An International Journal of Optimization
and Control: Theories & Applications
Vol.6, No.2, pp.85-102 (2016) © IJOCTA
ISSN: 2146-0957 eISSN: 2146-5703
DOI: 10.11121/ijocta.01.2016.00296
http://www.ijocta.com

A stochastic mathematical model to locate field hospitals under disruption uncertainty for large-scale disaster preparedness

Nezir Aydin

Department of Industrial Engineering, Yıldız Technical University, Turkey
Email: nzraydin@yildiz.edu.tr

(*Received January 20, 2016; in final form February 2, 2016*)

Abstract. In this study, we consider field hospital location decisions for emergency treatment points in response to large scale disasters. Specifically, we developed a two-stage stochastic model that determines the number and locations of field hospitals and the allocation of injured victims to these field hospitals. Our model considers the locations as well as the failings of the existing public hospitals while deciding on the location of field hospitals that are anticipated to be opened. The model that we developed is a variant of the P-median location model and it integrates capacity restrictions both on field hospitals that are planned to be opened and the disruptions that occur in existing public hospitals. We conducted experiments to demonstrate how the proposed model can be utilized in practice in a real life problem case scenario. Results show the effects of the failings of existing hospitals, the level of failure probability and the capacity of projected field hospitals to deal with the assessment of any given emergency treatment system's performance. Crucially, it also specifically provides an assessment on the average distance within which a victim needs to be transferred in order to be treated properly and then from this assessment, the proportion of total satisfied demand is then calculated.

Keywords: Stochastic programming; humanitarian logistics; reliable facility location; field hospital; Istanbul.
AMS Classification: 90C11, 90C15.

1. Introduction

Disasters have always been parts of human life and continued to be a steady increase in the number and severity of natural disasters in recent years ([1-2]). Disaster can be defined as any expected or unexpected incident that causes catastrophic injuries to humans' life, or damage to the economy and environment. Past case studies relating to this specific area have shown that effective and well-organized preparation helps in decreasing the catastrophic effect of disasters [3]. Disasters can be natural (such as earthquakes, floods, tsunamis, storms or hurricanes) or man-made (such as terrorist attacks, industrial accidents, or war) ([3-5]). Both types of disasters can cause major economic loss and human fatalities. A recent earthquake occurred on April 2015 in Nepal (with 7.9 magnitude) and caused about 9,000 fatalities. Another example of such a disaster occurred in 2011 with 9.0 magnitude earthquake and tsunami in Japan, which caused around 19,000 fatalities and huge economic loss [6]. The earthquake that hit Haiti in January 2010 caused an estimated 230,000 deaths and 250,000 injuries [7]. Another tsunami occurred in the Indian Ocean on December 26th, 2004, which had a 9.0 magnitude which left in its wake a total of 229,866 people lost: 186,983 officially identified as dead and another 42,883 missing [3]. In relation to man-made disasters, a terrorist attack occurred on September 11, 2001 when terrorists attacked the World Trade Centre in New York, which caused

Corresponding Author. Email: nzraydin@yildiz.edu.tr

the death of 2,750 people and another 2,260 injures. The economic loss suffered as a result of these disasters amounted to trillions of dollars. Economic damage is recoverable while fatalities are not. Therefore, locating the injured people and moving them to the nearest emergency service/hospital for timely treatment is a vital process. Under a disaster scenario it is critical to have available and well-functioning hospitals close to areas where injured people are most densely located.

Even though we cannot forecast a disaster with significant certainty, emergency preparedness is crucial to eliminate or at least minimize potential fatalities ([3], [8]). Succeeding a disaster, hospitals can expect a sudden increase of injured victims which can easily overwhelm and crush a hospitals capacity. One way to be prepared for disasters, such as a bio-terrorist attack or an epidemic, is to have excess capacity as mentioned in [9] and [10]. Since the time and severity of disasters cannot be anticipated, the number of the injured victims is uncertain as highlighted in the author's research study in [12].

The number of injured victims is not the only uncertainty in a disaster. In addition to this, it is uncertain how much disruption will be experienced in hospitals. Therefore, in order to be fully prepared, taking these two uncertainties into account is vital for emergency management systems. Current literature considers the uncertainty in the number of injuries and the uncertainty regarding the disruption of hospitals. However, there is still lack of studies that considers both uncertainties at the same. Therefore, in this study we consider the disruption of hospitals to assist emergency management systems managers.

Despite the importance of field hospitals in mitigating the effects of disasters, there has been a lack of research in the area even there are some valuable studies in the related field ([2] , [5], [7], [12-18]) and some other analysis on capacity planning of hospitals for disaster preparedness ([3], [19-20]). In this paper, we want to separate and distinguish the general humanitarian relief chain from planning field hospitals because medical supplies and treatment are more important than other supplies, especially during the first 72 hours after a disaster occurs. This new area of research provided us with the requisite motivation to seek to determine the optimum number and location for these field hospitals in Zeytinburnu/Istanbul. We aimed to achieve the following objectives:

- To determine the optimal number of field hospitals in Zeytinburnu/Istanbul to satisfy all demand (injured disaster victims) whilst considering existing hospitals and their capacities.
- To determine the optimal locations of field hospitals in order to treat injured people on time.
- Optimal allocation of the demand to the hospitals (both to public hospitals and field hospitals).

This work focuses on developing and analyzing a model for field hospitals' locations and capacity allocation for regions subject to large-scale disasters. While achieving these objectives, we took the failure (disruption) of the existing public hospitals into account. A scenario based two-stage stochastic mathematical model was developed and the results were thereafter presented.

The paper is organized as follows: Section 2 reviews the relevant literature relating to the field hospitals, disaster relief chain and scenario based stochastic programs. Section 3 presents the stochastic P-median mathematical model. Section 4 describes the presented model and results. Analyses are also presented in Section 4. The final section includes conclusions and directions for future researches.

2. Literature review

Disaster literature is somewhat limited when compared with other fields of Operations Research. Nevertheless, the number of studies on disaster has increased in recent years. Altay and Green [21] identified 77 articles that have been published in OR/MS related journals out of a 109 disaster management studies. They stated that 40% of these 109 articles were published between 1990 and 2000, while the remaining articles were published after 2000 [22]. It could be argued, therefore, that more studies need to be done in these topic areas. As in our study, research studies were usually undertaken in some specific disaster regions that have suffered from some type of disaster.

In this literature review section, we analyze facility location problems that are related to disasters. Firstly, we review the logistical problems related to emergency response and disaster management operations. Later we set out a brief analyze of past studies on facility location literature that have touched on areas of research in common with our own proposed model.

Wright et al. [23] published a survey study on models and applications in homeland security.

Their analyses were on emergency preparedness and response, border security, port security, cyber security, and critical infrastructure protection. They proposed location and allocation evacuation models and disaster and response to natural disasters. They also highlighted the apparent lack of research into the whole area of disaster and response. Dekle et al. [24] developed a two-stage model to locate potential disaster recovery centers in the city of Florida. In the first stage of their study, a fixed, total disaster and response coverage area was assessed and determined (ie a 'set covering' problem is solved). They determined the requisite, optimal locations for the future facilities. The coverage of each disaster recovery center was assessed as being within a distance of 20 miles in the first stage. Subsequently, in the second stage, the initial "20 mile" constraints were then relaxed and new locations closest to the original optimal locations were determined and evaluated based on the combined evaluation criteria.

Facility location problem models for medical services relating to large scale disasters such as earthquakes, terrorist attacks, etc. were proposed by [25]. In their study, they reviewed three types of location models: p-median (PMP), p-center (PCP) and set covering (SC), for emergency services. A common formulation was proposed to generalize these three models. In this generalized formulation they presented scenarios and service level requirements. It was determined that each demand point would probably have a different service level requirement under any given scenario. Therefore the service level was calculated and determined by the number and condition of the facilities that served the demand point i.e. the higher the number of facilities and the better the facility conditions there were then the higher the service level one could attract. These two ideas are usually presented in disaster management studies. Balcik and Beamon [1] also proposed a scenario-based model with service levels in a humanitarian relief chain. In this study, they determined the number and the optimal location of the facilities and the amount of supplies stocked at each distribution centers. Their model considered multi commodity types, suppliers with capacity restrictions and a single demand point. Each commodity has a different weight, which shows the critical level of the commodity. Then the total expected demand was maximized by the located distribution centers. They showed the effects of budgetary constraints for both pre and post disaster relief funding separately arising out of the performance of the system. In another study, [26] proposed a facility location model for locating emergency response and distribution centers for the expected earthquake in Istanbul. The model they proposed, which is a two-stage stochastic programming problem, consists of five objectives: the average risk of each distribution center, the cost of opening a new distribution center, the maximum service time for each supply, the total response time and the expected unmet demand. They identified multiple criteria along with the priority level of each objective. A goal programming method was used to solve the proposed problem.

A multi-objective programming methodology for designing relief distribution system was suggested by [27]. Three objectives were featured: minimizing the total cost, minimizing travel time and maximizing the minimal satisfaction. Unlike other studies in the literature, they recommended locating temporary stocking centers due to permanent storage centers tendency to be fully capacitated. To assist with implementing this approach, fuzzy multi-objective linear programming was used. It is different than other studies in terms of the level of the problem it analyzes. In other words, their model is more at operational level.

Unmet daily emergency problems have led in the past to frequent criticism of disaster management models. A PMP on locating fire stations in Barcelona was studied by [28]. A scenario dependent demand and travel time model was developed in this study. The model was constructed considering uncertain parameters i.e. uncertain demand and travel time. Two objectives were sought, namely: the minimization of the maximum travel time per population and maximum regret. The regret was calculated by assessing the difference between optimal travel time and the realized average travel time. Barbarosoglu and Arda [29] proposed a two-stage stochastic programming model with uncertain demand on transportation planning for Istanbul in the event of an expected earthquake. Supply and arc capacities were assumed to be random. The location and the allocation decisions were respectively made in the first and second stages.

One way to measure the effectiveness of a facility location is to determine the average distance travelled [30] and one should make reference using this method to the PMP [31]. Assuming that locations become unreliable when the distance to a demand point increases then this is another method to model the effect of distance as modeled in [32]. Injured victims have different level of survivability defendant upon their injuries. Therefore it essentially follows that the transfer of injured victims to hospital locations should be prioritized based on the survivability times [15]. A study has been done on such prioritizing in [33].

However, essential measures in disaster are not only to minimize the distance travelled but also to maximize the survivability competence of the hospital that the patients are transferred to. Our study as far as we are aware uniquely considers both issues. Since existing public and field hospitals can be count as a facility, we also considered the facility location literature in our study as well. For the most part, the facility location literature assumes that the facilities function is always at a full capacity. This assumption is not realistic for disaster studies whilst recognizing that it is reasonable to make such an assumption for many other different scenarios. There have been various studies in the field of reliable facility location [34].

Next, we review some reliable facility location problem studies that are not necessarily related to disasters but instead are related to our studies in terms of failure/disruption of existing facilities. Facility location decisions are one of the main strategic supply chain decisions and should require noteworthy investment planning spanning over long- term planning horizons, e.g., ranging from 2 to 8 years depending on the business. Given the period of the planning horizon and the level of uncertainty in today's business world, the supply chain designers are now obligated to make an allowance for forestalling and for the planning of uncertain future events in their network design. A significant category of these supply chain uncertainties is the disruption/failure of facilities which affect the supply chain's capability to efficiently fulfill demand [35]. As mentioned earlier, these disruptions/failures can be either natural disasters or man-made (such as terrorist attacks, earthquakes etc.). In many cases, the disruption of a region may spread or migrate through the network and affect other fragments of the supply chain network [36].

Following a disruptive event, there is barely any recourse of action available to modify the supply chain infrastructure quickly [37]. As an alternative, a common recourse of action is to reallocate demand to other existing facilities or organize substitute sources of supply. In both cases, the cost of satisfying customer demand increases e.g., due to higher transportation costs. Over the past decade, consideration of such disruptions disturbing the supply chain network design has received substantial attention from both academics and practitioners.

An exemplary early research in this area can be found in [38]. Authors developed a reliability based formulation called Un-capacitated Facility Location Problem (UFLP) and the PMP. Later, Shen et al. [39] studied a variant of reliable UFLP model and proposed and applied efficient approximation algorithms to URFLP by using the special substructure of the problem. Nonetheless these approximations cannot be employed to the general class of facility location problems such as Capacitated Reliable Facility Location Problems (CRFLP).

In practice, capacity decisions are considered together with location decisions. Further, the capacity of facilities usually cannot be modified right after the event of a disruption. Following a facility failure, demands can be reassigned to other facilities only if these facilities have enough available capacity. Therefore CRFLPs are more complex than their un-capacitated counterparts [39] and the studies considering CRFLPs are limited. Snyder and Ülker [40] studied the CRFLP and developed an algorithm based on Sample Average Approximation (SAA) embedded with Lagrangean relaxation. Gade [41] employed the SAA method in combination with a dual decomposition method to solve CRFLP. Later, Aydin and Murat [34] applied Particle Swarm Optimization (PSO) based SAA to solve the same type of CRFLP faster.

3. Problem statement and methodology

As stated in the JICA report [42] Istanbul expects an earthquake in the near future. JICA provided four scenarios for the earthquake. In all four scenarios the magnitude that will most probably occur will be near to or over 7.0 on the Richter scale. An earthquake with this Richter scale recording will cause a huge number of deaths and injuries to people. This can be assessed from earlier earthquakes. For examples studies in ([3-4], [6-7]) provide valuable analyzes on earthquakes. Succeeding a disaster, a hospital emergency room might expect a rapid flow of injured people that can certainly crush hospital capacities [3], because treatment centers and hospitals are the very first places that injured people will run to after a disaster.

From now on in this study, we will refer to people who need medical treatment after a disaster as 'victims'.

The capacity of hospitals should, essentially, be sufficient to treat all injured victims. Also the distance of these hospitals to demand points is of equal importance. In our study, we determined the optimal number and location of field hospitals in a district of Istanbul-Zeytinburnu to minimize the distance that victims needed to travel. Zeytinburnu is thought to be one of the most risky earthquake places to live according to the [42]. There are six existing hospitals available in Zeytinburnu. Two of them are public hospitals while the others are privately owned. Besides these hospitals, possible locations were identified as suitable locate field hospitals in the event of a disaster. All these locations are public schools. Using the schools as distribution or emergency centers (field hospitals) was proposed in the [22] and [42]. Also the public schools were considered as possible locations for relief centers [43]. The Report also highlighted that it would not be useful to found a large number of facilities that stayed idle until a disaster occurs. Instead, the report concluded that it would be more effective to operate the existing public schools following a disaster. Thinking along the same lines we proposed to set up field hospitals once the disaster had occurred, in our simulated earthquake disaster, in the same way as the report suggested. Not that, in this study, we aim to determine the locations of field hospitals considering the disruption of field hospitals and not embedding the set up time of field hospitals, which is suggested as a future work.

The field hospitals would thus serve as temporarily located hospitals-field hospitals following a disaster. The main assumption in this study is that the existing hospitals may be disrupted. In our study scenario we assessed that this could happen in many ways, such as by the disruption of fallen buildings or damaged roads. We also considered that the hospitals (both existing and field hospitals) would be capacitated. Furthermore, we made an assumption that the hospitals would be identical in terms of services carried out within the hospitals. Here, we want to highlight another future work, which is restricting the assumption and considering the different capabilities of hospitals. Lastly, we assumed that the field hospitals would survive after the earthquake because these field hospitals are planned to be set up following a disaster and are selected among the schools that are resistant to the earthquakes.

3.1. Data collection

The data we used in this study was gathered from the websites of the Ministry of Health of Turkey [44], the Ministry of National Education of Turkey [45], the Municipality of Zeytinburnu/Istanbul [46] and the [42]. The JICA report provides analyzes for the disaster mitigation study which was compiled at the direction of and under the supervision of the IMM (Istanbul Metropolitan Municipality) and the JICA. Four possible earthquake scenarios in Istanbul were presented in the JICA, i.e. Model A, Model B, Model C and Model D. In the report, the number of victims, buildings and infrastructure damage estimates were provided for each district of Istanbul in Model A and Model C. Model A was identified as the most probable scenario with a magnitude of reading provided for on the Richter scale and Model C was reported as the worst-case scenario and was given a magnitude reading. The fault segment for these two models can be seen in Figure 1 (a) and (b). Each figure shows the entire fault line and the portion of the fault line estimated to be broken for the corresponding scenario.

The JICA [42] also reported that Model A was about km long. This segment starts from the west of the Izmit, where an earthquake occurred in 1999, and ends in Silivri. Model C assumes a simultaneous break of the entire km section of the NAF (North Anatolian Fault) in the Marmara Sea. In this study, we analyzed these two scenarios, separately.

As reported in the JICA [42], there are six existing hospitals and 35 public schools in Zeytinburnu. Each school is considered as a potential location for field hospitals. Coordinates of hospitals and schools were gained from google maps [47]. Figure 2 shows the existing hospitals and the potential school locations on the Zeytinburnu district's map. On the map, existing hospitals' locations were shown with "H" and public schools' locations were shown with circles. Lastly, the triangles represent demand points. Demand points were selected as the center of each neighborhood; these are commonly referred to as "mahalles" in Turkish.

The district based expected number of injured victims are provided as an estimate in JICA [42]. In variance to the JICA [42] and in order to represent the distribution of demand more accurately we used the neighborhoods as the demand points. We identified each neighborhood's location with a single (x,y)

Figure 1 (a). Fault segment for Model A [42]

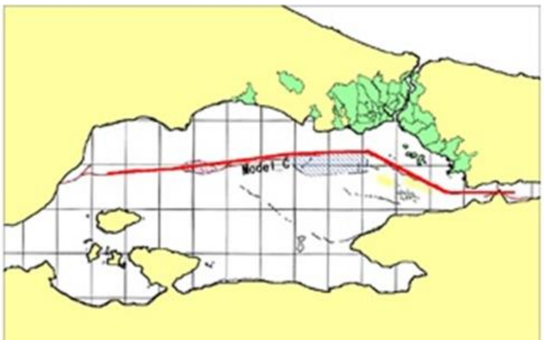


Figure 1 (b). Fault segment for Model C [42]

coordinate. There are neighborhoods in the Zeytinburnu, and the center of each neighborhood was considered as the demand point.

Then, we calculated the expected total number of injured victims for each demand point via the production of population census of each specified neighborhood and the expected percentage of injuries, which is provided in the JICA [42]. When we obtained the numbers we rounded them up to the nearest integer. The population of each neighborhood was gained from the Turkish Statistical Institute [48]. The JICA [42] assumed that 2.80% of the Zeytinburnu's population would be heavily injured if Model A scenario occurs and 3.10 % of the population would be heavily injured if Model C scenario occurs. For instance, the population of Bestelsiz neighborhood was 26,524. Consequently, the number of heavily injured victims in Bestelsiz was calculated as follows: 26,524x0.028= 742.672 ≈ 742. It was assumed in the JICA [42] that the expected total number of injured victims would be three times as the number of heavily injured victims. Therefore the expected total number of victims in Bestelsiz would be 2,228. Lastly, the distance between the two (*x*,*y*) coordinates was calculated by using the Euclidean distance formula.

3.2. Stochastic p-median model

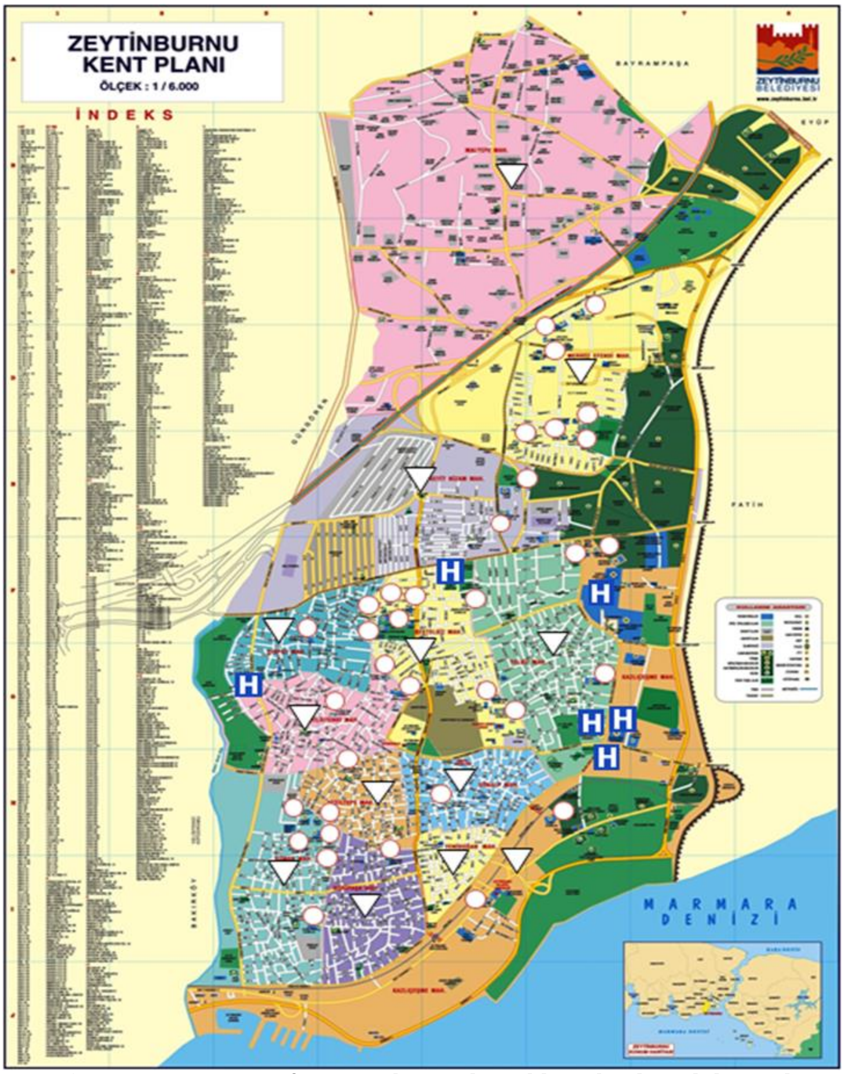


Figure 2. Locations of existing hospitals, public schools and demand points.[46]

We now introduce the following notation which we use throughout the rest of this paper: D denotes the set of demand points (i.e. effected areas in neighborhoods) and H denotes the set of school locations (possible field hospital locations). We let d_j be the demand at neighborhood $j \in D$, and we let f_{ij} denote the distance between the existing or field hospital i and demand point j. We also let H_E denote the set of existing hospitals and H_F denote the set of field hospitals. It was clear that the set of hospitals was $H_E \cup H_F = H$. Each hospital i had a limited capacity and could serve at most, c_i victims. Existing hospitals may have failed during a disaster and may not have been available after the event.

Therefore, victims could not be treated by any of the hospitals when all the other existing hospitals failed, there would not be sufficient capacity at the field hospitals and/or victim treatment at other available hospitals would be prohibited. In such cases, the victim would be assigned to the hospitals in other districts and a large penalty, in terms of distance, would occur. Assigning victims to the hospitals in the other districts could be seen as representing a transportation of victims to hospitals that are not within range. For simplicity, we denoted the last location in H_F as a hospital which was located out of the specified district. Then, $f_{|H_F|j}$ denoted the distance between demand point j and the hospital which was located out of the district. We let Q denoted the number of hospitals that were allowed to be opened (including existing hospitals, $Q \geq |H_E|$). This constraint is added to help decision makers consider their budget while deciding to open field hospitals. This constraint easily can be removed is budget is not an issue for decision makers.

We formulated the problem as a stochastic P-median model. In the first stage, the location decisions for field hospitals were made before random failures of the existing hospitals had occurred (before the event-earthquake occurs). In the second stage, following the existing hospital failures, the victim-hospital assignment decisions were made for each victim on the basis that the existing hospitals had survived or that field hospital were located. The goal was to identify the set of field hospitals to be opened while minimizing the maximum service distance for all the demand points. The service distance for a demand point j was defined as the distances from demand point j to its nearest h_i hospitals.

In the scenario based formulation of the P-median problem, we let s denote a failure scenario and a set of all failure scenarios we denoted as being S, where $s \in S$. We let p_s be the probability when a scenario s occurred and we let $\sum_{s \in S} p_s = 1$. Further we let k_i^s denote whether the hospital i survived (i.e., $k_i^s = 1$, and $k_i^s = 0$ otherwise). For instance, in the case of independent hospital failures, we had $|S| = 2^{|H_E|}$ possible failure scenarios for $|H_E|$ hospitals. Note that our proposed methodology did not require any assumption on independence and distribution for each hospital's failure. Please note that the field hospitals and the hospital that were out of district were perfectly reliable, as abovementioned in detailed.

The binary decision variable y_i specified whether the hospital i was opened or not. Note that $y_i = 1$ where $i \in H_F$. Integer variable x_{ij}^s specified the number of victims that were at demand point j and assigned to hospital i in scenario s. We noted that while the single sourcing assumption was a favored method in practice, it was not restricting for the proposed model.

The scenario-based formulation of two stage stochastic P-median model is as follows:

$$minimize \sum_{s \in S} p_s \left(\sum_{i \in H} \sum_{j \in D} f_{ij} x_{ij}^s \right) \qquad (1)$$

$$\sum_{j \in D} x_{ij}^s \leq c_i k_i^s y_i \quad , \forall i \in H, s \in S \qquad (2)$$

$$\sum_{i \in H} x_{ij}^s \geq d_j \quad , \forall j \in D, s \in S \qquad (3)$$

$$\sum_{i \in H_F} y_i = Q \qquad (4)$$

$$\sum_{i \in H_E} y_i = |H_E| \qquad (5)$$

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

$$x_{ij}^s \geq 0 \; and \; integer \quad , \forall i \in H, j \in D, s \in S \qquad (7)$$

The objective function in (1) finds an optimal facility location solution while minimizes the expected total distance travelled by service victims. The constraints in (2) prevent the assignment of any victim to a hospital that have been failed and ensure that the total demand assigned to the hospital does not exceed hospital's capacity in all scenarios. The constraints in (2) also ensure that a hospital could not function unless it is opened. The constraints in (3) ensure that demand of all affected areas are satisfied in all scenarios. The constraints in (4) guarantee that in total the Q field hospitals function. The constraints in (5) ensure that all existing hospitals are opened (does not matter they are failed or survived, because Constraints in (2) prevent any hospital to serve if it is failed). The constraints in (6) and (7) are integrality constraints.

4. Results

In this section, we provide the results for both un-capacitated and capacitated versions of the P-median model for field hospitals in Zeytinburnu/Istanbul.

We solved both problems optimally by using the deterministic equivalent formulations of the stochastic mathematical models. Models were programmed using MATLAB R2010b and the integer programs were solved by using CPLEX 12.1 (IBM Ilog). The experiments were conducted on a laptop with Intel(R) Core (TM) i7-CPU, a 2.10 GHz processor and a 12.0 GB RAM running on Windows 7 OS. Next, we describe the data in detail.

4.1. Un-capacitated field hospitals and capacitated existing public hospitals

Initially, we analyzed the un-capacitated version of the P-median model. The objective function stayed the same just as in (1). However, we revised the constraints in (2) as follows:

$$\sum_{j\in D} x_{ij}^{s} \le M k_i^s y_i \quad ,\forall i \in H, s \in S \qquad (8)$$

where M represent a sufficiently big number. The constraints (3)-(7) stayed the same.

Then, we introduce an artificial hospital to ensure that unsatisfied demand was satisfied by hospital(s) that were located outside the neighborhoods as stated in Section 3.2. The distance between the artificial hospital and all other hospitals was set to $5km$, which was larger than the maximum distance (4.11) between any demand point and the hospitals. The capacities of the existing hospitals were selected based on the data provided by hospital managers. It was note that the total available capacity of the existing hospitals was 31,500 less than expected total demand for both models (i.e., Model A and Model C). The expected total demand for Model A and Model C were estimated as 32,652 and36,151, respectively. (Detailed data can be found in Appendix). As already mentioned in this section the field hospitals were un-capacitated.

In generating the failure scenarios, we assumed that the failure of existing hospitals was independently and identically distributed according to the Bernoulli distribution with probability q_i (i.e. the failure probability of hospital i). In our experiments, we used uniform failure probability (i.e., $q_{i=1,\dots,|H_E|} = q$) and considered the cases $q = \{1.0, 0.5, 0.2, 0.1, 0.0\}$. All field hospitals and artificial hospital were assumed to be perfectly reliable (i.e., $q_{i=1,\dots,|H_F|} = 0$). We noted the case scenario that when $q = 0$ this corresponds to the deterministic P-median problem and when q=1 this corresponds to the case scenario that all existing hospitals fail. The failure scenarios $s \in S$ were generated as follow: We let $H_E^f \subset H_E$ be the set of hospitals that failed, and $H_E^r \equiv H_E \backslash H_E^f$ be the set of hospitals that were reliable (i.e., not failed). We let the hospital failure indicator ($\mathrm{k_i^s}$) be equal to 1 otherwise if $\mathrm{i} \in \mathrm{H_E^r}$, then $\mathrm{k_i^s} = 0$. The probability of scenario s was then calculated as $\mathrm{p_s} = \mathrm{q}^{|\mathrm{H_E^f}|}(1-\mathrm{q})^{|\mathrm{H_E^r}|}$. The size of the failure scenario set $|\mathrm{S}|$ assessment$= 64$. The deterministic equivalent formulation was found to have 42 binary variables, $\mathrm{y_i}$, and 34,944 ($:= |\mathrm{H}| \times |\mathrm{D}| \times |\mathrm{S}|$) integer variables, $\mathrm{x_{ij}^s}$. Similarly, it had constraints (3), (4), (5) and (8) totaling 3,522 ($:= |\mathrm{D}| \times |\mathrm{S}| + 1 + 1 + |\mathrm{H}| \times |\mathrm{S}| = 13 \times 64 + 1 + 1 + 42 \times 64$) constraints. Note that all datasets used in the paper are available from the authors upon request.

We then presented the results relating to the un-capacitated field hospitals. As mentioned earlier, there were six existing public hospitals in Zeytinburnu. The locations of existing hospitals were fixed and unchangeable. In determining the locations of the field hospitals, the location of existing hospitals were considered. We provided the results for five different failure probabilities relating to the existing hospitals. That is, we considered the following case scenarios: that all the existing hospitals failed (i.e.,$q_i = 1.0$), existing hospitals failed with 50% (i.e.,$q_i = 0.5$), 20% (i.e.,$q_i = 0.2$) and 10% (i.e.,$q_i = 0.1$) probability and finally that all the existing hospitals survived (i.e.,$q_i = 0.0$).

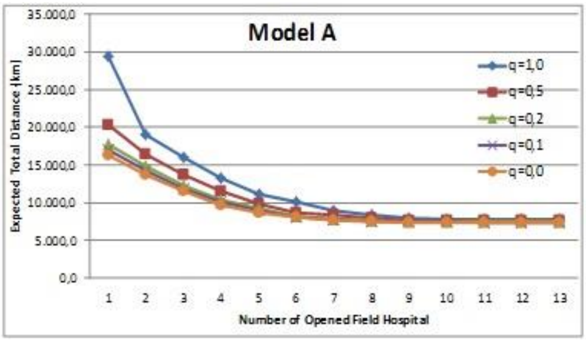
First, we solved the model for both Model A and Model C under all five failure scenarios. The objective function values of these two models (Model A and Model C) are provided in Table 1. The first column in Table 1 shows the number of opened field hospitals (public schools that were going to serve as field hospitals). Column 2 shows the expected total distance for Model A when all existing public hospitals failed (i.e.,$q_i = 1.0$), and columns $3-6$ show the expected total distance when the public hospitals failed with a probability of $0.5, 0.2$ and 0.1 and then when all public hospitals survived consecutively. Columns $7-11$ show relative results for Model C.

We noted that the solutions in column 2 were the same in the case scenarios where 12 or more field hospitals were opened. In other words, we showed that if the events in Model A occurred and all the public hospitals failed, opening up 12 field hospitals would be sufficient enough to transport victims within a minimum distance. Again, we showed that 12 field hospitals were sufficient if the failure probability was reduced to $0{,}5$, $0{,}2$ and $0{,}1$, as seen in columns $3, 4$, and 5. On the other hand, if all public hospitals survived, only 11 field hospitals would be needed to transport all victims within a minimum distance. Since we assessed that 12 field hospitals would be needed for the case scenario where the public hospitals failed with a probability of $1{,}0$, 0.5, $0{,}2$ and $0{,}1$, we deduced that decision makers should consider providing a service of at least 12 field hospitals in order to be able to transport victims within a minimum distance if scenario A occurs.

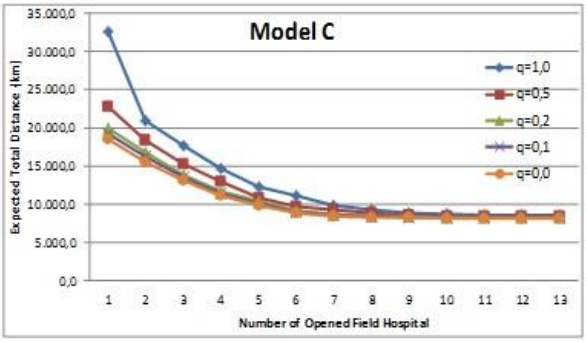
Table 1. Expected total distance.

Number of Opened Field Hospitals	**Model A: Total Distance (m)**					**Model C: Total Distance (m)**				
	Failure Probability					**Failure Probability**				
	1.0	**0.5**	**0.2**	**0.1**	**0.0**	**1.0**	**0.5**	**0.2**	**0.1**	**0.0**
0	163260.0	96390.8	60289.8	48954.9	37994.4	180755.0	113128.5	76144.1	64367.9	52837.9
1	29399.9	20341.6	17686.2	16970.5	16348.7	32551.6	22858.8	19996.1	19198.6	18512.5
2	18976.5	16464.6	14915.7	14321.9	13756.5	21011.0	18343.3	16821.4	16215.7	15608.7
3	16011.1	13720.7	12294.6	11895.9	11501.5	17727.3	15268.7	13893.8	13487.5	13097.9
4	13259.8	11595.9	10413.2	10064.9	9728.8	14681.1	12921.5	11738.4	11416.8	11077.4
5	11147.1	9839.5	9293.2	8979.2	8684.7	12342.2	10915.0	10400.6	10176.6	9876.7
6	10027.1	8719.5	8243.7	8123.6	8019.1	11102.1	9674.9	9160.4	9031.6	8920.0
7	8954.0	8321.1	7845.4	7725.2	7620.7	9914.0	9233.9	8719.5	8590.6	8479.0
8	8378.6	7954.1	7603.3	7524.9	7462.0	9276.8	8827.5	8451.5	8368.7	8303.3
9	7980.2	7721.1	7544.6	7477.0	7423.9	8835.9	8569.6	8377.2	8305.3	8250.7
10	7834.8	7629.9	7506.5	7438.9	7386.9	8674.9	8462.8	8334.8	8262.9	8208.3
11	7796.7	7591.8	7468.8	7427.1	7375.1	8632.5	8420.4	8293.2	8249.8	8195.2
12	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8249.8	8195.2
13	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
14	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
15	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
16	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
17	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
18	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
19	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
20	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
21	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
22	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
23	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
24	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
25	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
26	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
27	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
28	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
29	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
30	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
31	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
32	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
33	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
34	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2
35	7784.9	7580.0	7457.1	7416.1	7375.1	8619.4	8407.3	8280.0	8237.6	8195.2

We assessed that in scenario C, at most 13 hospitals would be needed and that this would occur when the failure probability was 0.1. We concluded that regardless of any of the occurrences in Model A or Model C scenarios. 13 schools would be sufficient enough to serve as field hospitals. It was noted that the improvement in expected total distance was significantly larger for the first few field hospitals than for the others and it was very small after 6-8 field hospitals. We also noted that. no improvement could be attained in expected total traveled distance after a certain number of field hospitals were opened. This state was achieved when all demand points could be assigned to their closest potential hospital out of the 41 locations. Since the field hospitals were un-capacitated. there would be no restriction on the allocation of demand points to assign to their closest field hospital. establishing an additional field hospital could not improve the reduced service distance. We randomly selected 7 as the maximum number of opened field hospitals. This was also meaningful since it was unlikely that a service could be provided to a large number of field hospitals due to the budget constraints that would be imposed in a real life scenario.



(a)



(b)

Figure 3. Expected total distances under different failure probabilities for un-capacitated field hospitals.

As was observed in Figure 3 a) and b). the improvement rate in expected total distance reduction got slower when 7 or more field hospitals were opened. in both models. The results were very similar because it was apparent that in only a few neighborhoods reallocation of demand was advantageous. In the majority of the neighborhoods, the schools were sufficiently close to demand points. It was considered that this was also reasonable since there would have been some other public schools that could have been allocated for treatment operations. We concluded that opening only 7 field hospitals would be an acceptable and sufficient number in order to service victims over a reasonable and rational distance.

Table 2. Distance differences between opening 7 and 12 field hospitals.

Number of Opened Field Hospitals	Differences in Distances for 7 and 12 Field Hospitals (km)									
	Model A Failure Probability					Model C Failure Probability				
	1.0	0.5	0.2	0.1	0.0	1.0	0.5	0.2	0.1	0.0
7	11,147	8,321	7,845	7,725	7,621	9,914	9,234	8,719	8,591	8,479
12	7,785	7,580	7,457	7,416	7,375	8,619	8,407	8,280	8,250	8,195
Difference	3,362	741	388	309	246	1.295	827	439	341	284
Average Distance per Victim	0.10	0.02	0.01	0.01	0.01	0.04	0.02	0.01	0.01	0.01

In Table 2 we illustrated that if 12 field hospitals were opened in case of all public hospitals failed. victims would be transported for 3,362 (km) more if only 7 field hospitals were opened. We deduced that if this value was divided by the expected total demand for Model A $(:= 32652)$. each victim would be transported only 0.1 (km) on average. In the cases where the failure probability was reduced to $0.2, 0.1$ and 0.0 each victim would be transported only for 0.01 (km) on average. In Model C, when failure probabilities were $0.2, 0.1$ and 0.0, these values were also 0.01 (km). However, when the failure probability was 1.0 the expected average distance per victim became 0.04. Interestingly. we were able to conclude that opening 7 field hospitals provided a better solution in terms of expected average or total reduced distance. Please note that that distances were divided by $32{,}652$ which was the expected total demand for the Model C.

Table 3. Opened field hospitals under different failure probabilities.

Failure Probability	Open 7 Field Hospitals: Model A	Open 7 Field Hospitals: Model C	Open 12 Field Hospitals: Model A	Open 12 Field Hospitals: Model C
1.0	15,18, 19, 20, 26, 27,38	15, 18, 19, 20, 26, 27, 38	12, 15, 17, 18, 19, 20, 22, 23, 26, 27, 36, 38	12, 15, 17, 18, 19, 20, 22, 23, 26, 27, 36, 38
0.5	15, 18, 19, 20, 22, 26, 27	15, 18, 19, 20, 22, 26, 27	12, 15, 17, 18, 19, 20, 22, 23, 26, 27, 36, 38	12, 15, 17, 18, 19, 20, 22, 23, 26, 27, 36, 38
0.2	15, 18, 19, 20, 22, 26, 27	15, 18, 19, 20, 22, 26, 27	12, 15, 17, 18, 19, 20, 22, 23, 26, 27, 36, 38	12, 15, 17, 18, 19, 20, 22, 23, 26, 27, 36, 38
0.1	15,18, 19, 20, 22, 26, 27	15,18, 19, 20, 22, 26, 27	12, 15, 17, 18, 19, 20, 22, 23, 26, 27, 36, 38	12, 15, 17, 18, 19, 20, 22, 23, 25, 26, 27, 36
0.0	15,18, 19, 20, 22, 26, 27	15,18, 19, 20, 22, 26, 27	12, 15, 17, 18, 19, 20, 22, 23, 26, 27, 29, 36	12, 15, 17, 18, 19, 20, 22, 23, 26, 27, 36, 41

Table 4. Average distance per victim for capacitated field hospitals.

Number of Opened Field Hospital	Model A: Average Distance Per Victim										Model C: Average Distance Per Victim									
	Capacity=1000					Capacity=2000					Capacity=1000					Capacity=2000				
	Failure Probability					Failure Probability					Failure Probability					Failure Probability				
	1.0	**0.5**	**0.2**	**0.1**	**0.0**	**1.0**	**0.5**	**0.2**	**0.1**	**0.0**	**1.0**	**0.5**	**0.2**	**0.1**	**0.0**	**1.0**	**0.5**	**0.2**	**0.1**	**0.0**
0	5.00	2.95	1.85	1.50	1.16	5.00	2.95	1.85	1.50	1.16	5.00	3.13	2.11	1.78	1.46	5.00	3.13	2.11	1.78	1.46
1	4.85	2.80	1.70	1.35	1.02	4.70	2.66	1.57	1.24	0.95	4.86	3.00	1.97	1.65	1.33	4.73	2.86	1.84	1.51	1.19
2	4.70	2.66	1.57	1.25	0.95	4.40	2.37	1.33	1.05	0.84	4.73	2.86	1.84	1.52	1.20	4.46	2.60	1.58	1.25	0.93
3	4.55	2.51	1.45	1.15	0.89	4.10	2.08	1.10	0.88	0.74	4.60	2.73	1.71	1.38	1.07	4.19	2.33	1.34	1.05	0.79
4	4.41	2.37	1.33	1.05	0.84	3.81	1.81	0.92	0.75	0.66	4.46	2.60	1.58	1.25	0.93	3.93	2.07	1.13	0.89	0.71
5	4.26	2.23	1.22	0.97	0.79	3.52	1.54	0.77	0.64	0.58	4.33	2.47	1.46	1.14	0.84	3.66	1.82	0.94	0.75	0.64
6	4.11	2.09	1.11	0.88	0.75	3.23	1.30	0.64	0.55	0.51	4.20	2.34	1.35	1.06	0.80	3.40	1.58	0.79	0.64	0.57
7	3.97	1.95	1.01	0.81	0.71	2.94	1.08	0.54	0.47	0.44	4.07	2.21	1.24	0.97	0.75	3.14	1.35	0.66	0.55	0.50
8	3.82	1.81	0.93	0.75	0.66	2.65	0.88	0.46	0.41	0.39	3.94	2.08	1.14	0.90	0.72	2.87	1.14	0.56	0.49	0.45
9	3.68	1.68	0.85	0.70	0.63	2.36	0.71	0.39	0.36	0.34	3.81	1.96	1.04	0.82	0.68	2.61	0.94	0.48	0.42	0.40
10	3.53	1.56	0.78	0.65	0.59	2.07	0.58	0.35	0.32	0.30	3.67	1.83	0.95	0.76	0.65	2.35	0.77	0.41	0.37	0.35
11	3.39	1.43	0.72	0.61	0.56	1.79	0.48	0.32	0.30	0.29	3.54	1.71	0.88	0.71	0.62	2.10	0.64	0.37	0.34	0.32
12	3.24	1.32	0.66	0.57	0.53	1.50	0.40	0.30	0.29	0.27	3.41	1.59	0.81	0.66	0.59	1.84	0.52	0.33	0.31	0.30
13	3.10	1.21	0.62	0.54	0.50	1.22	0.35	0.29	0.28	0.27	3.28	1.48	0.75	0.62	0.56	1.59	0.44	0.31	0.29	0.28
14	2.96	1.10	0.57	0.50	0.47	0.94	0.32	0.28	**0.27**	**0.26**	3.15	1.37	0.70	0.59	0.54	1.33	0.38	0.30	0.29	0.28
15	2.81	1.00	0.53	0.47	0.45	0.67	0.30	**0.27**	0.27	0.26	3.03	1.26	0.64	0.55	0.51	1.08	0.34	0.29	**0.28**	**0.27**
16	2.67	0.91	0.49	0.45	0.42	0.40	0.29	0.27	0.27	0.26	2.90	1.16	0.60	0.52	0.49	0.83	0.31	**0.28**	0.28	0.27
17	2.53	0.83	0.46	0.43	0.40	0.31	**0.28**	0.27	0.27	0.26	2.77	1.07	0.56	0.50	0.47	0.58	0.30	0.28	0.28	0.27
18	2.39	0.76	0.44	0.41	0.39	**0.30**	0.28	0.27	0.27	0.26	2.64	0.98	0.52	0.47	0.45	0.34	**0.29**	0.28	0.28	0.27
19	2.25	0.69	0.42	0.40	0.38	0.30	0.28	0.27	0.27	0.26	2.51	0.90	0.50	0.45	0.43	**0.31**	0.29	0.28	0.28	0.27
20	2.11	0.63	0.41	0.38	0.37	0.30	0.28	0.27	0.27	0.26	2.39	0.83	0.47	0.44	0.41	0.31	0.29	0.28	0.28	0.27
21	1.97	0.59	0.40	0.37	0.36	0.30	0.28	0.27	0.27	0.26	2.26	0.76	0.45	0.42	0.40	0.31	0.29	0.28	0.28	0.27
22	1.83	0.54	0.38	0.37	**0.35**	0.30	0.28	0.27	0.27	0.26	2.13	0.70	0.44	0.41	0.39	0.31	0.29	0.28	0.28	0.27
23	1.69	0.50	0.38	0.36	0.35	0.30	0.28	0.27	0.27	0.26	2.01	0.64	0.42	0.40	0.39	0.31	0.29	0.28	0.28	0.27
24	1.55	0.47	0.37	0.36	0.35	0.30	0.28	0.27	0.27	0.26	1.88	0.60	0.41	0.39	0.38	0.31	0.29	0.28	0.28	0.27
25	1.42	0.44	**0.36**	0.36	0.35	0.30	0.28	0.27	0.27	0.26	1.76	0.56	0.40	0.39	0.38	0.31	0.29	0.28	0.28	0.27
26	1.28	0.42	0.36	**0.35**	0.35	0.30	0.28	0.27	0.27	0.26	1.64	0.52	0.40	0.39	0.38	0.31	0.29	0.28	0.28	0.27
27	1.15	0.41	0.36	0.35	0.35	0.30	0.28	0.27	0.27	0.26	1.52	0.49	**0.39**	**0.38**	0.38	0.31	0.29	0.28	0.28	0.27
28	1.02	0.40	0.36	0.35	0.35	0.30	0.28	0.27	0.27	0.26	1.39	0.47	0.39	0.38	**0.37**	0.31	0.29	0.28	0.28	0.27
29	0.89	0.39	0.36	0.35	0.35	0.30	0.28	0.27	0.27	0.26	1.27	0.45	0.39	0.38	0.37	0.31	0.29	0.28	0.28	0.27
30	0.76	0.39	0.36	0.35	0.35	0.30	0.28	0.27	0.27	0.26	1.16	0.44	0.39	0.38	0.37	0.31	0.29	0.28	0.28	0.27
31	0.63	**0.38**	0.36	0.35	0.35	0.30	0.28	0.27	0.27	0.26	1.04	0.43	0.39	0.38	0.37	0.31	0.29	0.28	0.28	0.27
32	0.52	0.38	0.36	0.35	0.35	0.30	0.28	0.27	0.27	0.26	0.93	0.43	0.39	0.38	0.37	0.31	0.29	0.28	0.28	0.27
33	**0.46**	0.38	0.36	0.35	0.35	0.30	0.28	0.27	0.27	0.26	0.83	0.43	0.39	0.38	0.37	0.31	0.29	0.28	0.28	0.27
34	0.46	0.38	0.36	0.35	0.35	0.30	0.28	0.27	0.27	0.26	0.74	0.43	0.39	0.38	0.37	0.31	0.29	0.28	0.28	0.27
35	0.46	0.38	0.36	0.35	0.35	0.30	0.28	0.27	0.27	0.26	**0.66**	**0.42**	0.39	0.38	0.37	0.31	0.29	0.28	0.28	0.27

In Table 3, we presented the opened field hospitals for seven and twelve field hospital cases under different failure probabilities. In the opening seven field hospitals case scenarios, when the failure probability was 1.0, schools in regions 15,18,19,20,26,27 and 38 were selected for both Model A and Model C. When the failure probability was reduced to 0.5,0.2,0.1 and 0.0 existing hospitals had more chance to survive, then model substituted school in region 38 by 22 and it decided to open schools in regions 15,18,19,20,26 and 27. We determined the effect of such changes in a scenario where twelve field hospitals were opened as well. Surprisingly, we concluded that high demand had the same effect on the decision making if the field hospitals had infinite capacity and the number of opened field hospitals stayed the same. Next, we analyzed the capacitated field hospitals case scenarios.

4.2. Capacitated field and capacitated existing public hospitals

In the previous section, we assumed that the field hospitals were un-capacitated, whereas the existing public hospitals and field hospitals would have been capacitated in real life. In this section, we present the results and analysis where both field and existing hospitals were deemed to be capacitated. In this approach, we assumed that the total capacity of the existing hospitals was the same as in the previous section (31,500). We analyzed the capacitated version of the problem for multiple cases such as low capacity and high capacity and each case tested for 5 different failure scenarios.

The values in the Table 4 show the average distances per victim. The averages that have been taken represent the division of expected total distances dependent upon demand. The first column in Table 4 shows the number of opened field hospitals. Columns 2-6 show the average distances per victim in Model A for 5 different failure scenarios when the capacity of the field hospitals was 1,000. Columns 7 to 11 show the results, when the capacities of the field hospitals were increased to 2,000. Likewise, columns 12 to 16 and 17 to 21 show the average distance per victim in Model C for 5 different failure scenarios when the capacities of the field hospitals were equal to 1,000 and 2,000, consecutively.

As expected, the average serving distance decreased as the demand decreased. The locations of the field hospitals were selected as close as possible to the most populated neighborhoods. In comparison with the un-capacitated case scenario, the requisite number of field hospitals was higher in order to provide a service within the same distance range. For instance, in Model A when all existing hospitals failed the minimum average distance that could be achieved was (km) with 33 field hospitals. However, the minimum average distance that could be achieved in the un-capacitated case scenario was 0.24 (km) and with only 9 field hospitals. This comparison is valid for all the other cases as predicted. Further, the average serving distance decreased as the failure probability decreased in both the capacitated and un-capacitated cases because as the failure probability is decreased more existing hospitals are survived and more capacity is became available to serve victims.

If the capacities of the field hospitals were equal to 1,000, the total available capacity would be 35,000 and if the capacities were equal to 2,000, the total available capacity would be 70,000. The total demand was always less than the total available capacity in Model A. However, the total demand was higher than the total available capacity in Model C when the capacities of the field hospitals were restricted to 1,000. Obviously, the total demand would be always less than the total available capacity in un-capacitated cases. This is because in capacitated cases, the selected locations of the field hospitals were farther away than in the un-capacitated cases. The capacitated model could not achieve as lower an average distance per victim as in the case of the un-capacitated model. In other words, in capacitated cases, the model does not allow for an allocation of victims to the closest field or existing hospitals because of the capacity constraints. Therefore as a result, higher than expected serving distance would occur.

As seen in Figure 4 a) 33 field hospitals were needed to achieve a minimum average distance per victim when all existing hospitals failed and 31,25,26 and 22 field hospitals were needed when the failure probabilities reduced to 0.5,0.2,0.1 and 0.0 (all existing hospitals survived), respectively. When capacities increased to 2,000, (Figure 4b) the number of needed field hospitals decreased to 18,17,15,14, and 14. Even though, the total demand and the minimum average distance that could be achieved is higher in model C, there was really little difference between Model A and Model C when the capacities of the field hospitals were equal to 2,000 this was because the capacity of the field hospitals was doubled while the demand increased only by 0.3%-which represents a figure of only 3,499 more victims.

We went on to analyze the effect of the different failure probabilities and field hospital capacities on expected total unsatisfied demand. We presented the results in Table 5. The first observation we gained was that when the failure probability was very high or high, i.e., q=1.0,0.5, and the capacities of the field hospitals were equal to 1,000, full satisfaction of demand could not be achieved even if all 35 field hospitals were opened, in Model C.

As mentioned earlier, these circumstances occurred when the total capacity of the field hospitals was less than the total demand. In another words, some of the victims needed to be transported to the hospitals located on the other regions because of the lack of capacity. Therefore, in this event it should have been suggested to decision makers to set up higher capacitated field hospitals. Secondly, at least 11 field hospitals for Model A and 13 for Model C would be needed to satisfy demand even if the failure probability was very low, i.e., q=0.1, and the capacities of the field hospitals was equal to 2,000. This may be a reference point for how failure of the existing hospitals effects satisfying the demand.

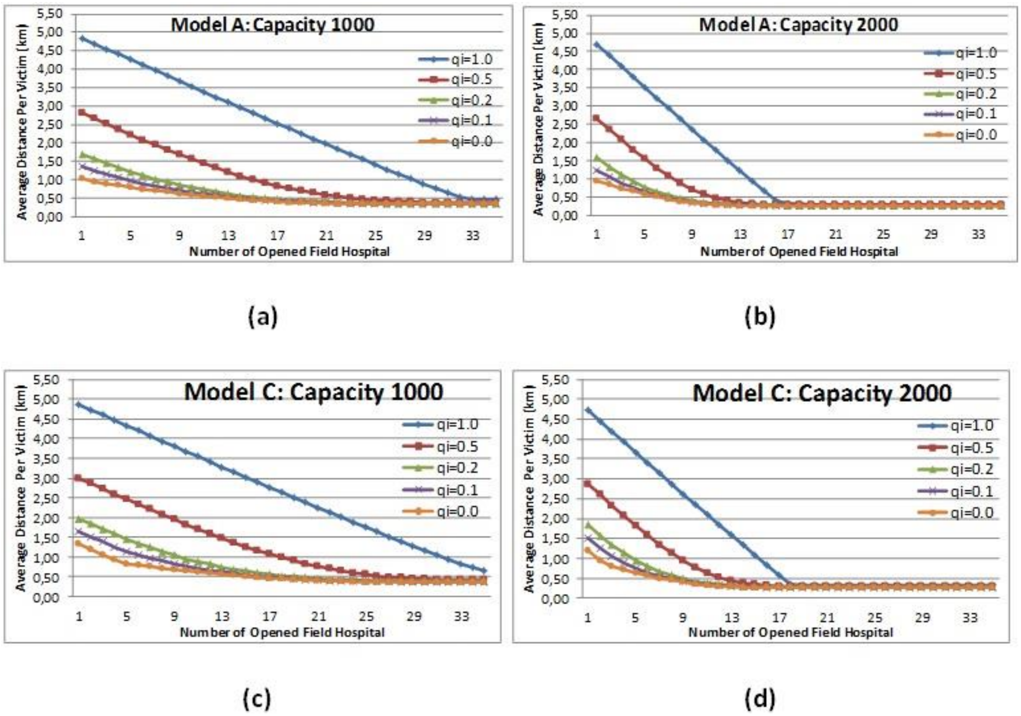


Figure 4. Average distance under different failure probabilities for capacitated field hospitals.

Consequently, decision makers or managers may in the future be better off giving greater attention to the infrastructure of the existing public hospitals as well as and strengthening the buildings. We want to state out that if public hospitals are projected to fail then its whole capacity is unusable. Here, we would like to point out a future study, which will be the next step of this study and consider partial failure of the existing public hospitals. Lastly, it was observed that the demand satisfaction rate increased with a smaller number of field hospitals when the failure probability of the existing hospitals decreased. We therefore deduced from this that this further observation supported our second observation.

5. Conclusions and future studies

The next predicted earthquake is anticipated to cause major havoc to many regions of Istanbul. The anticipated earthquake severely threatens human life and health, not to mention the substructure and it even threatens the economy of Turkey as a whole. The Government and the Istanbul Metropolitan Municipality have taken preparatory action, both for pre-disaster and post disaster scenarios, against possible earthquakes to mitigate the effects of such a disaster. Locating the disaster relief facilities is one of the crucial tasks to strategically prepare for this event. Life-saving decisions on the location of hospitals, such as field hospitals, essentially must rank as one of the most important managerial issues.

Table 5. Percentage of unsatisfied demand for Model A and Model C under different failure probabilities and field hospital capacities.

	Model A: Percentage of Unsatisfied Demand										Model C: Percentage of Unsatisfied Demand									
	Capacity=1000					Capacity=2000					Capacity=1000					Capacity=2000				
	Failure Probability					Failure Probability					Failure Probability					Failure Probability				
Number of Opened Field Hospital	1.0	0.5	0.2	0.1	0.0	1.0	0.5	0.2	0.1	0.0	1.0	0.5	0.2	0.1	0.0	1.0	0.5	0.2	0.1	0.0
0	100.00	51.76	22.82	13.18	3.53	100.00	51.76	22.82	13.18	3.53	100.00	56.43	30.29	21.58	12.87	100.00	56.43	30.29	21.58	12.87
1	96.94	48.70	19.76	10.11	0.47	93.87	45.68	17.38	8.43	**0.00**	97.23	53.67	27.53	18.81	10.10	94.47	50.90	24.76	16.05	7.33
2	93.87	45.68	17.38	8.43	**0.00**	87.75	39.67	12.93	5.62	0.00	94.47	50.90	24.76	16.05	7.33	88.94	45.37	19.23	10.51	1.80
3	90.81	42.66	15.12	7.00	0.00	81.62	33.73	8.81	3.11	0.00	91.70	48.13	21.99	13.28	4.57	83.40	39.89	14.67	6.96	**0.00**
4	87.75	39.67	12.93	5.62	0.00	75.50	28.10	5.98	1.76	0.00	88.94	45.37	19.23	10.51	1.80	77.87	34.48	10.75	4.51	0.00
5	84.69	36.70	10.87	4.37	0.00	69.37	22.80	3.85	0.94	0.00	86.17	42.62	16.71	8.26	**0.00**	72.34	29.17	7.22	2.42	0.00
6	81.62	33.73	8.81	3.11	0.00	63.25	17.87	2.29	0.46	0.00	83.40	39.89	14.67	6.96	0.00	66.81	24.13	4.83	1.35	0.00
7	78.56	30.89	7.26	2.32	0.00	57.12	13.50	1.27	0.20	0.00	80.64	37.17	12.63	5.67	0.00	61.27	19.45	3.09	0.73	0.00
8	75.50	28.10	5.98	1.76	0.00	51.00	9.88	0.71	0.09	0.00	77.87	34.48	10.75	4.51	0.00	55.74	15.13	1.82	0.35	0.00
9	72.44	25.38	4.77	1.25	0.00	44.87	6.86	0.37	0.04	0.00	75.10	31.81	8.89	3.38	0.00	50.21	11.30	0.99	0.14	0.00
10	69.37	22.80	3.85	0.94	0.00	38.75	4.41	0.15	0.01	0.00	72.34	29.17	7.22	2.42	0.00	44.68	8.16	0.54	0.07	0.00
11	66.31	20.27	3.00	0.67	0.00	32.62	2.72	0.07	**0.00**	0.00	69.57	26.64	5.96	1.83	0.00	39.14	5.59	0.27	0.03	0.00
12	63.25	17.87	2.29	0.46	0.00	26.50	1.56	0.03	0.00	0.00	66.81	24.13	4.83	1.35	0.00	33.61	3.58	0.11	0.01	0.00
13	60.19	15.65	1.76	0.32	0.00	20.37	0.79	0.01	0.00	0.00	64.04	21.75	3.87	0.98	0.00	28.08	2.14	0.05	**0.00**	0.00
14	57.12	13.50	1.27	0.20	0.00	14.25	0.33	**0.00**	0.00	0.00	61.27	19.45	3.09	0.73	0.00	22.55	1.19	0.02	0.00	0.00
15	54.06	11.61	0.95	0.13	0.00	8.12	0.13	0.00	0.00	0.00	58.51	17.20	2.37	0.50	0.00	17.01	0.58	0.01	0.00	0.00
16	51.00	9.88	0.71	0.09	0.00	2.00	0.03	0.00	0.00	0.00	55.74	15.13	1.82	0.35	0.00	11.48	0.25	**0.00**	0.00	0.00
17	47.94	8.25	0.51	0.06	0.00	**0.00**	**0.00**	0.00	0.00	0.00	52.98	13.14	1.36	0.23	0.00	5.95	0.09	0.00	0.00	0.00
18	44.87	6.86	0.37	0.04	0.00	0.00	0.00	0.00	0.00	0.00	50.21	11.30	0.99	0.14	0.00	0.42	0.01	0.00	0.00	0.00
19	41.81	5.53	0.24	0.02	0.00	0.00	0.00	0.00	0.00	0.00	47.44	9.70	0.75	0.10	0.00	**0.00**	**0.00**	0.00	0.00	0.00
20	38.75	4.41	0.15	0.01	0.00	0.00	0.00	0.00	0.00	0.00	44.68	8.16	0.54	0.07	0.00	0.00	0.00	0.00	0.00	0.00
21	35.69	3.53	0.11	0.01	0.00	0.00	0.00	0.00	0.00	0.00	41.91	6.80	0.39	0.04	0.00	0.00	0.00	0.00	0.00	0.00
22	32.62	2.72	0.07	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	39.14	5.59	0.27	0.03	0.00	0.00	0.00	0.00	0.00	0.00
23	29.56	2.09	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	36.38	4.46	0.17	0.01	0.00	0.00	0.00	0.00	0.00	0.00
24	26.50	1.56	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	33.61	3.58	0.11	0.01	0.00	0.00	0.00	0.00	0.00	0.00
25	23.44	1.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	30.85	2.80	0.08	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00
26	20.37	0.79	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	28.08	2.14	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00
27	17.31	0.51	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	25.31	1.65	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
28	14.25	0.33	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	22.55	1.19	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
29	11.18	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	19.78	0.84	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
30	8.12	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	17.01	0.58	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31	5.06	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	14.25	0.36	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32	2.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	11.48	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33	**0.00**	**0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.72	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.95	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.18	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

In this study, we developed models and solutions for the problem of locating field hospitals in Zeytinburnu/Istanbul in the event of a major earthquake hitting this region. Using our representative, we divided the hospitals into two categories: existing public hospitals and field hospitals. Existing public hospitals are the hospitals that are already functioning and that are supposed to function or fail with a probability in a post-disaster scenario.

On the other hand, field hospitals are defined as schools that will function as emergency centers or as hospital post-disaster. However, the decision making about the location of these field hospitals must be done prior to the occurrence of any such disaster. Therefore we set out to determine the possible and preferable locations of the field hospitals whilst collaterally also considering the existing public hospitals functionality after a disaster. We also considered, within our analysis, optimizing the number of such field hospitals needed in the event of a failure of the existing hospitals. We developed a two stage stochastic P-median model and then identified the number, location and size of the field hospitals in Zeytinburnu/Istanbul. The district of Zeytinburnu has multiple neighborhoods. Each neighborhood has different sizes of population and the locations of these neighborhoods were taken as the demand points whilst we were constructing our solution model to determine the field hospitals locations.

We constructed and provided solutions to numerous case scenario models for this purpose and after analyzing the results further provided alternate, more efficient solution improvements. Two different earthquake scenarios, called Model A and Model C and provided by [42], are analyzed separately in detailed.

In the first case, we considered un-capacitated field hospitals and analyzed how to minimize the expected total distance to them. The marginal development of establishing an additional field hospital reduced abruptly after the first few field hospitals. We observed that seven field hospitals would be satisfactory for both Model A and Model C scenarios. While analyzing Model A, it was realized that nine field hospitals could reasonably serve the victims with an average distance of 0.24 km even if all the existing hospitals failed. Generally, the average serving distances were found to be between 0.23 km and 0.30 km, even with only a few field hospitals in the un-capacitated field hospitals case scenarios. However, more field hospitals were needed for capacitated cases. If capacities of the field hospitals were low (1,000 km), then we found that these ranges were never reached. In Model C, the same ranges of expected total distance as was the case with Model A could be achieved for un-capacitated field hospital cases. The expected total distance when comparing locating either 7 or alternatively 12 field hospitals had a significant different resulting effect in Model A and Model C. Under high failure probabilities locating 7 field hospitals in Model C provided more advantages than in locating 7 field hospitals in Model A. For example, in the 1.0 failure probability case the difference in the expected total distance between locating 7 field hospitals and 12 field hospitals was 3,362 km in Model A while it was as low as 1,295 km in Model C. However we demonstrated that an opposing, opposite analysis could be obtained if the failure probability was lower. In the second case, we consider capacitated field hospitals and the whole question of how to minimize the expected total distance as well as calculating average distances per victim. We found that there was no marginal development requirement for establishing an additional field hospital in both Models A or C when the capacity of the field hospitals was 1,000. As increasing number of opened field hospitals improved average distance reductions but we concluded that more than 35 field hospitals would be needed, [which would be very costly], to achieve the requisite average level of distance reduction achieved in the un-capacitated case scenario. The average distance levels that were achieved in the un-capacitated case with up to 7 field hospitals could be achieved with more than 20 field hospitals in capacitated cases.

The selected numbers of field hospitals under the various case scenarios were found to be sufficient. However, the result of introducing capacity limits to field hospitals caused the need for a higher number of field hospitals in order to gain the desired level of average distances. Since the un-capacitated field hospitals are not practical in real life and the capacity expansion of field hospitals makes a high impact on serving victims within a minimum distance a higher level of capacity is desirable.

In our study we analyzed the effects of available earthquake scenarios on existing hospitals. In our opinion the associated damage estimates of earthquake scenarios on roads, substructure, and network could usefully be incorporated into the models. Furthermore, in this study, if public hospitals are projected to fail then its whole capacity is unusable. Another future study, which will be the next step of this study, may be considering partial failure of the existing public hospitals and categorizing type of victims (as in [2]) and the service type that a hospital serve because all public hospitals do not serve the same types treatments. Also for a larger number of case scenarios heuristic methods, such as SAA (Sample Average Approximation [49]) and GA (Genetic Algorithm), etc., could usefully be applied. We believe that our study provides valuable, contributory information for the benefit of the aforementioned decision makers.

Acknowledgments

The author would like to thank the Editors Ramazan Yaman, Ibrahim Kucukkoc and Gerhard Wilhelm Weber, and the three anonymous referees for their helpful comments and suggestions. Also, any opinions, findings, and conclusions are those of the author and do not necessarily reflect the view of the Governmental (GO) and Non-Governmental Organizations (NGO).

Appendix

Demand for Model A and Model C of neighborhoods in Zeytinburnu/Istanbul

		Model A			Model C		
	Population	**Heavily Injured**	**Injured**	**Total**	**Heavily Injured**	**Injured**	**Total**
Beştelsiz	26,524	743	2,228	2,971	822	2,467	3,289
Çırpıcı	29,946	838	2,515	3,354	928	2,785	3,713
Gökalp	20,978	587	1,762	2,350	650	1,951	2,601
Kazlıçeşme	1,289	36	108	144	40	120	160
Maltepe	153	4	13	17	5	14	19
Merkezefendi	22,413	628	1,883	2,510	695	2,084	2,779
Nuripaşa	27,885	781	2,342	3,123	864	2,593	3,458
Sümer	37,565	1,052	3,155	4,207	1,165	3,494	4,658
Telsiz	38,742	1,085	3,254	4,339	1,201	3,603	4,804
Yenidoğan	10,709	300	900	1,199	332	996	1,328
Yeşiltepe	23,026	645	1,934	2,579	714	2,141	2,855
Seyitnizam	23,405	655	1,966	2,621	726	2,177	2,902
Veliefendi	28,914	810	2,429	3,238	896	2,689	3,585
Total	**291,549**	**8,163**	**24,490**	**32,652**	**9,038**	**27,114**	**36,151**

References

[1] Balcik, B., and Beamon B.M.,. Facility location in humanitarian relief. International Journal of Logistics, 11(2): 101-121 (2008).

[2] Paul JA, Hariharan G. Location-Allocation Planning of Strategic Stockpile Locations for Effective Disaster Mitigation. Annals of Operations Research 196(1): 469-490 (2012).

[3] Pengfei, Y., Santhosh K.G., Jomon A.P., and Lin L. Hospital capacity planning for disaster emergency management. Socio-Economic Planning Sciences. 44(3): 151-160 (2010).

[4] Sheffi, Y. The resilient enterprise: overcoming vulnerability for competitive ad¬vantage. MIT Press Books. 1 (2003).

[5] Pinto, C. M., Lopes, A. M., and Machado, J. T. Casualties Distribution in Human and Natural Hazards. In Mathematical Methods in Engineering (pp. 173-180). Springer Netherlands (2014).

[6] Unesco. Learning from the great east japan earthquake and tsunami policy perspectives. Available from: http://www.unesco.org/new/en/media-services/singleview/news/learning_from_the_great_east_japan_earthquake_and_tsunami_policy_perspectives/. Accessed 4 March 2015.

[7] Kreiss, Y., Merin, O., Peleg, K., Levy, G., Vinker, S., Sagi, R., Abargel, A., et al. Early disaster response in Haiti: the Israeli field hospital experience. Annals of Internal Medicine. 153 (1): 45-48 (2010).

[8] Kaji, A.H., Koeing, K.L., and Lewis, R.J. Current hospital disaster preparedness. Jama: The Journal Of The American Medical Association. 298 (18): 2188-2190 (2007).

[9] Rubinson, L., Nuzzo, J.B., Talmor, D.S., O'Toole, T., Kramer, B.R., and Inglesby, T.V.

Augmentation of hospital critical care capacity after bioterrorist attacks or epidemics: Recommendations of the Working Group on Emergency Mass Critical Care++. Critical Care Medicine. 33(10): E2393 (2005).

[10] Kanter, R.K., and Moran J.R. Pediatric hospital and intensive care unit capacity in regional disasters: expanding capacity by altering standards of care. Pediatrics. 119(1): 94-100 (2007).

[11] Murali, P., Ordóñez, F., and Dessouky, M.M. Facility location under demand uncertainty: Response to a large-scale bio-terror attack. Socio-Economic Planning Sciences. 46(1): 78-87 (2012).

[12] Bar-Dayan, Y., et al.,. A multidisciplinary field hospital as a substitute for medical hospital care in the aftermath of an earthquake: the experience of the Israeli Defense Forces Field Hospital in Duzce, Turkey. Prehospital and Disaster Medicine. 20 (2): 103-106 (1999).

[13] Bar-Dayan, Y., et al.,. An earthquake disaster in Turkey: an overview of the experience of the Israeli Defence Forces Field Hospital in Adapazari. Disasters. 24(3): 262-270 (2000).

[14] Berman, O., and Gavious, A. Location of terror response facilities: A game between state and terrorist. European Journal of Operational Research, 177(2), 1113-1133 (2007).

[15] Paul, J.A., and Batta, R. Models for hospital location and capacity allocation for an area prone to natural disasters. International Journal of Operational Research. 3(5): 473-496 (2008).

[16] Salmerón, J., and Apte, A. Stochastic optimization for natural disaster asset prepositioning. Production and Operations Management, 19(5), 561-574 (2010).

[17] Campbell, A. M., and Jones, P. C.. Prepositioning supplies in preparation for disasters. European Journal of Operational Research, 209(2), 156-165 (2011).

[18] Galindo, G., and Batta, R.. Prepositioning of supplies in preparation for a hurricane under potential destruction of prepositioned supplies. Socio-Economic Planning Sciences, 47(1), 20-37 (2013).

[19] Kaji, A.H., and Lewis, R.J. Hospital disaster preparedness in Los Angeles county. Academic Emergency Medicine. 13(11): 1198-1203 (2006).

[20] Paul, J.A., and Hariharan, G. Hospital capacity planning for efficient disaster mitigation during a bioterrorist attack. In Proceedings of the 39th conference on Winter simulation: 40 years! The best is yet to come. IEEE Press.:1139-1147 (2007).

[21] Altay, N., and Green-III, W.G.,. OR/MS research in disaster operations management. European Journal of Operational Research. 175(1): 475-493 (2006).

[22] Gormez, N.,. Disaster response and relief facility location for Istanbul. PhD dissertation. Middle East Technical University (2008).

[23] Wright, P.D., Liberatore, M.J., and Nydick, R.L. A survey of operations research models and applications in homeland security. Interfaces. 36(6): 514-529 (2006).

[24] Dekle, J., Lavieri, M.S., Martin, E., Emir-Farinas, H., and Francis, R.L.,. A Florida county locates disaster recovery centers. Interfaces. 35(2): 133-139 (2005).

[25] Jia, H., Ordóñez, F., and Dessouky, M.,. A modeling framework for facility location of medical services for large-scale emergencies. IIE Transactions. 39(1): 41-55 (2007).

[26] Gunnec, D., and Salman, F.,. A two-stage multi-criteria stochastic programming model for location of emergency response and distribution centers. International Network Optimization Conference (2007).

[27] Tzeng, G-H., Cheng, H-J., and Huang, T.D. Multi-objective optimal planning for designing relief delivery systems. Transportation Research Part E: Logistics and Transportation Review. 43(6): 673-686 (2007).

[28] Serra, D., and Marianov., V. The p-median problem in a changing network: the case of Barcelona. Location Science. 6(1):383-394 (1998).

[29] Barbarosoğlu, G., and Arda, Y.,. A two-stage stochastic programming framework for transportation planning in disaster response. Journal of the Operational Research Society 55(1): 43-53 (2004).

[30] Drezner, Z., and Hamacher, H.W.Eds.,. Facility location: applications and theory. Springer. Verlag (2004).

[31] Church, R., and Velle, C.R.,. The maximal covering location problem. Papers in Regional Science. 32(1): 101-118 (1974).

[32] Berman, O., Drezner, Z., and Wesolowsky, G.O.,. Locating service facilities whose reliability is distance dependent. Computers & Operations Research. 30(11): 1683-1695 (2003).

[33] Batta, R., Larson, R.C., and Odoni, A.R.,. A single-server priority queueing location model. Networks.18(2): 87-103 (1988).

[34] Aydin, N., and Murat, A.,. A swarm intelligence based sample average approximation algorithm for the capacitated reliable facility location problem. International Journal of Production Economics. 145(1):173-183 (2012).

[35] Schütz, P., Tomasgard, A., and Ahmed, S. Supply chain design under uncertainty using sample average approximation and dual decomposition. European Journal of Operational Research. 199(2): 409-419 (2009).

[36] Masihtehrani, B.,. Stochastic analysis of disruption in supply chain networks. PhD dissertation. The Pennsylvania State University, (2011).

[37] Snyder, L.V., Scaparra, M.P., Daskin, M.S., and Church, R.L. Planning for disruptions in supply chain networks. Tutorials In Operations Research (2006).

[38] Snyder, L.V., and Daskin, M.S. Reliability models for facility location: the expected failure cost case. Transportation Science. 39(3): 400-416 (2005).

[39] Shen, Z.J.M., Zhan, R.L., and Zhang, J. "The reliable facility location problem: Formulations, heuristics, and approximation algorithms. INFORMS Journal on Computing. 23(3): 470-482 (2011).

[40] Snyder, L.V., and Ülker, N.Ş. A model for locating capacitated, unreliable facilities. In IERC Conference, Atlanta, GA (2005).

[41] Gade, D.,. Capacitated facilities location problems with unreliable facilities. ProQuest (2007).

[42] JICA. The study on a disaster prevention / mitigation basic plan in Istanbul including seismic micronization in the republic of Turkey. Final report, Japan International Cooperation Agency (2002).

[43] Gormez, N., Koksalan, M., and Salman, F.S.,. Locating disaster response facilities in Istanbul. Journal of the Operational Research Society. 62(7): 1239-1252 (2010).

[44] Saglik (2015). Available from: http://www.saglik.gov.tr/EN/ana-sayfa/2-0/20130617.html. Accessed 20 September 2015.

[45] Meb. (2015). Available from: http://www.meb.gov.tr/english/indexeng.html. Accessed 12 December 2015.

[46] Zeytinburnu (2015). Available from: http://www.zeytinburnu.bel.tr/Page/376/news/news-from-municipal.aspx. Accessed 17 August 2015.

[47] Google (2015). Available from: http://maps.google.com/. Accessed 24 December 2015.

[48] Tuik (2015). Available from: http://www.tuik.gov.tr/AltKategori.do?ust_id=11. Accessed 18 October 2015.

[49] Ayvaz, B., Bolat, B., and Aydin, N. (2015). Stochastic reverse logistics network design for waste of electrical and electronic equipment. Resources, Conservation and Recycling, 104, 391-404.

__Nezir Aydin__ currently works as an Assistant Professor at the Department of Industrial Engineering at the Yildiz Technical University/Istanbul/Turkey, which he joined in 2014. He received BSc. and MSc.in Industrial Engineering from Yildiz Technical University/Istanbul/Turkey in 2005 and 2007, respectively. Later, he received PhD degree at Industrial and Systems Engineering from Wayne State University/Detroit/MI/USA. He worked as a researcher (in several projects) and an instructor (taught several graduate and undergraduate level courses) during his PhD studies. He is currently conducting projects related to his research area, which includes optimization, mathematical modeling, humanitarian logistics, decision making, supply chain management, and stochastic optimization.