A Fuzzy Integer Programming Model to Locate Temporary Medical Facilities as Part of Pre-Disaster Management

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ABSTRACT

The number and the scale of natural disasters have drastically increased over the last decades. One of the most vital stages of disaster preparedness is disaster response planning, and it plays an important role in limiting material and immaterial consequences, such as those caused by large scale earthquakes. In order to minimize human suffering and death, the aim of establishing a well-designed humanitarian relief chain must be to provide medicine, water, shelter, emergency food and supplies to the affected areas. From a holistic perspective, providing timely first aid and rapid transfer of injured victims to a medical facility is one of the most essential component of such chain. Thus, the location of first aid hospitals must be determined following a careful thought and planning process. This study presents a fuzzy integer programming model to determine the best location of the temporary hospitals which are expected to support extant state hospitals after a major earthquake. This study applies the proposed fuzzy model to the Üsküdar province of Istanbul and identifies optimum number and locations of field hospitals for a severe earthquake scenario.

KEYWORDS

Disaster Management, Fuzzy Integer Programming, Location Allocation Problem, Verdegay Method

INTRODUCTION

Over the recent decades, the number of natural disasters (such as earthquakes, flood, drought, civil unrest, war, political/tribal disturbance) has dramatically increased all over the world. According to the Center for Research on the Epidemiology of the Disasters, 6.637 natural disasters occurred between 1974 and 2003 worldwide, with more than 5.1 billion affected people, 182 million homeless, 2 million deaths, and with a reported damage of \$1.38 trillion USD (Ergun et al., 2009) The International Strategy for Disaster Reduction (ISDR) calculates that the global cost of natural disasters would exceed \$300 billion annually by the year 2050 (European Commission, 2003). The deadliest disasters since 1900 are shown in Figure 1 (Chakravarty, 2014b).

A disaster is the result of a vast ecological breakdown in the relations between human and her/his environment (Caunhye, Nie, & Pokharel, 2012). A disaster is defined by The International Strategy for Disaster Reduction (UN/ISDR) as “a serious disruption of the functioning of society, posing a

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Figure 1. The deadliest disasters since 1900 (Chakravarty, 2014b)

significant, widespread threat to human life, health, property or the environment, whether caused by accident, nature or human activity, and whether developing suddenly or as a result of complex, long-terms processes” (Kaynak & Tuğer, 2014). The disasters can be categorized as given Table 1 (Van Wassenhove, 2006; Pettit & Beresford, 2005).

Humanitarian supply chain can be defined as the flow of supplies through the relief chain from the contributors to the consumers. Due to the escalating number of natural and man-made catastrophes, the researchers must seriously address the issue of humanitarian logistics network design to be able to respond to extreme events in time.

Humanitarian supply chain management and logistics is important research area as its effectiveness directly correlates with the quality of the humanitarian aid effort (Beamon & Kotleba, 2006; Kunz & Gold, 2015). Additionally, disasters are among the major sources of supply chain risk (Liao, Bayazit, & Wang, 2014) due to their unpredictable nature (Balakrishnan, Bowne, & Eckstein, 2008).

The cycle of disaster management consists of four main phases: mitigation, preparation, response, and recovery. The mitigation phase includes efforts to prevent the occurrence of disasters or to decrease their effects. In the preparation phase, some strategic decisions (such as number and locations of main distribution centers) are made before a disaster occurs. The response phase involves operational decisions such as vehicle routings, personnel and equipment, as well as the last mile distribution of relief goods to affected areas after the occurrence of a disaster. In the recovery phase, restoring

Table 1. Disaster categories

Natural	Man-Made
Earthquake Hurricane Flood Famine Drought	Terrorist attack Coup d’Etat Political Crises Refugee Crises Civil unrest War

the previous states of the affected areas is the main activity of the agents involved in disaster relief (Ahmadi, Seifi, & Tootooni, 2015).

The objective of disaster response in humanitarian supply chain is to provide food, water, medicine, shelter, and supplies to areas affected by large-scale events, in order to minimize human suffering and death (Balcik & Beamon, 2008). In humanitarian logistics, the initial response should be given in the first 72 hours after the occurrence of an earthquake (Ahmadi et al., 2015). The first 12 hours, standard relief time (SRT), are very critical. Much of successful relief operation depends on the logistical operations of humanitarian supply chain system (de la Torre, Dolinskaya, & Smilowitz, 2012). An effective humanitarian logistics system must minimize human losses by dispatching and delivering relief goods to affected areas within the SRT (Ahmadi et al., 2015).

Furthermore, predetermining the quantity and locations of the items to be stored is an important issue (Vargas Florez, Lauras, Okongwu, & Dupont, 2015). Humanitarian logistic center selection in pre-disaster planning process is of vital importance on reducing the arrival time of relief items to the affected areas (Renkli & Duran, 2015). Many studies have handled the importance of the preparedness phase and the need for pre-positioned warehouses in humanitarian relief logistics, but only a small number of papers are related to the humanitarian warehouse location decision (Balcik & Beamon, 2008; Ukkusuri & Yushimito, 2008; Rawls & Turnquist, 2010; Gatignon, Van Wassenhove, & Charles, 2010; Roh, Jang, & Han, 2013).

Throughout the history, Istanbul has been exposed many devastating earthquakes. More precisely, 32 earthquakes between the 4th and 19th centuries have affected Istanbul (see Figure 2). Approximately every 300 years, Istanbul has been exposed to very severe earthquakes (Istanbul Metropolitan Municipality, 2009).

In this study, a fuzzy integer programming model is introduced for disaster management in order to determine the best locations of the temporary hospitals which support to extant hospitals providing first aid to affected people after earthquakes. Coordination in a relief chain is complex issue because of the uncertainties associated with disaster intensity, strike probability, infrastructure- disruption, and actual damage (Chakravarty, 2014b). The proposed model is applied to the Üsküdar district of Istanbul to serve potentially affected population that is considered as an uncertain factor by the model.

The main contributions of this work are threefold: Firstly, this study takes into account the number of heavily injured victims as uncertain parameter. Due to unforeseeable nature of a possible

Figure 2. 20th century seismicity of the region encircling Istanbul (Istanbul Metropolitan Municipality, 2009)

earthquake and lack of sufficient historical data, we introduced fuzzy linear programming model with Verdegay method to address the uncertainty. To the best of our knowledge, this research is the first study that suggests a fuzzy integer programming with Verdegay method for disaster management problem. Secondly, the validity of the model is tested on one of the most crowded districts of Istanbul, Üsküdar. Lastly, this work provides an effective tool while establishing disaster management decisions for managers and decision makers.

The rest of the paper covers the following: In Section 2, a comprehensive literature review is presented related to humanitarian logistics network design. Section 3 draws a framework for the problem faced with. In Section 4, the solution approach and the mathematical model are presented. Section 5 evaluates the results and discusses the findings of the study. Lastly, we conclude the work and summarize possible directions of future research.

LITERATURE REVIEW

Literature review section consists of studies on disaster logistics network design with a focal point of fuzzy linear programming approach.

Disaster Logistics Network Design

The first optimization models in emergency logistics were developed in the late 1970s following several maritime disasters, such as the Torrey Canyon shipwreck off the coast of England in 1967 and that of Argo Merchant near Massachusetts in 1976. From the 1980s up to now, researchers have addressed other large-scale emergencies such as hurricanes, floods, and earthquakes (Caunhye et al., 2012).

Beamon and Kotleba (2006) developed a stochastic inventory control model that determines optimal order quantities and reorder points for a long-term emergency relief response in humanitarian supply chain management. Tzeng et al. (2007) developed a relief-distribution model using the multi-objective programming. The model addressed three objectives; minimizing total cost and travel time, and maximizing minimal satisfaction during the planning period. Balcik and Beamon (2008) presented a variant of the maximal covering location model to ascertain the number and locations of distribution centers and the amount of relief goods to be stocked at each distribution center.

Rawls and Turnquist (2010) proposed a two-stage stochastic mixed integer program to determine the locations of warehouses and quantities of various types of emergency supplies to be pre-positioned under uncertain availability of the transportation network after a catastrophic event. Mete and Zabinsky (2010) proposed a two-stage stochastic model approach to select the storage locations of medical supplies and required inventory levels for each type of medical supply for disaster management under a wide variety of possible disaster types and magnitudes. They applied the presented model a case study for disaster planning under various earthquake disaster scenarios in the Seattle area. Görmez, Köksalan, & Salman (2011) introduced a mathematical model to determine the locations of the disaster response and relief facilities for Istanbul case with the objectives of minimizing the average-weighted distance between casualty locations and closest facilities. Ben-Tal et al. (2011) proposed a robust logistics plan to cope with demand uncertainty in humanitarian relief supply chains. The proposed robust optimization model applied to dynamically assigning emergency response and evacuation traffic flow problem with time dependent demand uncertainty.

Döyen et al. (2012) developed a two-stage stochastic programming model for a humanitarian relief logistics problem that determines locations of pre- and post-disaster rescue centers and amount of relief items to be stocked. The objective is to minimize the total cost of facility building, inventory holding, transportation and shortage. The presented model solved by using a heuristic method based on Lagrange relaxation. Bozorgi-Amiri et al. (2012) presented a mixed-integer nonlinear programming that determines the location of relief distribution centers and their allocation to the affected areas to minimize the sum of the expected total cost and the variance of the total cost for a relief chain design problem under uncertain demand-supply and cost of procurement and transportation. They used

particle swarm optimization in order to solve the proposed model. Yushimito et al. (2012) focused on locating a finite number of distribution centers to provide a quick response for disaster relief incorporating social costs within the modeling framework. They developed a heuristic algorithm to solve the problem. Najafi et al. (2013) introduced a multi-objective, multi-mode, multi-commodity, multi-period stochastic model under combined transportation, vehicle capabilities to organize logistics of relief commodities and injured people in the initial phase of earthquake response. The proposed stochastic model has three hierarchical objective functions: minimization of weighted waiting time of unserved population, minimization of weighted lead time of meeting the commodity needs, and minimization of total vehicles utilized in the response, respectively.

Ransikarbum and Mason (2014) presented a multiple objective, integrated network optimization model for making strategic decisions in the supply distribution and network restoration phases of humanitarian logistics operations. Rennemo et al. (2014) developed three-stage mixed-integer stochastic programming model for distribution of relief goods in the response phase. Hasanzadeh and Bashiri (2015) addressed the relief transportation network design based on the hub location problem. The Lagrange relaxation method was employed to find a proper lower bound of the problem for large instances. Hong et al. (2015) presented a risk-averse stochastic modeling approach for a pre-disaster relief network design problem under demand and transportation capacity uncertainties. The model determined the location of the disaster response facilities and the positioning of the relief supplies to improve the effectiveness of the post-disaster operations. Renkli and Duran (2015) proposed a mixed integer programming model in order to pre-position warehouses throughout potentially affected areas and determine the amount of relief items to be held in those warehouses. The aim of the study was to minimize time between the strike of the disaster and arrival of relief items at the affected areas. Salman and Yücel (2015) developed a stochastic integer programming model that determines the locations of emergency response facilities among a set of potential ones to maximize expected total demand covered within a predetermined distance parameter, over all possible network realizations. Tofighi et al. (2015) developed a novel two-stage scenario-based possibilistic stochastic programming approach for humanitarian logistics network design problem involving multiple central warehouses and local distribution centers. During the first stage, the locations for central warehouses and local distribution centers are determined along with the prepositioned inventory levels for the relief supplies under uncertain supply and demand assumption. In the second stage, a relief distribution plan is proposed for various disaster scenarios. Kilci et al. (2015) developed a mixed integer linear programming model maximizing the minimum weight of open shelter area. They applied the mathematical model by generating a base case scenario using real data on Kartal, Istanbul. Huang et al. (2015) proposed a multi-objective optimization model including the lifesaving utility, delay cost and fairness objectives.

Khayal et al. (2015) developed a network flow model for dynamic selection of temporary distribution facilities and allocation of resources for emergency response planning. The model analyzes the transfer of excess resources between temporary facilities operating in different time periods to reduce deprivation. Noyan et al. (2015) introduced a distribution network design problem that determines the locations and capacities of the relief distribution points in the last mile network, while considering demand- and network-related uncertainties in the post-disaster environment. Another novel work is conducted by Aydin (2016) where a stochastic model considering the locations as well as the failing probabilities of the existing public hospitals while deciding on the location of field hospitals. The model is applied on a real life case problem in Zeytinburnu, İstanbul.

Recently, Noham and Tzur (2018) presented mixed integer programming for the pre- and post-disaster humanitarian supply-chain design problem, which addressed facility location and inventory allocation decisions in a two-echelon humanitarian supply chain. They used a novel solution method to solve small/medium-size instances whereas Tabu search heuristic was employed for large scale problems. Rodríguez-Espíndola, Albores and Brewster (2018) proposed a disaster preparedness system based on a combination of multi-objective optimization and geographical information systems to support a decision problem covering multiple partner organizations. They used a cartographic model

to avoid the selection of floodable facilities within the scope of a bi-objective optimization model used to determine the location of emergency facilities, stock prepositioning, resource allocation and relief distribution.

Fuzzy Approaches in Disaster Logistics Network Design

Fuzzy integer programming models find place in various real-life cases in different scientific disciplines. Thus, a vast literature on this domain has been bred since the first introduction of fuzzy sets. However, we will content ourselves with fuzzy models in logistics network design. Despite the multitude of fuzzy approaches employed in logistics network design (Azadeh, Rao, & Zarrin, 2015; Balaman & Selim, 2014; Baykasoğlu & Subulan, 2015; Bilgen, 2010; Mousavi, Vahdani, Tavakkoli-moghaddam, & Hashemi, 2014; Turgay & Taşkın, 2015), the number of applications in disaster logistics remained very limited. Two noteworthy studies are conducted by Liu et al. (2013) and Zheng and Ling (2013). The former developed a bi-objective fuzzy mixed integer programming model in order to determine the location of emergency material warehouses and they used a heuristic algorithm to solve presented model whereas the latter one used a multi-objective fuzzy optimization approach to solve problem of emergency transportation planning in disaster relief supply chains. In order to handle uncertainty, they used three correlated fuzzy ranking criteria, and defined the beta dominance relation for evaluating the solutions of the problem. To solve the presented case, they also proposed a cooperative optimization method that divides the integrated problem into a set of subcomponents, evolves the sub-solutions concurrently, and brings together the sub-solutions to construct complete solution.

The literature review above indicates that most studies handle the issue of uncertainty in disaster logistics network design by using stochastic programming approaches (Beamon & Kotleba, 2006; Bozorgi-Amiri et al., 2012; Döyen et al., 2012; Rawls & Turnquist, 2010; Rennemo et al., 2014; Salman & Yücel, 2015; Tofghi et al., 2015). However, their computational complexity and the lack of sufficient historical data for factual determination of distributions of uncertain model parameters are two burdens to be faced with in the real-life applications (Pishvaei & Razmi, 2012). To cope with this shortcoming, the fuzzy programming is considered as a competitive tool (Fazlollahi & Tehranchian, 2014; Pishvaei & Torabi, 2010).

To contribute to the extant rare efforts in the domain, this study presents a fuzzy integer programming model for disaster management problem in order to determine the best locations of the temporary hospitals supporting to the current hospitals. To the best of our knowledge, this research is the first study that suggest fuzzy linear programming model with Verdegay approach for disaster management problem under the assumption of uncertain number of victims. To validate its practical applicability, the model is used to solve a real-life case.

PROBLEM DEFINITION

After a large-scale disaster, medical treatment of disaster-victims is one of the first and most vital issue. To serve this purpose, the extant hospitals are of paramount importance, yet possibly insufficient depending on the scale of the event. Thus, temporary field hospitals should be established, that offer first aid material and medical assistance starting from the very early hours of the incidence. Additionally, the population hit by the disaster should be effectively destined to the prepared hospitals considering their capacities and transfer times. While modeling the problem, a fuzzy environment may rule due to the uncertainties associated with disaster intensity, strike probability, infrastructure- disruption, and the scale of the damage in a relief chain (Chakravarty, 2014b). In addition, the dominating characteristics that bring additional complexity and unique challenges in case of a disaster are as follows (Ivgin, 2013):

- Unpredictability of demand, in terms of timing, location, type and impact;
- Suddenly occurring demand and short lead times for a wide variety of supplies; and
- High cost of unsatisfied demand (i.e. loss of lives).

In this study, we addressed the unpredictability of the demand aspect by modeling a fuzzy location and allocation problem where locations of the field hospitals additional to the available current medical centers are determined and dead and heavily injured population in each neighborhood of Üsküdar is allocated to these centers in a fuzzy environment.

RESEARCH METHODOLOGY

This section includes three main subsections: model formulation, fuzzy integer model with Verdegay approach and application.

Mathematical Model

The presented model can be formulated as follows.

Sets

i : Set of candidate hospitals where $i = \{1, 2, \dots, I\}$

j : Set of districts where $j = \{1, 2, \dots, J\}$

C : Set of extant hospitals where $i = \{1, 2, \dots, H_C\}$ and $H_C \leq I$

Parameters

N_j : Number of casualties at district j

d_{ij} : Distance between hospital i and district j

H_C : Number of extant hospitals

Q : Number of hospitals allowed to be opened

K_i : Capacity of hospital i

Variables

y_i : 1, given hospital i is open; 0, otherwise.

x_{ij} : Number of casualties at district j assigned to hospital i .

The proposed deterministic model specifying appropriate location of temporary hospitals and assigns the victims to the hospitals is formulated as:

$$\min \sum_i \sum_j d_{ij} x_{ij} \quad (1)$$

$$\sum_j x_{ij} \leq K_i y_i, \quad \forall i \quad (2)$$

$$\sum_i x_{ij} \geq N_j, \quad \forall j \quad (3)$$

$$\sum_i y_i = Q \quad (4)$$

$$\sum_{i \in C} y_i = H_C \quad (5)$$

$$y_i \in \{0,1\}, \quad \forall i \quad (6)$$

$$x_{ij} \geq 0 \text{ and integer, } \forall i, \forall j \quad (7)$$

Equation (1) shows the objective of weighted distance minimization. The expected number of injuries at each district expresses the weight in the objective function. Equation (2) ensures that the total number of injuries transferred to hospital i cannot exceed its capacity given i serves. Equation (3) guaranties that each disaster victim should be assigned to a hospital. Equation (4) determines the number hospital. According to Equation (5), current available hospitals should be opened assuming that they will survive the earthquake without serious damage. Lastly, Equations (6) and (7) ensure decision variables are binary and integer, respectively.

Fuzzy Integer Model With Verdegay Approach

We extent the presented deterministic model to its fuzzy variant considering the fact the parameter N_j . number of casualties in each district j , possesses a serious uncertainty. In contrast to deterministic case, Equation (3) is reformulated in the fuzzy model as:

$$\sum_i x_{ij} \geq \widetilde{N}_j \quad (8)$$

Tolerance limits for the fuzziness (T_i), assumed to be %10 of the deterministic value given at the right-hand side of the constraint, N_j . To solve the fuzzy model, it is transformed into a parametric linear programming model by the membership function proposed by Verdegay. Accordingly, Equation (8) can be rewritten as follows:

$$\forall k \quad (9)$$

Here, α denotes the level of crispness of the related parameter where $\alpha = 0$ represents a highly fuzzy environment and $\alpha = 1$ fully deterministic case. We make various analyses for different precision levels, $\alpha = (0, 0.1, 0.2, 0.3, \dots, 0.9, 1)$, by using GAMS 23.5 package program. The membership function of $\widetilde{N}_j$ on the right-hand side of the equation can be depicted as in Figure 3.

Application

Geologically, Turkey is located at the boundary area where the Arabian Plate and African Plate move north towards the Eurasian Plate. A large-scale fault line called North Anatolian Fault extends more than 1.000 km long from east to west in the northern territory of Turkey where many strong earthquakes have occurred. Especially, on August 17th, 1999, an earthquake recorded at a magnitude

Figure 3. Membership function of $\widetilde{N}_j$

of 7.4 in Kocaeli province (Pektas, 2004). This earthquake with its aftershocks caused over 20.000 casualties and resulted in collapse of more than 110.000 buildings (Karaman et al., 2008).

The centers of 33 neighborhoods serve as demand points where their coordinates are derived from Google Maps. Distances between hospitals and neighborhoods were calculated using the Euclidean distance formula. Population data of the neighborhoods are extracted from Turkish Statistical Institute (see Table 2).

In Istanbul, the mayor of the city is responsible for the coordination duty, which is realized through disaster coordination center of Municipality of Istanbul, AKOM. The mission of AKOM is to coordinate and ensure cooperation between all the organizations in Istanbul before, during, and after a natural disaster (Kaynak & Tuğer, 2014). As the application area of this study, Üsküdar is one of the most crowded districts among 39 districts of Istanbul, and is located in the first and second degree earthquake zone (see Figure 4). Table 3 summarizes some relevant data on Üsküdar.

Based on a scenario (scenario C) extracted from a comprehensive report (İstanbul Metropolitan Municipality, 2002) prepared jointly by the İstanbul Metropolitan Municipality and Japan International Cooperation Agency (JICA) in 2002, the number of casualties (dead and injured population) estimated was determined as 1.1% of the population living in the area (see Table 4).

As seen in Figure 5, there are 11 state hospitals in the Üsküdar province. Obviously, the total capacity of these facilities is far less than the total number of expected disaster victims by JICA report (İstanbul Metropolitan Municipality, 2002), which was estimated about 1.1% of the population (around 6410 people). Thus, 102 schools may serve as candidate locations for temporary field hospitals in 33 neighborhoods. In the figure, the yellow dots represent the center of neighborhoods whereas schools and hospitals are shown as *green home* and *red H* shapes.

Table 2. The Üsküdar district in numbers

Population	582.666
Number of Neighborhoods	33
District Area	35.7 km ²
Street Number	2501
Length of Streets / Roads	466.735 meter
Road / Street Area	2472 m ²
Number of Main Arteries	89

Figure 4. Istanbul earthquake zones distribution map (Earthquake Zoning Map Index of Turkey, 2017)

Table 3. Population living in neighborhoods of Üsküdar

Neighborhood	Population	Neighborhood	Population
Acıbadem	24.004	Kuleli	3.485
Ahmediye	9.755	Kuzguncuk	4.535
Altunizade	14.366	Küçük Çamlıca	9.483
Aziz Mahmut Hüdayi	9.432	Küçüksu	18.940
Bahçelievler	21.792	Küplüce	17.591
Barbaros	18.906	Mehmet Akif Ersoy	21.284
Beylerbeyi	5.810	Mimar Sinan	12.480
Bulgurlu	30.817	Murat Reis	14.059
Burhaniye	16.408	Salacak	9.940
Cumhuriyet	34.733	Selamiali	13.015
Çengelköy	14.384	Selimiye	8.582
Ferah	19.566	Sultantepe	11.534
Güzeltepe	13.126	Ünalan	34.149
İcadiye	17.646	Valide-i Atik	21.953
Kandilli	1.565	Yavuztürk	34.787
Kısıklı	19.845	Zeynep Kamil	13.139
Kirazlıtepe	13.525		

Table 4. Expected number of victims in each neighborhood

Neighborhood	# of Victims	Neighborhood	# of Victims
Acıbadem	240	Kuleli	34
Ahmediye	97	Kuzguncuk	45
Altunizade	143	Küçük Çamlıca	94
Aziz Mahmut Hüdayi	94	Küçüksu	189
Bahçelievler	217	Küplüce	175
Barbaros	189	Mehmet Akif Ersoy	212
Beylerbeyi	58	Mimar Sinan	124
Bulgurlu	308	Murat Reis	140
Burhaniye	164	Salacak	99
Cumhuriyet	347	Selamiali	130
Çengelköy	143	Selimiye	85
Ferah	195	Sultantepe	115
Güzeltepe	131	Ünalan	341
İcadiye	176	Valide-i Atik	219
Kandilli	15	Yavuztürk	347
Kısıklı	198	Zeynep Kamil	13
Kirazlıtepe	135		

Figure 5. The location of hospitals and candidate field hospitals and center of neighborhoods in Üsküdar/Istanbul (produced with Google Earth)

To sum up, the case study comprises 33 neighborhoods, 102 schools serving as candidate locations for temporary field hospitals, and 11 state hospitals. Table 5 shows the coordinates and capacities of current hospitals.

RESULTS AND DISCUSSION

The problem was solved using GAMS 23.5.1 and processed by a server equipped with 2.40 GHz Intel Core Processor and 8 GB RAM. The results are given in Table 6 for various α level.

Recall that as α approaches to 0, the fuzziness in the model gradually increases. According to Table 6, if the model is completely fuzzy, in other words, if α is 0, the objective function reaches

Table 5. Relevant data for extant hospitals

Hospitals	Bed Cap.	X and Y Coordinates	
i1	149	41,02501300	29,040984000
i2	600	41,00133800	29,019710000
i3	263	41,01534600	29,038987000
i4	709	41,00129400	29,019706000
i5	350	41,01533700	29,025476000
i6	360	41,00405400	29,024336000
i7	22	41,02517000	29,082263000
i8	100	41,02143500	29,015854000
i9	58	41,05129600	29,076367000
i10	91	41,02468400	29,083819000
i11	87	41,0198940	29,0346820

Table 6. Objective function values with respective α values

α Value	Objective Function Value
0.0	2069.902
0.1	2042.955
0.2	2012.139
0.3	1988.543
0.4	1960.148
0.5	1939.692
0.6	1911.364
0.7	1883.997
0.8	1861.417
0.9	1832.884
1.0	1809.670

its worst value. If α is equal to 1, then the fuzzy model is equal to the deterministic model. As expected, the objective function attains its maximum value for $\alpha = 0$ case. Considering this case, 73 hospitals, namely 62 temporary medical facilities addition to the extant 11 state hospitals, are needed. On the other hand, 69 hospitals may suffice for deterministic case as depicted in Figure 6.

Figure 7 and 8 show number of disaster victims to be transferred from each neighborhood to each hospital for two extreme cases, the crisp and the fuzzy cases. Here, we note that both figures appear in Appendix of this paper. Interestingly, considering the assignments, we observe that some state hospitals are not going to be utilized despite the fact that they will be available as imposed by the constraint formulating that all state hospitals have to be ready for service (Equation 5). This may seem to be underutilization of the given resources. However, the proposed model does not require that each hospital has to be used if opened as the objective function does solely concern timely transfer of the injured people.

For $\alpha=1$, temporary hospitals to be opened are listed as: i1, i2, i3, i4, i5, i6, i7, i8, i9, i10, i11, i12, i14, i15, i16, i17, i19, i20, i26, i28, i31, i34, i36, i37, i38, i39, i40, i42, i44, i47, i48, i51, i53, i54, i56, i58, i60, i61, i63, i64, i67, i68, i70, i72, i73, i74, i76, i77, i78, i81, i85, i88, i89, i90, i93, i97, i98, i99, i100, i101, i103, i104, i105, i106, i107, i108, i109, i112, i113.

For $\alpha=0$, the same list is composed of: i1, i2, i3, i4, i5, i6, i7, i8, i9, i10, i11, i12, i14, i16, i17, i19, i20, i26, i28, i31, i32, i34, i36, i37, i38, i39, i40, i42, i44, i47, i48, i51, i53, i54, i56, i58, i60, i61, i63, i64, i67, i68, i70, i72, i73, i74, i76, i77, i78, i81, i85, i88, i89, i90, i93, i97, i98, i99, i100, i101, i103, i104, i105, i106, i107, i108, i109, i112, i113.

CONCLUSION

Disasters are tragic events causing severe material and immaterial cost. In recent era, the numbers of natural disasters have dramatically increased. Considering the case of Turkey, a similar picture emerges.

Coordination in a relief chain is a complex task due to the uncertainties associated with various aspects of the faced disaster (Chakravarty, 2014b). In this study, we presented a fuzzy integer programming model for disaster management process in order to determine the best location of the temporary field hospitals which intend to support extant state hospitals to provide first aid service to injured disaster victims. While making a pre-disaster plan, one of the most uncertain factors is the size of the affected population. The proposed model was adopted to the Üsküdar district of İstanbul due to the poor physical conditions of the buildings in its populated neighborhoods, its dense population and high-risk level of earthquake.

Figure 6. Total number of hospitals needed for different α levels

Keeping fuzzy nature of the problem in mind, this study considered the size of heavily injured population as uncertain. Accordingly, we construct a fuzzy linear programming model with Verdegay method. The presented fuzzy model minimizes the total distance of transferred victims under the assumption that the demand is fuzzy. According to C scenario of the JICA report, the estimated number of affected people was %1.1 of the total population. To meet this urgent and irrecusable demand, additional 62 schools should be used as temporary medical facilities along with the current 11 state hospitals.

This study may extend in various directions. Firstly, the model can be modified by inserting uncertain parameters such as, service time, facility location risks, and availability of transfer routes. In order to cope with uncertain parameters, robust or fuzzy possibilistic programming approaches are also feasible options. Furthermore, the problem we address here can be combined with routing problems, inventory problems, resource allocation problems, and community flow problems.

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APPENDIX

Figure 7. Number of people in each neighborhood assigned to each hospital for $\alpha=1$

	j1	j2	j3	j4	j5	j6	j7	j8	j9	j10	j11	j12	j13	j14	j15	j16	j17	j18	j19	j20	j21	j22	j23	j24	j25	j26	j27	j28	j29	j30	j31	j32	j33	
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i7																																	22	
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i109															15																			
i112																														100				
i113																																		13

Figure 8. Number of victims in each neighborhood assigned to each hospital for $\alpha=0$

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