objective is to determine the set of facilities to be located while minimizing the total cost of open facilities and the expected cost of satisfying demand for affected regions from new opened facilities.

Using the notation, we present the mathematical model for the scenario based CFLAP as a two-stage stochastic program as below, starting with the objective function.

$$\text{Minimize} \quad \sum_{i\in I} f_i x_i + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}(c^k + h^k) y_{ij}^k + \sum_{s\in S} p_s \left(\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c^k z_{ij}^{ks} + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} t_{ij}(y_{ij}^k + z_{ij}^{ks}) + \sum_{i\in I}\sum_{k\in K} u^k \alpha_j^{ks} \right) \quad (1)$$

Subject to

$$\sum_{j\in J}\sum_{k\in K} v^k (y_{ij}^k + z_{ij}^{ks}) \le cap_i x_i \quad \forall i \in I, s \in S \quad (2)$$

$$\sum_{i\in I} (y_{ij}^k + z_{ij}^{ks}) + \alpha_j^{ks} \ge d_j^{ks} r_j^s \quad \forall j \in J, k \in K, s \in S \quad (3)$$

$$\sum_{i\in I} y_{ij}^k \ge md_j^k d_j^{ks} \quad \forall j \in J, k \in K, s \in S \quad (4)$$

$$v^k (y_{ij}^k + z_{ij}^{ks}) \le cap_i \beta_{ij} \quad \forall i \in I, j \in J, k \in K, s \in S \quad (5)$$

$$\beta_{ij} \le x_i \quad \forall i \in I, j \in J \quad (6)$$

$$dis_{ij}\beta_{ij} \le max dis \quad \forall i \in I, j \in J \quad (7)$$

$$y_{ij}^k, z_{ij}^{ks}, \alpha_j^{ks} \in \text{int and} \ge 0 \quad \forall i \in I, j \in J, k \in K, s \in S \quad (8)$$

$$x_i, \beta_{ij} \in \{0,1\} \quad \forall i \in I, j \in J \quad (9)$$

The objective function in formulation (1) minimizes the total fixed cost of locating facilities and the expected second stage cost of satisfying demand through opened facilities. Constraint (2) ensures that the total procured commodities at a facility do not exceed its capacity. Constraint (3) ensures that demand of each demand point is satisfied by either open facilities or alternative sourcing, or penalized. Constraint (4) ensures minimum procurement amounts for each commodity and facility. Constraints (5) and (6) prevent procurement at a facility and assignment of any demand point to a facility if it is not opened. Constraint (7) ensures that demand points are assigned to facilities that are within maximum distance. Finally, the constraints (8) and (9) are integrality constraints.

The proposed model provides a generic scenario based model to handle uncertainty in demand. The model can be applied to any region or case where uncertainty occurs in demand. Additionally, the model is easy adaptable to the cases where capacity of the facilities are not issue. By replacing cap_i in the right hand side of constraints (2) and (5) by a big number (let say M) is enough to develop an uncapacitated version of the model. Furthermore if maximum distance to travel per region is not an issue removing constraint (7) will be good enough to revise the model and apply. Another robustness of the model is that it can be solved by heuristics approaches if number of scenarios or number of nodes or number of regions is very large.

4. The case of Turkey

In this section, we present a case study motivated by a real-world problem from eastern and southeastern parts of Turkey. We describe the case details in Section 4.1 and present the results in Section 4.2.

4.1. Case description and data acquisition

This case study focuses on locating new DCs at the eastern and southeastern Anatolian sides of Turkey in response to possible large-scale emergencies. Turkish Red Crescent (TRC) is responsible for administration of Turkish domestic relief networks with a number of DCs, which preserve inventory for emergency supplies [60]. Balcik and Ak [60] note that the TRC currently works on pre-positioning some emergency supplies for a large scale emergency. One of our motivations is to determine the number of DCs to effectively satisfy all demands that may be caused by large scale emergencies.

Although facility location problems are widely experienced in large-scale emergency field, the detailed data related to this problem and DCs' features are not publicly available. Furthermore, there is no standard data set that contains data for emergency event scenarios and demand estimates for relief supplies. We obtain the most of our data from governmental and non-governmental organizations; for the missing parts we develop sample problem sets to perform numerical analysis. Subsequently, the parameters are set realistically without any limiting assumptions. Therefore, the results from these data set samples can be generalized. Medical and protective materials are the most critical supplies for the victim's survival and health. An emergency event might be very severe and affect thousands of people in a very short time period. Therefore, it is very important to distribute medical and protective materials to demand points immediately after or before (if the event is expected beforehand) the emergency event occurs.

In this case study, we address the problems of pre-positioning DCs at specified regions of Turkey and procurement of multiple items (medical and protective materials) at these DCs for pre and post large scale emergencies. The population of the regions (demand points), the distance between DCs and regions, the locations and capacities of current DCs and the cost of critical items are problem specific and based on real data. Therefore, we propose the demand scenarios and related parameters as explained below.

Demand Scenarios: Each scenario represents the set of regions that might be affected by emergency event and the severity level of the event. Demand of each region for a specific scenario is calculated via logic in Jia et al. [4]. Four levels are used in Jia et al. [4], such as ''low, intermediate, intermediate-high and high''. We practice four levels of severity as well. Let sev (:={0.03,0.05,0.07,0.09}) be the severity set of the emergency event, and sev_w^s be the scenario s's severity at level w,w∈sev. Let ρ_j denote the population of the affected region j. The population data of demand points are obtained from Turkish Statistical Institute's database from its formal website [59] and provided in Table 2. Note that, the demand for different types of commodities is considered to be the same, which is a non-restrictive assumption and easily can be generalized. Then, demand for a scenario is calculated as below.

$$d_j^{ks} = sev_w^s \rho_j \quad \forall j \in J, k \in K, w \in sev, s \in S \quad (11)$$

Lastly, note that each problem set consists of 1024 ($|S| = 2^{|\#\text{of Demand Points}|}$) scenarios. The deterministic equivalent formulation has variables x_i, β_{ij}, y_{ij}^k, z_{ij}^{ks} and α_j^{ks}, in total |I||+|I|×|J|+|I|×|J|×|K|+|I|×|J|×|K|×|S|+|J|×|K|×|S|= 10+10×10+10×10×2+10×10×2×1024+10×2× 1024 = 225,590 variables. Similarly, it has constraints (2), (3), (4), (5), (6), (7) and (8), in total 461,200 constraints.

Table 2. The populations of the regions (demand points)

Region	Population	Region	Population
1	2,125,635	**6**	762,366
2	1,592,167	**7**	1,063,174
3	778,195	**8**	773,026
4	1,799,558	**9**	1,762,075
5	1,483,674	**10**	1,051,975

Minimum Stocked Demand: Medical and protective materials are vital for victims; therefore, these supplies need to be distributed immediately to the affected regions. Pre-positioning a particular amount of supplies at DCs is one of the best ways to respond emergency events on time. Thus, we add the minimum demand constraints to the formulation. As described earlier, md_j^k represents the minimum percentage of demand in affected region j from commodity k that needs to be procured pre-disaster. We practice one for md_j^k $(:= \{0.3\})$. The minimum demand that needs be procured is calculated as the production of demand and percentage levels ($md_j^k d_j^{ks}$). Since pre-positioning is the first stage decision variables in SP, the amount of demand that needs to be stocked has to satisfy the constraints in (4) for all scenarios.

Scenario Probabilities: In generating the scenarios, we assume that the regions are affected independently and identically, as the events have Bernoulli distribution with probability q_j (i.e., the occurrence probability of the event at region j). In our experiments, we use two types of occurrence probabilities; uniform failure probability (i.e., $q_j = 1, \dots, |J| = q$), which considers the cases $q = \{0.3, 0.5, 0.8\}$, and randomly selected values.

Capacity: Based on the information obtained from a non-governmental organization, whose major motivation is to manage the distribution of supplies to victims who are affected by disasters, the capacity of DCs varies between $15Km^3$ and $50Km^3$. Therefore, we test eight capacity levels in this study, such as $15K\,m^3$, $20Km^3$, $25Km^3$, $30Km^3$, $35Km^3$, $40Km^3$, $45Km^3$ and $50Km^3$.

Max Distance: Since responding large-scale emergencies is like racing with time, we consider maximum distance constraints, what ensure that a commodity can only be transported from a distribution center to affected regions that are in a specific range. In other words, the service distance levels are identified. Detailed information on service distance minimization can be found in Jia et al. [4] and Lin et al. [40]. The experimental samples are tested with respect to six different levels of distance ranges, such as $350km$, $400km$, $450km$, $500km$, $550km$ and $600km$.

Table 3. Distances between distribution centers and regions (demand points)

	Distances between DCs and Regions (km)									
DCs	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Adana	0	522	808	209	191	392	189	534	346	899
Diyarbakir	522	0	324	313	509	251	369	95	176	377
Elazig	490	153	318	345	477	98	321	248	329	475
Erzurum	808	324	0	637	795	416	639	419	500	414
Mus	742	258	266	571	729	350	573	353	434	223
Gaziantep	209	313	637	0	196	247	80	325	137	690
Hatay	191	509	795	196	0	379	176	521	333	886
Malatya	392	251	416	247	379	0	223	346	269	573
Sanliurfa	346	176	500	137	333	269	217	188	0	553
Van	899	377	414	690	886	573	746	452	553	0

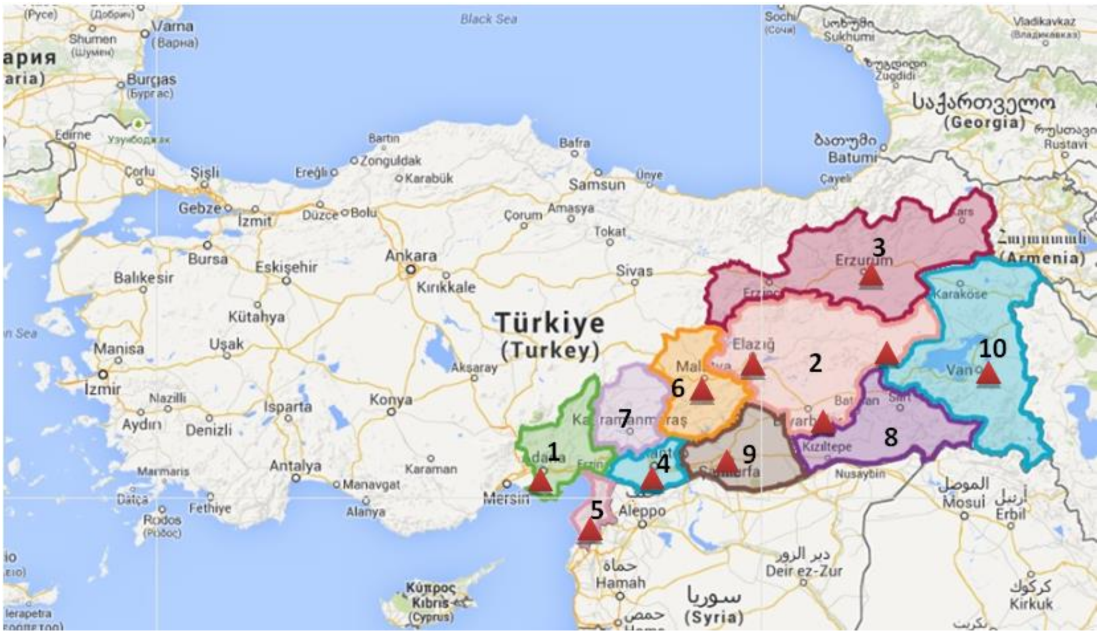


Figure 1. Regions and locations of DCs

Table 4. Effects of capacity on location decisions and total cost

Capacity	Impact	Objective	Open Decisions	Impact	Objective	Open Decisions
15K		50,599,764	1,2,3,4,5,6,7		187,188,418	1,2,3,4,5,6,7,8,9,10
20K		51,984,362	1,3,5,6,7,9		166,402,454	1,2,3,4,5,6,7,8,9,10
25K		52,035,866	5,6,7,8,9		147,390,098	1,2,3,4,5,6,7,8,9,10
30K		52,509,772	5,6,7,8,9		132,785,959	1,2,3,4,5,6,7,8,9,10
35K	**0.03**	51,397,250	5,6,7,9	**0.07**	124,952,934	1,2,3,4,5,6,7,8,9,10
40K		51,828,149	5,6,7,9		122,077,183	1,3,4,5,6,7,8,9,10
45K		52,424,826	5,6,7,9		119,405,632	1,3,5,6,7,8,9,10
50K		50,696,695	5,7,9		116,448,701	1,3,6,7,8,9,10
15K		94,740,147	1,2,3,4,5,6,7,8,9,10		320,907,135	1,2,3,4,5,6,7,8,9,10
20K		87,766,262	1,2,3,4,5,6,7,8,9,10		265,670,113	1,2,3,4,5,6,7,8,9,10
25K		87,536,511	1,3,4,5,6,7,8,9,10		242,583,042	1,2,3,4,5,6,7,8,9,10
30K		86,923,893	1,3,5,6,7,8,9,10		220,700,621	1,2,3,4,5,6,7,8,9,10
35K	**0.05**	85,888,361	1,3,6,7,8,9,10	**0.09**	199,740,250	1,2,3,4,5,6,7,8,9,10
40K		84,395,974	3,6,7,8,9,10		181,120,654	1,2,3,4,5,6,7,8,9,10
45K		84,988,539	4,6,7,8,9,10		166,774,135	1,2,3,4,5,6,7,8,9,10
50K		83,031,958	3,6,7,9,10		157,792,895	1,2,3,4,5,6,7,8,9,10

Distances between DCs and demand points are obtained from the Republic of Turkey General Directorate of Highways' database [61]. The distances between projected to be opened DCs and regions (demand points) are presented in Table 3.

Regions: We group the regions based on their populations (i.e., including overcrowded cities) and strategic importance (i.e., location, population, locating military quarters, etc.). Ten regions are determined at eastern and southeastern Anatolian sides of Turkey. Each region is numbered and differently colored as in Figure 1. The triangles show the possible locations to set up DCs at.*Other Costs:* Set up cost for each DC changes based on its capacity level. Furthermore, this cost does not increase linearly with the incremental in capacity. Set up cost is determined as follows: Incremental cost for one of unit capacity up to $15Km^3$ is $100(TL - Turkish\ Lira)$, between $15K$ and $20K$ is $95(TL)$, and for the ranges between $20K-25K$, $25K-\ 30K$, $30K-35K$, $35K-40K$, $40K-45K$ and $45K-50K$ are $90, 85, 80, 75, 70$, and 65 (TL), respectively. Then, for instance, cost of locating a DC with $15Km^3$ is $1.5M$ $(= 15{,}000x100)$ and with $20Km^3$is $1.9M$ $(= 20{,}000x95)$. As mentioned earlier, two types of commodities (medical and protective materials) are considered here. Purchasing cost of each unit is $70\ (TL)$ and $40\ (TL)$ for medical and protective supplies, consecutively. Holding cost for one unit of medical supply is $30\ (TL)$, and for one unit of protective materials is $20\ (TL)$. Penalty cost for each unit of unsatisfied demand is considered as $500(TL)$ for medical, and $300(TL)$ for protective materials.

4.2. Results and discussions

The case samples are solved by using IBM ILOG/CPLEX 12.1.0 on a desktop computer with Intel (R) Core (TM) i5-2400M 3.10GHz CPU.

Effect of capacity decisions: In this subsection, minimum average demand is fixed to 30%, maximum distance to $400(km)$, and scenario probabilities are considered to be random.

Changes in capacities have larger effect on facility decisions when large-scale emergencies have low impact. In other words, results show that the number of opened facilities is more sensitive to capacities in cases of low impact events. On the contrary, the capacity changes have less effect on location decisions, when large-scale emergencies have larger impact. For instance, when capacity is increased from its minimum value $(15K)$ to the maximum value $(50K)$, the number of opened facilities decreases from seven to three, under the impact factor 0.03, and from ten to five, under the impact factor 0.05. Since a large number of facilities are necessary to create extra capacity for responding to large-scale emergencies, more possible facility locations are needed to be determined; because even if all facilities are decided to be opened with the maximum capacity, the demand is still not fully satisfied.

As seen in Table 4, the number of opened facilities reduces along with the increment in capacities. Seven facilities are decided to be located when capacity is $15K$, six when $20K$, five when $25K$ and $30K$, four when $35K, 40K$ and $45K$, and three when $50K$, under the 0.03 impact factor case. The same changes can be observed when impact factor is increased to 0,05. All facilities are opened if selected capacity is less than $25K$. Number of opened facilities continuously reduces from 10 to 5, when capacity is increased up to $50K$. The reason of opening all facilities can be explained with the lack of capacity to satisfy all demand. The lack of capacity causes to open all facilities in almost all cases except when capacity is higher than $35K$ under 0.07 impact factor case. All facilities are opened when impact factor is 0.09. This explanation can be fortified by analyzing the cost elements that constitute the expected total cost. For instance, in the case when impact factor is 0.09 and capacity is $15K$, then 67% of expected total cost is the penalty cost of not being able to satisfy demand, while $5\%, 18\%$, and 10% are fixed, pre-procurement and post-procurement costs, consecutively. The transportation cost constitutes only less than 1% of expected total cost. Moreover, the results indicate that larger number of facilities would be used only for meeting demand requirements if reserve capacities are set sufficiently large.

The results in Figure 2 indicate that the expected total cost generally is sensitive to facility capacities, especially when large-scale emergencies have higher impact. Expected total cost decreases by 62% when capacity is increased to its maximum level from its minimum level under high impact events. In other words, the 67.5% of the expected total cost is caused from expected penalty cost when capacity is at its minimum level $(15K)$, and penalty cost reduces to 4.75% when capacity is at its maximum level $(50K)$. The same conclusion is attained from the case with 0,07 impact events. As a result, larger savings in penalty costs occur in the cases with high impact events via increased facility capacity. Since total available capacity is sufficiently enough to satisfy all demand under low impact events (i.e.0.03), expected total cost may increases, because of redundancy in capacity. We conclude that, any large-scale emergency with a lower impact than 0.03 can be responded with the minimum cost and 100% satisfaction. This satisfaction can be responded either by seven facilities with $15K$ capacity level or three one with $50K$ capacity level. Therefore, it is valuable information for decision makers to locate facilities with higher capacities to response high impact events and lower capacities to response low impact events.

Effect of maximum distance: In this subsection, minimum average demand is fixed to 30%, capacity to $30K\ and\ 50K$, separately, and scenario probabilities are considered to be random.

Facility capacities and maximum distance may highly affect the total costs in settings under high and low impact large-scale emergencies. The samples include a combination of scenarios with high and low impact events, and demand fluctuations across scenarios are large. In this section, we test the sensitivity of costs and location decisions with respect to the changes in capacities and maximum distance. Specially, we perform experiments with maximum distance values that range from $350\ to\ 600\ (km)$ and facility capacities. Two levels of capacities are performed, such as $30K$ and $50K$. as shown in Table 5, total costs and number of opened facilities are sensitive to maximum distance and capacity, which is consistent with our previous observations.

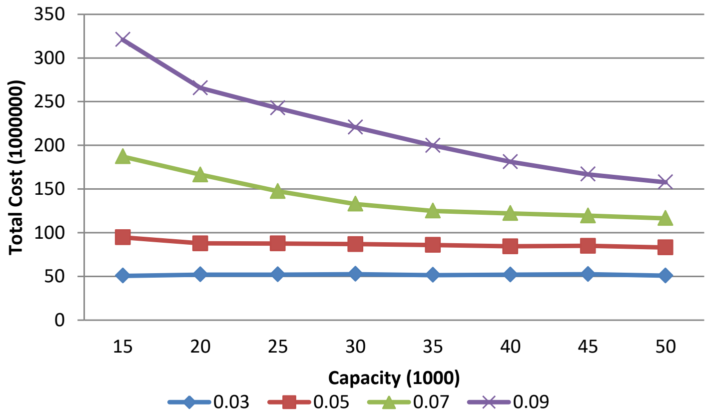
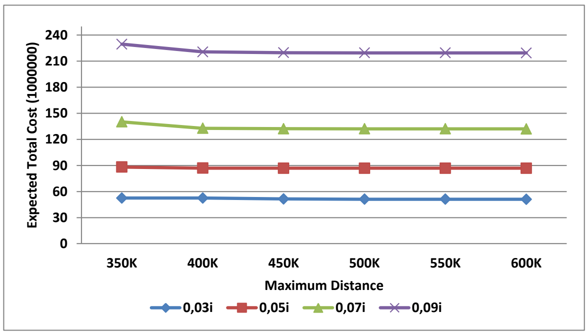


Figure 2. Effects of capacity on total cost

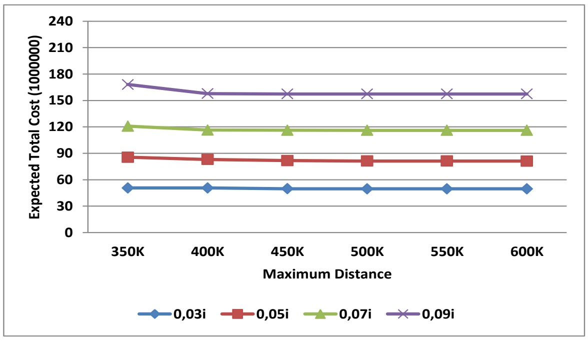
Table 5. Effects of maximum distance on location decisions and total cost

Maximum Distance(km)	Impact	Capacity=30,000 Objective	Capacity=30,000 Open Decisions	Capacity=50,000 Objective	Capacity=50,000 Open Decisions
350	**0.03**	52,510,024	5,6,7,8,9	50,703,287	5,7,9
400		52,509,772	5,6,7,8,9	50,696,695	5,7,9
450		51,464,657	6,7,9,10	49,797,837	7,9,10
500		51,153,242	6,7,9,10	49,694,821	7,9,10
550		51,153,242	6,7,9,10	49,694,821	7,9,10
600		51,062,473	6,7,9,10	49,691,690	7,9,10
350	**0.05**	88,091,898	1,3,4,5,6,7,8,9	85,546,944	4,6,7,8,9,10
400		86,923,893	1,3,5,6,7,8,9,10	83,031,958	3,6,7,9,10
450		86,809,666	1,3,4,6,7,8,9,10	81,774,616	6,7,9,10
500		86,798,057	1,3,4,6,7,8,9,10	81,255,582	6,7,9,10
550		86,798,057	1,3,4,6,7,8,9,10	81,255,582	6,7,9,10
600		86,797,263	1,3,4,6,7,8,9,10	81,104,293	6,7,9,10
350	**0.07**	140,215,849	1,2,3,4,5,6,7,8,9,10	120,816,966	1,3,4,6,7,8,9,10
400		132,785,959	1,2,3,4,5,6,7,8,9,10	116,448,701	1,3,6,7,8,9,10
450		132,226,870	1,2,3,4,5,6,7,8,9,10	116,214,909	1,4,6,7,8,9,10
500		132,144,639	1,2,3,4,5,6,7,8,9,10	116,142,857	1,4,6,7,8,9,10
550		132,144,639	1,2,3,4,5,6,7,8,9,10	116,142,857	1,4,6,7,8,9,10
600		132,080,556	1,2,3,4,5,6,7,8,9,10	116,140,350	1,4,6,7,8,9,10
350	**0.09**	229,490,054	1,2,3,4,5,6,7,8,9,10	168,121,111	1,2,3,4,5,6,7,8,9,10
400		220,700,621	1,2,3,4,5,6,7,8,9,10	157,792,895	1,2,3,4,5,6,7,8,9,10
450		219,702,659	1,2,3,4,5,6,7,8,9,10	157,420,474	1,2,3,4,5,6,7,8,9,10
500		219,585,144	1,2,3,4,5,6,7,8,9,10	157,364,838	1,2,3,4,5,6,7,8,9,10
550		219,584,994	1,2,3,4,5,6,7,8,9,10	157,364,838	1,2,3,4,5,6,7,8,9,10
600		219,438,357	1,2,3,4,5,6,7,8,9,10	157,340,757	1,2,3,4,5,6,7,8,9,10

The samples, in which the maximum distances are increased to $600km$ of their minimum levels, $(350km)$, lead to less expected total cost in all cases and less opened facilities in some cases. For instance, in low impact events (0.05) six facilities $(4, 6, 7, 8, 9,$ and $10)$ are opened when maximum distance is restricted to $350km$. However, the number of opened facilities is reduced to five $(3, 6, 7, 9,$ and $10)$ when maximum distance is increased to $400km$. The only change is not restricted with the number of opened facilities. Design of the solution is changed; facilities 4 and 8 are not selected to be opened and facility 3 is opened instead.



a) Capacity=30.000



b) Capacity=50.000

Figure 3. Effect of maximum distance on total costs

As realized in Figure 3, expected total costs are more sensitive to maximum distance under high impact events and less sensitive to low impact events. Total expected costs decrease continuously with the increments in maximum distance. In Figure 3 a), expected total cost decreases by 4% under 0.09 impact factor, when maximum distance increases from $350km$ to $600km$. Expected total cost decreases by $6\%, 1\%$ and 3% under $0{,}07, 0{,}05$ and $0{,}03$ impact factor cases, consecutively. The same observation can be gained in Figure 3 b). Expected costs decrease by $2\%, 5\%, 4\%,$ and 6% for cases $0.03, 0.05, 0.07,$ and 0.09 impact factors, consecutively. Note that capacities are considered $30{,}000$ and $50{,}000$ in Figure 3 a) and b), sequentially. Another observation is that the expected total costs decrease even if the solutions (number of and opened facilities) do not change. We conclude that maximum distance and capacity decisions have relatively high impact on expected total cost and solution.

Effect of scenario probability: In this subsection, minimum average demand is fixed to 30%, capacity to $30K$ and $50K$, separately, and maximum distance is considered as $4{,}5$ km.

In this subsection, we analyze the effects of scenario probabilities on expected total costs and location decisions. We perform experiments with scenario probability values that range from 0.3 to 0.8 (km). Lastly, we make a test with a random scenario probability. In the unique cases, demand points are subjected to be affected with the same probability (i.e., 0.3), while they are subjected to be affected based on their strategic importance and population in the random case.

According to Figure 4 a) and b), we conclude that expected total costs are very sensitive to scenario probabilities. Note that, figure in a) shows the fluctuations of expected total costs respect to scenario probabilities when facilities' capacities are selected as 30K, while figure b) shows the changes when facilities' capacities are selected as 50K. In both cases, expected total costs increase with the increase in scenario probabilities. In figure a), expected total cost is about $24M$ when demand points are subjected to be affected with 0.3 probability with a low impact event (i.e., 0.03). Expected total cost increases to $92M$ if being effected probability is increased to 0.8; this means an 377% increment in expected total cost. Scenario probability has higher effect on higher impact events in terms of expected total cost. For instance, the increment in expected total cost is 449% when scenario probability is increased from 0.3 to 0.8, under high impact events (0.05). Expected total costs are very high under very high impact events $(0.07$ and $0.09)$. This is because even if all facilities are opened, demands of affected regions are still not satisfied and penalty cost occurs. The same analyzes are showed for the results shown in Figure4 b).

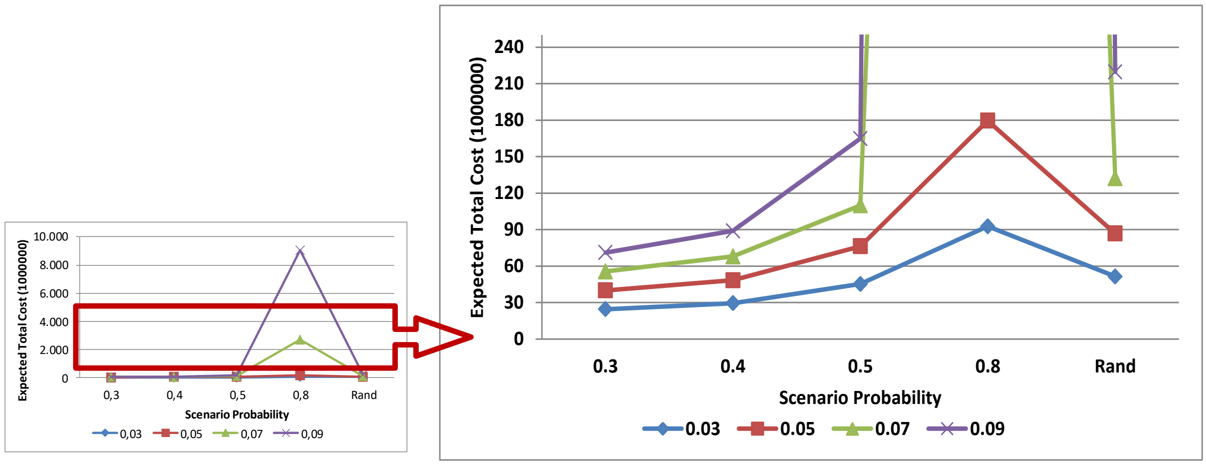
As expected, fewer facilities are needed to satisfy demand with a minimum cost under low occurrence probability of an event or less impact events and/or higher facility capacities. It is clearly seen from Table 6. We compare the case where impact factor is $0{,}05$ in Table 6; only two facilities $(5$ and $6)$ are opened if capacity is $50K$ and three facilities (in regions $6{,}9$ and 10) are opened if capacity is $30K$. The number of opened facilities and solution change and expected total cost decreases.

In summary, given the same data, considering different large-scale emergencies' impact levels in scenario generation may have different cost implications. Therefore, it is important to test the inferences of alternative set of large-scale emergency scenarios in making decisions. In particular, the effects of high impact large-scale emergencies must be wisely analyzed in establishing response strategies.

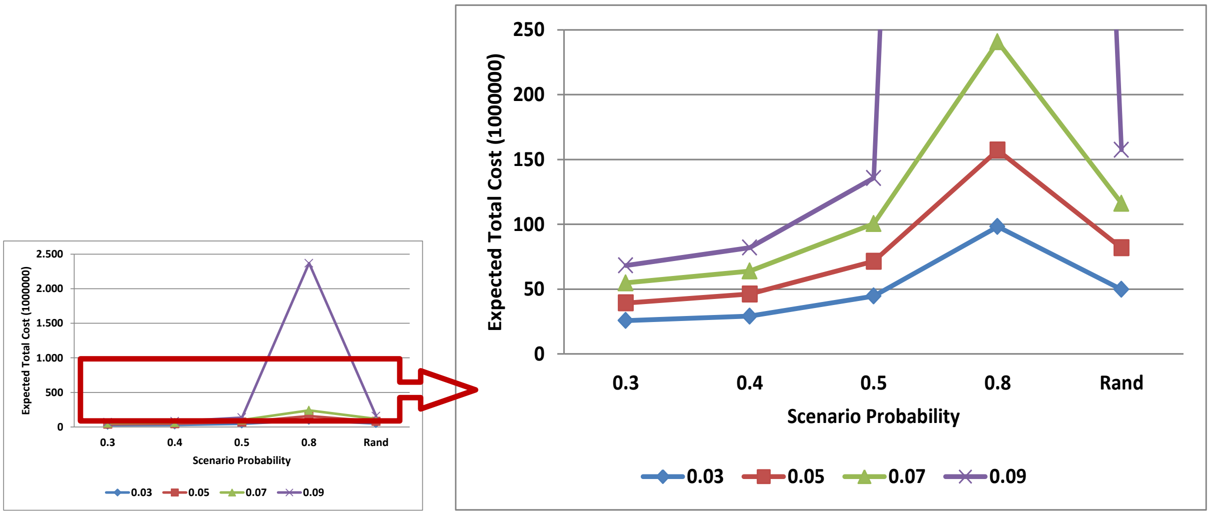
As can be implied from the analysis, managers face tradeoffs between capacity, number of facilities and cost/distance minimization. To handle these tradeoffs the analyses provided above are good guides to take strategical decisions.

5. Conclusions and future directions

This study addresses a facility location problem for responding large-scale emergencies. We aim to pre-position DCs at the eastern and southeastern Anatolian sides of Turkey to response to any large-scale emergency. Multi supplies, such as medical and protective materials, are considered.



a) Capacity=30,000



b) Capacity=50,000

Figure 4. Effect of scenario probability

A relief organization must determine the optimal number of opened DCs and locations of DCs pre-disaster under demand uncertainty. We illustrate the uncertainty in demands by defining a set of probabilistic scenarios and developing a scenario based stochastic programming model. Scenarios are created based on impact (severity) of the event and probability of being affected. We perform numerical experiments on a real case study to understand the effects of parameters that may influence the solution. Capacity of facilities, probability of being affected for each demand points, severity of events, maximum distance between a demand point and distribution center are main parameters that are tested. The results provide a framework for relief organizations to determine the location and number of DCs in different settings. The key contribution of this study is to design a response strategy to distribute supplies in a large-scale emergency, that considers distance coverage and demand uncertainty, in addition, multi-type supplies.

The contributions of the paper to the literature are specified as follows: (1) The existing facilities are capacitated; (2) the demand is satisfied which depends on distance to DCs. If distance between any DC and an affected region exceeds a non-desirable distance, then no supply is distributed between them. This is because while planning response to a large-scale emergency scenario, it is rational to assume that the number of people expected to be assigned to a specific DC decreases as their distance to that DC increases; (3) given the unpredictability as to when and where such an emergency scenario could occur and how many people would be affected, there is a significant uncertainty in demand values. Since the amount of demand is uncertain and unknown, a two stage stochastic programming model is developed to express the effects of uncertainty on the strategic decisions; (4) the goal is to determine locations of new DCs while taking into consideration the existing DCs' locations and capacities. Consideration of existing DCs while determining the location of the new DCs is an important contribution to the large-scale emergencies literature; (5) multi type supplies are considered, because in the case of large-scale emergencies not only medical materials but also protective materials should be considered; (6) a real world case study is presented from the eastern and southeastern Anatolian sides of Turkey to response to any large-scale emergency. It is a novel case study and unique for this region; (7) it is aimed that, the proposed method will be used in different regions of different countries, to evaluate and improve their response strategies to any type of large-scale emergencies.

Table 6. Effect of scenario probability on expected total cost and location decisions

Scenario Probability	Impact	Capacity=30,000 Objective	Capacity=30,000 Open Decisions	Capacity=50,000 Objective	Capacity=50,000 Open Decisions
0.3	**0.03**	24,555,936	5.6	25,702,438	6,10
0.4		29,495,398	7,9,10	29,157,840	6,10
0.5		45,252,520	6,7,9,10	44,574,995	7,9,10
0.8		92,658,994	1,2,4,6,7,8,9,10	98,246,602	1,2,4,6,7,8,9,10
Rand		51,464,657	6,7,9,10	49,797,837	7,9,10
0.3	**0.05**	40,029,240	6,9,10	39,260,126	5,6
0.4		48,382,553	7,8,9,10	46,159,088	7,9,10
0.5		76,311,612	1,3,6,7,8,9,10	71,421,004	6,7,9,10
0.8		179,579,410	1,2,3,4,5,6,7,8,9,10	157,134,539	1,2,4,6,7,8,9,10
Rand		86,809,666	1,3,4,6,7,8,9,10	81,774,616	6,7,9,10
0.3	**0.07**	55,530,956	6,8,9,10	54,751,772	6,9,10
0.4		67,909,481	6,7,8,9,10	63,880,905	7,8,9,10
0.5		109,898,741	1,2,3,4,5,6,7,8,9,10	100,492,515	6,7,8,9,10
0.8		2,721,559,062	1,2,3,4,5,6,7,8,9,10	240,715,621	1,2,3,4,5,6,7,8,9,10
Rand		132,226,870	1,2,3,4,5,6,7,8,9,10	116,214,909	1,4,6,7,8,9,10
0.3	**0.09**	71,119,761	6,7,8,9,10	68,257,643	7,9,10
0.4		89,018,805	1,5,6,7,8,9,10	81,966,059	6,7,8,9,10
0.5		164,871,554	1,2,3,4,5,6,7,8,9,10	135,735,487	1,3,4,5,6,7,8,9,10
0.8		9,059,054,031	1,2,3,4,5,6,7,8,9,10	2,368,833,930	1,2,3,4,5,6,7,8,9,10
Rand		219,702,659	1,2,3,4,5,6,7,8,9,10	157,420,474	1,2,3,4,5,6,7,8,9,10

Since there is lack of studies on these topics, we discuss several future researches. Firstly, some other sources can be used to satisfy demand besides prepositioning, such as framework agreements. More than one option can be considered simultaneously, which may be more effective in response to large-scale emergencies. For example, a future research can consider the decisions related to the amount of supplies to pre-position and reserve from framework agreements in an integrated way. Secondly, since the presented problem is a cost minimization problem, budget constraints can be incorporated into the model. Thus, the problem will be held into a more realistic way. Thirdly, as DCs are located before the large-scale emergencies occur, they may already got affected by the events. Therefore, future research can focus on developing models which incorporate the reliability of the DCs as another uncertainty while designing the network. Lastly, since capacitated facility location problems are very difficult problems, in terms of computational cost, approximation methods such as sample average approximation, genetic algorithms, etc. can be used to solve larger networks.

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