Emergency Response Facility Location in Istanbul for Effective Distribution of Relief Aid

by

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This is to certify that I have examined this copy of a master's thesis by

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ABSTRACT

We consider the problem of locating emergency response facilities for disaster preparedness. The facilities are established to preposition durable relief items before a disaster and as coordination and supply points for the distribution of relief items in case of a disaster. The distribution of the items is carried on a highway network which may be damaged due to the disaster. We model the post-disaster condition of the network by probabilistic failures of the links of the network. Relief item requirements throughout the disaster area are represented by demand points with estimated weights. For rapid disaster response, a facility should be located close to each demand point considering the shortest path distances in the surviving network. However, this may not be possible and therefore the goal is to maximize the expected demand coverage within a predetermined distance limit after a disaster, over possible surviving network realizations. We construct a two-stage stochastic programming model to select the locations of the facilities among a set of potential ones and develop a tabu search heuristic that relies on sampling network scenarios to evaluate each candidate solution in each iteration. The sampling algorithm estimates total demand covered by open facilities by checking the survival of alternative shortest paths in each sampled surviving network realization. We apply this method to the case of Istanbul. We construct a large scale network with real road distances and generate link survival probabilities by considering the vulnerability of the highway system. We provide a detailed analysis of model solutions under no failure, independent failure and dependent failure cases with various parameter settings. The results demonstrate that incorporating link failures to the model influences both covered demand percentages at the proposed facility locations and provide useful guidelines for earthquake-preparedness in Istanbul.

ÖZET

Bu çalışmada İstanbul Büyükşehir Belediyesi Afet Koordinasyon Merkezi'nin (AKOM) kurmayı planladığı Afet Müdahale Merkezlerinin (AMM) Yerleştirilmesi Problemi için deprem sonrası yolların çökme ve kapanma olasılıkları da göz önüne alınarak bir çözüm yöntemi ve karar sürecine destek olmak üzere çözümler önerilmektedir. AMM'nin kurulma amacı, afet durumunda acil yardım malzemelerinin en kısa zamanda, gereken yerlere ve gereken miktarda dağıtılmasıdır. Ayrıca bu merkezler bölgesel koordinasyon noktaları olarak planlanmıştır. AMM'de dayanıklı acil yardım malzemeleri deprem öncesi depolanıp deprem sonrasında diğer malzemeler ve ekipler ile birlikte kurulacak yerel dağıtım merkezlerine ulaştırılacaktır. Problemin amacı, İstanbul mahallelerinde deprem sonrası ortaya çıkacak yardım malzemesi taleplerinin, yolların açık olma durumlarına göre ortaya çıkan her senaryoda belirli mesafe sınırı altında müdahale merkezlerinden talep noktalarına ulaştırılmasıdır. Karşılanabilen beklenen talep miktarının en büyüklenmesini sağlayan müdahale merkezlerinin yerleşim yerlerinin belirlenmesi için bir rassal programlama modeli önerilmiştir. İstanbul için AKOM'un belirlediği olası AMM yerleri ve yerel talep noktaları arasındaki karayollarını ve bunların risk durumunu göz önüne alan bir ağ oluşturulmuş ve buradaki bağlantılar için deprem sonrası kapanma olasılıkları atanmıştır. Ortaya çok fazla sayıda senaryo çıkması sebebiyle örnekleme metodu kullanan bir tabu sezgisel çözüm yöntemi geliştirilmiştir. Farklı parametreler ile elde edilen yer seçimleri incelenmiştir. Bağlantıların deprem sonrası kapanma olasılıklarının, açık olan müdahale merkezleri tarafından karşılanan talep miktarlarını etkiledikleri gözlemlenmiş ve geliştirilen tabu sezgisel yönteminin olası İstanbul depremi için deprem öncesi hazırlık rehberi olabileceği sonucuna varılmıştır.

To my family…

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Chapter 1

INTRODUCTION

Devastating natural disasters experienced worldwide, especially within the last decade, showed the enormous damage potential of disasters. Disasters have the power to cause a high number of casualties, environmental damage, disruption of infrastructure, and economic loss [17].

The destruction caused by disasters to civil structures and the associated human and economic losses can be reduced by effective disaster management that puts mitigation, preparedness and response strategies into action. Such strategies focus on identifying the risk of vulnerable regions, strengthening the structures and lifelines and developing the capability for rapid response and recovery. The success of disaster mitigation and response activities depend on many factors ranging from organizational to operational. Raising public awareness, preparing procedures and action plans, developing the required funds, acquiring resources and training the personnel all contribute to better capability to mobilize the required resources rapidly after a disaster.

The logistics activities related to mitigation, preparedness and response require the procurement, storage, distribution, dispatching and coordination of a large number of entities under extraordinarily demanding and highly uncertain circumstances. Planning of such a complex system could be conducted more effectively by guiding critical decisions through quantitative analysis. Operations Research methods have been applied increasingly to provide solutions to logistic problems related to disaster management. Such methods offer a systematic approach to identify major objectives, system parameters and constraints, in addition to providing optimal or near optimal solutions under different settings defined in a modeling framework.

Humanitarian logistics is defined as ”the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from point of origin to point of consumption for the purpose of meeting the end beneficiary’s requirements” by Thomas and Mizushima [31]. Humanitarian logistics cover similar activities as the classical logistics; however, differences arise due to the uncertainties prevalent in pre-disaster planning, as well as the large-scale, dynamic and time-critical nature of post-disaster operations [24]. It is very difficult to predict the timing, exact location and the magnitude of a disaster. The damage expected from a disaster depends on both the characteristics of the occurring disaster and the vulnerability of the affected region. Hence, uncertainty on the impact of the disaster presents a challenge to the implementation of disaster logistics strategies. The inherent uncertainty creates the need to consider possible disaster scenarios in the planning stage. Under each possible scenario, damage estimates should identify possible outcomes for the status of the lifelines, in particular the road conditions, as well as requirements of the affected population. Since the functionality of the transportation systems after a disaster is critical for disaster response, their possible status should be predicted for effective planning. Another complicating factor is the fact that the situation evolves dynamically after a disaster, with the involvement of many actors, such as government and non-government response agencies, outside parties, and the people affected. This further complicates predicting post-disaster parameters such as travel times. Mathematical models of relief aid supply and distribution, and emergency medical response are subject to these complications.

We address a relief aid supply chain design problem in this thesis. We focus on determining the locations of emergency response and distribution centers to be used in case of a disaster. To reach this goal, analysis of different scenarios generated regarding the failure probabilities of the roads in the network will be instrumental. The facility locations and the demand points constitute nodes of this network and each existing road between the nodes form the links. In this study, we focus on the case of a major earthquake expected to affect the Istanbul metropolitan area and the planning phase of the relief facility locations. The goal is to predetermine emergency response and distribution center locations which maximize the coverage of demand for relief aid commodities.

The North Anatolian Fault Line (NAFL), which extends from Eastern Turkey to Northwestern Turkey for 1000 kilometers, is an active fault line that was the culprit of many high-magnitude earthquakes along Northern Turkey which caused significant damage in the cities located along the fault. Herewith, pre- and post-disaster activities come into prominence to mitigate both casualty numbers and building damage. The Kocaeli earthquake in 1999, which occurred along the NAFL, cost tens of thousands of people their lives and left many more without a home. Since Kocaeli is one of the industrial centers of Turkey, the 1999 earthquake had an adverse impact on the country's economy as well. However, what is more threatening is the fact that Istanbul is in close proximity to NAFL which is prone to a potential earthquake in the near future. Therefore, Istanbul Municipality (IM) and Turkish government focus on this danger to avoid high casualties and economic deterioration both for Istanbul and Turkey.

In a study conducted after the Kocaeli earthquake, IM collaborated with Japan International Cooperation Agency (JICA) on the identification of potential disaster scenarios in Istanbul and their impact on the city. We use the disaster scenarios and casualty percentages of each district in Istanbul that are presented in the JICA report [22]. In addition to the collaboration with JICA, IM established a Disaster Coordination Center

(AKOM) and prepared an earthquake master plan in collaboration with researchers at several universities. AKOM is planning to establish a relief supply chain and position durable items and equipment at emergency response facilities (ERFs in short) throughout Istanbul. AKOM has already determined potential ERF locations which are reliable and will be responsible for storage of the relief items which will be distributed to casualty points in case of a disaster. We study the facility location problem that aims to decide on the number and locations of ERFs to be operational among these predefined potential candidates. In the data preparation step, in order to provide a comprehensive research, we devoted much effort to gather necessary data and organize it properly in the desired form. Primarily, we acquired a geographic information system and mapping software from ESRI Company [11]. We purchased the road data for Istanbul from the same company and adopted it to our software. In addition, Istanbul population data is obtained from both Turkish Statistical Institute (TÜİK, Türkiye İstatistik Kurumu) and ESRI Company [11] and organized according to our relief aid supply chain design.

The ERFs to be established will distribute aid materials to demand points. The goal is to maximize the number of people that can be reached within a short time after the disaster. For this purpose, we propose a mathematical model that selects the locations of ERFs while maximizing the expected demand coverage within a distance parameter over possible network realizations. We construct a network whose node set consists of demand points, potential facility locations and main junctions in the highway system. The edges of the network represent the connections with respect to the paths in the highway system. An edge is included between each pair of potential facility location and demand point nodes to represent the shortest path between them. Furthermore, alternative paths between them that pass through the junction nodes are also added to the network via edges. In addition, edges are included between demand points that are close to each other to create more alternative paths in the network. In this way, we constructed a large network to test our algorithm which consists of 267 nodes and 9587 links. Another contribution of this study is the evaluation of network status after a possible earthquake. We include a survival probability for each link in the network based on an analysis of the risk level of the regions and the vulnerable components in the highway system of Istanbul. A link may fail because of building collapse and road damages. Hence it may be unavailable for the distribution of the relief items to casualty points. As a result, we propose a two-stage stochastic programming model which calculates the locations of the facilities among a set of potential ones and a tabu search heuristics which evaluates several open facility combinations and selects the one which maximizes the expected demand coverage within a predetermined distance limit after a disaster, over possible surviving network realizations. Our thesis comes into prominence in the disaster management literature by assessing a large scale relief aid supply chain network over its possible realizations obtained by the sampling average method which includes link survival probabilities of each link between each network node. Further details are organized as follows. In Chapter 2, we present the literature review which includes previous studies related to our thesis. Next, in Chapter 3, we clarify our problem details and solution approach and in Chapter 4 we provide the application of our approach to Istanbul's earthquake preparedness. Subsequent to the detailed computational analysis, the summary of our results and further extensions which can be implemented to this thesis are covered in the last chapter.

Chapter 2

LITERATURE REVIEW

2.1. **Overview**

In preparation for a possible disaster to affect an urban area, in order to speed up the delivery of required emergency commodities right after the disaster, establishing a relief supply chain beforehand has been investigated in the literature in recent years. A relief supply chain aims to provide required relief items such as first-aid kits, drugs, water, food, hygiene products to the affected population. Researchers have focused on new network design investigations in order to provide reliable and agile storage and distribution capabilities in areas potentially susceptible to disasters. In order to improve the functionality of networks in humanitarian logistics, it is essential to analyze and identify the prevalent risk factors in disaster zones and their corresponding affects. Moreover, the objectives for relief supply chain design are aligned towards providing the best possible service in the shortest possible time, as opposed to cost minimization. Accordingly, with the aim of diminishing undesirable outcomes after a disaster, it is crucial to prepare pre- and post-disaster plans. Several quantitative approaches were developed to address this problem. In this section, we review studies on determination of distribution channels, emergency response center locations and the assessment of network vulnerability.

2.2. **Disaster Management and Facility Location**

Green and Altay [17] classified the research on disaster operations management (DOM) into four areas: 1) Mitigation; 2) Preparedness; 3) Response; and 4) Recovery. Several methodologies have been applied to solve disaster logistics problems for various types of catastrophes, such as hurricanes and earthquakes that have occurred worldwide. The prominent approaches are mathematical programming, probabilistic and statistical applications and simulation modeling.

According to Green and Altay's [17] survey, the majority of the studies is focused on the mitigation step. Another summary statistics category for DOM is identified in terms of research contribution to the literature. Some of the articles proposed models; some are applications to a specific city or country and there are a number of theoretical studies. Here, we review primarily research on facility location in case of a disaster.

Dekle et al. [7] study identification of disaster recovery center (DRC) locations for the state of Florida by the request of the Federal Emergency Management Agency (FEMA). They develop their problem in order to minimize the total number of DRCs while covering county residents within a distance parameter, R. They propose a two-stage solution process. In order to predetermine the potential DRC locations, FEMA set up some criterion, i.e. transportation convenience to DRCs and building safety. At the first stage, they ignore the FEMA criterion and determine DRC locations within the distance limit R. County residences which are close to the DRCs are defined using the optimum solution of the first stage. Then, at the second stage, county residences are classified according to the FEMA criterion and the proposed model improves the first stage solutions.

Balçık and Beamon [1] study an emergency response facility (ERF) location problem. They present a scenario-based model and their objective function is to maximize the satisfied demand to the relief items with respect to their types. They determine the types with respect to response time criticalities. They model the uncertainties of disaster locations and demand quantities to identify number and locations of distribution centers and their optimum inventory levels. They create intervals where k different types of items are supplied by the ERFs. The coordination centers have capacity limit for holding relief item type k. Demand amount for each item k is changing in each disaster scenario s. Finally, service level quality is measured by proportion of item type k demand satisfied by distribution centre j in scenario s. Unlike Balçık and Beamon [1], we define our disaster scenarios analyzing link status in the network after a possible earthquake.

Görmez, Köksalan and Salman [15] address ERF location problem in the Istanbul metropolitan area where a destructive earthquake is expected to occur. The objectives are to minimize the total distance between the ERFs and the demand points and the number of opened facilities. They model a two-stage distribution network and evaluate the model both for capacitated and uncapacitated ERFs. Solutions are obtained both for the European and Asian sides of Istanbul and they observed that small number of ERFs would be enough to distribute relief items after a potential earthquake. Failure probability of the roads on the network is omitted in order to get exact solutions to the models. In this study, we explicitly consider link failures and provide a model that maximizes expected demand coverage within a distance limit. We develop a heuristic solution approach.

Another study about ERF location problem has been conducted by Duran, Gutierrez and Keskinocak [8]. They developed a mixed-integer programming inventory location model in order to pre-position emergency items at warehouses worldwide for CARE International (Cooperative for Assistance and Relief Everywhere) and set the objective function value to minimize the response time from open warehouses to the demand points. They classify needs to different relief items at demand points as high, medium and low with 0.75, 0.50 and 0.25 likelihood values, respectively. They determine three inventory levels, namely, high, medium and low corresponding to 100%, 50% and 25% of the average demand. They run their model in order to analyze the effect of the number of facilities to be open and inventory level kept at each open centre into the average response time to the demand points. They observe that as the number of open emergency centres and amount of relief items stored at ERFs increase, ERFs response quickly to casualty points. The authors test the robustness of the results using simulation techniques. They compare the results of the sensitivity analysis with the ones obtained from their algorithm and observe that the inventory levels are similar and the ERF locations is different for only one location in Central America. In this study, the status of the transportation network which can be damaged after a possible disaster is not included. But we evaluate failure probabilities of each link which may be destroyed after a possible earthquake because of building collapse or road damages, by identifying the vulnerability of the roads due to the distance to the earthquake fault line.

2.3. **Transportation Planning of Relief Items**

Apart from the studies on facility location, there are also research papers on post-disaster logistics management. Haghani and Oh [19] concentrate on the supply of several types of commodities via different types of transportation modes. The objective of the model is to minimize the total cost, i.e. the vehicular flow costs, the commodity flow costs, the supply or demand carry-over costs, the transfer costs over all time periods. They develop two heuristic methods which are Lagrange Relaxation Method and “interactive fix-and-run process”, respectively. Barbarosoğlu, Özdamar and Çevik [3] discuss two conflicting objectives that decision makers face often in disaster management, namely minimizing response time and costs. They suggest a helicopter mission plan for disaster relief operations which minimizes response time and at the same time generates cost-effective decisions. They aim to decide types of helicopter fleet in charge based on their technical characteristics and performance capabilities (D1), assignment of the pilots to the selected helicopters (D2), determine the number of tours to be undertaken by each helicopter (D3), vehicle routing of helicopters from the operation center to disaster points (D4), the load/unload, delivery, transshipment and rescue plans of each helicopter in every tour (D5) and the re-fueling schedule of each helicopter at the operation center (D6). They propose a two-level hierarchical decomposition, top level and base level respectively, to solve the problem. At the top level they cover first three tactical decisions which are defined as D1, D2 and D3, whereas at base level addresses to D4, D5 and D6 as operational decisions. They formulate both of the two levels as a mathematical model. In the first phase, they set their objective function as the minimization of tactical operations costs and in the second phase the objective is to minimize makespan for all of the helicopters. They also use earthquake scenarios taken from Turkish Army but in small number because of the complexity of the problem solved. Unlike this approach, we deal with a high number disaster scenarios in our study. Finally, they conclude that as long as there are sufficient number of pilots, the helicopter selection will be done more easily; however when the number of pilots is restrictive, the helicopter selection will be dominated by pilot availability. In addition, the link between total capacity amount obtained in top level and total demand requirements in base level affects overall solutions.

Barbarosoğlu and Arda [2] propose a two-stage stochastic programming framework for planning the transportation of relief items from suppliers to affected areas during a disaster response in case of an earthquake. As it is hard to predict the scale of the effect of any disaster and the demand occurring after this ruin, the randomness emerges in such a situation. Subsequently, the authors represent the post-disaster demand as a random variable. Moreover, the capacities of each edge in the network and the supply amount of the commodities are considered to be random. The first stage provides supply amount input to the second stage. In the first stage, demand is collected at some distribution nodes where the demand amount and the demand locations are random. Then a relief item distribution problem is solved for a given realization scenario of demand and arc capacity data. The two-stage stochastic model is solved for a pilot area of Istanbul with OSL software. The two-stage solution approach is implemented to our problem. However, unlike Barbarosoğlu and Arda [2], there exists failure probability of the links on our network which results in different disaster scenarios. We solve our problem for the entire Istanbul metropolis.

Özdamar et al. [26] deal with emergency logistics planning at a macro level in disaster management. Macro level planning covers inter-city transportation of commodities such as medical support items and personnel. The problem analyzed in this study is classified as a hybrid problem combining multi-period and multi-commodity network flow problems with the vehicle routing problem. The problem is converted to a mixed integer multi-period multi-commodity network flow problem with arc capacities that are assigned as variables. Vehicle Routing Problem (VRP) described in this article treats vehicles as commodities and differs from the VRPs with its setting. Supply is assumed not to be abundant and its availability varies over the planning prospect. The objective is to deliver the aid items on time to affected areas in case of a disaster. Lagrangean relaxation is proposed as a solution approach and compared to a greedy heuristic method which is developed specifically for this problem.

2.4. **Networks Subject to Link Failures**

There are studies on facility location problems where the network may be subject to link failures. In case of an earthquake, road blockages may be observed due to the possible building collapses and ruptures on the roads. Furthermore, bridges and viaducts may collapse. In order to supply demand occurred after a disaster, a durable road infrastructure has to be built. Since the post-disaster network status affects the supply capability of relief items, edge or node failure probability should be taken into consideration. Earlier works on this subject are restricted to a single-edge failure or single-facility location assumption on a tree network where there is no failure dependency.

Eiselt, Gendreau and Laporte [9] study emergency response facility location problem and observe a network where there is a single edge failure. Their model solves the facility location problem in polynomial time and finds an exact solution. The objective of the study is to minimize total expected demand disconnected from the facilities. In their succeeding work [10], they focus on the case with an unreliable node or link.

Melachrinoudis and Helander [25] study the problem of determining the location of a single facility on a network with unreliable links. Each edge may fail independently. They assume that the nodes are perfectly reliable. The objective is to maximize the number of nodes which are reachable by surviving paths. The network model is tree shaped. They develop two different algorithms. One is an adaptation of Floyd-Warshall and the second is based on depth-first node traversal and the decomposition nature of an operational path.

Hassin, Ravi and Salman [20] examine the problem of locating facilities to maximize expected demand covered in a network. Unlike the other studies, they consider a disaster case where the links of the network may fail dependently. Under the VB-dependency failure model, which was proposed by Günneç and Salman [18], and when there is no distance limit on covered demand, they provide an exact solution by both a greedy algorithm and dynamic programming. They show that the problem becomes NP-hard when the demand coverage has a distance limit. The problem we study in this paper also has the objective of maximizing expected demand coverage within a distance limit. However, we do not apply the VB-dependency, but instead consider an alternative version of it based on network distances.

Rawls and Turnquist [28] study the problem of pre-positioning facilities in emergency management. Their goal is to locate emergency facilities and determine relief items quantities at each center. They consider uncertainty in demand and transportation network structure after a potential event scenario. They formulated the problem as a two-stage stochastic mixed integer program (SMIP) and set the objective function value as the minimization of the expected costs. As a result of the computational complexity of the problem, the Lagrangian L-shaped method (LLSM), is suggested in order to solve great-extent-networks. They created a network with 30 nodes and 58 links and evaluated a set of 51 scenarios. Unlike the study of Rawls and Turnquist [28], we generate a large scale of network with 267 nodes and 9587 links and assess location of open facilities while calculating the expected covered demand to relief items with 10,000 network realizations. As a conclusion, the implementation of their approach is not suitable to our approach. In their next study, Rawls and Turnquist [29] extend their earlier study by adding service quality constraints. They create disaster scenarios by measuring the percentage amount of damaged materials for all of the nodes in their network considering that there are relief items stocked at these points which will be distributed after a disaster to demand locations. They assign occurrence probability to each node as well. Based on those two criteria, they identify the reliability measurement for each node in the network. In this way, facilities which will be open are located in safer locations in the network. They compare their former approach and the new one and conclude that the newer model provides more facility locations and more widely dispersed ones while providing a larger range of commodity types to be stored. But clearly, in the new study they observe higher cost values than the former one. They state that they do not consider the link failure probability in their last paper and study with 30-nodes in their network. Unlike these assumptions, we investigate both on the survival probabilities of the network links and a larger network size with 267 nodes and 9587 edges.

Günneç and Salman [18] model the dependency relationship among link failures on the network. They focus on minimizing the expected distances between origins and destination (O-D) pairs and the assessment of the reliability and the expected performance of a network under disaster risk. They determine link subsets which are disjoint from each other so that links in different subsets fail independently. They assume that a particular link e in a subset fails if any of the links in the same subset which are stronger than link e in terms of survival probability fails. According to this failure dependency model, named VB-dependency, the number of possible network realizations reduces significantly to merely m+1, where m is the number of edges. Hence, the measures of interest can be calculated in polynomial time. In contrast to Günneç and Salman [18], we determine the link subsets jointly, with respect to distances between the links. For links within the distance parameter we implement VB-dependency. As a result, a link may fail due to the failure of links that are stronger than itself and close to it in the network. In comparison, links in a VB-dependent subset do not have to be necessarily geographically close to each other in Günneç and Salman's [18] paper. Hassin, Ravi and Salman [20] implemented the same dependency model in Günneç and Salman's [18] paper, to facility location problems under single or multiple disaster scenario cases, with several different objectives. Here we consider multiple network realizations and the objective of maximizing the expected demand coverage within a distance limit by opening a predetermined number of facilities among the potential ones. We consider the no failure, independent failure and dependent failure cases for the links of the supply network. The dependent failure is modeled by distance-based dependency, which is proposed for the first time in this study.

2.5. **Maximum Covering Location Model**

We model our problem as a maximum covering location problem (MCLP), if we consider the no failure case. The first study on MCLP is proposed by Church and ReVelle [5]. The objective is to cover as many demand points as possible within a given service distance. In disaster management, ability of supplying casualty demand is vital. Therefore, the objective function is set to maximize the demand by Church and ReVelle [5] after a potential disaster. We concentrate on locating emergency response centers under consideration of link failure probabilities on our network. Daskin [6] proposes a maximum covering location model where the facilities are unreliable and formulated as an integer program. He assumes that not all facilities are able to respond to demand points permanently with probability p and call the problem as maximal expected covering location problem (MEXCLP). He suggests a node substitution heuristic approach which evaluates the expected covered demand for all values of probability p. Batta, Dolan and Krishnamurthy [4] concentrate on maximal expected covering location problem (MEXCLP) by relaxing the three assumptions of Daskin [6] about the independency of the operated servers, the busy probability which is the same for all facilities and the invariance of the servers' busy probability with respect to their locations. They set the hypercube queuing model in a heuristic optimization procedure with single node substitution. No link failure probability is taken into account in these studies.

2.6. **Contributions of This Study**

Unlike the previous studies in humanitarian logistics, we consider a large-scale network with probabilistic link failures in order to provide a relief aid supply chain design that can be used in real-life applications. In our implementation to the Istanbul case, we generate a large-scale network that is based on real road data and actual representative demand points for relief supplies after the disaster. In addition, we incorporate the network reliability into our model by evaluating post-disaster conditions of roads in the network according to their survival probabilities. We integrate the existing data to our two-stage stochastic model and apply a tabu search algorithm to maximize the expected covered demand over sampled network realizations. We apply our algorithm to Istanbul's earthquake case in order to decide on the locations of ERFs which will be established by the Istanbul Municipality and evaluate the results under various parameter settings.

Chapter 3

PROBLEM DEFINITION AND SOLUTION APPROACH

In this chapter, we provide a detailed explanation of the problem studied in this thesis, our proposed model and solution methodology. In section 3.1, we clarify inputs, parameters of our algorithm and their representations in the problem. Subsequently, in part 3.1.1 we present mathematical model of our problem and finally the solution approach summarized in Figure 1 will be described comprehensively

3.1. **Problem Definition**

We consider a two-stage-distribution network. First, we locate Q number of emergency response facilities (ERFs) named as *primary facilities* (PFs) which store relief items used in case of a potential earthquake and ERFs are uncapacitated by assumption considering that they will be supplied the commodities needed. The PFs will be located at one of the pre-determined and secure candidate ERF sites. Then, we identify the *secondary facility* (*SF*) locations as the demand points for the ERFs. The SFs will serve as local distribution points which are supplied by PFs and fulfil post-disaster casualty demand arising at the neighborhoods. PFs are large facility centres which operate at the regional level and send relief items towards SFs located at the neighborhoods. For this reason, we constitute such a two-stage-distribution network in order to decrease fixed costs of the PFs, which emerge during the pre-disaster period of time, by locating a small number of them. The SFs could utilize existing public facilities in the neighborhoods, such as schools, hospitals and recreational areas. SFs are referred to as demand points in the input network of our problem.

We consider an undirected graph $G = (V, E)$, with vertex set $V = \{v_1, v_2, \dots, v_n\}$ and edge set $E = \{e_1, e_2, \dots e_m\}$. Given a set of potential facilities J which are defined as origin points in the solution methodology (Figure 1) and a set of demand points I called as destination points (**Error! Reference source not found.**) where $J, I \subset V$. For each $j \in J$ and $i \in I$, a set of shortest paths in G is represented by $\Pi_{ji} = \{\pi_{ji1}, \pi_{ji2}, \dots, \pi_{jik}\}$. The kth-shortest-path is denoted by π_{jik} and has total distance l_{jik}. Each demand point $i \in I$ possess demand amount $d_i \geq 0$.

We call a possible network realization as a *scenario*. The set of possible scenarios are represented by $\Delta = \{\delta_1, \delta_2, \dots, \delta_{|\Delta|}\}$ where each scenario occurs with probability p^s . The summation of the occurrence probabilities p^s overall scenarios adds up to one. Each link in the set E possesses a survival probability p_{e_i}. Links in the network may fail due to a possible disaster independently or with statistical dependence. Each p_{e_i}value calculation will be explained in detail in succeeding chapters.

We define a coverage distance limit $R > 0$. Demand point i is covered by a facility located at j if at least one of the paths in the set Π_{ji} survives and the shortest among the surviving paths in Π_{ji} has length less than the distance limit R. We keep a zero – one parameter a_{ijs} which takes the value 1 if the demand point i is covered by a facility location j in scenario δ_s and 0 otherwise. This parameter is computed by checking the survival of each path π_{jik} in Π_{ji} in scenario s and the distance limit.

Another important parameter in our study is the dependency distance limit $D > 0$ which defines the elements of the dependency subset $A_i = \{e_{i1}, e_{i2}, \dots, e_{iu}\}$ of a link e_i . Each element in A_i is called as neighbour link. A_i includes all the links within D distance from e_i and which are weaker than the survival probability $\wp_{e_i}$ of link e_i. In order to determine the distance from e_{vu} between nodes v and u to its neighbour links e_{wt}'s symbolized by nodes w and t, we calculate real road distance from v to w and t , then from u to w and t, respectively and select and add the links within distance D to the dependency subset A_{vu}. We state our subsets A_i's jointly. For links that are in the intersection of more than 1 set, the failure of a link may be caused by a link in any of the sets that include this link.

We set the objective of the model as the maximization of expected covered demand. The model is a 0-1 linear program. However the evaluation of the expected covered demand overall possible scenarios is time consuming and requires a lot of computational memory. In order to formulize an efficient algorithm, we apply a sampling method and predetermine a sample size N as the number of scenarios for the estimation of the demand covered by ERFs. Then, we use Tabu Search heuristics to find a facility location represented by the 0-1 vector y which maximizes expected covered demand.

3.1.1.Model Formulation

Index set

I: set of demand point locations.

J: set of potential facility locations.

S: set of disaster scenarios.

Decision variables

$$x_{ijs} = \begin{cases} 1, if\ demand\ point\ i\ is\ covered\ by\ a\ facility\ at\ j\ in\ scenario\ s, \\ 0, otherwise. \end{cases}$$

$$y_j = \begin{cases} 1, if\ a\ facility\ is\ located\ at\ j, \\ 0, otherwise. \end{cases}$$

$$z_{is} = \begin{cases} 1, if\ demand\ point\ i\ is\ covered\ in\ scenario\ s, \\ 0, otherwise. \end{cases}$$

Input parameters

p^s : Occurrence probability of scenario s.

d_i: Demand amount at location i.

Q: Number of facilities to be open.

a_{ijs}: 1 if the demand point i is covered by a facility location j in scenario δ_s and 0 otherwise.

Model

$$Max \quad \sum_{i \in I} \sum_{s \in S} p^s \times d_i \times z_{is} \quad (1)$$

$$s.t.$$

$$x_{ijs} \leq a_{ijs} \times y_j \quad i \in I, j \in J, s \in S \quad (2)$$

$$\sum_{j \in J} y_j \leq Q \quad (3)$$

$$z_{is} \leq \sum_{j \in J} x_{ijs} \quad i \in I, s \in S \quad (4)$$

$$x_{ijs}, y_j, z_{is} \in \{0, 1\} \quad i \in I, j \in J, s \in S \quad (5)$$

In this model, the objective is to maximize the expected demand. Constraint (2) ensures that a demand point i is covered by facility j if and only if there exists a path shorter than service limit R between i and j in scenario s. Constraint (3) ensures that Q number of facilities will serve in case of an earthquake. Lastly, constraint (4) indicates if a demand point i is covered by an open facility j in scenario s or not.

3.2. **Solution Approach**

We propose a Tabu Search algorithm that uses sampling for evaluating the demand coverage by potential facility centres in a network whose links may fail, with estimated probabilities, due to a possible earthquake. During this assessment, as the number of links m in the edge $E = \{e_1, e_2, \dots e_m\}$ set increases, number of scenarios 2^m increases dramatically. This complicates the analysis of the solution because doing calculations with such a big number of scenarios is time-consuming and requires a lot of computational memory. Thus, we use *sampling average method* and create N number of realizations to evaluate in Tabu Search algorithm the objective function value which is the expected covered demand by each open ERF.

We provide flow of the solution methodology sequentially in Figure 1 whose inputs of each calculation described in section 4.1. Additionally, methods and algorithms in the solution approach are portrayed in chapter 3.2. Initially, in Figure 1, we construct our network and we select the elements of our origin and destination sets which include potential facility locations, junction and demand points, respectively. Then, we generate k number of alternative paths between each element of origin and destination data sets with which we create possible network realizations in a certain number. Finally, we aim to calculate a facility location solution which provides maximum expected covered demand value by evaluating possible sample scenarios.

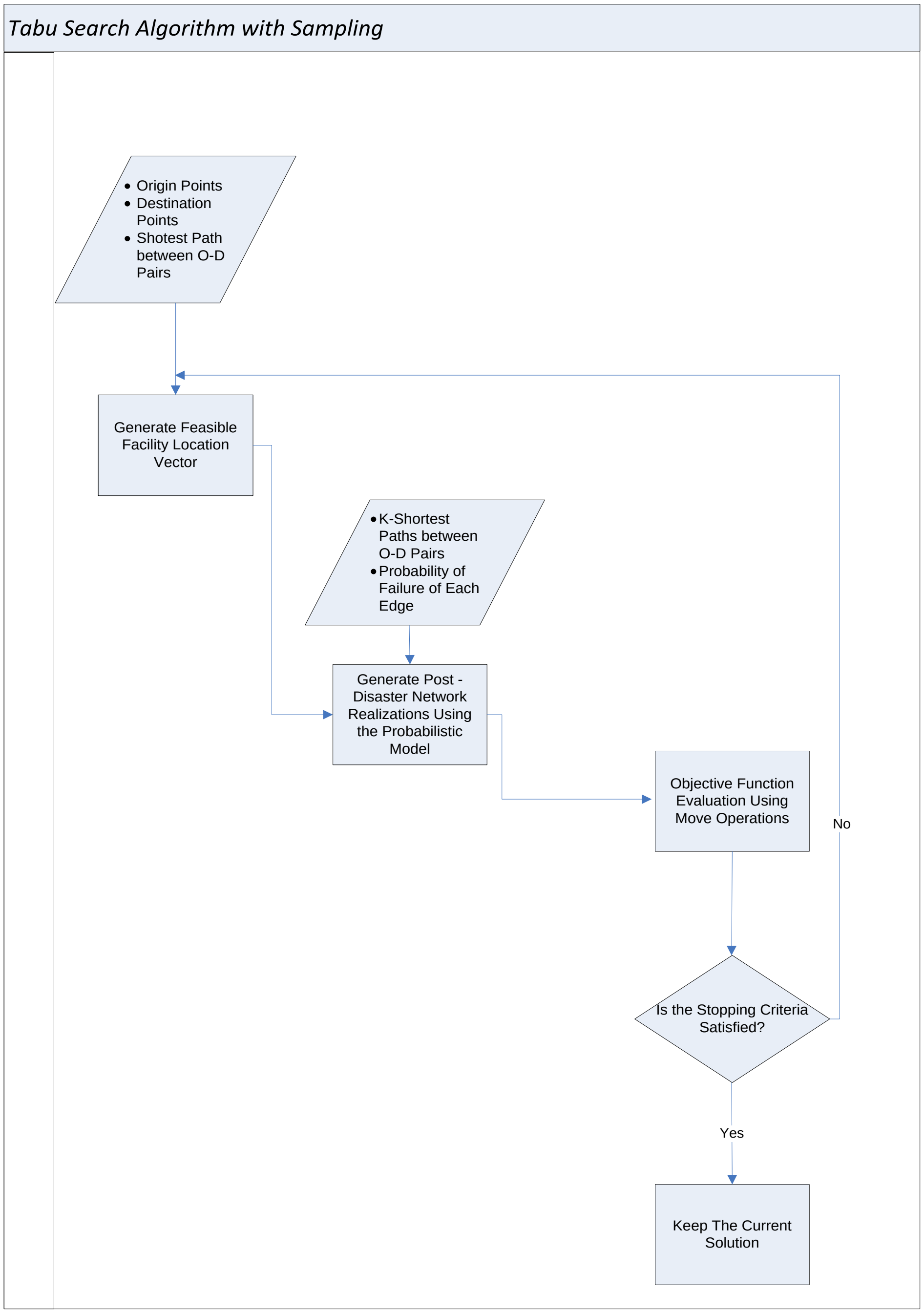

Figure 1 Solution Methodology

3.2.1. Sampling Average Method

Exact calculation of network reliability measures over the entire possible earthquake is NP hard [23]. For this reason, we appeal to the sampling average algorithm and generate of N number of earthquake scenarios which will be used as input to Tabu Search method to estimate expected covered demand. Firstly, we evaluate the status of each link in edge set E, second calculation in Figure 1, after a possible earthquake according to its survival probability $\wp_{e_i}$. Links in the network may fail due to a possible disaster independently or with statistical dependence. We call these two approaches as independent failure case (IF) and dependent failure case (DF), respectively and generate network realizations in the set $\Delta = \{\delta_1, \delta_2, \dots, \delta_{|\Delta|}\}$ using IF and DF and then acquire parameter a_{ijs} for each element of set Δ.

3.2.1.1. Independent Failure Case (IF)

In IF (Table 4) approach, we assume that links in the network fail or survive independently after an earthquake (Figure 2). Initially, we create a random number between 0 and 1. If survival probability $\wp_{e_i}$ is less than this number the corresponding link $e_i$fails, else it survives and exists in the current network realization. Subsequently, we define a_{ijs} which takes the value 1 if the demand point i is covered by a potential facility location j in scenario δ_s and 0 otherwise. To this end, for each potential facility $j \in J$ and demand point $\in I$, we assess set of shortest paths in our graph G which is represented by $\Pi_{ji} = \{\pi_{ji1}, \pi_{ji2}, \dots, \pi_{jik}\}$. We compute parameter a_{ijs} by checking the survival of each path π_{jik} in Π_{ji} in scenario s and the coverage distance limit > 0 . If there exists an alternative path π_{jik} which is shorter than R, then demand point i is covered by potential facility j in scenarios s and a_{ijs} is assigned to 1, otherwise to 0.

Notation Set #1	Description
RGN	Randomly generated number
NC	Set of the uncovered nodes
C	Set of the covered nodes
O	Set of open facilities
T	Tabu list
y	Solution vector which demonstrates open facility numbers
$N(y)$	Neighborhood of solution vector y
H	Set of elements of neighborhood $N(y)$
$N_h(y)$	Element of $N(y)$
x_h	Estimated value of solution $N_h(y)$ of neighborhood $N(y)$
x_s	Estimated value of sample scenario s
e_i	Edge i in the edge set E
p_{e_i}	Survival probability of link e_i
Π_{ji}	Set of shortest paths in $G = (V, E)$
π_{jik}	k^{th}-shortest-path in Π_{ji}
A_i	Dependency subset of link e_i

Table 1 Notation set#1

Generate an initial solution $\boldsymbol{y}$. Keep it as the current best-known solution.
Set $\boldsymbol{T} = \emptyset$.
While the conditions are not satisfied
Construct the neighborhood $\boldsymbol{N}(\boldsymbol{y})$ by swapping each pair of open facility $\boldsymbol{j} \in \boldsymbol{O}$ and not open facility $\boldsymbol{j} \in \boldsymbol{J} \setminus \{\boldsymbol{O}\}$.
For each $\boldsymbol{N_h}(\boldsymbol{y})$, $\boldsymbol{h} \in \boldsymbol{H}$;
    Set $\mathbf{x_h}, \mathbf{x_s} = \mathbf{0}$;
    For s=1… n;
        Generate sample scenario $\boldsymbol{s}$:
            Generate a number (RGN) uniformly distributed between 0 and 1.
                For each link $\boldsymbol{e_i}$
                    If $\boldsymbol{p_{e_i}}$> RGN
                        $\boldsymbol{e_i}$ fails and assign the length of link $\boldsymbol{e_i}$ to infinity,
                    end
                end
        Calculate estimated value $\mathbf{x_s}$:
            If there exist a path $\boldsymbol{\pi_{jik}}$ between an open facility $\boldsymbol{j} \in \boldsymbol{O}$ to the demand point $\boldsymbol{i} \in \boldsymbol{I}$ which is in the set $\boldsymbol{NC}$
                $\mathbf{x_s} \leftarrow \mathbf{x_s} + \mathbf{d_i}$
                $\boldsymbol{i} \in \boldsymbol{C}$
            end

Calculate average estimated value:

$$\mathbf{x_h} \leftarrow \mathbf{x_h} + \mathbf{x_s}/\mathbf{n}.$$

end

Pick the solution $\boldsymbol{N_h}(\boldsymbol{y})$ which provides maximum estimated value $\mathbf{x_h}$.

If the swap move of the new solution $\boldsymbol{N_h}(\boldsymbol{y})$ is not in tabu list $\boldsymbol{T}$

Keep the new solution $\boldsymbol{N_h}(\boldsymbol{y})$ and assign it as the current solution.

Add the current move to the tabu list $\boldsymbol{T}$ and update the tabu list $\boldsymbol{T}$.

Else

if the current solution $\boldsymbol{N_h}(\boldsymbol{y})$ is the best solution ever, however in the tabu list $\boldsymbol{T}$

Keep the new solution and assign it as the current best-known solution.

Update the tabu list $\boldsymbol{T}$.

Elseif the swap move of the new solution $\boldsymbol{N_h}(\boldsymbol{y})$ is in tabu list $\boldsymbol{T}$

Check the next best-known solution $\boldsymbol{N_h}(\boldsymbol{y})$ of neighborhood $\boldsymbol{N}(\boldsymbol{y})$.

end

end

Figure 2 Pseudo code of tabu search method with IF

3.2.1.2. Dependent Failure Case (DF)

Unlike IF in dependent failure case (DF, Table 4); status of links in the network is assigned with statistical dependence (Figure 3). One of the previous studies on dependent failure in a network belongs to Günneç and Salman [18]. They modelled dependent failure case of the links in a network to evaluate the impacts of a possible earthquake and called their methodology as *Vulnerability-Based Dependency* (VB-dependency). They determined link subsets which are disjoint from each other. According to their approach, a link in a subset may fail if, in the related subset, any of the stronger links fail. Additionally, links in a VB-dependent subset do not have to be necessarily geographically adjacent to each other. Unlike Günneç and Salman [18], we select each element in subset A_i of link e_i from its neighbourhood. The neighbourhood of link e_i covers the links in dependency distance limit D and which are weaker than survival probability of the link e_i. Furthermore, we call our methodology developed in this study as *distance based dependency* since each link e_i in graph G may fail depending upon another neighbour link e_i within distance D. In the implementation of DF, at first we generate A_i's for each link e_i. Then, similarly to IF, we create a random number between 0 and 1. If survival probability $\wp_{e_i}$ is less than this number the corresponding link $e_i$and moreover, neighbours in subset A_i fail, else it survives and exists in the current network realization. Since our subsets A_i's are determined jointly, links that are in the intersection of more than 1 set may fail due to a failure of any its neighbour link. Subsequently, for each $i - j$ pair, we define parameter a_{ijs} which takes the value 1 if the demand point i is covered by a potential facility location j in scenario δ_s and 0 otherwise. To this end, for each potential facility $j \in J$ and demand point $\in I$, we assess set of shortest paths in our graph G which is represented by $\Pi_{ji} = \{\pi_{ji1}, \pi_{ji2}, \dots, \pi_{jik}\}$. We compute parameter a_{ijs} by checking the survival of each path π_{jik} in Π_{ji} in scenario s and the coverage distance limit > 0 . If there exists an alternative path π_{jik} which is shorter than R, then demand point i is covered by potential facility j in scenarios s and a_{ijs} is assigned to 1, otherwise to 0.

Generate an initial solution $\boldsymbol{y}$. Keep it as the current best-known solution.
Set $\boldsymbol{T} = \emptyset$.
While the conditions are not satisfied
Construct the neighborhood $\boldsymbol{N}(\boldsymbol{y})$ by swapping each pair of open facility $\boldsymbol{j} \in \boldsymbol{O}$ and not open facility $\boldsymbol{j} \in \boldsymbol{J} \setminus \{\boldsymbol{O}\}$.
For each $\boldsymbol{N_h}(\boldsymbol{y})$, $\boldsymbol{h} \in \boldsymbol{H}$;
  Set $\mathbf{x_h}, \mathbf{x_s} = \mathbf{0}$;
  For s=1… n;
    Generate sample scenario $\boldsymbol{s}$:
      Generate a number (RGN) uniformly distributed between 0 and 1.
        For each link $\boldsymbol{e_i}$
          If $\boldsymbol{p_{e_i}}$> RGN
            $\boldsymbol{e_i}$ and neighbours in subset $\boldsymbol{A_i}$fails and assign the
            length of link $\boldsymbol{e_i}$to infinity,
          end

---

end
Calculate estimated value $\mathbf{x}_s$:
If there exist a path $\boldsymbol{\pi}_{jik}$ between an open facility $\boldsymbol{j} \in \boldsymbol{O}$ to the demand point $\boldsymbol{i} \in \boldsymbol{I}$ which is in the set $\boldsymbol{NC}$
$\mathbf{x}_s \leftarrow \mathbf{x}_s + \mathbf{d}_i$
$\boldsymbol{i} \in \boldsymbol{C}$
end
Calculate average estimated value:
$$\mathbf{x}_h \leftarrow \mathbf{x}_h + \mathbf{x}_s / \mathbf{n}.$$
end
Pick the solution $\boldsymbol{N_h}(\boldsymbol{y})$ which provides maximum estimated value $\mathbf{x}_h$.
If the swap move of the new solution $\boldsymbol{N_h}(\boldsymbol{y})$ is not in tabu list $\boldsymbol{T}$
Keep the new solution $\boldsymbol{N_h}(\boldsymbol{y})$ and assign it as the current solution.
Add the current move to the tabu list $\boldsymbol{T}$ and update the tabu list $\boldsymbol{T}$.
Else
if the current solution $\boldsymbol{N_h}(\boldsymbol{y})$ is the best solution ever, however in the tabu list $\boldsymbol{T}$
Keep the new solution and assign it as the current best-known solution.
Update the tabu list $\boldsymbol{T}$.
Elseif the swap move of the new solution $\boldsymbol{N_h}(\boldsymbol{y})$ is in tabu list $\boldsymbol{T}$
Check the next best-known solution $\boldsymbol{N_h}(\boldsymbol{y})$ of neighborhood $\boldsymbol{N}(\boldsymbol{y})$.
end
end

Figure 3 Pseudo code of tabu search method with DF

3.2.2. No Failure Case (NF)

We investigate to the performance measurement of coverage distance limit $R > 0$ and facilities which need to be open in Q number where it is supposed that there exists no link failure after the earthquake and name this structure as *no failure case* (NF, Table 4) (Figure 4). In this case, if there exists an alternative path π_{jik} which is shorter than R, then demand point i is covered by potential facility j, else its demand is not satisfied.

Generate an initial solution $\boldsymbol{y}$. Keep it as the current best-known solution.
Set $\boldsymbol{T} = \emptyset$.
While the conditions are not satisfied
Construct the neighborhood $\boldsymbol{N}(\boldsymbol{y})$ by swapping each pair of open facility $\boldsymbol{j} \in \boldsymbol{O}$ and not open facility $\boldsymbol{j} \in \boldsymbol{J} \setminus \{\boldsymbol{O}\}$.
For each $\boldsymbol{N_h}(\boldsymbol{y})$, $\boldsymbol{h} \in \boldsymbol{H}$;
Calculate $\mathbf{x_h}$.

Pick the solution $\boldsymbol{N_h}(\boldsymbol{y})$ which provides maximum value $\mathbf{x_h}$.
If the swap move of the new solution $\boldsymbol{N_h}(\boldsymbol{y})$ is not in tabu list $\boldsymbol{T}$
Keep the new solution $\boldsymbol{N_h}(\boldsymbol{y})$ and assign it as the current solution.
Add the current move to the tabu list $\boldsymbol{T}$ and update the tabu list $\boldsymbol{T}$.
Else
if the current solution $\boldsymbol{N_h}(\boldsymbol{y})$ is the best solution ever, however in the tabu list $\boldsymbol{T}$
Keep the new solution and assign it as the current best-known solution.
Update the tabu list $\boldsymbol{T}$.
Elseif the swap move of the new solution $\boldsymbol{N_h}(\boldsymbol{y})$ is in tabu list $\boldsymbol{T}$
Check the next best-known solution $\boldsymbol{N_h}(\boldsymbol{y})$ of neighborhood $\boldsymbol{N}(\boldsymbol{y})$.
end
End

Figure 4 Pseudo code of tabu search method with NF

3.2.3. Tabu Search Algorithm

Rego and Alidaee [30] studied on metaheuristic optimization and defined tabu search as follows. Tabu search was proposed by Glover [12] and has quickly become one of the best and most widespread local search methods for combinatorial optimization. The method performs an exploration of the solution space by moving from a solution x_t identified at iteration t to the best solution x_{t+1} in a subset of the neighborhood $N\ (x_t)$ of x_t. Since x_{t+1} does not necessarily improve upon x_t, a tabu mechanism is put in place to prevent the process from cycling over a sequence of solutions. A natural way to prevent cycles is to forbid the process from going back to previously encountered solutions, but doing so would typically require excessive bookkeeping. Instead, some attributes of past solutions are registered and any solution possessing these attributes may not be considered for μ iterations. This mechanism is often referred to as short term memory. Other features such as diversification and intensification are often implemented. The purpose of diversification is to ensure that the search process will not be restricted to a limited portion of the solution space. It keeps track of past solutions and penalizes frequently performed moves. This is often called long term memory. Intensification consists of performing an accentuated search around the best known solutions. Several survey papers and books have been written on TS, among which we recommend Glover and Laguna [13],[14] and Hertz and de Werra [21].

We use Tabu Search algorithm to find a facility location represented by a binary vector y which maximizes expected covered demand. We want to locate Q number of facilities where each open facility is represented by 1. Since our solution representation is a binary vector and has a simple structure, we implement tabu search heuristics for the local search which will be used to select a facility location solution which maximizes expected covered demand.

We apply add/drop procedure to y in order to obtain members of its neighbourhood structure. For a solution vector y, we close one of the open facilities and simultaneously open one of the closed potential facility location. As an example, let's us consider $y = [1\ 0\ 1\ 0\ 0\ 0\ 1\ 0]$ and by implementing add/drop move, one of the member of the neighbourhood of y becomes to $y_1 = [0\ 1\ 1\ 0\ 0\ 0\ 1\ 0]$ where second potential facility location is open in stead of the first open facility. In this way, we obtain $Q \times (P - Q)$ number of neighbourhood elements where P represents the total number of potential facility locations. Next, we calculate objective function value for each member of the neighbourhood of y. All of the network realizations in the sample set $\Delta = \{\delta_1, \delta_2, \dots, \delta_{|\Delta|}\}$

are evaluated during this procedure and according to parameter a_{ijs} , tabu algorithm calculates the locations of Q number of facilities for each element of the neighbourhood while maximizing expected covered demand. In each of the tabu iterations, current and best solutions ever are kept.

Tabu list keeps add/drop move which gives the best known solution so far for next t iterations, where t symbolizes tabu tenure, to prevent repetition of the assessment of same solution vectors. In addition, this solution vector is selected as the initial solution of next tabu iteration. We also enforce tabu algorithm to select solution y which is in tabu list but gives the best solution ever as the next initial solution. This procedure is called as aspiration criterion. Furthermore, we allow occasionally, 10% of iterations, tabu search method to select some moves as the initial solution for next iteration even though they do not provide best known objective function value so far. This application provides diversity for tabu search algorithm results. We stop tabu algorithm when the predetermined number of iterations is satisfied and keep solution vector y which provides the best objective function value so far.

Chapter 4

APPLICATION TO ISTANBUL'S EARTHQUAKE PREPAREDNESS

Istanbul Metropolitan Municipality (IMM) plans to establish emergency facility centers which will provide service to the areas affected by a possible earthquake. IMM established a Disaster Coordination Center (AKOM) and the center determined 41 potential emergency response facility (ERF) locations with respect to the transportation convenience and resistance to earthquake. The ERFs have multiple functions such as the pre-disaster storage of the emergency aid items, procurement and distribution of relief items in case of an emergency.

4.1. Data Generation

We consider a large sized network which consists of the vertex set $V = \{v_1, v_2, \ldots, v_n\}$ and the edge set $E = \{e_1, e_2, \ldots e_m\}$ whose elements are described in detail in the next sections. We analyze the results of our algorithm that we proposed in this study with two different earthquake models named as $Model\,A$ and $Model\,C$ (Figure 5), most probable earthquake scenario and worst-case scenario, respectively and addressed by JICA report [22]. The equivalent magnitudes of these models are determined as 7.4 and 7.7 on the Richter scale (Table 2).In addition, each demand value to relief items $d_i \geq 0$ and the survival probabilities $\mathscr{p}_{e_i}$'s assigned to each e_i in the network are identified distinctively for both of the two scenarios.

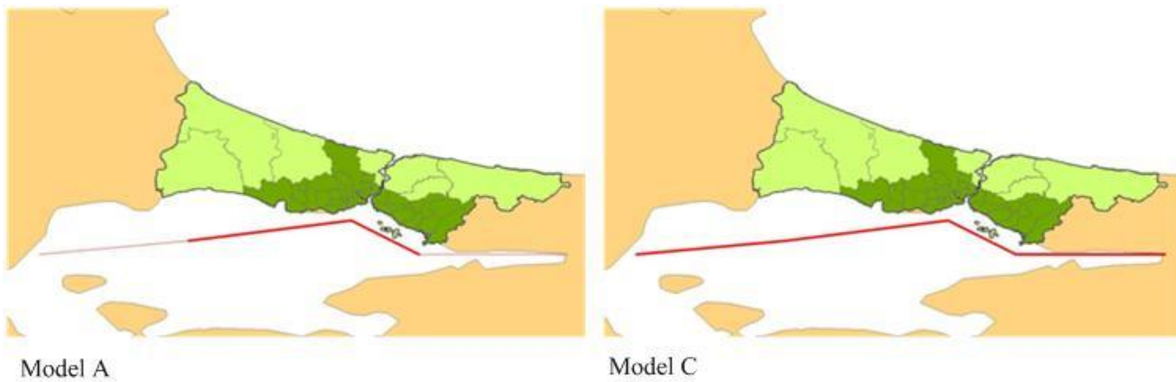

Figure 5 Earthquake models fault line drawings

	Model A	Model C
Length (km)	119	174
Magnitude (Mw)	7.4	7.7

Table 2 Parameters for earthquake models

4.1.1. Network Nodes

As mentioned before there exists three types of nodes in the vertex set V. One of the components of this set is potential facility locations which are already set by Istanbul Municipality and named as primary facilities (PFs) in our study. Figure 7 shows the potential facility locations prepared using ArcMap [11] software package. We establish Q number of PFs and decide on PFs to be open with a computational study.

Number of potential facility locations	41
Number of clustered-demand points	186
Number of road junction points	40
Number of nodes in the network	267
Number of edges in the network	9587

Table 3 Istanbul network components

In the context of traffic networks, a junction is a point where several or different types of routes meet or link. In our study, we identify the entries and exits of bridges and viaducts in Istanbul (Figure 8) as separate nodes in the vertex set V because of their critical role in the highway system of a city and sensitivity to a possible disaster. We aim to define the road sections between these intersection points individually in order to decide which path in the set $\Pi_{ji} = \{\pi_{ji1}, \pi_{ji2}, \dots, \pi_{jik}\}$ is safer to serve from a facility $j \in J$ to a demand point $i \in I$ after a possible earthquake.

Lastly, vertex set V includes 186 clustered-demand point locations which are considered as second-stage distribution points, serve relief items to all of the 962 neighbourhoods in Istanbul and possess demand amount $d_i \geq 0$ that are distinct for each of the two earthquake models, $Model\ A\ and\ Model\ C$ respectively. To set the d_i values, at first we requested demand data (Figure 6) from ESRI Company [11] for each neighbourhood in Istanbul and derived their corresponding casualty percentages from JICA report [22]. By multiplying each demand data by its corresponding percentage value, we identified the aid materials requirements for each neighbourhood. Afterwards, we clustered 962-neighbourhood visually by using Istanbul city map provided by ESRI and obtained 186 clustered-demand point locations and named them as secondary-stage facility locations. We located the secondary-stage facilities in densely populated places in each district with a population of more than ten thousand. In addition, each district centre defined as secondary-stage facility. Subsequently, we determined relief item supplies for each clustered-demand point, which need to be satisfied in case of a disaster, by summing up the requirements of surrounding residential areas where there no SF.

Figure 6 Population for each neighbourhood in Istanbul

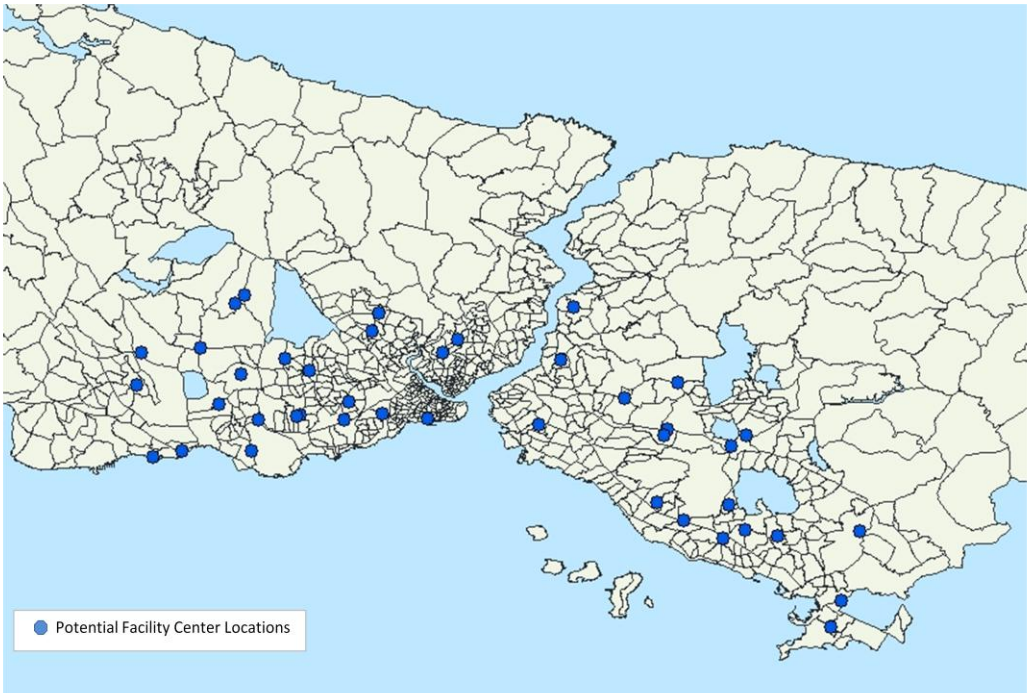

Figure 7 All of the 41 potential facility centre locations predetermined by Istanbul Municipality

Figure 8 All of the 40 road junction points in the network

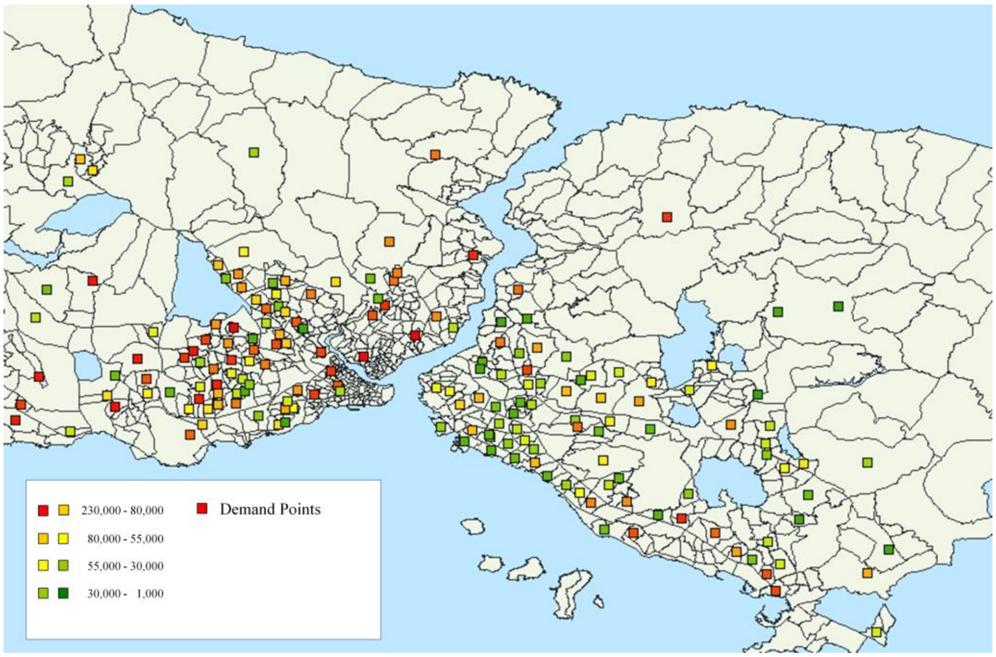

Figure 9 Demand amount values for each Secondary Facility

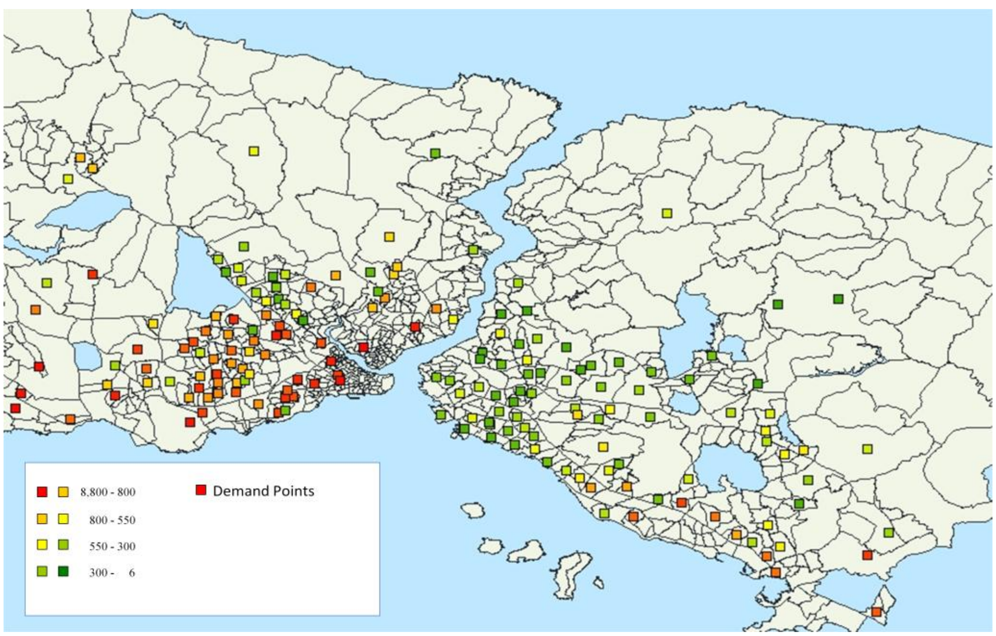

Figure 10 Requirement values of Model A for each Secondary Facility

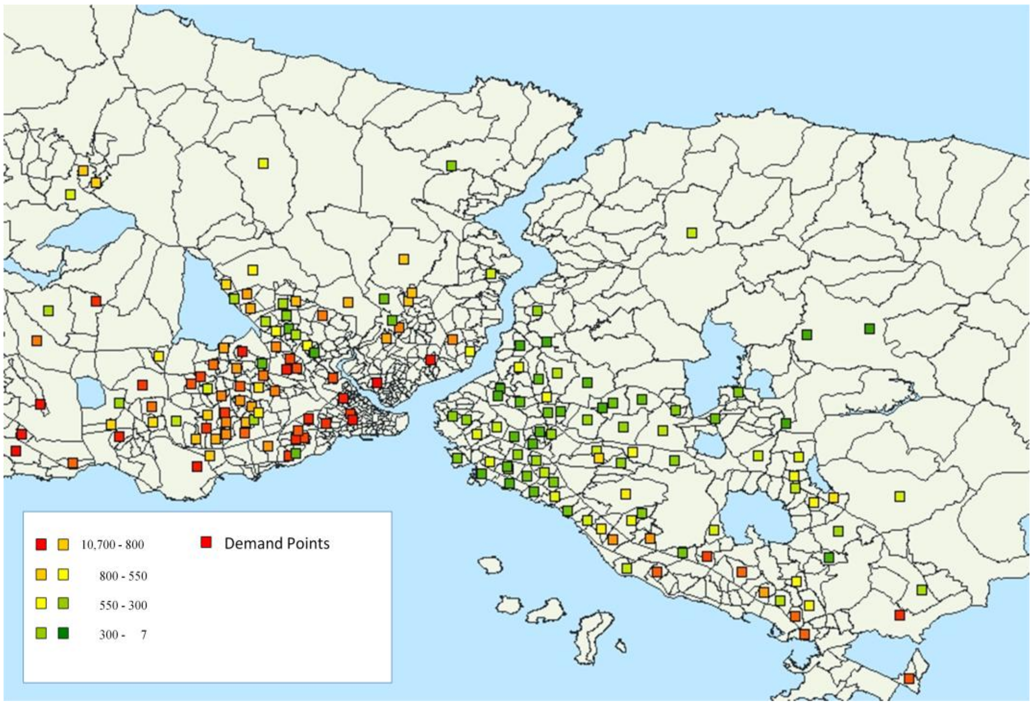

Figure 11 Requirement values of Model C for each Secondary Facility

4.1.2. Network Links

The links representing road segments between potential facility locations, SFs and major road junction points in the network are the elements of the edge set E.We generated these real roads in $G = (V, E)$ using ArcMap [11] software package. Then, we applied k-shortest-path algorithm [32] applied to MATLAB software in order to obtain the set of shortest paths in G which is represented by $\Pi_{ji} = \{\pi_{ji1}, \pi_{ji2}, \dots, \pi_{jik}\}$ and their corresponding distance values l_{jik} 's (Figure 12).

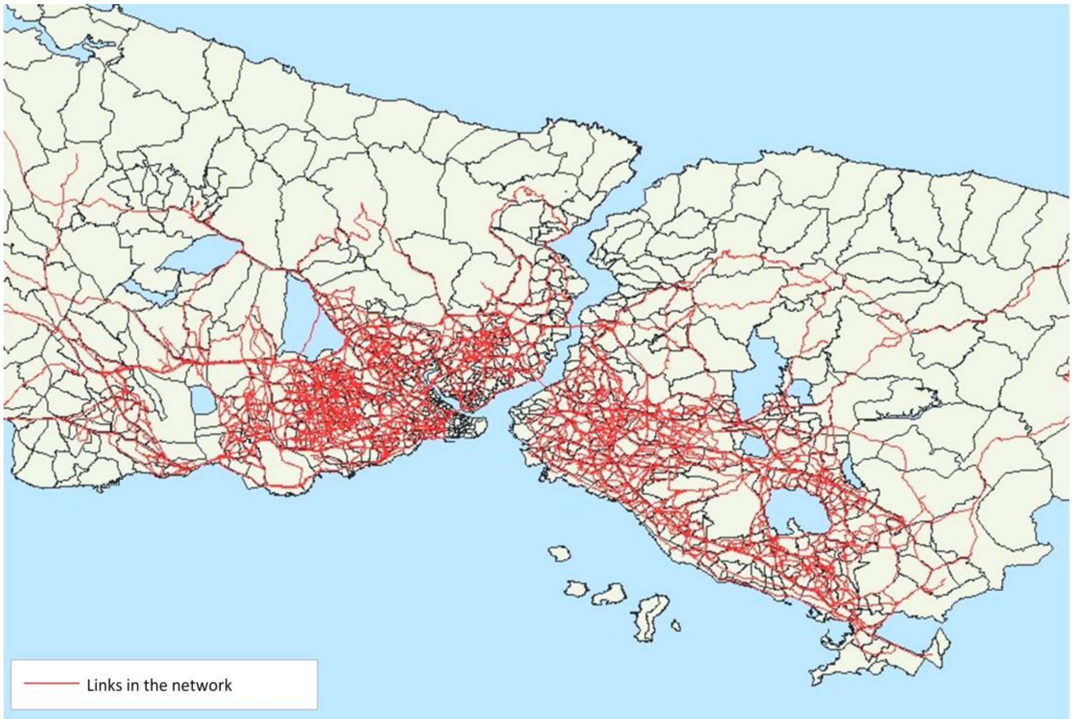

Figure 12 All links in the network representing road segments between potential facility locations, demand points and major road junction points

4.1.3. Probability Generation

As explained previously, each link in the set E possesses a survival probability $\wp_{e_i}$. In order to determine $\wp_{e_i}$values for each link e_i, we consider three criteria; seismic zone where $e_i$is located (Figure 13 and Figure 14), distance from the fault line of the earthquake to link e_i and earthquake magnitude. First, we calculate PGA_{e_i}(peak ground acceleration) [16] acceleration values in m/s^2 for each link e_i. Distance from earthquake fault line (r) in km, earthquake magnitude (m), $m = 7.4$ for $Model\ A$, $m = 7.7$ for $Model\ C$ respectively, and the constant α are the inputs to PGA [27] which is formulated as:

$$PGA = \alpha \times \frac{e^{0.8m}}{(r+40)^2}$$

Secondly, we multiply each PGA_{e_i} by the seismic zone factor which is determined as 0.95 for risk zone 1, 0.85 for zone 2, 0.75 for zone 3 and 0.65 for zone 4. These earthquake zones and their corresponding probabilities are derived from JICA report [22] where Istanbul is categorized into 4 seismic zones. Zone 1 represents the most risky regions where the casualty amount is in high level after a possible earthquake in Istanbul. We set the constant alpha (α) to 2 because we want survival probabilities of each link e_i in Model A distribute between 0.75 and 0.95 and in Model C between 0.70 and 0.90. Finally, we obtain failure probabilities for each link e_i , and subsequently, subtracting those probabilities from one we acquire survival probabilities for each e_i, which are distinct for $Model\ A$ and $Model\ C$.

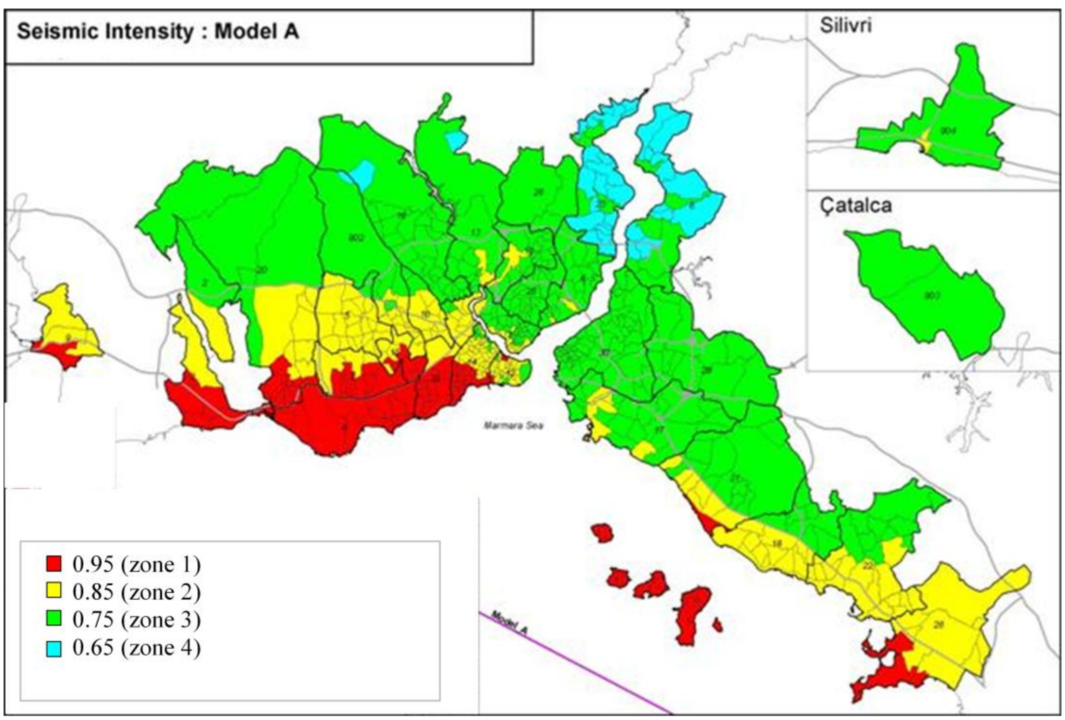

Figure 13 Seismic zone factors assigned to each risk zone for Model A

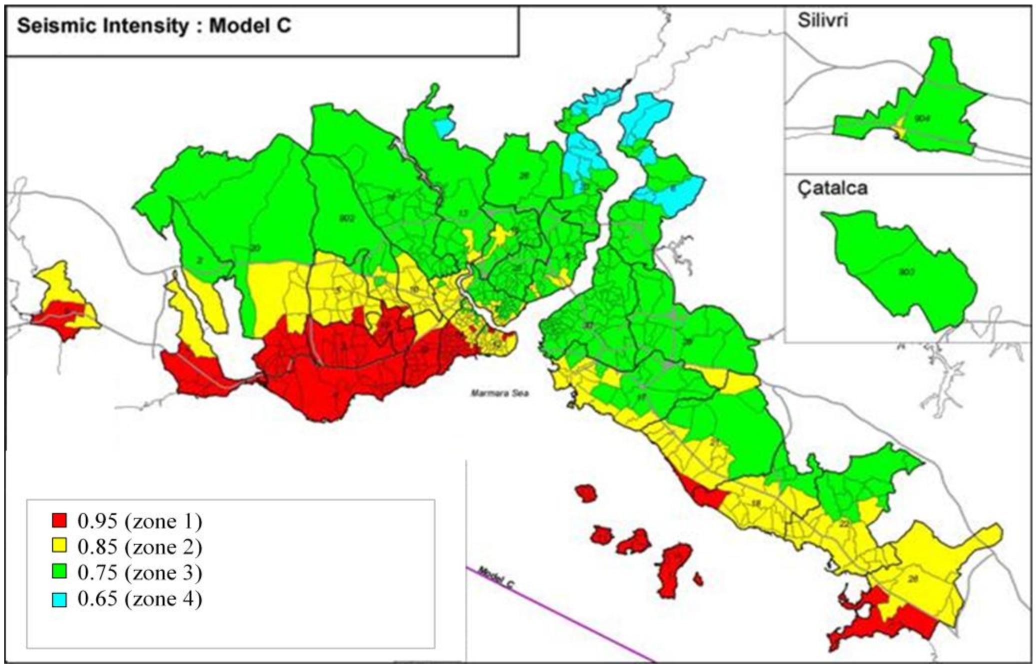

Figure 14 Seismic zone factors assigned to each risk zone for Model C

4.2. **Computational Study**

We investigate in computational study with the proposed algorithm and evaluate the results of facility locations and their corresponding expected covered demand values on a PC with a 3.33GHz Intel® Core™ i5 processor. We intend to set the parameters and observe the effect of their different values to solution vector y (Table 1) and the objective function. First, we analyze sample size N, then test the algorithm by assigning distinct values to number of open facilities Q (Table 4). In sections 3.5.3 and 3.5.4, we examine coverage distance limit R and dependency distance limit D. Finally, we present the evaluation of average expected covered demand EC% of each demand point i over all scenarios.

4.2.1. Sample Size (N) Analysis

The evaluation of the objective function overall possible scenarios is time consuming and requires extensive computational memory. We aim to develop an efficient algorithm to solve large scale problems. Thus, we apply sampling average method and set the sample size N as the number of scenarios in order to determine the expected covered demand (EC, Table 4) by open facilities. In Table 5 and Table 6, we observe how expected covered demand percentage (EC%, Table 4) changes as N increases. In these tables, we assign several values to N for $Model\ C$ while setting number of open facility, Q to 8, defining R as 10km and D as 5km, respectively. We evaluate EC% values and open facility solutions y (Table 1) with 3 different batches for each sample size to point out to the consistency in results of the proposed algorithm. There is no significant gap between expected EC% values as N augments. Maximum EC% obtained is equal to 78.12% when N is 2,000 and it is equal to 78.29% when N is 10,000 when we refer to IF outcomes (Table 5). We are not able to test our sampling method with a bigger sample size more than ten thousand due to lack of sufficient memory. Hence, we continue to our analysis by setting N to 10,000. Another important remark to be considered is that the average number of failed links (FL, Table 4) is higher and consequently EC% values are smaller for DF than as per IF (Figure 15). On the average 19.33% of total links fail in IF (Table 5) whereas the same measurement is 20.07% for DF (Table 6). In addition, EC% for DF is 76.73% on average and less than the one acquired for IF which is equal to 78.16%. This result demonstrates that it is essential to investigate in network reliability analysis by evaluating post-disaster status of the network elements in relief aid supply chain design. We observe dissimilar facility location solutions with different objective function values when we compare results of DF and IF. Potential facility location #4 operates only in DF results whereas potential locations #14, 16 and 27 are open just with IF approach.

We observe that EC values in Table 5 and Table 6 do not increase in parallel with the sample size N. For this reason we continue to test the parameters in our tabu search algorithm with a fixed sample size value.

Notation Set #2	**Description**
NF	No Failure Case
IF	Independent Failure Case
DF	Dependent Failure Case
EC%	Expected Covered Demand Percentage
EC%(i)	Average EC% of each demand point i over all scenarios
R	Coverage Distance Limit (km)
D	Dependency Distance Limit (km)
FL	Average Number of Failed Links
FL%	Average Number of Failed Links Percentage
Q	Number of Open Facilities

Table 4 Notation set #2 and their corresponding descriptions

Q	***R(km)***	***N***	***FL***	***y***	***EC***	***EC%***
8	10	**2,000**	1,851	5 12 23 27 28 32 35 38	154,172	**78.12%**
8	10	**2,000**	1,851	9 14 16 23 28 32 35 38	154,118	**78.10%**
8	10	**2,000**	1,851	12 19 23 27 28 32 35 38	154,044	**78.06%**
8	10	**4,000**	1,849	12 19 23 27 28 32 35 38	154,248	**78.16%**
8	10	**4,000**	1,851	2 7 12 21 23 27 28 35	154,167	**78.12%**
8	10	**4,000**	1,850	7 12 19 23 27 28 32 35	154,113	**78.09%**
8	10	**6,000**	1,851	5 7 9 12 23 28 32 35	154,318	**78.20%**
8	10	**6,000**	1,850	2 7 9 12 15 23 28 35	154,068	**78.07%**
8	10	**6,000**	1,851	7 9 12 19 23 28 32 35	154,157	**78.12%**
8	10	**8,000**	1,850	5 7 12 23 27 28 32 35	154,355	**78.22%**
8	10	**8,000**	1,851	2 9 12 21 23 28 35 38	154,312	**78.20%**
8	10	**8,000**	1,851	2 7 12 15 23 27 28 35	154,299	**78.19%**
8	10	**10,000**	1,851	7 12 16 23 27 28 35 38	154,450	**78.27%**
8	10	**10,000**	1,851	2 14 15 23 27 28 35 38	154,501	**78.29%**
8	10	**10,000**	1,851	5 9 12 23 28 32 35 38	154,449	**78.26%**
Total Number of Links			***9,578***	***Total Demand***	***197,342***	

Table 5 Sample size analysis for IF of Model C

Q	*R(km)*	*D(km)*	*N*	*FL*	*y*	*EC*	*EC%*
8	10	5	**2,000**	1,922	7 9 12 15 23 28 33 35	150952	**76.49%**
8	10	5	**2,000**	1,923	7 9 12 21 23 28 34 35	151116	**76.58%**
8	10	5	**2,000**	1,923	7 9 12 21 23 28 34 35	150934	**76.48%**
8	10	5	**4,000**	1,922	5 7 9 12 23 28 32 35	151,581	**76.81%**
8	10	5	**4,000**	1,923	9 12 15 23 28 33 35 38	150,976	**76.50%**
8	10	5	**4,000**	1,921	5 7 9 12 23 28 32 35	151,807	**76.93%**
8	10	5	**6,000**	1,921	2 7 9 12 21 23 28 35	151,246	**76.64%**
8	10	5	**6,000**	1,922	5 9 12 23 28 32 35 38	151,780	**76.91%**
8	10	5	**6,000**	1,922	5 7 9 12 23 28 32 35 38	151,742	**76.89%**
8	10	5	**8,000**	1,921	9 12 15 23 28 33 35 38	151,174	**76.61%**
8	10	5	**8,000**	1,923	5 7 9 12 23 28 32 35	151,825	**76.93%**
8	10	5	**8,000**	1,922	2 7 9 12 21 23 28 35	151,328	**76.68%**
8	10	5	**10,000**	1,922	2 7 9 12 21 23 28 35	151,393	**76.72%**
8	10	5	**10,000**	1,921	5 7 9 12 23 28 32 35	151,921	**76.98%**
8	10	5	**10,000**	1,922	4 7 9 12 19 23 28 32	151,412	**76.73%**
Total Number of Links				***9,578***	***Total Demand***	***197,342***	

Table 6 Sample size analysis for DF of Model C

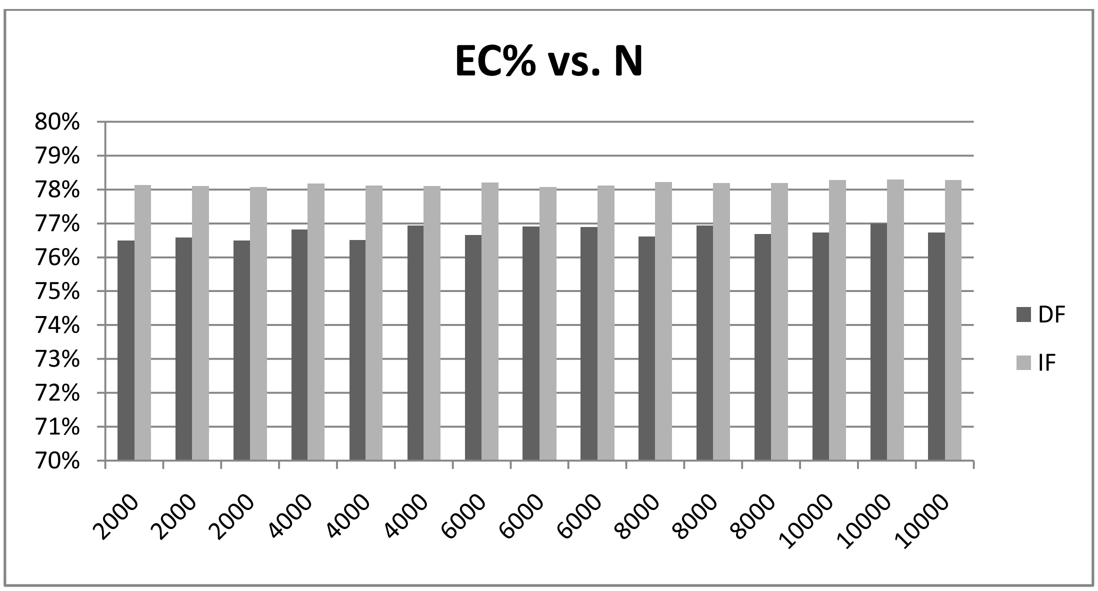

Figure 15 EC% values versus increasing sample size numbers comparison for DF and IF of Model C

4.2.2. Open Facility (Q) Numbers Analysis

We examine the effect of different values of Q to EC%. As the number of Q augments, EC%'s do too. However EC% values following the point where Q is 8 do not increase (Figure 16) significantly. At this point, to decide on value of Q we consider the marginal benefit of opening an additional facility. Since opening a facility requires some efforts and costs, Istanbul Municipality as a decision maker would like to have a high level of efficiency in terms of served demand point numbers per an open facility which can be interpreted as marginal benefit. Thus, number of open facilities Q can be selected as 8 where there is no more benefit in terms of satisfied expected demand to relief items. As a conclusion, it is reasonable to fix Q to 8 and assign this value as the open facility number for subsequent studies.

Our main goal is to provide realistic solutions to relief aid supply chain design while choosing the locations of open ERFs among potential facility locations. To this end, we appeal the DF, IF and NF cases (Figure 16). When the network is totally reliable where all the links survive, expected covered demand value is reasonably high. If we set coverage distance limit R to 60km for NF where Q is 8, open facilities can reach to all of the demand points in the network (Table 9) and all the requirements which is 197,342 for $Model\ C$ is satisfied by solution y. However, due to failure probabilities, the EC% demand values may be less in DF and IF than it is in NF. In addition, assigning the coverage distance limit to 60km is not affordable in case of a disaster. It is required to reach to casualty point as soon as possible in case of an emergency which is inconvenient when an ERF is far away from demand locations. The observations obtained from DF and IF ensure more realistic facility location solutions and objective function values. Because, they include the reliability of network links which will be unavailable after the disaster most probably. In addition, there is no prominent increment for EC% in NF compared with DF and IF in the observations after the point where Q is 8 (Figure 16). These results may mislead the decisions on the locations of open facilities since they do not reflect effects of the earthquake to the roads which are used to distribute aid material supplies to casualty points.

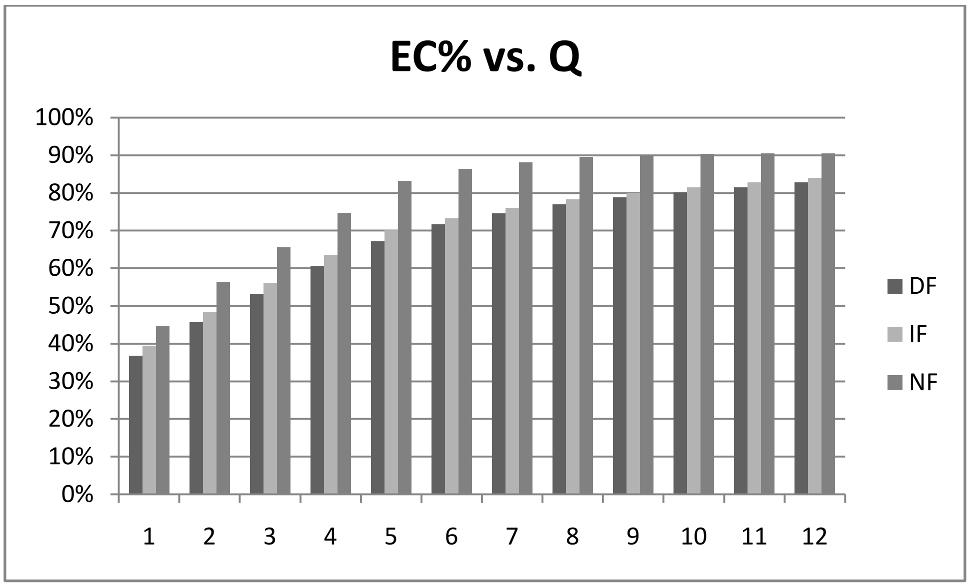

Figure 16 EC% values as Q is increasing

We observed where the proposed algorithm locates the open facilities while designating distinctive values to Q. As it can be seen in Figure 17, for Q = 4 facilities are located equally in both of the two continents, Asia and Europe, and where the population amount is pretty high (Figure 11). For Q = 8 there are 3 open facilities in Asia, as for Q=12 there are 5. Since the demand quantity and consequently requirements in Europe are higher than in Asia, the majority of open facilities are established in European side of Istanbul.

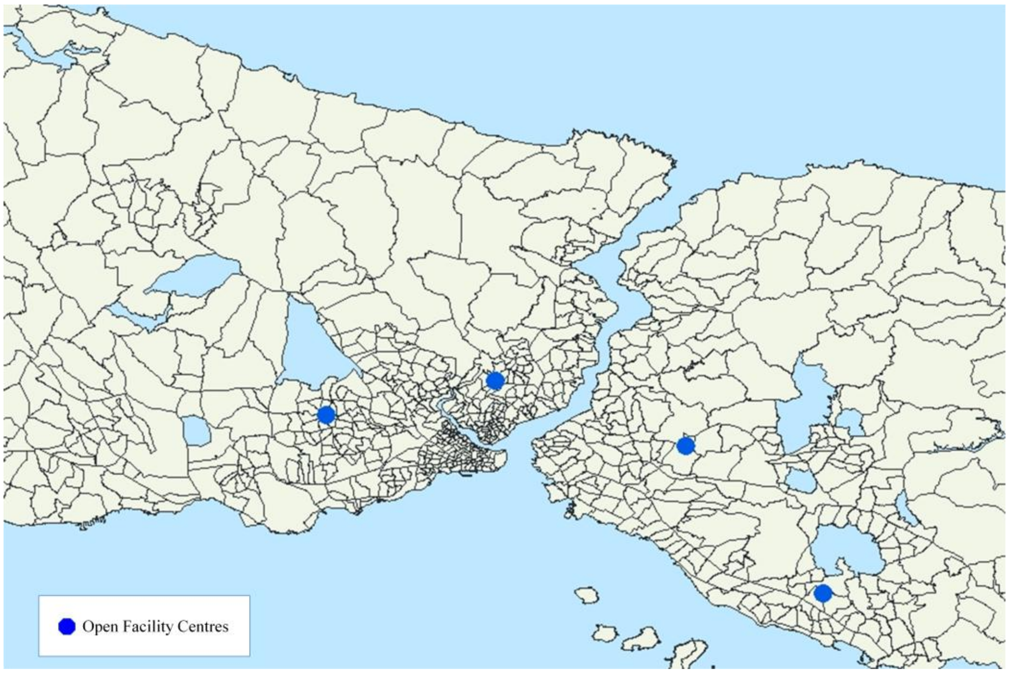

Figure 17 Open facility centre locations when Q = 4 for DF of Model C

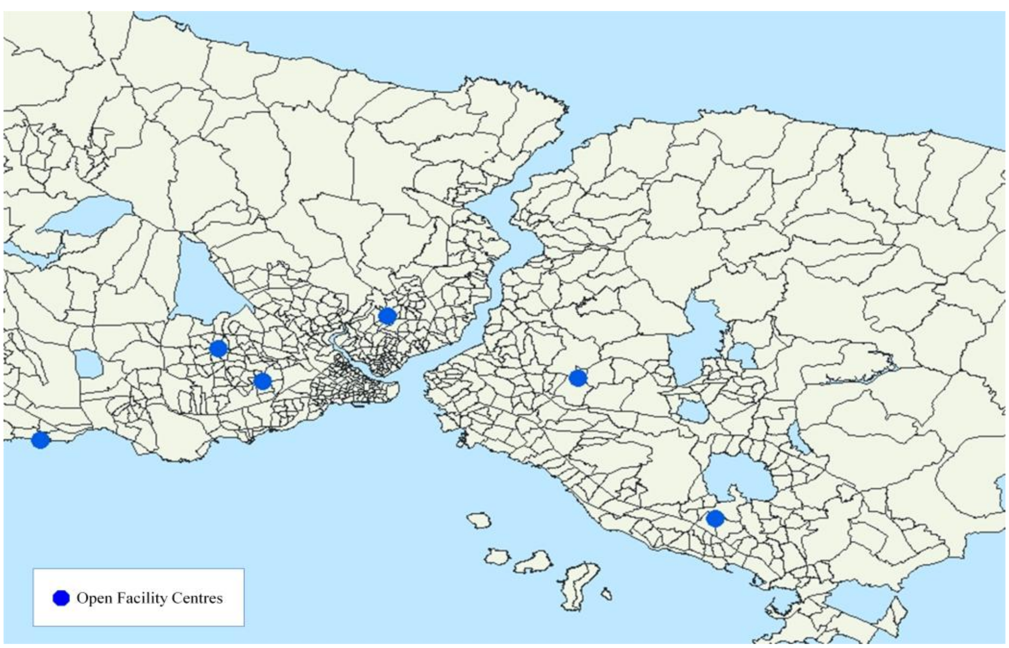

Figure 18 Open facility centre locations when Q = 6 for DF of Model C

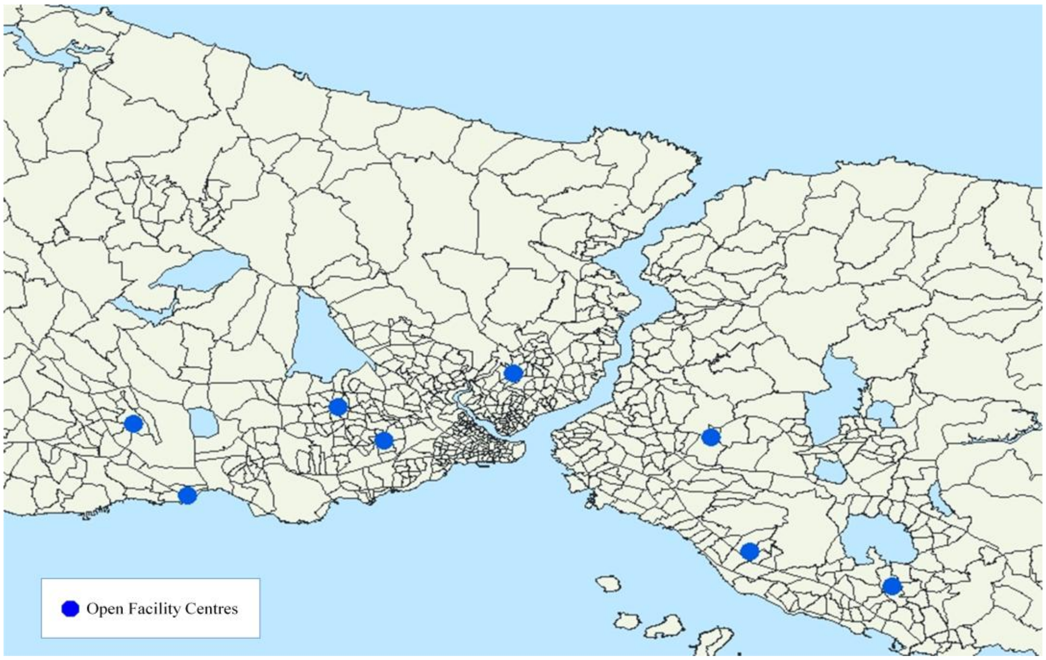

Figure 19 Open facility centre locations when Q = 8 for DF of Model C

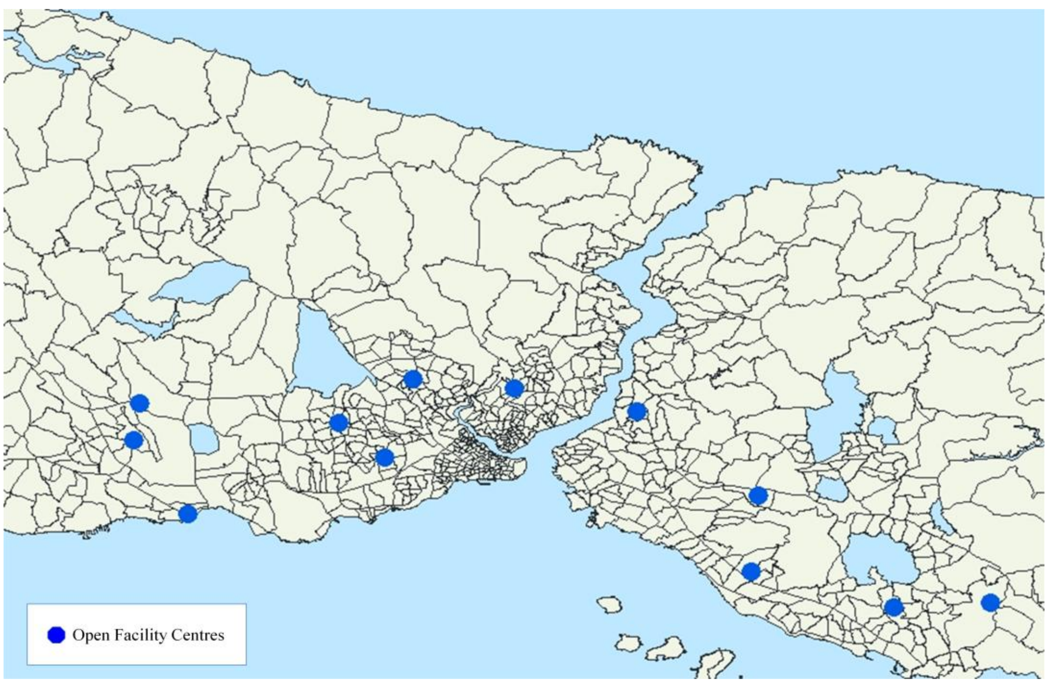

Figure 20 Open facility centre locations when Q = 12 for DF of Model C

4.2.3. Dependency Distance Limit (D) Analysis

Parameter Ddetermines the list of links which belong to the subset A_i of a link in the network. As the length of D increases, number of FLs increases too (Figure 22), on the other hand EC% value decreases (Figure 21). This observation implicates that increase in the number of FLs reduces the number of alternative paths, which are shorter than R, that can be used to serve relief items from an open facility to a demand point. This diminishes number of demand points that are reachable from an open facility and as a result total EC% (Figure 21) decays.

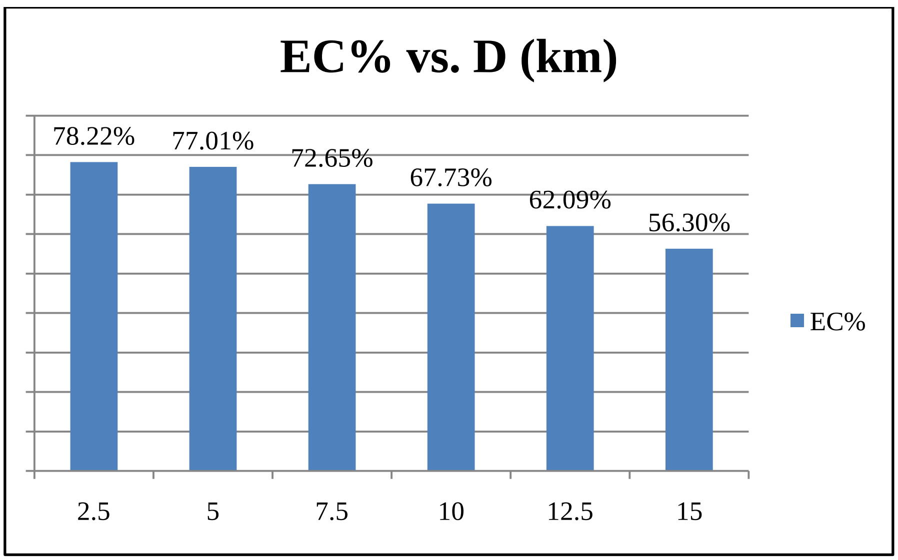

Figure 21 EC% change as D increases for DF of Model C

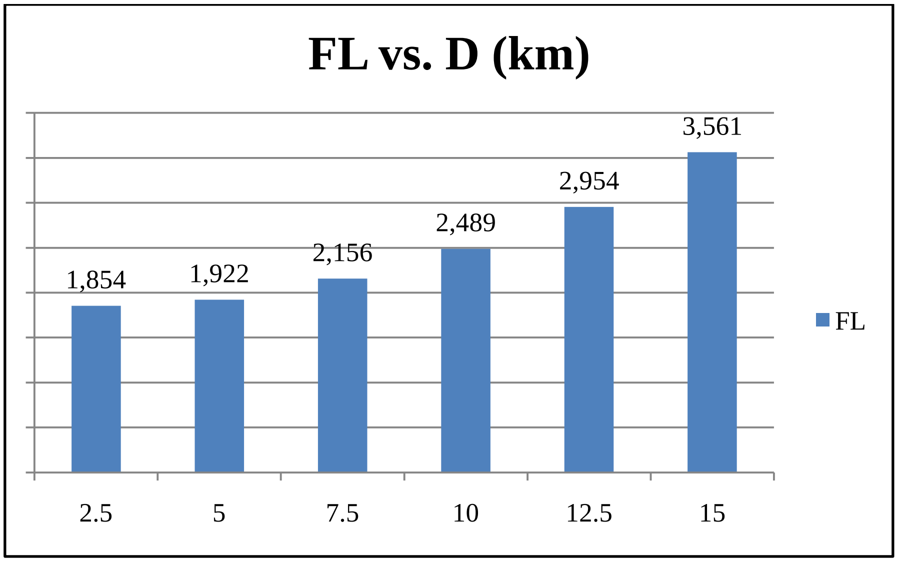

Figure 22 FL change as D increases for DF of Model C where the total number of links is 9587

In order to set a reasonable value to D, we examined thoroughly EC%(i) values for each demand point $i \in I$ and evaluated variation on EC%(i) by assigning 2.5, 5, 7.5, 10, 12.5 and 15km to D, respectively. EC%(i) values are decreasing while D is increasing (Figure 21). As a conclusion, in terms of EC%(i) values, D=5 km is a reasonable candidate to use in further studies.

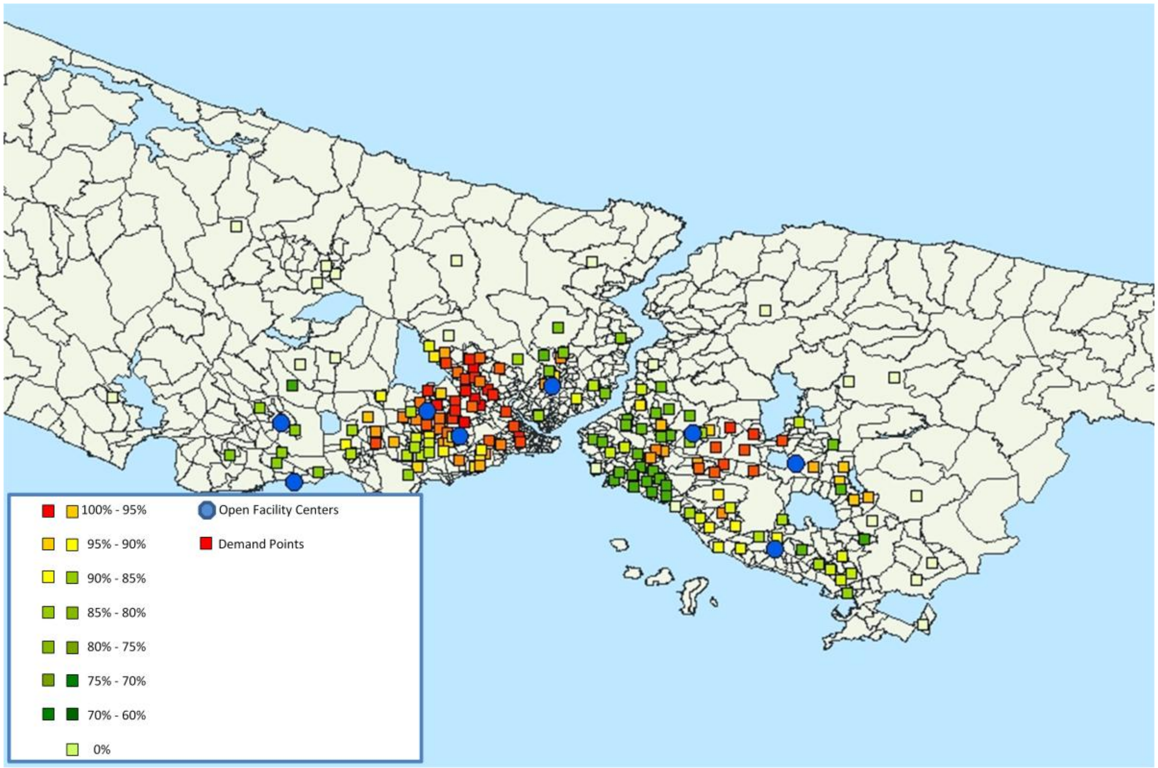

Figure 23 Facility locations and average demand coverage (within R = 10km) percentage values for each demand point over all network realization samples for Model C (worst-case earthquake scenario) where D = 5km

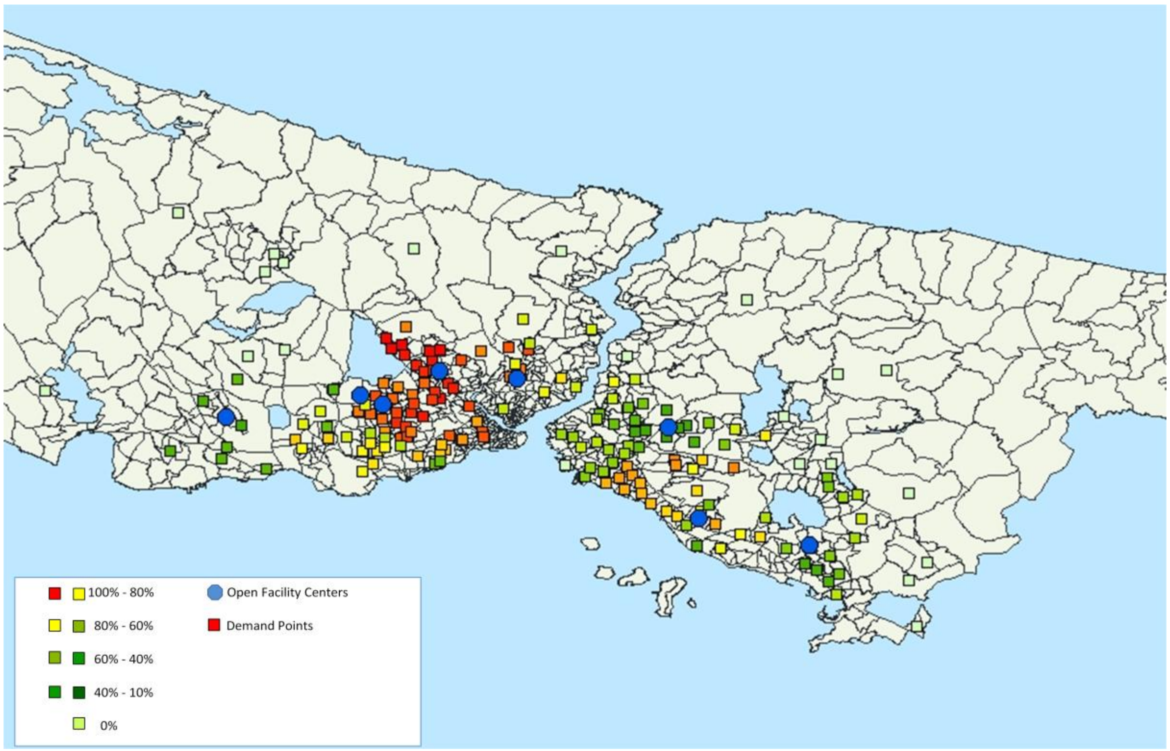

Figure 24 Facility locations and average demand coverage (within *R* = 10km) percentage values for each demand point over all network realization samples for Model C (worst-case earthquake scenario) where *D* = 10km

4.2.4. Coverage Distance Limit (*R*) Analysis

One of the most important parameters to be investigated in our algorithm is the R, named as coverage distance limit. Demand points will be served by open facilities according to this distance limit after a possible earthquake which makes the definition of R critical.

We derive from Table 7 and Table 8, where different R values are evaluated, that as R increases, EC% augments correspondingly. Secondly, there is a dramatic change in EC%' s when we augment R from 5 km to 10 km for both of the three cases DF, IF and NF (Figure 25). As R continues to increase after 10 km, EC% values do not differ significantly at none of the three cases. Based on this observation, we decided to assign the value of R to 10 km. 10km is a realistic value to provide a high service quality and aid materials to regions destroyed by a disaster in a short period of time. When we compare EC% values in DF (Table 7) with the ones in IF, they are lower. EC% is 77.01% in DF where R = 10km and 78.27% (Table 8) in IF for $Model\ C$. The change in R affects open facility locations which are represented by solution vector y for both DF, IF and RF (Table 7, Table 8 and Table 9). We examined carefully NF to comprehend the point of greatest change of EC% values which are greater than 91.85% where R = 18.5km. Between 18.61km and 18.65km, EC% improves from 91.85% to 97.23% when there is no link failure.

p	*R(km)*	*D*	*N*	*FL*	*y*	*EC*	*EC%*
8	**5**	5	10,000	1,922	5 9 12 13 25 28 30 38	86,588	**43.88%**
8	**10**	5	10,000	1,922	5 9 12 23 28 32 35 38	151,978	**77.01%**
8	**15**	5	10,000	1,922	6 9 12 15 18 24 32 38	173,691	**88.02%**
8	**20**	5	10,000	1,922	15 17 21 23 26 29 34 41	187,089	**94.80%**
8	**25**	5	10,000	1,922	4 5 14 23 24 27 33 38	192,452	**97.52%**
8	**30**	5	10,000	1,922	4 5 6 19 23 25 30 41	193,749	**98.18%**
Total Number of Links				***9,587***	***Total Demand***	***197,342***	

Table 7 EC% change while *R* is increasing for DF of Model C

p	*R(km)*	*N*	*FL*	*y*	*EC*	*EC%*
8	**5**	10,000	1,851	5 9 12 13 25 28 30 38	91,216	**46.22%**
8	**10**	10,000	1,850	7 9 12 16 23 28 32 35	154,458	**78.27%**
8	**15**	10,000	1,851	12 19 24 29 31 32 38 41	174,999	**88.68%**
8	**20**	10,000	1,851	2 15 17 21 23 29 34 41	188,238	**95.39%**
8	**25**	10,000	1,851	14 16 23 24 33 35 38 41	192,852	**97.72%**
8	**30**	10,000	1,851	5 10 14 15 17 19 22 41	194,095	**98.35%**
Total Number of Links			***9,587***	***Total Demand***	***197,342***	

Table 8 EC% change while *R* is increasing for IF of Model C

In addition, there exist some demand locations which are far away from all potential facility locations and the city centre but reachable within high distance limit such as 60km in NF where there is no link failure (Table 9).

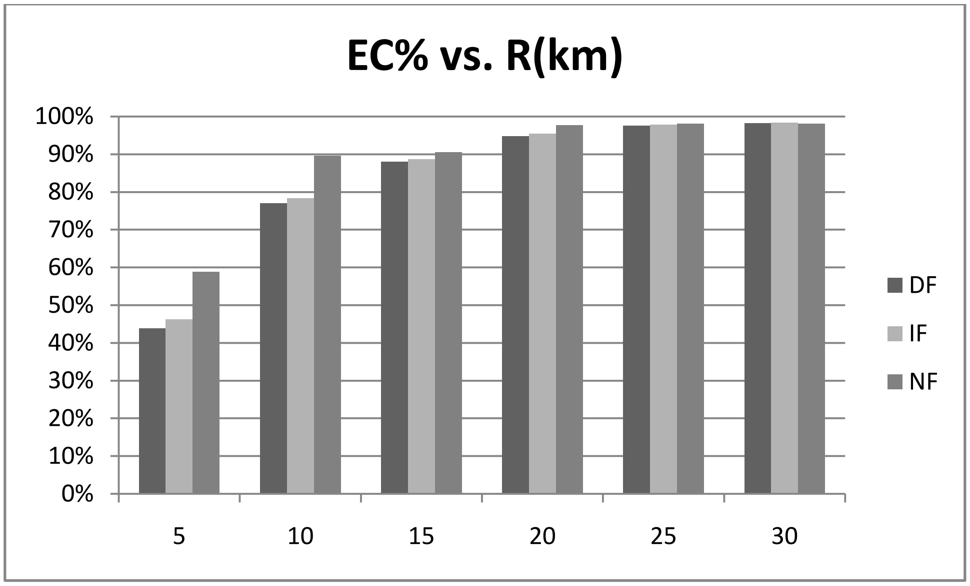

Figure 25 EC% change as *R* increases for DF, IF and NF evaluated for Model C

p	*R (km)*	*y*	*EC*	*EC%*
8	**5**	3 5 7 9 12 13 25 30	116,003	**58.78%**
8	**6**	3 12 16 23 25 28 29 35	128,329	**65.03%**
8	**7**	5 14 23 25 28 30 32 35	147,302	**74.64%**
8	**8**	1 2 3 14 21 23 29 39	166,265	**84.25%**
8	**9**	1 3 12 16 21 23 29 39	172,711	**87.52%**
8	**10**	1 3 7 9 12 21 34 41	176,742	**89.56%**
8	**15**	1 4 6 7 20 24 29 32	178,644	**90.53%**
8	**16**	1 3 4 17 21 24 29 30	179,778	**91.10%**
8	**17**	1 2 3 7 17 21 29 39	179,778	**91.10%**
8	**18**	3 4 6 15 17 21 29 40	179,778	**91.10%**
8	**19**	2 3 4 17 20 23 29 41	191,878	**97.23%**
8	**20**	3 4 15 17 20 23 29 41	192,810	**97.70%**
8	**25**	1 4 5 12 24 35 36 38	193,540	**98.07%**
8	**30**	1 4 5 6 27 31 33 41	193,540	**98.07%**
8	**40**	1 4 5 14 23 32 33 36	195,243	**98.94%**
8	**45**	2 5 6 20 22 24 28 39	196,296	**99.47%**
8	**50**	1 4 5 21 22 23 30 31	196,353	**99.50%**
8	**55**	3 4 5 20 22 24 28 31	196,541	**99.59%**
8	**60**	3 5 6 15 17 21 23 30	197,342	**100.00%**
		Total Demand	***197,342***	

Table 9 EC% change while *R* is increasing for NF of Model C

4.2.5. Evaluation of Average EC% of Each Demand Point i Over All Scenarios

We aim to observe the change for EC%(i) values for each demand point $i \in I$ assigning 5 and 10 km to D respectively for DF. Individual EC% values for each demand is higher for DF(D=5). We explain this situation referring to the number of links in the subset of each link in the edge . If D increases the number of the elements of a subset augments too, due the definition of each subset. We investigate to unexpected observations in Appendix A. As an example, demand point named as "Küçükyali Mh." has 0% value which corresponds to DF(D=5) and IF. However, at the beginning of the computational analysis we were expecting to obtain an augmentation for EC%(i) values from DF(D=10) to IF. Thus, first we investigated on open facility locations for DF(D=5) and IF, and realized that there were no open facilities within 10 km to "Küçükyali Mh." both for DF(D=5) and IF. We conclude that such an observation is anticipated in this case. Another examination in Appendix A difficult to interpret is that there are some demand points $i \in I$, i.e. "Suadiye Mh.", where it is observed EC%(i) values for DF(D=5) or IF bigger then 0% but smaller than the ones for DF(D=10). In such a case, we examined each alternative path in the set Π_{ji} from an open facility $j \in J$ and which is capable to serve to the concerned demand point $i \in I$. In such a case, we realized that there exists only 1 path which has length less than the coverage distance limit R. Another important remark is that this path possesses solely 1 edge. In such a case, whatever the sampling method is, either DF or IF, once the link between $i \in I$ and $j \in J$ fails after a possible earthquake, demand point $i \in I$is inaccessible from any facility $i \in I$ for the corresponding sample scenario. This proves the low EC%(i) value observed for "Suadiye Mh." in DF(D=5) and IF.

4.2.6. Elapsed Time Analysis for Sampling Average Method of IF vs. DF

Sampling average method spends more time Figure 27 in DF than in IF to generate N number of samples since it looks into the subset A_i of a failed link e_i and assign them to the set of unavailable links in the current network realization. As for IF, the sampling method identify a failed link e_i unusable for relief item service independently and do not look for other links which may be destroyed because of the corresponding failed link e_i. The run time of the tabu search algorithm for different sample sizes are compared for the IF and DF models in Figure 26. We see that as the sample size increases the difference between the IF and DF cases increases and DF starts to take much longer running time due to its more sophisticated approach and higher computational requirements.

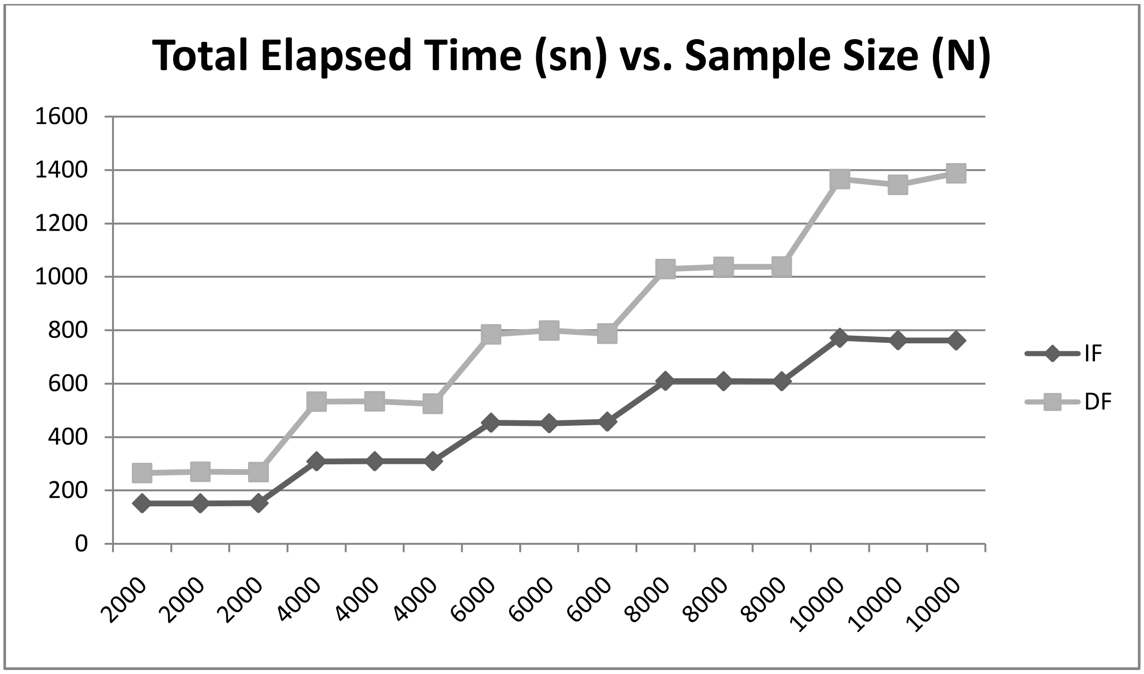

Figure 26 Total elapsed time spent for IF and DF of Model C in proposed algorithm

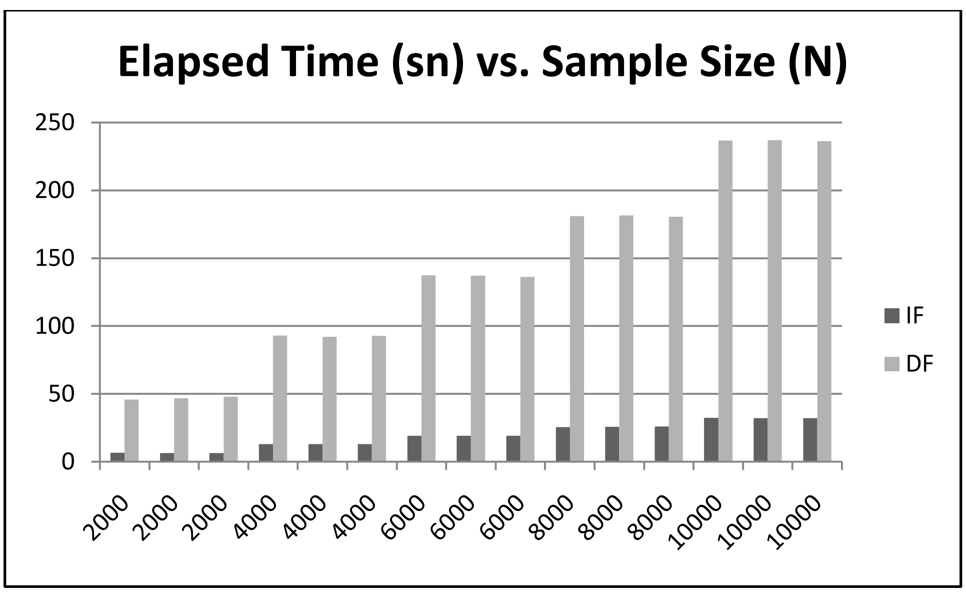

Figure 27 Total elapsed time (sn) passed to generate *N* number of samples in IF and DF for sampling average method

4.2.7. Evaluation of Solution Quality of Tabu Search Algorithm for Disaster Management with Sampling

We run a computational study with CPLEX using GAMS modelling system for mathematical programming formulation of our problem in section 3.1.1 and compare the results with Tabu Search Algorithm for Disaster Management with Sampling (TS4DM) which proposes a solution for emergency response facility locations and aims to maximize expected covered demand amount by evaluating a certain number of network scenarios. During this analysis, in order to provide a reasonable and consistent comparison of results of GAMS and TS4DM, we used the same set and size of scenarios and network, which includes potential facility locations, demand point locations, junction point on a path and paths, as the input to both mathematical model and heuristics approach. In Table 10, we insert expected covered demand values obtained from GAMS and TS4DM respectively for 5 different sets, each containing one hundred numbers of network realizations. Minimum gap from the optimal solution is 0.07% whereas the maximum is 1.64% in terms of objective function value, and on the average, the gap is 0.714%. In addition, when the coverage gap percentage from the optimal solution is minimal, 0.07%, facility location solution y for both GAMS and TS4DM is almost the same except one location. Furthermore, tabu search algorithm produces solutions in considerably short time in comparison with GAMS results (Figure 28). TS4DM with IF provides solutions in 2 s with 100 samples whereas GAMS does in 60 s. Moreover, total elapsed time difference increases dramatically as the sample size increments. It takes 2880 s for GAMS to obtain the optimal solution where N = 800 while TS4DM with IF is able to terminate the calculations in only 15 s for the same sample size and identical scenarios. In Figure 29, objective function values are compared for GAMS and TS4DM with IF and GAMS results are better than the ones of tabu search but benefit of TS4DM is in terms of total elapsed times which are pretty low (Figure 28).

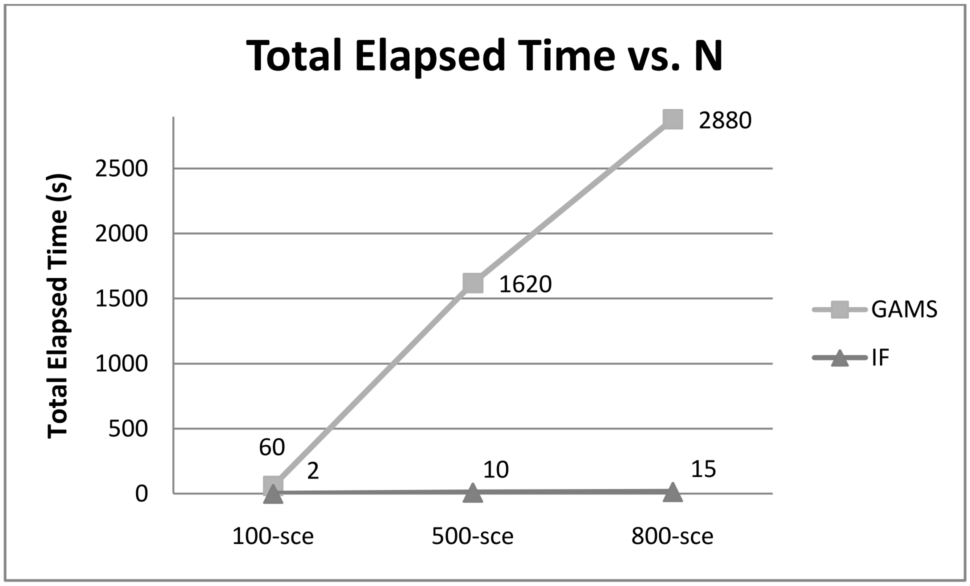

Figure 28 Total elapsed time comparison between GAMS and Tabu Algorithm for Model C with IF for 3 different sample sizes 100, 500 and 800 respectively

1st set of 100-sce	***y***	*obj func value*	*coverage %*	*elapsed time (s)*
GAMS	4 7 12 19 23 27 28 32	153,883	**77.98%**	56
TS4DM	1 4 5 21 23 28 29 41	151,352	**76.70%**	2
	gap %	**1.64%**	total demand	197,342

2nd set of 100-sce	***y***	*obj func value*	*coverage %*	*elapsed time (s)*
GAMS	2 7 9 12 15 23 28 35	153,938	**78.01%**	71
TS4DM	1 5 7 9 14 23 28 35	152,178	**77.11%**	2
	gap %	**1.14%**	total demand	197,342

3rd set of 100-sce	***y***	*obj func value*	*coverage %*	*elapsed time (s)*
GAMS	4 9 12 19 23 28 32 38	155,047	**78.57%**	60
TS4DM	4 12 19 23 27 28 32 38	154,933	**78.51%**	2
	gap %	**0.07%**	total demand	197,342

4th set of 100-sce	***y***	*obj func value*	*coverage %*	*elapsed time (s)*
GAMS	2 7 9 12 21 23 28 35	154,252	**78.16%**	71
TS4DM	2 7 10 12 23 30 35 41	153,418	**77.74%**	2
	gap %	**0.54%**	total demand	197,342

5th set of 100-sce	***y***	*obj func value*	*coverage %*	*elapsed time (s)*
GAMS	4 7 9 12 19 23 28 32	154,904	**78.50%**	52
TS4DM	2 7 9 12 21 23 28 35	154,622	**78.35%**	2
	gap %	**0.18%**	total demand	197,342

Table 10 GAMS versus Tabu Algorithm results for Model C with IF

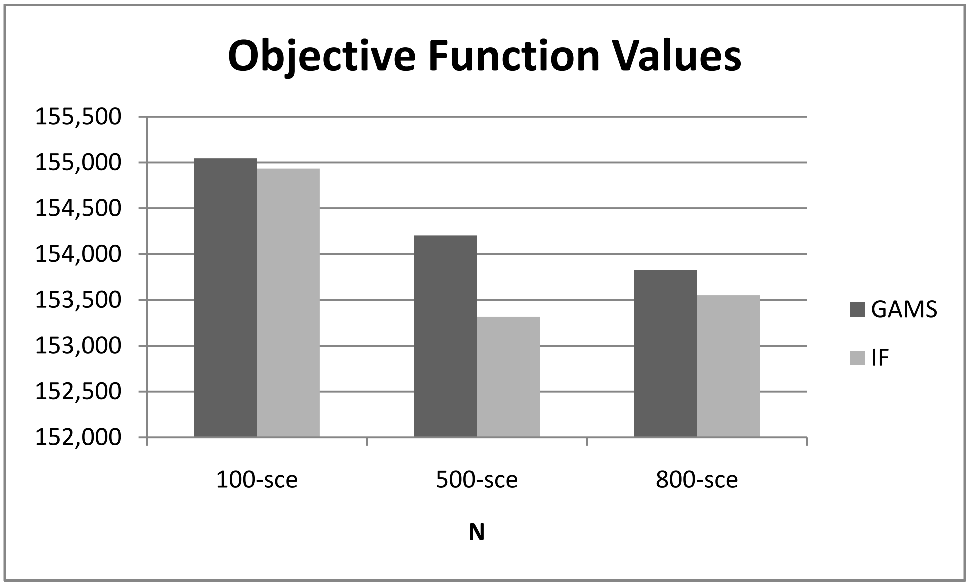

Figure 29 Objective function values achieved by GAMS and TS4DM with IF for 3 different sample sizes 100, 500 and 800 respectively

We determine the maximum scenario size which GAMS and TS4DM reach, respectively. We observe that GAMS procures the optimal solution up to 1,000 scenarios. It takes one and a half hours for GAMS to complete the job with a 900-scenario-set which is its highest scenario size and the realization number is limited to 900 because of the lack of sufficient memory. On the other hand, TS4DM heuristics method achieves 10,000 as the maximum scenario size on the average in 13 minutes for IF and 23 minutes for DF, respectively.

As a conclusion of this evaluation study, we come through that tabu search approach, which we developed to find a facility location solution in order to attain maximum expected covered demand amount by considering possible realizations in a network, is capable of providing solutions with higher number of network realizations in a reasonably short period of time and moreover when we compare objective function values of TS4DM with the optimal results where the same network, set and size of realizations are used as input, gap percentage is considerably low (Table 10).

4.2.8. Small Network Example for DF

We illustrate dependency distance limit D impact on EC%(i) with an example using the real network data. We represent each link (i,j) with two nodes i, starting node, and j, destination node. In illustrated example, we focus on one of the open facilities in 16th potential location and 169th node in the network which is a demand point location and named as "Orhantepe Mh.". First, we assign D to 5km and R to 10km. We generate the link subsets A_i's based on D and link survival probabilities p_{e_i}'s. We take N = 1,000 as network realizations number where open facility number Q is 8 and observe that EC%(i) between open facility 16 and demand point 169 (Orhantepe Mh.) is equal to 90.1%. This coverage value is an expected result because if we inspect alternative paths between nodes 16 and 169 there are several available to service paths (Table 11). Namely, assume that link (16,169) fails in one of the network realizations in the sampling average method. Since D is equal to 5km, link (170,169) is within a distance less than 5km to link (16,169) (refering to Problem Definition section for detailed explanation of links subsets A_i's) and survival probability of link (170,169) which is 0.767 is less than the one of link (16,169) 0.772, paths # 1 and 2 can not operate in the corresponding network realization. However, there are 8 alternative paths left whose links may survive and may be used for relief item distribution to demand point 169. Secondly, we set D to 10km and do not modify the rest of the parameters. In this case, if link (16,169) fails in one of the network realizations in the sampling average method, the number of links which are within D distance, 10km, and less than equal the survival probability of link (16,169) increases and consequently number alternative paths is reduced (Figure 30). In conclusion, EC%(169) diminishes to 20%.

Path #	Paths	Path Distances (m)
1	16 169	3354.68
2	16 170 169	4954.9
3	16 177 169	5677.22
4	16 171 170 169	7139.34
5	16 176 169	7263.58
6	16 177 170 169	7950.94
7	16 177 5 169	8217.91
8	16 177 176 169	8399.21
9	16 177 5 176 169	8964.14
10	16 176 5 169	9244.67

Table 11 Alternative paths and their corresponding distance values in meter between potential facility 16 and demand point 169 (Orhantepe Mh.)

Herewith, we demonstrate how the dependency distance limit $\boldsymbol{D}$ determines elements of dependency subsets $\boldsymbol{A_i}$'s and thereupon individual expected covered demand value EC%($\boldsymbol{i}$) of casualty point $\boldsymbol{i}$.

Node #	Node #	Link Distances (m)	Link Survival Probabilities
5	**169**	4375.65	0.773
5	**176**	1363.66	0.78
5	**177**	2086.77	0.783
16	**169**	3354.68	0.772
16	**170**	2447.35	0.774
16	**171**	1939.40	0.78
16	**176**	3505.36	0.779
16	**177**	1755.49	0.782
169	**5**	4375.65	0.773
169	**16**	3354.68	0.772
169	**170**	2507.55	0.767
169	**176**	3758.22	0.772
169	**177**	3921.72	0.775
170	**16**	2447.35	0.774
170	**169**	2507.55	0.767
170	**171**	2692.38	0.775
170	**177**	3687.90	0.777
171	**16**	1939.40	0.78
171	**170**	2692.38	0.775
176	**5**	1363.66	0.78
176	**16**	3505.36	0.779
176	**169**	3758.22	0.772
176	**177**	2885.49	0.782
177	**5**	2086.77	0.783
177	**16**	1755.49	0.782
177	**169**	3921.72	0.775
177	**170**	3687.90	0.777
177	**176**	2885.49	0.782

Table 12 Links in the example network in Figure 30 and their nodes, corresponding distance values in meter and survival probabilities

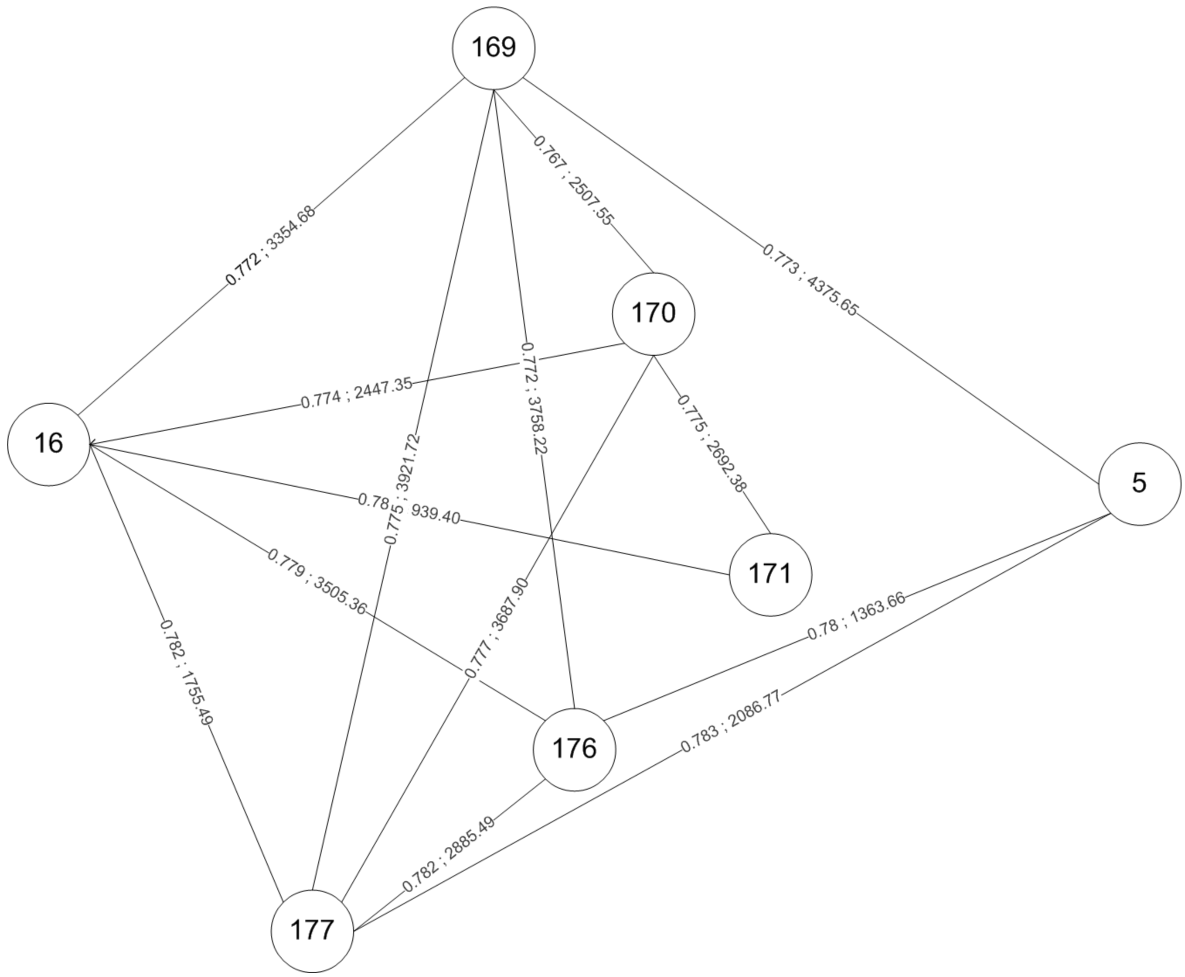

Figure 30 Alternative paths drawing from potential facility location 16 to demand point 169 (Orhantepe Mh.) with node numbers on paths, link survival probabilities and links distances for Model C

Chapter 5

CONCLUSIONS

In this thesis, relief aid supply chain design in disaster management is analyzed. We concentrate on pre-disaster stage and propose a model to locate emergency response facilities which store relief aid supplies before the disaster and distribute them effectively to casualty points in case of a disaster. Distribution network includes highway system and casualty points which are hit by a disaster. Links in the network may fail or survive after being struck by a disaster. Thus, we evaluated the reliability of each link in the network by assigning them survival probability values and generated network realizations by checking the link status in the current network. We used sampling average method to create the sample set. The node set of our network consists of potential facility locations, junction points in the highway system and demand points which are vulnerable to the disaster. Requirements to aid material supplies are determined for each demand point based on the historical data. We identified alternative paths from a potential facility location to a casualty point. In order to provide a sustainable relief item distribution network, a reasonable service distance limit R is inserted to the facility location problem. According to the status of links in the paths set, we determined the surviving shortest paths within distance R between each potential facility – demand point pair and decided if the demand of a casualty point can be satisfied by one of the open facilities in Q number or not. Accordingly, we calculated total expected covered demand by open facilities and applied tabu search heuristics to propose a facility location solution which maximizes total expected covered demand.

We applied the above procedure to Istanbul Earthquake case. First, we made a great effort to obtain real road and population data of each district in Istanbul and then to adopt it to the model in order to provide a realistic relief aid distribution design. After customizing the data for our network, we began to compose our data sets. We included potential facility locations determined by the municipality to the node set of the network. Then we identified critical junction points in the highway system of Istanbul which are entrances and exits of viaducts and bridges. Finally, we added demand points to the node set V. We calculated alternative paths and their corresponding distances between facility locations and demand points and add them to the link set E. We identified each demand point by assigning them the relief aid requirements which are calculated based on the previous earthquakes database. Furthermore, we characterized each link e_i in set E by defining their survival probabilities p_{e_i} for $Model\ A$ and $Model\ C$ respectively. We considered three criteria while calculating each p_{e_i}. First, we analyzed the earthquake-resistance of ground where link e_i is located and classified the ground features to 4 seismic zones. Then, we calculated distance from the fault line to each link and included the earthquake magnitude to the formula. For the post-disaster evaluation of the network, we examined the link reliability and implemented sampling average method to identify the link status, fail or survive, after the earthquake. We called each network realization after a disaster as scenario and performed 2 types of failure cases in order to decide the surviving link in scenarios. First approach is called the Independent Failure Case where the failure of a link does not depend on another one. Second technique is Dependent Failure Case where the survival of a link depends on any of the neighbor links within distance D and we named our method Distance-Based dependency (DB-dependency) model. We evaluated all network realizations to calculate total expected covered demand value by a facility location representation in tabu search heuristics and find a y solution which maximizes expected satisfied demands to relief items.

We succeeded to generate a large-scale network with 267 nodes and 9587 links and to obtain the results of our algorithm in a fairly short time. We provided a realistic relief aid supply network design with a scenario based approach where we inspected the status of the network links to decide if they survive or not in the relevant network realization. We investigated the independent and dependent failure cases to define the surviving link elements and analyze the proposed facility location solutions and their objective function values by both methods. We managed to observe that the objective function value for DF was the minimum among the ones of IF, DF and NF and detect the variation for open facility location for all three cases, IF, DF and NF respectively. There are alternative facility location representations with the same objective function value and a facility location solution may offer diverse total expected covered demand values where link failure exists, as expected. In addition, we were able to compare our results by assigning N to 10,000 which is considerably a higher value than the sample sizes utilized in previous studies in humanitarian logistics literature.

The new extensions may be implemented to this thesis in order to provide more efficient and realistic results. In terms of data generation, number of alternative paths may be increased which affect the covered demand percentage by open facilities. Further studies may assign capacity for each relief item to potential facility locations and compare the facility location solutions with the results obtained for the uncapacitated case. Finally, new approaches may be developed for the dependent failure case unlike our DB-dependency model. This new procedure may suggest a network realization method which presents outcomes between IF and DF.

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A. Appendix

Demand Points	*Dependent D = 10 km*	*Dependent D = 5 km*	*Independent*	*No Failure*
Gürsel Mh.	94.61%	96.66%	98.91%	100%
Kuruçesme Mh.	75.03%	74.41%	74.06%	100%
Hasan Halife Mh.	96.22%	99.80%	99.29%	100%
Merkezefendi Mh.	95.90%	98.87%	99.55%	100%
Uzun Yusuf Mh.	89.68%	97.95%	96.81%	100%
Telsiz Mh.	88.00%	96.36%	95.62%	100%
Osmaniye Mh.	87.62%	97.17%	99.12%	100%
Ataköy 7-8-9-10. Kisim	84.14%	94.75%	97.73%	100%
Zümrütevler Mh.	81.66%	96.88%	97.81%	100%
Sifa Mh.	0%	0%	0%	100%
Ugurmumcu Mh.	72.96%	86.91%	92.80%	100%
Idealtepe Mh.	85.56%	84.52%	84.41%	100%
Bogazköy Merkez Mh.	0%	0%	0%	0%
Arnavutköy Merkez	0%	0%	0%	0%
Ardiçlievler Mh.	44.72%	80.28%	80.39%	100%
Mustafa Kemal Pasa	54.06%	80.45%	80.05%	100%
Gümüspala Mh.	54.14%	77.65%	84.95%	100%
Sahintepe Mh.	0%	0%	0%	100%
Mehmetakif Mh.	53.82%	90.57%	92.81%	100%
Kanarya Mh.	86.66%	90.97%	98.46%	100%
Cumhuriyet2 Mh.	83.24%	87.28%	92.06%	100%
Halkali Mh.	77.90%	95.48%	97.43%	100%
Inönü2 Mh.	60.77%	96.33%	98.26%	100%
Tevfikbey Mh.	85.92%	99.17%	99.65%	100%
Günesli Mh.	93.57%	97.48%	99.75%	100%
Fatih5 Mh.	96.30%	98.49%	99.91%	100%
Kirazli Mh.	95.54%	97.45%	99.78%	100%
Inönü3 Mh.	95.29%	99.10%	99.97%	100%
Çinar1 Mh.	98.44%	98.56%	99.99%	100%
100. Yil Mh.	93.06%	99.78%	99.88%	100%
Günestepe Mh.	99.18%	98.14%	99.95%	100%
Haznedar Mh.	95.92%	96.45%	99.89%	100%

Güven Mh.	98.54%	95.80%	99.86%	100%
Merkez7 Mh.	98.71%	98.68%	99.98%	100%
Muratpasa2 Mh.	99.74%	99.92%	99.98%	100%
Kartaltepe2 Mh.	98.97%	99.91%	100%	100%
Yildirim Mh.	95.43%	99.86%	99.99%	100%
Kemer Mh.	94.16%	99.70%	99.96%	100%
Nine Hatun Mh.	98.92%	99.54%	99.95%	100%
Fevzi Çakmak2 Mh.	98.65%	99.81%	99.94%	100%
Davut Pasa Mh.	99.56%	99.96%	100%	100%
Tuna Mh.	95.51%	99.90%	99.97%	100%
Nuripasa Mh.	60.22%	94.74%	94.97%	100%
Bestelsiz Mh.	87.32%	94.62%	96.17%	100%
Yenidogan2 Mh.	61.22%	96.00%	96.16%	100%
Karadeniz Mh.	99.28%	98.50%	99.93%	100%
Baglarbasi1 Mh.	99.30%	99.84%	100%	100%
Sarigöl Mh.	99.41%	99.72%	99.97%	100%
Karayollari Mh.	99.69%	99.94%	99.99%	100%
Barbaros Hayrettin Paşa Mh.	99.20%	99.48%	99.98%	100%
Yeni6 Mh.	98.84%	99.68%	99.99%	100%
Aksemsettin1 Mh.	97.88%	98.86%	84.77%	100%
Islambey1 Mh.	0%	0%	0%	0%
Güzeltepe1 Mh.	91.40%	83.90%	85.02%	100%
Seyrantepe Mh.	98.03%	97.18%	97.56%	100%
Çaglayan Mh.	93.96%	94.29%	98.27%	100%
Hamidiye1 Mh.	96.19%	71.02%	72.42%	100%
50. Yil Mh.	99.73%	99.33%	99.11%	100%
Ugur Mumcu Mh.	99.93%	96.09%	98.02%	100%
75. Yil Mh.	99.81%	98.76%	92.16%	100%
Sultançiftligi1 Mh.	99.91%	93.50%	96.26%	100%
Ismetpasa2 Mh.	99.91%	89.98%	85.55%	100%
Yunus Emre Mh.	99.78%	99.72%	99.55%	100%
Baris Mh.	53.01%	76.98%	75.92%	100%
Ayazaga Mh.	76.30%	75.72%	76.88%	100%
Dervis Ali Mh.	88.75%	99.17%	97.87%	100%
Yeni7 Mh.	74.99%	74.02%	73.89%	0%
Kavacik Mh.	0%	0%	0%	0%

Mehmet Akif Ersoy3	75.45%	99.58%	99.53%	100%
Çamlik1 Mh.	0%	88.19%	88.22%	100%
Ömerli Merkez Mh.	0%	0%	0%	0%
Çavus Mh.	0%	0%	0%	0%
Güzelyali Mh.	74.56%	81.36%	80.82%	100%
Güllübaglar Mh.	68.39%	89.88%	93.36%	100%
Çamçesme Mh.	52.88%	89.70%	89.25%	100%
Dumlupinar1 Mh.	41.81%	85.11%	90.83%	100%
Fevzi Çakmak3 Mh.	40.79%	89.46%	93.27%	100%
Kavakpinar Mh.	62.90%	88.50%	88.95%	100%
Kurtköy Mh.	72.47%	61.41%	61.36%	100%
Yenisehir2 Mh.	75.38%	0%	0%	100%
Aydinli Mh.	0%	0%	0%	100%
Hamidiye3 Mh.	72.29%	95.24%	95.30%	100%
Battalgazi Mh.	0%	95.15%	94.59%	100%
Ahmetyesevi Mh.	65.31%	94.76%	94.85%	100%
Mecidiye2 Mh.	73.32%	95.53%	95.80%	100%
Osmangazi2 Mh.	0%	95.98%	95.31%	100%
Inönü6 Mh.	83.82%	99.16%	99.05%	100%
Orhantepe Mh.	45.42%	90.21%	92.78%	100%
Atalar Mh.	81.13%	90.19%	94.09%	100%
Soganlik Yeni Mh.	83.20%	86.96%	94.63%	100%
Hürriyet6 Mh.	69.90%	71.31%	88.21%	100%
Küçükyali Mh.	87.72%	0%	0%	100%
Basibüyük Mh.	84.75%	93.98%	94.57%	100%
Altayçesme Mh.	85.79%	89.83%	91.74%	100%
Baglarbasi2 Mh.	70.62%	91.35%	95.70%	100%
Esenkent2 Mh.	88.64%	91.00%	94.33%	100%
Yeni Çamlica Mh.	85.83%	99.24%	99.93%	100%
Kayisdagi Mh.	82.72%	98.96%	99.93%	100%
Ferhat Pasa1 Mh.	92.09%	99.13%	99.21%	100%
Atatürk7 Mh.	91.53%	96.04%	98.55%	100%
Mustafa Kemal1 Mh.	58.56%	96.16%	97.90%	100%
Esatpasa Mh.	71.67%	97.46%	97.88%	100%
Örnek2 Mh.	72.84%	96.19%	96.54%	100%
Asagi Dudullu Mh.	67.43%	99.64%	99.47%	100%

Atatürk5 Mh.	57.10%	95.54%	96.33%	100%
Yukari Dudullu Mh.	42.36%	99.14%	99.14%	100%
Ihlamurkuyu Mh.	18.22%	95.13%	95.35%	100%
Çakmak Mh.	14.24%	82.84%	82.56%	100%
Istiklal3 Mh.	21.41%	72.19%	71.84%	100%
Kazim Karabekir3 Mh.	63.90%	73.47%	74.24%	100%
Inkilap Mh.	39.83%	74.12%	73.46%	100%
Esensehir Mh.	67.22%	99.14%	99.22%	100%
Namik Kemal5 Mh.	39.08%	72.66%	72.04%	100%
Acibadem2 Mh.	73.89%	89.19%	89.06%	100%
Ünalan Mh.	71.76%	71.73%	72.50%	100%
Zeynep Kamil Mh.	71.39%	73.00%	71.85%	100%
Barbaros3 Mh.	70.99%	71.73%	71.67%	100%
Küçüksu Mh.	82.84%	88.97%	89.18%	100%
Güzeltepe2 Mh.	75.00%	93.30%	92.97%	100%
Kisikli Mh.	61.96%	72.86%	72.85%	100%
Küplüce Mh.	62.48%	72.47%	73.67%	100%
Yavuztürk Mh.	62.96%	73.14%	72.29%	100%
Bahçelievler2 Mh.	73.47%	92.64%	98.76%	100%
Fenerbahçe Mh.	69.52%	70.30%	69.98%	100%
Feneryolu Mh.	70.59%	71.21%	70.57%	100%
Merdivenköy Mh.	69.94%	70.34%	71.34%	100%
Sahrayicedit Mh.	88.76%	70.94%	70.79%	100%
Acibadem1 Mh.	74.94%	89.00%	89.05%	100%
19 Mayis3 Mh.	88.79%	70.79%	71.60%	100%
Kozyatagi Mh.	88.49%	69.93%	70.42%	100%
Göztepe3 Mh.	70.40%	70.33%	71.13%	100%
Erenköy Mh.	89.05%	70.58%	70.37%	100%
Caferaga Mh.	0%	0%	0%	100%
Caddebostan Mh.	88.56%	70.17%	70.53%	100%
Suadiye Mh.	88.60%	69.13%	69.84%	100%
Bostanci Mh.	88.46%	70.20%	69.74%	100%
Fevziçakmak2 Mh.	83.42%	87.65%	96.57%	100%
Sirinevler Mh.	84.11%	88.37%	96.70%	100%
Cumhuriyet7 Mh.	89.15%	93.21%	98.41%	100%
Soganli Mh.	73.89%	89.57%	98.33%	100%

Kocasinan Merkez Mh.	73.64%	89.71%	98.30%	100%
Siyavuspasa Mh.	83.49%	88.35%	97.16%	100%
Yenibosna Merkez Mh.	75.51%	95.82%	98.17%	100%
Alibey2 Mh.	0%	0%	0%	0%
Yeni2 Mh.	0%	0%	0%	0%
Cihangir1 Mh.	53.95%	79.15%	79.34%	100%
Tahtakale1 Mh.	59.61%	59.44%	60.02%	100%
Basaksehir	0%	0%	0%	100%
Sultangazi	92.86%	0%	70.57%	0%
Atasehir	90.60%	98.78%	99.03%	100%
Sancaktepe	0%	73.25%	73.71%	100%
Çekmeköy	0%	0%	0%	0%
Arnavutköy	0%	0%	0%	0%
Bakirköy	82.89%	81.71%	82.20%	100%
Besiktas	84.47%	87.75%	89.93%	100%
Beykoz	0%	0%	0%	0%
Beyoglu	74.70%	83.02%	83.80%	100%
Büyükçekmece	0%	0%	0%	0%
Çatalca	0%	0%	0%	0%
Eyüp	0%	0%	0%	0%
Fatih	96.22%	99.28%	98.05%	100%
Gaziosmanpasa	94.53%	98.12%	99.21%	100%
Ümraniye	13.26%	83.09%	83.09%	100%
Maltepe	63.49%	89.81%	89.75%	100%
Kadiköy	70.15%	70.60%	71.13%	100%
Kagithane	79.43%	75.01%	74.17%	100%
Kartal	84.36%	90.73%	95.36%	100%
Küçükçekmece	77.77%	84.22%	80.64%	100%
Pendik	0%	0%	0%	0%
Sariyer	0%	0%	0%	0%
Silivri	0%	0%	0%	0%
Sile	0%	0%	0%	0%
Sisli	74.75%	74.81%	74.88%	100%
Üsküdar	72.05%	72.59%	71.79%	100%
Zeytinburnu	87.04%	92.29%	90%	100%
Bayrampasa	98.66%	98.70%	99.46%	100%

Avcilar	32.93%	79.30%	79.74%	100%
Bagcilar	78.64%	87.21%	95.67%	100%
Bahçelievler	84.02%	86.96%	96.93%	100%
Güngören	93.45%	90.24%	97.41%	100%
Sultanbeyli	64.18%	71.04%	71.68%	100%
Tuzla	0%	0%	0%	100%
Esenler	90.97%	95.09%	96.60%	100%
Dikilitaş Mh.	79.57%	90.10%	91.68%	100%
Nişancı Mh.	98.06%	99.32%	99.37%	100%
İstinye Mh.	76.03%	77.81%	76.58%	100%
Average Coverage %	**66.72%**	**75.79%**	**77.23%**	**89.25%**
Total Covered Demand	**133,400**	**151,464**	**154,390**	**176,742**
Covered Demand %	**67.60%**	**76.75%**	**78.23%**	**89.56%**
Total Demand	***197,342***			

Table 13 EC% values for each demand point on the network obtained with DF(D=10km), DF(D=5km), IF and NF approaches