PRE-POSITIONING DISASTER RESPONSE FACILITIES AND RELIEF ITEMS CONSIDERING PROBABILISTIC CONSTRAINTS: A CASE STUDY ON ISTANBUL REGION

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ABSTRACT

PRE-POSITIONING DISASTER RESPONSE FACILITIES AND RELIEF ITEMS CONSIDERING PROBABILISTIC CONSTRAINTS: A CASE STUDY ON ISTANBUL REGION

RENKLİ, ÇİĞDEM
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Large-scale disasters cause enormous damage to people living at the affected areas. Providing relief quickly to the affected is a critical issue in recovering the effects of a disaster. Pre-disaster planning has an important role on reducing the arrival time of relief items to the affected areas and efficiently allocating the them. In this study, an MIP model is proposed in order to pre-position warehouses throughout an affected area and determine the amount of relief items to be held in those warehouses. Time between the strike of a disaster and arrival of relief items at the affected areas is aimed to be minimized. In addition, using probabilistic constraints, the model ensures that relief items arrive at affected areas within a certain time window with a certain reliability. Considering instable fault lines on which Istanbul is located, the proposed model is applied to Istanbul case for pre-positioning warehouses a priori to the possible expected large-scale earthquake.

Keywords: Disaster Management, Humanitarian Logistics, Mixed Integer Programming

ÖZ

ÖN-KONUMLAMA DEPOLARININ VE TEMEL İHTİYAÇ MADDELERİNİN RASSAL KISITLAR KULLANILARAK YERLEŞTİRİLMESİ: İSTANBUL ÜZERİNE BİR VAKA ANALİZİ

RENKLİ, ÇİĞDEM

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Büyük ölçekli felaketler gerçekleştikten sonra, etkilenen insanlara yardım götürmek felaketin etkisini azaltmak için gereklidir. Felaketler gerçekleşmeden önce plan yapmak ve önlem almak, ihtiyaç maddelerinin etkilenen alanlara ulaşma zamanının azaltılmasında ve kaynakların verimli kullanılmasında önemli bir rol oynar. Bu tez çalışmasında, ön-konumlama depolarının yerleştirilmesi ve bu depolarda tutulacak ihtiyaç maddelerinin miktarlarının belirlenmesi için bir karışık tamsayı matematiksel modeli önerilmektedir. Amaç, felaketin gerçekleşmesi ile etkilenen alanlara yardım gönderilmesi arasında geçen zamanı en aza indirmektir. Bu çalışmayı özgün kılan özellik olarak, matematiksel model rassal kısıtlar kullanarak, ihtiyaç maddelerinin belirlenen zaman içinde, belirli bir olasılıkla etkilenen alanlara ulaştırılmasını sağlamaktadır. Önerilen model İstanbul bölgesine uygulanmış ve olası bir depreme karşı yerleştirilmesi gereken ön-konumlama depolarının yerleri belirlenmiştir.

Anahtar Kelimeler: Afet Yönetimi, İnsani Yardım Lojistiği, Karışık Tamsayı Programlama

To my parents and my sister

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CHAPTER 1

INTRODUCTION

Centre for Research on the Epidemiology of Disasters (CRED) defines a disaster as a 'situation or event, which overwhelms local capacity, necessitating a request to national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction and human suffering'. According to the Office of U.S. Foreign Disaster Assistance OFDA/CRED International Disaster Database, EM-DAT, 336 natural disasters were reported in 2011; number of deaths due to natural disasters is 31,105 and number of affected people is 209 million worldwide. Also, EM-DAT shows that between 2002 and 2011, 3,963 natural disasters caused 1,145,015 deaths and affected 2,682,800 people [1].

Disasters are stochastic in their nature; exact time, place and magnitude of disasters cannot be known before they strike. They are unpreventable events that cause many deaths and affect even more people. People, that are lack of survival needs like immediate medical assistance, food, water, and need immediate assistance, are defined as affected people. [2] Assisting affected people by responding quickly and effectively is a crucial but difficult task due to these uncertainties. For quick and effective response, humanitarian logistics plans should be prepared. Apte [3] defines humanitarian logistics as 'that special branch of logistics which manages response supply chain of critical supplies and services with challenges such as demand surges, uncertain supplies, critical time windows in face of infrastructure vulnerabilities and vast scope and of the operations'.

Thomas [4] states that 'humanitarian supply chains are among the most dynamic and complex supply chains in the world'. Challenges due to unpredictability of disasters must be considered in humanitarian logistics. Balcik and Beamon [5] describe the challenging characteristics of humanitarian logistics as

- 'Unpredictability of demand, in terms of timing, location, type and size,
- Suddenly occurring demand in very large amounts and short lead times for a variety of supplies,
- High stakes associated with adequate and timely delivery,
- Lack of resources (supply, people, technology, transportation capacity, and money).'

In addition to these challenging characteristics, survivability of infrastructure of affected areas is another concern [6]. A large-scale disaster may destroy paths linking locations on the affected area and block the roads for relief transportation. In these highly unpredictable situations, an adequate and thorough pre-disaster planning gains importance in reducing response time after a disaster strikes and sending relief items to the affected people efficiently.

Humanitarian logistics operation can be divided into three stages: preparation, disaster response and humanitarian relief [3]. Focus of this study is on the preparation stage. Preparation stage includes pre-positioning disaster response facilities and relief items a priori to a disaster. Facilities are pre-positioned in order to reduce the response time. Although the exact time, magnitude and the place of a disaster cannot be known, the effect can be predictable. This is why possible disaster scenarios are used in the literature. In the literature, mostly, stochasticity of the situation is employed considering possible scenarios and expected value of an objective function with respect to the scenarios. For example, when the number of affected people in a population center is not known due to unpredictable magnitude of the disaster, different scenarios with different disaster magnitude and thus with different number of affected people can be employed. However, it is not realistic to think that using possible scenarios prevents the results of the unpredictability of a disaster. Probabilistic elements are present in disaster scenarios. Survivability of infrastructure is one of the probabilistic elements. A disaster response facility can be pre-positioned and some affected areas can be assigned to that facility to be served; however, assuming that relief item transportation is not blocked during the happening time of the disaster is not realistic. This is why, in this thesis, probabilistic constraints are used to provide a certain reliability of transportation.

Motivation of this thesis is the lack of formulations that give attention to survivability of infrastructure in the literature. Probabilistic constraints, that are similar to the ones used in facility location problems in order to provide reliability in serving a demand point, are modified and adapted to humanitarian logistics area for serving the purpose of providing reliability for an affected area to get its relief items. The problem of pre-positioning disaster response facilities and relief items is formulated with the probabilistic constraints, which are also called as chance constraints. Effect of the chance constraints on the solutions is discussed and the results of chance-constrained formulation and scenario-based formulation are compared first using a simple example consisting of four locations. Then, on a simulated data consisting of 16 affected areas and 65 candidate disaster response facility locations, both formulations are solved and results are discussed. Afterwards, introducing the related data of Istanbul European Side, the formulation is used in a real life problem with some variations.

Shortly, a mixed-integer programming model is proposed in order to pre-position disaster response facilities and relief supplies minimizing total response time. This problem is stochastic in its nature and proposed models in the literature mostly handle stochastic nature of the problem by using possible scenarios. In this study, probabilistic constraints are used for this purpose. The motivation of the thesis is analysing the usage of the chance constraints in humanitarian logistics area.

In the remainder of this study, literature on location problems and humanitarian logistics are reviewed in Chapter 2. In Chapter 3, the proposed model is presented. In addition to the proposed model, formulations which are the variations of the proposed model and a scenario-based formulation to be compared with the proposed model are introduced in this chapter. In Section 4, numerical examples are presented and the formulations introduced in Chapter 3 are used on these examples. Additionally, a numerical study which consists of a real life problem, problem of pre-positioning disaster relief facilities and relief items in Istanbul a priori a large-scale earthquake, is introduced. Data of the Istanbul problem is presented and formulations are solved. Solutions of different formulations on the numerical example and on the Istanbul problem are commented in Chapter 4, also. Chapter 5 is the ending chapter of the thesis and it includes a summary, comments and suggestions of the future studies.

CHAPTER 2

LITERATURE REVIEW

Humanitarian logistics is ‘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 end beneficiary’s requirements’ [7]. Humanitarian logistics is a broad area that includes different stages of disaster management. Literature on humanitarian logistic can be classified as literature on preparedness, literature on disaster response and literature on relief operations [3]. Only the literature on preparedness in humanitarian logistics is addressed here considering the focus of this thesis. Location problems are often encountered in the literature on humanitarian logistics. Therefore, the literature review section is divided into two parts: literature on location problems and humanitarian logistics.

2.1 Literature Review on Location Problems

Before continuing with the literature, two measures of location problems should be stated. One measure is total weighted distance or time and the other is maximal service distance or time. As stated by ReVelle and Church [8], usage of notions of time and distance are equally acceptable.

Daskin et al. [9], the single facility location problem which minimizes the total distance between the single facility and several customers as stated as the beginning of location theory in 1909. Then, Hakimi [10] studies on finding locations of switching centers in a communication network and locations of police stations in a highway system. He advances the study of location problems by locating multiple facilities that minimizes the total distance between facilities and the customer or minimizes the maximum distance between a customer and its closest facility. Consequently, the p-center problem, which locates p facilities that cover all demand nodes minimizing the maximum distance between a demand node and its closest facility, and the p-median problem, which located p facilities minimizing the total distance between the facilities and the demand nodes, are introduced by Hakimi [10].

ReVelle and Swain [11] focus on the p-median problem introduced by Hakimi [10] and propose an equivalent linear integer problem. The model finds the location of the facilities and the decides on the assignments of demand nodes to the nodes on which the facilities are located while minimizing the demand weighted distance between the facility nodes and their assigned demand nodes. Formulation of p-median problem is as follows:

$$\text{Minimize} \quad \sum_{i=1}^{n}\sum_{j=1}^{n} a_i d_{ij} x_{ij} \tag{2.1}$$

$$\text{subject to} : \sum_{j=1}^{n} x_{ij} = 1 \qquad \forall i \in I \tag{2.2}$$

$$x_{ij} \leq x_{jj} \qquad \forall i \in I, \forall j \in J, i \neq j \tag{2.3}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i \in I, \forall j \in J \tag{2.4}$$

where

I : set of demand nodes

J : set of candidate facility nodes

a_i : demand of node i

d_{ij} : shortest distance between nodes i and j

x_{ij} : 1, if $i \neq j$ and demand node i is assigned to facility at node j; 0, otherwise

x_{jj} : 1, if a facility is located at candidate node j.

Daskin and Dean [12] address three classic facility location models as basic location models. One of these basic location models is the p-median problem. The others are the location set covering model and the maximal covering model. These models are discrete facility location models and they locate facilities on a finite number of candidate locations [12]. Location set covering problem (LSCP) is structured and solved by Toregas et al. [13] and Toregas and ReVelle [14]. The problem aims to find minimum number of facilities in order to cover all demand nodes within a specified maximal service distance. Formulation of LSCP is as follows:

$$\text{Minimize} \quad \sum_{j \in J} x_j \tag{2.5}$$

$$\text{subject to} : \sum_{j \in N_i} x_j \geq 1 \qquad \forall i \in I \tag{2.6}$$

$$x_j \in \{0, 1\} \qquad \forall j \in J \tag{2.7}$$

where

I : set of demand nodes

J : set of candidate facility nodes

N_i : set of candidate facility nodes that can serve to demand point i not exceeding maximal service distance

x_j : 1, if a facility is opened at candidate facility node j; 0, otherwise.

Objective function (2.5) minimizes the total number of facilities to be located. Constraint set (2.6) ensures that each demand point has at least one facility within the maximal service distance. Later, considering that covering all demand nodes may not be feasible due to insufficient resources, ReVelle and Church [8] introduce the maximal covering location problem. The model locates a fixed number of facilities by maximizing coverage within a given maximal service distance. ReVelle and Church [8] propose solution techniques like heuristic approaches and linear programming solutions. In addition, they propose the maximal covering location model with mandatory closeness constraints. This formulation is proposed especially for public location problems. It is a maximal covering location problem (MCLP) and at the same time it ensures the distance between a facility and a demand point to be not greater than a desired distance level, which is greater than the specified maximal service distance. Formulation of MCLP is as follows:

$$\text{Maximize} \quad \sum_{i \in J} a_i y_i \tag{2.8}$$

$$\begin{aligned} \text{subject to :} \sum_{j \in N_i} x_j &\geq y_i && \forall i \in I && (2.9) \\ \sum_{j \in J} x_j &= P && && (2.10) \\ y_i &\in \{0, 1\} && \forall i \in I && (2.11) \\ x_j &\in \{0, 1\} && \forall j \in J && (2.12) \end{aligned}$$

where

I : set of demand nodes

J : set of candidate facility nodes

N_i : set of candidate facility nodes that can serve to demand point i not exceeding maximal service distance

x_j : 1, if a facility is opened at candidate facility node j; 0, otherwise

y_i : 1, if demand node i is covered within the maximal service distance; 0, otherwise

a_i : population of demand node i

P : number of facilities to be located.

Objective function of MCLP maximizes covered population. By substituting variable y with $\bar{y}$, the problem is converted to a problem which minimizes the population left uncovered:

$$\text{Minimize} \quad \sum_{i \in J} a_i \bar{y}_i \tag{2.13}$$

$$\text{subject to} : \sum_{j \in N_i} x_j + \bar{y}_i \geq 1 \qquad \forall i \in I \tag{2.14}$$

$$\sum_{j \in J} x_j = P \tag{2.15}$$

$$\bar{y}_i \in \{0, 1\} \qquad \forall i \in I \tag{2.16}$$

$$x_j \in \{0, 1\} \qquad \forall j \in J \tag{2.17}$$

where

$\bar{y}_i$: 1, if demand node i is not covered by a facility within the maximal service distance; 0, otherwise

All other notation is the same and two problems are equivalent. Additionally, Church and ReVelle [15] study on theoretical links between the p-median problem, the location set covering problem and the maximal covering location problem. They also present a historical perspective of development of location models. They stated that it is possible to structure the maximal covering location problem and the maximal covering location problem with mandatory closeness constraints as their equivalent p-median formulations.

The literature discussed up to here consists of deterministic location problems. There are also probabilistic location problems in the literature introduced to handle uncertainty in location of demand points or uncertainty in availability of facilities. First probabilistic location problem was proposed by Chapman and White [16]. It is a probabilistic version of the location set covering problem (PLSCP) and has a constraint which forces a demand area to be covered by multiple facilities [17]. Formulation of the problem is as follows:

$$\text{Minimize} \quad \sum_{j \in J} x_j \tag{2.18}$$

$$\text{subject to} : \sum_{j \in N_i} x_j \geq s_{min}(i) \qquad \forall i \in I \tag{2.19}$$

$$x_j \in \{0, 1\} \qquad \forall j \in J. \tag{2.20}$$

All notation is the same as the notation of LSCP. Its difference from LSCP is the right hand side of Constraint set (2.19). It provides that demand point i is covered with a certain probability α_i. Define probability of being busy of a facility is p, number of vehicles to cover demand point i is $s(i)$ and let H_i is the event that there is at least one vehicle available for serving demand node i. Probability that H_i occurs is given by

$$P(H_i) = 1 - p^{s(i)}. \tag{2.21}$$

It is required that $P(H_i)$ is greater than α_i; therefore, it is required that $s(i)$ is greater than or equal to a specific number, $s_{min}(i)$, given by Equation (2.22):

$$s_{min}(i) = \lceil \frac{ln(1 - \alpha_i)}{ln(p)} \rceil. \tag{2.22}$$

Therefore, using multiple coverage, PLSCP provides that the probability of coverage for a demand node is greater than a specified value.

Aly and White [18] study on probabilistic formulation of emergency service facility location problem. In this study, random variables are the locations of incidents and uniform distribution is used for probability distribution of rectilinear travel time between a new facility location and the random location of the incident. Probabilistic set covering and probabilistic central facility problems are introduced. Solution procedures for these two problems are described. From the results that they obtain from computational experiments, they concluded that probabilistic formulations require higher number of assigned facilities than the deterministic problems and increasing the speed of emergency vehicles decreases the required number of assigned facilities.

Daskin [19] extends the maximal covering location model to account for the chance that when a demand arrives at the system it will not be covered since all facilities capable of covering the demand are engaged serving other demands. The extended model, named as maximum expected covering location model (MEXCLP), takes the probability that a facility is not working (p) into consideration while maximizing the expected covered demand. Relating with the probability a facility is not working, some assumptions are made. One of them is the known and same busy probabilities among facilities. The other assumption is the independency of the probabilities that a facility is not working. Therefore, a random variable, $M_{i,k}$ can be defined as the number of demands at node i covered by a working facility given k facilities are eligible to cover demand node i. $M_{i,k}$ equals to demand of node i, d_i, with probability of 1-p^k; it equals to zero with probability p^k. Expected value of $M_{i,k}$ is given by

$$E(M_{i,k}) = d_i(1 - p^k) \qquad \forall i, k. \tag{2.23}$$

Formulation of MEXCLP is as follows:

$$\text{Maximize} \quad \sum_{l \in L} \sum_{k \in K} (1-p) p^{l-1} d_i y_{il} \tag{2.24}$$

$$\text{subject to :} \sum_{l \in L} y_{il} - \sum_{j \in J} a_{ij} x_j \leq 0 \qquad \forall i \in I \tag{2.25}$$

$$\sum_{j \in J} x_j \leq G \tag{2.26}$$

$$x_j = 0, 1, ..., G \qquad \forall j \in J \tag{2.27}$$

$$y_{il} \in \{0, 1\} \qquad \forall i, l \tag{2.28}$$

where

y_{il} = 1, if demand node i is covered by at least l facilities; 0, otherwise

x_j =number of facilities located at candidate facility node j

a_{ij}= 1, if a facility at node j is eligible to cover demand node i; 0, otherwise.

The model decides on location of the facilities and the least number of facilities that cover a demand point and objective function maximizes the expected coverage of demand. Daskin proves the several structural properties of the formulation and presents a heuristic solution algorithm to solve the problem.

Batta et al. [20] relax some of assumptions made by Daskin [19]. These relaxed assumptions are the independency of servers (facilities), same busy probabilities (propability that a facility is not working) for all servers and invariance of busy probabilities with respect to their locations. They use the hypercube queuing model introduced by Larson [21] in a heuristic optimization procedure, and they aim to maximize the expected coverage while determining a set of server locations. In addition, they structure correction factors and add them to the objective function of MEXCLP to relax the independence assumption and introduced the adjusted-MEXCLP (AMEXCLP).

ReVelle and Hogan [22] introduce the maximal availability location problem (MALP) which is the probabilistic version of the maximal covering location problem used in emergency response systems. Considering the randomness in service availability, the model locates p servers maximizing coverage of population within a given time standard and a reliability. They propose two versions of MALP; MALP I and MALP II. MALP I assumes identical busy fractions for all servers. They use the estimation of Daskin [19] for busy fractions which is found by dividing daily hours of service needed in the system by daily hours of service available. A chance constraint on service availability is introduced ensuring that the probability of one or more vehicles is available within the maximal service distance is greater than a given reliability is introduced. The chance constraint is linearized and converted into a constraint forcing that a demand point is covered at least b times. Let q be the busy fraction of servers and α is the desired reliability of serving to demand points. Probability that one or more vehicles are available to serve within maximal service distance should be greater than α, which can be represented by inequality (2.29):

$$1 - q^{\sum_{j \in N_i} x_j} \geq \alpha \tag{2.29}$$

where

I : set of demand points

J: set of candidate locations

N_i : the set of candidate sites that can serve to demand point i not exceeding maximal service distance

x_j : integer number of servers positioned at site j.

Inequality (2.29) can be equivalently written as:

$$\sum_{j \in N_i} x_j \geq b \tag{2.30}$$

where

$$b = \lceil \frac{log(1 - \alpha)}{log(q)} \rceil. \tag{2.31}$$

In the objective function of MALP I, total population weighted number of demand points that are covered at least b times is maximized. Formulation is as follows:

$$\text{Maximize} \quad \sum_{i \in I} f_i y_{ib} \tag{2.32}$$

$$\text{subject to :} \sum_{k=1}^{b} y_{ik} \leq \sum_{j \in N_i} x_j \qquad \forall i \in I \tag{2.33}$$

$$y_{ik} \leq y_{ik-1} \qquad \forall i \in I, k = 2, ..., b \tag{2.34}$$

$$\sum_{j \in J} x_j = p \tag{2.35}$$

$$y_{ik} \in \{0, 1\} \qquad \forall i \in I, k = 1, ..., b \tag{2.36}$$

$$x_j \in \{0, 1\} \qquad \forall j \in J \tag{2.37}$$

where

y_{ik} : 1, if demand point i has at least k servers within the maximal service distance

f_i: the population at demand point i

p : total number of vehicles to be positioned.

MALP II uses busy fractions that are different in various locations. Those busy fractions are area-specific not site-specific. However, they present formulation of chance constraints and its linearization for site-specific busy fractions, also. Define r_j as the busy fraction of a vehicle at site j and all other notation is the same as notation of MALP I. Then, Inequality (2.38) ensures that the probability of being covered for a demand point j is greater than a specified reliability, α:

$$1 - \prod_{j \in N_i} r_j^{x_j} \geq \alpha. \tag{2.38}$$

Taking logarithms of both sides of (2.38), we obtain Inequality (2.39):

$$\sum_{j \in N_i} (log(r_j))x_j \leq log(1 - \alpha) \tag{2.39}$$

ReVelle and Hogan [22] state that if these chance constraints are used, an efficient zero-one code capable of solving large problems, which does not exists for general problems, will be needed to solve the problem. However, they do not conduct any computational study. In MALP II, area-specific busy fractions are used and chance constraints which force each demand area has a server available to respond within maximal service time with a certain reliability. Therefore, for each demand area, a chance constraint is written and linearized as system-wide chance constraints in MALP I. Linearized chance costraints are given by

$$\sum_{j \in N_i} x_j \geq b_i \qquad \forall i \in I, \tag{2.40}$$

where b_i is the smallest integer satisfying Inequalities (2.41):

$$1 - (\frac{f_i}{b_i})^{bi} \geq \alpha \qquad \forall i \in I. \tag{2.41}$$

Formulation of MALP II is as follows:

$$\text{Maximize} \quad \sum_{i \in I} f_i y_{ib_i} \tag{2.42}$$

$$\text{subject to} : \sum_{k=1}^{b_i} y_{ik} \leq \sum_{j \in N_i} x_j \qquad \forall i \in I \tag{2.43}$$

$$y_{ik} \leq y_{ik-1} \qquad \forall i \in I, k = 2, ..., b \tag{2.44}$$

$$\sum_{j \in J} x_j = p \tag{2.45}$$

$$y_{ik} \in \{0, 1\} \qquad \forall i \in I, k = 1, ..., b \tag{2.46}$$

$$x_j \in \{0, 1\} \qquad \forall j \in J \tag{2.47}$$

All notation is the same as that of MALP I. Only difference here is that b_i values are used instead of b. These two models are applied to the data of Baltimore fire system. Both problems are solved using MPSX and in several instances branch-and-bound applications are used to resolve fractional solutions.

ReVelle and Hogan [23] propose two problems which are modifications of the probabilistic location set covering problem introduced by Chapman and White [16]. They show that original probabilistic location set covering model (PLSCP) which uses one estimate of busy fraction for the system is extremely sensitive to this busy fraction. One of the modified models is the α-reliable p-center problem that positions p facilities minimizing the maximum time within which service is available with α-reliability. When α is specified, PLSCP is solved for successively smaller values of maximal service time. The other modified model is the maximum reliability location problem locating p facilities which provide service within a specified maximal service time units maximizing minimum reliability of service. Comparison of system estimate of busy fraction and sector specific estimate of busy fraction is presented and relation of busy fraction and reliability is shown.

A reliability model, called Rel-P, is proposed by Ball and Lin [24]. Unavailability of an emergency service vehicle to respond a demand call in a specific time is defined as system failure. Reliability is defined for individual demand points, not for the system as a whole. Rel-P decides on the number of vehicles in each station whose location is selected among candidate sites, minimizing the total cost of number of vehicles located in stations. Number of calls arose and serviced by site j is defined as a random variable D(j). A probabilistic constraint forcing the probability of D(j) is greater than the number of vehicles in site j, which covers that demand point, is less than a certain reliability. The constraint is linearized by taking the logarithms of both side as proposed in ReVelle and Hogan (1989) as an alternative approach and a linear IP model is obtained. In the study, distribution of demand calls is assumed to be Poisson distribution and valid inequalities are constructed as preprocessing technique and the problem is solved using branch-and-bound algorithm. Computational results and sensitivity analysis are presented.

Different from emergency service location problems, Synder and Daskin [25] propose a reliability model based on p-median and uncapaciated facility location problems. They consider the probability that a facility will fail to operate due to poor weather conditions, labor actions, changes of ownership or other factors. They introduce two models locating facilities to minimize cost considering the expected transportation cost after failure of facilities. One of them is the reliability p-median problem where each facility fails with a given probability and multiple facilities can fail at the same time. Also, some of the facilities may be fail-proof. There are two objectives: minimizing p-median cost of serving customers from the primary facilities and minimizing expected cost of failure. The weighted sum of these two objectives is minimized. If a customer is assigned to a fail-proof facility, it makes no contribution to expected failure cost. Otherwise, the customer is served by its closest facility with probability that its closest facility will not fail and it is served by its second closest facility with probability that its closest facility will fail and its second closest facility will not fail and so on. The second problem is reliability fixed-charge location problem which do not have a limit on the number of facilities. Synder and Daskin [25] present an optimal Lagrangean relaxation algorithm to solve the reliability problems.

Aim to provide a 'site selection model for emergency resources', Hole and Moberg [26] propose a model that determines number and location of facilities. They describe a secure site location decision process which can be summarized in four steps. First, emergency resources to be stored at each secure location are identified. Second, all critical facilities within supply chain are identified. Third, maximum response time and minimum distance from location of emergency situations for security are decided. Fourth, the proposed model which decides on the number and location of service facilities is used. The model minimizes number of service facilities providing that distance between a location of emergency situation (demand point) and its closest service facility is not smaller than the minimum distance chosen at the fourth step for security and not greater than the maximum distance for service quality while covering all demand points.

2.2 Literature Review on Humanitarian Logistics

So far, literature on location problems are reviewed. Most of the location models proposed for preparedness stage of humanitarian logistics are based on the location models explained before. In this section, a review of literature on preparedness stage of humanitarian logistics is given.

Barbarosoglu and Arda [6] propose a multi-commodity, multi-modal network flow formulation for the transportation of first-aid commodities to affected people after a disaster strikes. Their model is a two-stage stochastic programming problem which handles the uncertainty of a disaster using possible scenarios. Those uncertainties are demand for first-aid commodities, vulnerability of facilities and survivability of the connecting paths in the disaster area. The aim is to minimize to transportation costs, inventory holding costs and mode shift costs while transporting the commodities with finite and random capacity and meeting the random demand. The model is applied to Avcilar district of Istanbul region and different solution approaches were discussed. Actually, it is not a location problem; the model is introduced for the transportation phase of disaster response.

Hongzhong at al. [27] propose a model that optimizes the location of facilities for medical supplies to address large scale emergencies in the Los Angeles area. In this study, an emergency service location problem is examined considering large-scale emergency situations and characteristics of a large scale facility location problem are included. Proposed large scale emergency facility location problem (LEMS) mainly decides on location of the facilities. Uncertainty of demand is handled by defining a set of possible emergency situations, and using parameters representing both the 'likelihood that a certain emergency situation affects a demand point and impact that the emergency situation will have on the population of a demand point' [27]. Additional coverage for the demand points is provided by forcing the expected coverage of a demand point is greater than a required number.

Balcik and Beamon [5] study a variant of maximal covering location problem which determines number and location of distribution center and amount of relief supplies to be stored considering quick-onset disasters. The problem includes multiple relief items with different coverage requirements, a pre-disaster budget constraint, an expected post-disaster budget constraint, capacity constraints and stepwise partial coverage. Uncertainty is again handled by using possible scenarios. The model decides on proportion of a relief item type demand satisfied by a distribution center in a scenario, inventories to be held in distribution centers and the location of the distribution centers, maximizing the expected coverage with respect to scenarios. They conduct a numerical analysis focused on earthquake-caused disasters using parameters obtained by analyzing historical hazards data from the National Geophysical Data Center. The model is solved using GAMS/Cplex solver. They present results analyzing the models sensitivity to parameters and they evaluate the coverage performance on the numerical problem.

Mete and Zabinsky [28] also propose a two-stage stochastic programming problem that determines locations of the facilities and inventory levels to be held. Their formulation is for storage and distribution of medical supplies. Using possible disaster scenarios, the model handles the uncertainty coming with a disaster. They used the model for a case study for earthquake scenarios in the Seattle area where hospitals use their own warehouses or shared warehouses to store relief items. In the case study, the authors aim to use pre-positioning warehouses to store additional items by considering timely delivery. At the first stage of the model, warehouses are selected and inventory levels are determined minimizing total cost of operating warehouses and the expected value of second-stage solutions with respect to scenarios. At the second stage, response time and the penalty of unmet demand are minimized determining transportation plans and giving demand satisfaction decisions.

Another two-stage stochastic programming model is proposed by Rawls and Turnquist [29] to decide the location and amounts of various types of emergency supplies to be positioned a priori to a disaster. Uncertainties in demand and in transportation network availability are handled using scenarios. In addition, probability that supplies are damaged is considered in the model. At the first stage, facility locations, facility capacities and stocking levels for various items are determined minimizing the opening cost of facilities and total inventory holding cost with the expected value of the second stage solutions with respect to scenarios. At the second stage spoilage, shortage and transportation costs are minimized determining the distribution plan of available supplies in response to the scenarios. They stated that solving deterministic equivalent of the two-stage stochastic programming model is problematic with large data and used L-shaped method to solve it. The model is applied at a case study on hurricane threats in southeastern USA.

Later, Rawls and Turnquist [30] extend the model proposed by Rawls and Turnquist [29] by adding reliability and maximal service distance constraints. They define reliable set of scenarios and allow the model to endogenously select the reliability set of scenarios. Demand in a reliable set is certainly covered within the maximal service distance. Sum of occurring probabilities of the reliable scenarios is forced to be greater than a given reliability so that probability of covering all demand within the maximal service distance is greater than or equal to that given reliability.

Again, Rawls and Turnquist [31] extend their previous model with reliability constraints proposed in the study of Rawls and Turnquist [30] by adding time periods. Motivation behind this extension is that there may be policies in disaster planning like that at least one-half of the supplies will arrive at affected area by 12 hours and the left portion will arrive at by 24 hours. They applied the dynamic allocation model to the case study application of hurricane events that affect coastal North Carolina.

Duran et al. [32] conduct a study to improve CARE International's emergency response times. The model finds optimal number and location of pre-positioning warehouses given that demand for relief supplies can be met from both pre-positioned warehouses and suppliers. They allow multiple events to occur within a replenishment lead time. Their MIP model minimizes the average response time over all demand instances and gives decisions on location of warehouses, quantities of supply from warehouses and from suppliers and the quantity of supply held in a warehouse. Two types of capacity constraints are considered; one of them is the number of warehouses to open and the other is inventory to keep throughout the prepositioning network. CPLEX solver is used to solve the model including 22 demand points, 12 candidate warehouse locations, 7 relief items and 240 demand instances. All computational runs reach optimal solution within 4 hours. Their findings of solving the model and implementing sensitivity analysis lead CARE's decisions of opening a warehouse in Dubai.

There are academic dissertations on humanitarian logistic area submitted to Industrial Engineering Department of METU, also. One of them is the study of Bozkurt [33]. In the thesis, the effects of natural disaster trends on the pre-positioning implementation in humanitarian logistics networks are examined. Using the data obtained from EM-DAT database and the formulation proposed by Duran et al. [32], it is analysed that whether the disaster trends affect the location of pre-positioned facilities.

Another academic dissertation of the Industrial Engineering Department of METU is the masters thesis of Görmez [34]. In the study, the disaster response and relief facility location problem for Istanbul is addressed. In terms of purposes, it is very similar to this thesis. However, the formulations that are proposed are different. The data used in the study is obtained from the report prepared by JICA & IMM [35]. Facilities are separated into two groups as temporary and permanent facilities. Permanent facilities are the actual facilities to be opened and in which the relief items are stocked. Temporary facilities are public buildings which can be used as distribution centers of relief items after the earthquake. In the study, location of temporary facilities are taken as at the center of the districts and optimal location of permanent facilities are determined minimizing the average distance by limiting the number of temporary facilities in the districts. Then, a two-stage approach is proposed in order to determine the number of temporary facilities in each neighbourhood and the number of affected people in a neighbourhood that are served by a temporary facility in another one. The proposed models are single-item models and they are deterministic. Stochastic elements are not included in the formulations.

In humanitarian logistics literature as explained so far, formulations that capture the stochastic properties of disaster by considering a set of possible scenarios are frequently used. In this study, a chance constrained formulation is used to handle the uncertainties imposed by a disaster. Some chance constrained formulations are covered in the literature on location problems, especially in emergency service facility location problems (ReVelle and Hogan [23] , Ball and Lin [24]). Formulation and linearization of the chance constraints used in emergency facility location problems are adapted to humanitarian logistics case and used in the model proposed in this study.

CHAPTER 3

MATHEMATICAL MODELS

Before introducing the mathematical models, it is better to define the problem to be solved. Mainly, the problem is to find the optimal locations for disaster response facilities and to determine multiple relief items' inventories of the facilities which is a problem belonging to preparedness stage of humanitarian logistics literature. In this chapter, firstly, a deterministic location-allocation formulation which simply captures the structures of the problem is introduced and it is called as uncapacitated location problem (UNLP). UNLP chooses the optimal locations of disaster response facilities (DRFs) among candidate sites, it assigns the affected areas to the DRF to be served and it determined the inventories of relief items in the DRFs minimizing the average distance between the DRFs and their assigned affected areas. However, it does not capture the stochastic elements of the problem like infrastructure survivability. This is why we introduce chance constraints that make relief item transportation more reliable. The formulation in which the chance constraints are included is called the uncapacitated location problem with chance constraints (UNLP-C). Afterwards, capacity constraints are added to UNLP and UNLP-C and they are named as capacitated location problem (CLP) and capacitated location problem with chance constraints (CLP-C), respectively. In addition, fixed costs to open a DRF to candidate locations are considered and a prefix 'fix' is added to the name of formulations denoting that we use fixed costs and corresponding constraints in that formulation.

Since the literature mostly consists of the scenario-based formulations, it is reasonable to solve the problem using a scenario-based formulation and compare the results. For this purpose, a scenario-based formulation (SBP) is introduced for the problem. Also, the results of the scenario-based formulation with chance constraints (SBP-C) are examined.

The formulations mentioned so far are to minimize the average distance. This objective is related to minimizing the response time which is very crucial for reducing human suffering in the case of a disaster. However, it is also important that the relief items actually arrive at the affected areas. Because of this, we introduce a different objective function to be minimized which is the expected unsatisfied percentage of total demand with respect to probabilities of paths between the DRFs and the affected areas being blocked or destroyed by the disaster.

In the remainder of this chapter, the formulations mentioned above are explained in detail.

First, UNLP is formulated. The aim is to minimize response time after a disaster strikes by locating disaster response facilities and positioning relief items in those facilities a priori to a possible disaster. Mainly, the model chooses the location of disaster response facilities among candidate sites and determines inventories of multiple relief items to be held. Formulation is as follows:

Sets		
I		set of candidate DRF locations
J		set of affected areas
K		set of relief items
Parameters		
d_{ij}	$i \in I, j \in J$	shortest distance between DRF i and affected area j
n_{jk}	$j \in J, k \in K$	need (demand) for relief item k in affected area j
m_k	$k \in K$	maximal service distance of relief item k
w		number of DRFs to be located
Q_k	$k \in K$	total number of relief item k to be allocated
Variables		
y_i	$i \in I$	1, if a DFR is located on candidate location i; 0, otherwise
t_{ijk}	$i \in I, j \in J, k \in K$	1, if DFR located on candidate location i sends relief item k to affected area j; 0, otherwise
x_{ijk}	$i \in I, j \in J, k \in K$	amount of relief item k sent from DFR located on candidate location i to affected area j
h_{ik}	$i \in I$	amount of relief item k held at DRF located in candidate site i

Objective function

$$\text{Minimize} \quad z = \frac{\sum_{i \in I} \sum_{j \in J} \sum_{k \in K} d_{ij} x_{ijk}}{\sum_{j \in J} \sum_{k \in K} n_{jk}} \tag{3.1}$$

$$\text{subject to} : \sum_{i \in I} x_{ijk} \geq n_{jk} \qquad \forall j \in J, k \in K \tag{3.2}$$

$$\sum_{j \in J} x_{ijk} = h_{ik} \qquad \forall i \in I, k \in K \tag{3.3}$$

$$\sum_{j \in J} \sum_{k \in K} t_{ijk} \leq M_1 y_i \qquad \forall i \in I \tag{3.4}$$

$$x_{ijk} \leq M_2 t_{ijk} \qquad \forall i \in I, j \in J, k \in K \tag{3.5}$$

$$t_{ijk} \leq x_{ijk} \qquad \forall i \in I, j \in J, k \in K \tag{3.6}$$

$$d_{ij} t_{ijk} \leq m_k * y_i \qquad \forall i \in I, j \in J, k \in K \tag{3.7}$$

$$\sum_{i \in I} y_i \leq w \tag{3.8}$$

$$\sum_{i \in I} h_{ik} \leq Q_k \qquad \forall k \in K \qquad (3.9)$$

$$x_{ijk} \geq 0 \qquad \forall i \in I, j \in J, k \in K \qquad (3.10)$$

$$h_{jk} \geq 0 \qquad \forall j \in J, k \in K \qquad (3.11)$$

$$t_{ijk} \in \{0, 1\} \qquad \forall i \in I, j \in J, k \in K \qquad (3.12)$$

$$y_i \in \{0, 1\} \qquad \forall i \in I \qquad (3.13)$$

This problem is a simple location-allocation problem with multiple commodities and it is called as uncapacitated location problem (UNLP) in the remainder of the thesis. Objective function (3.1) minimizes total weighted distance between affected areas and their assigned DRFs. By this way, the model minimizes total response time after a disaster strikes. Weights are the fractions of total items sent from DRFs to affected areas. If flow between a DRF and an affected area is relatively more, penalty for distance between them is relatively higher.

Constraint set (3.2) ensures that demand of all affected areas for all types of relief items are met. Constraint set (3.3) forces that total amount of a relief item type held at a DRF equals to total amount of this relief item type sent from the DRF to its assigned affected areas. Constraint set (3.4) guarantees that any relief item cannot be sent to any affected area from a DRF at location if a DRF is not located there. M_1 stands for a big number in this constraint set. By Constraint set (3.5), a DRF cannot send the type of relief item to an affected area if that DRF is not assigned to that affected area for sending that type of relief item. M_2 stands for a big number in this constraint set. If any relief item k is not sent from a DRF on candidate location i to affected area j, then the corresponding binary variable takes the value of zero due to the Constraint set (3.6) for all DRFs, affected areas and relief item types. With the Constraint set (3.7), a DRF on candidate location i cannot be assigned to affected area j for sending relief item k, if the distance between the DFR and the affected area is greater than maximal service distance of that relief item. Maximal service distance increases as criticality of relief item decreases. Constraint sets (3.8) and (3.9) are budget-related constraints. Number of DRFs to be pre-positioned is limited by Constraint set (3.8) and total amount of relief items to be allocated is limited by Constraint set (3.9). Constraint sets (3.10) and (3.11) are nonnegativity constraints and Constraint sets (3.12) and (3.13) are integrality constraints.

The model simply finds the optimal locations of the disaster response facilities minimizing the average distance. Because the DRFs are uncapacitated, number of affected areas that can be assigned to an open DRF is not limited. Utilizing maximum service distance constraints, Constraint set (3.7), UNLP distinguishes between the relief items. Maximum service distance of a more critical item is less than the other items. Other than its objective function which minimizes the average response time and Constraint set (3.7), UNLP is a classical location-allocation problem which does not have any humanitarian perspective.

For humanitarian purposes, we introduce the reliability constraints to UNLP. Survivability of the infrastructure is an important concern in transportation of the relief items and we want to provide a certain reliability for meeting the demand for the relief items. New parameters must be introduced in order to formulate the reliability constraints.

α_k	$k \in K$	minimum service reliability of relief item k
v_{ij}	$i \in I, j \in J$	probability that path linking DRF i and affected area j is blocked

In the first chapter, it is said that probabilistic constraints are used for an emergency vehicle location problem [23]. First, using the notation introduced here, their probabilistic constraints are explained and then the constraints used in this thesis are presented. In the emergency vehicle problem, the aim is to provide a reliability value for that at least one vehicle is available to serve to demand point, which can be formulated as follows:

$$1 - \prod_{i \in I} v_{ij}^{t_{ijk}} \geq \alpha_k \qquad \forall j \in J, k \in K \tag{3.14}$$

They make the formulation of these reliability constraints by taking the logarithms of both sides of the Inequality (3.14).

$$\sum_{i \in I} log(v_{ij}) t_{ijk} \leq log(1 - \alpha_k) \qquad \forall j \in J, k \in K \tag{3.15}$$

However, providing that an affected area is served by at least one DRF is not meaningful in the case of a disaster because amount of relief items sent to the affected area is important for reducing human suffering. Therefore, the chance constraints are modified accordingly as in Inequality (3.16).

$$P(C_{jk}) \geq \alpha_k \qquad \forall j \in J, k \in K \tag{3.16}$$

where the event C_{jk} is defined as all of the relief item k sent to affected area j reached to the affected area j. The mathematical formulation is given in Inequality (3.17).

$$\prod_{i \in I} (1 - v_{ij})^{t_{ijk}} \geq \alpha_k \qquad \forall j \in J, k \in K \tag{3.17}$$

Left hand side of Inequality (3.17) is the probability that event C_{jk} occurs while right hand side is service reliability of item k. Service reliability is different for different relief items and it increases when criticality of the item increases. However, Constraint set (3.17) is a set of nonlinear constraints. In order to get rid of nonlinearity, we take the logarithms of both sides;

$$\sum_{i \in I} log(1 - v_{ij}) t_{ijk} \geq log(\alpha_k) \qquad \forall j \in J, k \in K \tag{3.18}$$

The formulation consisting of (3.1)-(3.13) and (3.18) is called as the uncapacitated location problem with chance constraints (UNLP-C), which is the proposed model in this thesis.

Both formulations introduced so far are uncapacitated problems. It is meaningful to study with uncapacitated facilities considering the humanitarian purposes in pre-positioning the facilities. However, in real life situations, using capacitated facilities might be required by environmental factors. For example, facilities located at heavily-populated areas might be able to stock less inventories than the others. To be able to analyse the results, we need capacitated formulations. For this purpose a new parameter should be defined.

cap_i	$i \in I$	total number of relief items that can be stocked in a DRF located at candidate location i

Capacity constraints are formulated as in Inequality (3.19).

$$\sum_{k \in K} h_{ik} \leq cap_i \qquad \forall i \in I \tag{3.19}$$

The formulation including (3.1)-(3.13) together with (3.19) is called capacitated location problem (CLP) and the formulation consisting of (3.1)-(3.13) together with (3.18) and (3.19) is called capacitated location problem with chance constraints (CLP-C).

In addition to the capacity of the disaster response facilities, fixed costs to open them should be considered in real life problems. Although our objective is a humanitarian one, the budget for public organizations might be limited. New parameters must be defined for this aim.

f_i	$i \in I$	fixed cost of opening a DRF at candidate location i
B		total budget for opening DRFs

Inequality (3.20) is formulated in order to introduce fixed cost concept to the formulations.

$$\sum_{i \in I} f_i * y_i \leq B \qquad \forall i \in I \tag{3.20}$$

Actually, by Constraint set (3.8), we set an upper limit for total number of DRFs to be opened. If fixed costs of opening is the same for all locations, then we do not need Inequality (3.20). However, fixed cost of opening a DRF might be more for heavily-populated and highly-occupied areas than the others. Therefore, when we use Inequality (3.20), we distract Inequality (3.8) from the formulations and have a prefix 'fix' for the formulation names like fix-UNLP and fix-CLP-C.

Objective function (3.1) minimizes the total average distance between the affected areas and the DRFs, which helps minimizing the total average response time. However, as well as the arrival time of the relief items, it is important that the relief items actually arrive at the affected areas. Therefore, it is important to minimize the expected unsatisfied demand. Let the event P_{ijk} to be defined as the event of relief item k sent form DRF i to affected area j does not arrive at the affected area j due to the blockage of the transportation. It is assumed that the events P_{ijk} are independent for different i and j. Expected number of item k that is blocked during the transportation between DRF i and affected area j is denoted by E_{ijk} and it is calculated as;

$$E_{ijk} = x_{ijk} * v_{ij} + 0 * (1 - v_{ij}) = x_{ijk} * v_{ij} \qquad (3.21)$$

Because the events are assumed to be independent, it is meaningful that we obtained the results in Inequality (3.21).

$$E_{jk} = \sum_{i \in I} x_{ijk} * v_{ij} \qquad \forall j \in J, k \in K \qquad (3.22)$$

Therefore, total expected number of unsatisfied relief item k demand denoted by E_k is calculated as;

$$E_k = \sum_{j \in J} E_{jk} \qquad \forall k \in K \qquad (3.23)$$

In order to be able to discuss on the results, we use PE_k values which are total expected number of unsatisfied relief item k as a percentage of the total demand of relief item k.

$$PE_k = \frac{E_k * 100}{\sum_{j \in J} n_{jk}} \qquad \forall k \in K \qquad (3.24)$$

Additionally, total amount of unsatisfied demand as a percentage of the total demand is denoted as E and its calculation is as follows:

$$E = \frac{\sum_{i \in I j \in J k \in K} v_{ij} * x_{ijk}}{\sum_{j \in J k \in K} n_{jk}} \qquad (3.25)$$

E is another humanitarian objective and is a concern of this study.

In order to understand functioning of the proposed model, to compare its results with the results of scenario-based model and to employ the chance constraints in the scenario-based model, we should give the formulation of scenario-based model first. The notation introduced before is used with some additions.

Additional Set		
S		set of possible scenarios
Additional Parameters		
n_{jks}	$j \in J, k \in K, s \in S$	need (demand) for relief item k in affected area j in scenario s
v_{ijs}	$i \in I, j \in J, s \in S$	probability of path linking DRF i and affected area j being blocked in scenario s
p_s	$s \in S$	occurrence probability of scenario s
Additional Variables		
t_{ijks}	$i \in I, j \in J, k \in K, s \in S$	1, if DRF located on candidate location i sends relief item k to affected area in scenario s j; 0, otherwise
x_{ijks}	$i \in I, j \in J, k \in K$	amount of relief item k sent from DRF located on candidate location i to affected area j in scenario s

Objective function

$$\text{Minimize} \quad z = p_s * \sum_{s \in S} \frac{\sum_{i \in I} \sum_{j \in J} \sum_{k \in K} d_{ij} x_{ijks}}{\sum_{j \in J} \sum_{k \in K} n_{jks}} \tag{3.26}$$

$$\text{subject to} : \sum_{i \in I} x_{ijks} \geq n_{jks} \qquad \forall j \in J, k \in K, s \in S \tag{3.27}$$

$$\sum_{j \in J} x_{ijks} \leq h_{ik} \qquad \forall i \in I, k \in K, s \in S \tag{3.28}$$

$$\sum_{j \in J} \sum_{k \in K} t_{ijks} \leq M_1 y_i \qquad \forall i \in I, s \in S \tag{3.29}$$

$$x_{ijks} \leq M_2 t_{ijks} \qquad \forall i \in I, j \in J, k \in K, s \in S \tag{3.30}$$

$$t_{ijks} \leq x_{ijks} \qquad \forall i \in I, j \in J, k \in K, s \in S \tag{3.31}$$

$$d_{ij} t_{ijks} \leq m_k \qquad \forall i \in I, j \in J, k \in K, s \in S \tag{3.32}$$

$$\sum_{i \in I} y_i \leq w \tag{3.33}$$

$$\sum_{i \in I} h_{ik} \leq Q_k \qquad \forall k \in K \tag{3.34}$$

$$x_{ijks} \geq 0 \qquad \forall i \in I, j \in J, k \in K, s \in S \tag{3.35}$$

$$h_{jk} \geq 0 \qquad \forall j \in J, k \in K \tag{3.36}$$

$$t_{ijks} \in \{0, 1\} \qquad \forall i \in I, j \in J, k \in K, s \in S \tag{3.37}$$

$$y_i \in \{0, 1\} \qquad \forall i \in I \tag{3.38}$$

Functions of the objective function and the constraints sets are the same with UNLP. The scenario-based formulation is called SBP in the remainder of the thesis. Using SBP, we find the optimal locations of DRFs and inventories to be held minimizing the expected average distance with respect to the scenarios.

Inequality (3.39) is the modified version of the chance constraints to be used in SBP.

$$\sum_{i \in I} log(1 - v_{ij}) t_{ijks} \geq log(\alpha_k) \qquad \forall j \in J, k \in K, s \in S \tag{3.39}$$

We call SBP with the chance constraints as SBP-C in the remainder.

In this chapter of the thesis, the proposed model is explained. In addition, the formulations that are the variations of the proposed one and the formulations that help understanding the contributions of the proposed model are explained. From now, the results are presented using simulated data and the real data of Istanbul case.

CHAPTER 4

COMPUTATIONAL STUDIES AND RESULTS

In this chapter, the formulations introduced in Chapter 3 are used in numerical examples created by simulated data and in a numerical study which is a real life problem of Istanbul city. Two different settings are used as numerical examples; the first, a four-location example and, the second, an example with 16 affected areas and 65 candidate DRF locations.

In the first example, we use different location patterns and different disaster intensities. After we realize that different distance patterns are not very defining, we use only one distance pattern in the second example with different disaster progression schemes and different intensities.

In the numerical study, first, we introduce the data of the Istanbul problem and then we use the formulations introduced in Chapter 3 to solve the problem.

Throughout this chapter, the effects of chance constraints on the optimal DRF locations, on the average distance and on the expected unsatisfied demand percentage are discussed. In addition, SBP is used and its solutions are compared with the solutions of UNLP-C.

4.1 Numerical Examples

In order to understand the functioning of the formulations mentioned, a small, simple example is used. Number of demand locations is limited but the distance relation between them changes. On this setting, different scenarios are generated using different parameters. Using the example and scenarios generated, effect of the chance constraints on the results is examined and the results of the model with chance constraints on the worst case scenario and results of the scenario-based model are compared in terms of different objectives.

In the small setting, there are four residential locations, namely A, B, C and D, and one DRF is to be opened at one of these four locations. For the sake of simplicity, one type of relief item is located at this relief location. Different scenarios include different parameters in terms of distances between the locations, demands of the locations for the relief items, center and intensity of the earthquake and vulnerabilities of the paths between the locations.

Four different distance patterns are created. Figure 4.1 shows the graphical representation of the distance patterns and the distances between the residential locations.

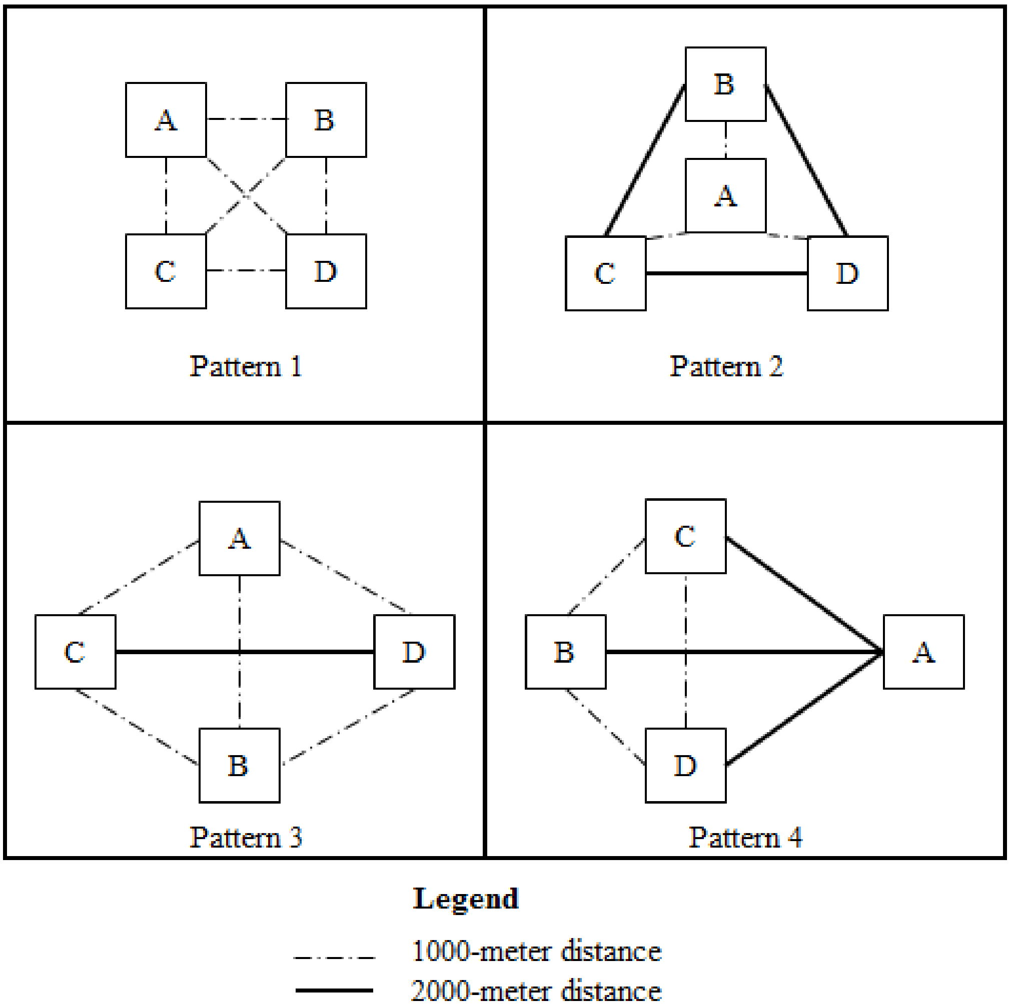


Figure 4.1: Location patterns and the distances between the residential locations

After the location patterns are determined, representative examples in terms of center and intensity of the earthquake are chosen to be examined. Let EI_j to stand for earthquake intensity of location j for j = A, B, C, D.

It is not unrealistic to assume that affected population of a location and vulnerability of the paths outgoing from that location are proportional to EI of that location. Therefore, to form scenarios serving the purpose, actual populations of each location are assumed to be equal. Different EI levels are utilized in the scenarios. Vulnerability factor (VF) of 0.8 is in the highest EI case, and by 0.2 decrements in each case, 0.2 is in the lowest case. For example, let vulnerability factor of the location A to be 0.8 and the population to be 1000 people. Then the probability of relief item transportation on the ongoing paths from this location being blocked is taken as 0.8 and the affected population at location A is considered as $0.8 * 1,000 = 800$ people.

In the first experiment, the relation between EI of the locations is $EI_A > EI_B = EI_C = EI_D$. Let VF_A equals to 0.8 and VF of the other locations equal to 0.2. Table 4.1 shows the results for different location patterns.

Table4.1: Solutions of the first experiment

	Results of UNLP-C			Results of UNLP			Difference	
Location pattern	A.D.	E.U.	DRF	A.D.	E.U.	DRF	A.D.	E.U.
1	857.14	17.14%	B or C or D	428.57	34.29%	A	100%	-50%
2	1142.85	17.14%	B or C or D	428.57	34.29%	A	167%	-50%
3	857.14	17.14%	B	428.57	34.29%	A	100%	-50%
4	1428.57	17.14%	B or C or D	428.57	34.29%	A	67%	-50%

* A.D. : average distance

* E.U. : expected unsatisfied demand

Total number of relief items to be allocated equals to the total demand in each location pattern. The maximum service distance is 2,000 meters and the minimum service reliability is 0.8 in these examples. If the chance constraints are not used, center of the earthquake, A is the optimal location to open a disaster response facility (DRF). Optimal objective function value and expected unsatisfied demand as a percentage of total demand are the same regardless of which location pattern is used. If a DRF is located on location A, in expectation, 34.29 % of the total population do not get their necessary relief items and the maximum service reliability is be 0.2. This means that the demands of locations B, C and are met with a probability of 0.2. If chance constraints are introduced to the model, there are alternative optimal solutions in patterns 1, 2 and 4; and the DRF is opened in location B in pattern 3. In this case, percent expected loss drops to its half (it is the minimum feasible value for this problem). In addition, minimum service reliability becomes 0.8 as chance constraints require. However, weighted distance increases in each of the patterns. In pattern 2, when the center of the earthquake is located at the geographical center of the locations, the increase caused by the chance constraints is larger than that of the other patterns. This is because the center has the highest vulnerability factor, so it demands the highest amount.

The only effect of minimum service reliability, α, on the results is related to the feasibility of chance-constrained formulation. When α is between 0 and 0.2, the chance constraints are redundant. When it is between 0.2 and 0.8, introducing the chance constraints changes the results as explained. When it is between 0.8 and 1.0, chance-constrained formulation is infeasible.

In the second experiment, the relation is changed and it becomes $EI_A = EI_B = EI_C > EI_D$. Let VF_D equals to 0.2 and VF of the other locations equal to 0.8. The results are summarized in Table 4.2.

Table4.2: Solutions of the second experiment

	Results of UNLP-C			Results of UNLP			Difference (%)	
Location pattern	A.D.	E.U.	DRF	A.D.	E.U.	DRF	A.D.	E.U.
1	923.07	18.46 %	D	692.30	55.38 %	A or B or C	33%	-67 %
2	1538.46	18.46 %	D	692.30	55.38 %	A	122%	-67 %
3	1230.76	18.46 %	D	692.30	55.38 %	A or B	78%	-67 %
4	1333.33	16.67 %	D	1000.00	40.00 %	B or C	33%	-58 %

* A.D. : average distance

* E.U. : expected unsatisfied demand

In the first and second experiments we use different disaster centers and different intensities. Solutions of both experiments show the similar results in terms of effect of chance constraints on average distance and expected unsatisfied demand. In addition, chance constraints cause that when location pattern 2 is used, the difference between the average distance values are the most this is because the high risky location is at the geographical center of four locations.

If the chance-constraints are not redundant, their effects on the results are similar in each scenario created with different combinations of intensity levels and location patterns. They increase the weighted distance in each pattern but mostly in pattern 2 and they cause a decrease in expected unsatisfied demand. The chance constraints are effective especially when high risky locations are at geographical centers of the other locations. When this is the case, the decrease in expected unsatisfied demand is more than that of the case in which high risky locations are at remote places of the graph.

In order to use SBP, four examples, in which there are four different scenarios, are presented. Scenarios are identified in terms of the vulnerability vector. Problems are solved both using UNLP-C on the worst case scenario and using SBP. Table 4.3 shows the vulnerability vectors used in the scenarios.

Table4.3: Vulnerability vectors under the scenarios

	Vulnerability vectors used in the scenarios			
Scenarios	A	B	C	D
1	0.8	0.6	0.4	0.2
2	0.8	0.8	0.8	0.4
3	0.6	0.4	0.4	0.4
4	0.4	0.4	0.2	0.2

It can easily be seen that Scenario 2 is the worst case. Therefore, UNLP-C is solved under Scenario 2 and SBP is solved when the occurrence of the scenarios are equally likely for different location patterns. Table 4.4 shows the average distance in the worst case scenario, the expected average distance with respect to all scenarios, the expected unsatisfied demand under the worst case scenario and the overall expected unsatisfied demand with respect to the scenarios according to the solutions of UNLP-C and SBP when the location pattern 1 is used.

Table4.4: Results of UNLP-C and SBP when the location pattern 1 is used

	UNLP-C	SBP	Difference(%)
Weighted distance in worst case scenario	857.14	714.28	16.7
Expected weighted distance wrt scenarios	117.42	105.27	10.3
Expected unsatisfied demand under worst case scenario	34.28 %	57.14 %	-67
Overall expected unsatisfied demand wrt scenarios	25.16 %	39.71 %	-58
Location of DRF	D	B	

SBP does not include the chance constraints. Even though it considers all possible scenarios, it is lack of reliability concept. This is why it gives better results in the weighted average of the worst case scenario and in the expected weighted average with respect to the scenarios. Chance-constrained formulation ignores the scenarios other than the worst case scenario; however, it gives less in total expected loss in the four examples. This is because chance constraints require that DRFs are opened in less risky locations so that the relief transportation is reliable.

Table 4.5 presents the same results when the location patterns 2,3 and 4 are used.

Table4.5: Results of UNLP-C and SBP when the location pattern 2,3 and 4 are used

Pattern 2	UNLP-C	SBP	Difference(%)
Weighted distance in worst case scenario	1428.57	714.28	50
Expected weighted distance wrt scenarios	1369.84	673.80	51
Expected unsatisfied demand under worst case scenario	34.28 %	57.14 %	-67
Overall expected unsatisfied demand wrt scenarios	25.16 %	43.42 %	-73
Location of DRF	D	A	
Pattern 3	UNLP-C	SBP	Percent difference of the results
Weighted distance in worst case scenario	1142.85	714.28	38 %
Expected weighted distance wrt scenarios	1096.42	673.80	39 %
Expected unsatisfied demand under worst case scenario	34.28 %	57.14 %	-67 %
Overall expected unsatisfied demand wrt scenarios	25.16 %	43.42 %	-73%
Location of DRF	D	A	
Pattern 4	UNLP-C	SBP	Percent difference of the results
Weighted distance in worst case scenario	1142.85	1000.00	30 %
Expected weighted distance wrt scenarios	1174.61	1052.77	22 %
Expected unsatisfied demand under worst case scenario	34.28 %	57.14 %	-40 %
Overall expected unsatisfied demand wrt scenarios	25.16 %	39.71 %	-37%
Location of DRF	D	B	

Differences between the results are higher than the others when the location pattern 2 is used. This is because the there is an obvious graphical center and its vulnerability is the highest value in all scenarios. UNLP-C opens the DRF at location D in all location patterns because it is the least risky location. Even though SBP considers all of the scenarios, it does not capture the risk that the relief item transportation is harmed by the disaster.

In the previous experiment, a simple example with four locations is examined. The results are analysed under different location patterns. Since the location pattern is not very defining, we create a bigger experimental setting where candidate DRF locations and demand points are evenly distributed over a square area. In this experiment, we do not use different location patterns but use different disaster scenarios in which the center, intensity and dissemination of the effect of a disaster. There are 16 affected areas and 65 candidate DRF locations in the example. Figure 4.2 below shows the places of affected areas and the locations of candidate DRF sites.

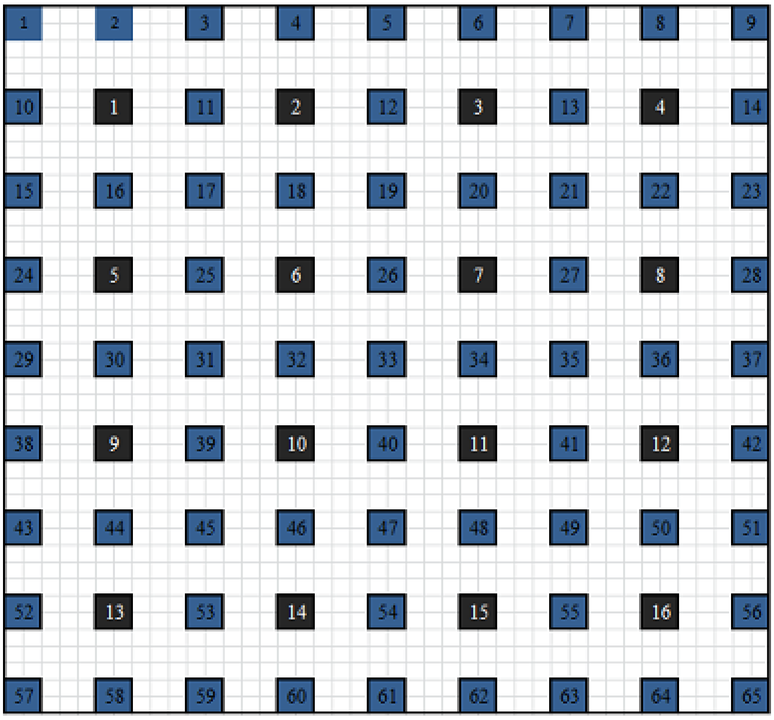


Figure 4.2: Locations of affected areas and candidate DRF locations

Centers of the black squares are the affected areas and centers of the blue squares are the candidate DRF locations of the simulated example. Every grid is a square which has a perimeter of 400 meters. We use rectilinear distance between the locations.

We consider four disaster progression schemes which can be seen in the Figure 4.3. In addition, in each of the disaster progression scheme center of the earthquake can be thought to be at different points. The colors represent the intensity of the disaster which is also explained in Figure 4.3.

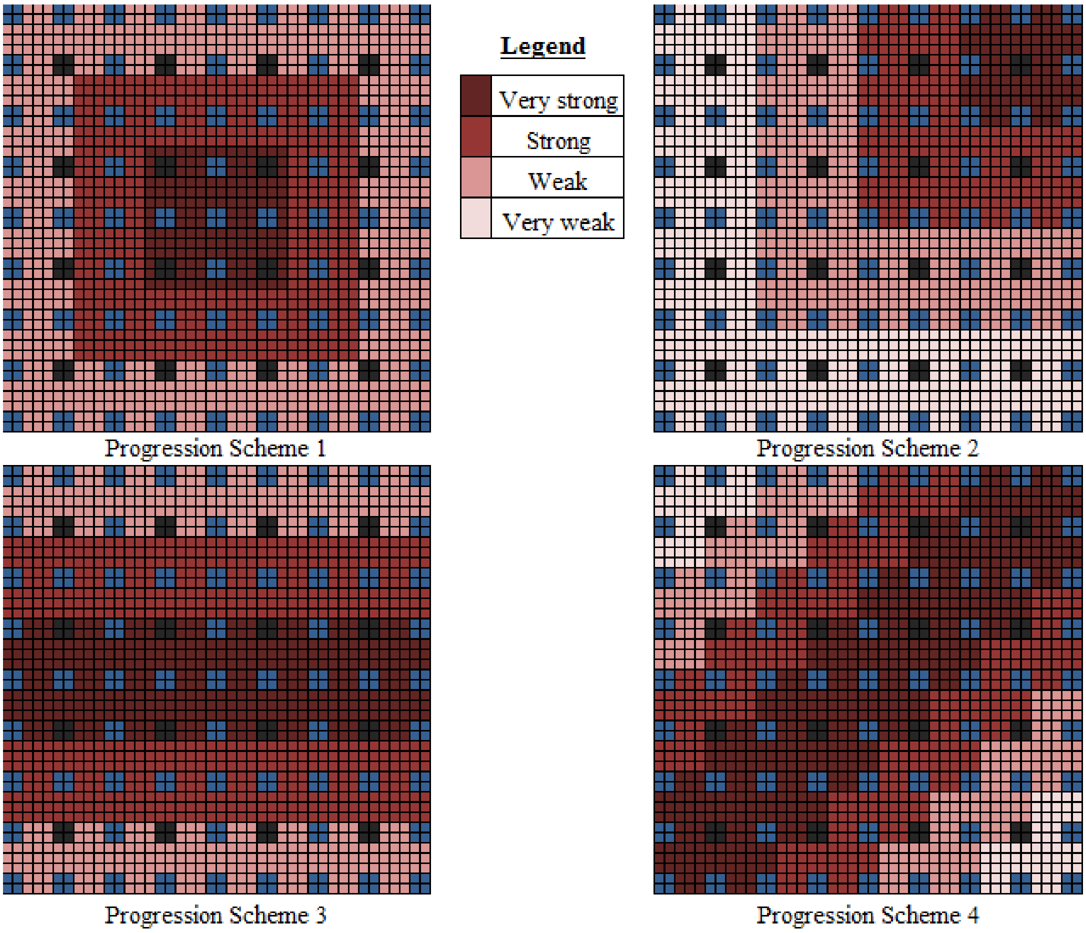


Figure 4.3: Scenarios of earthquakes which differs in center, intensity and dissemination

In addition, different vulnerability factors are assigned to the colors in order to create more scenarios and those are called vulnerability factor levels. Table 4.6 shows the vulnerability factor of each color in each level.

Table4.6: Vulnerability factor corresponding to intensity of the disaster and the level of the intensity

	Intensity			
Levels	Very strong	Strong	Weak	Very weak
1	0.8	0.6	0.4	0.2
2	0.6	0.4	0.2	0.2
3	0.8	0.4	0.2	0.2
4	0.8	0.84	0.4	0.2

In this setting, the scenarios are defined in terms of their progression schemes and the intensity levels.

Population of each center is taken as the same, 1000 people and it is assumed that number of affected people is directly proportional to the vulnerability factor of the area in which the population center is located. For example if a population center is located in an area whose vulnerability factor is 0.8, the number of affected people there is 800.

Vulnerability factors of the paths are calculated as follows. Let the path between candidate DRF location i and population center j consists of ten grids, four of which are in strong-intensity area, four of which are in very-strong intensity area and the remaining two are in the weak area. Vulnerability factors are 0.8, 0.6 and 0.4 in very strong-intensity, strong-intensity and weak-intensity areas, respectively. Then the vulnerability factor of the path is;

$$\frac{4 * 0.8 + 4 * 0.6 + 2 * 0.4}{10} = 0.64$$

Shortest distance paths are used between candidate location and population centers. Rectilinear distance is used.

For the sake of simplicity, one type of relief item is used and it is assumed that one affected person requires one relief item. In addition, maximum service distance is set to 7000 meters and total number of relief items to be allocated equals to the total demand.

There are four scenarios and four different intensity levels; therefore, total of 16 different problems are solved both using the chance constraints and without using them. Results are compared in terms of the average distance and total expected unsatisfied percentage of demand.

Introducing the chance constraint to the formulation causes an increase in the optimal objective function value which is the average distance in all of the scenarios. This is because the chance constraints require opening DRFs in safer places even if the weighted distance increases. In order to illustrate the situation, three scenarios are selected and their solutions are presented.

Scenario 1 consists of the progression scheme 1 with intensity level 2. When the total number of DRFs to be opened is four and the minimum service reliability is 0.7, the optimal DRF locations under Scenario 1 are presented in Figure 4.4.

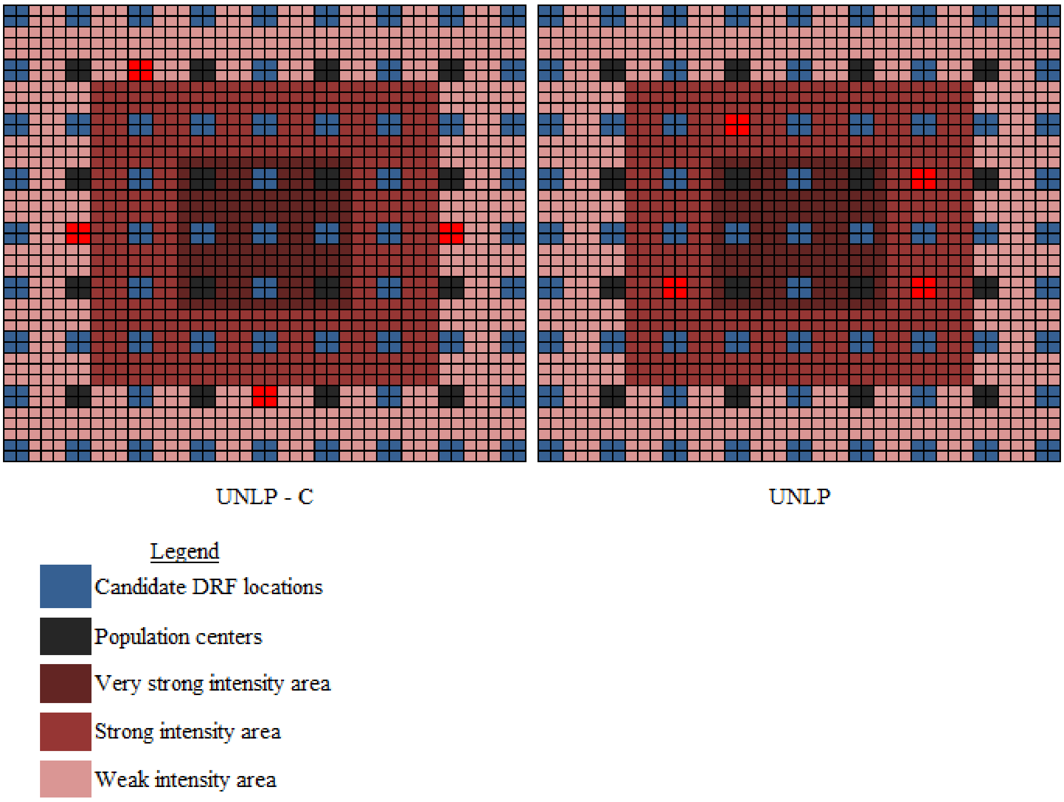


Figure 4.4: Optimal DRF locations under Scenario 1

The locations in red show the locations of DRFs in the optimal solutions of both problems. The average distance of UNLP-C is 1667 meters and it drops to 833 meters when UNLP is used. However, expected unsatisfied demand percentage increases from 24.5 % of the total demand to 38.3 %.

Second scenario includes the progression scheme 4 with intensity level 3. Optimal DRF locations are presented in Figure 4.5 when the total number of DRFs to be opened is three and the minimum service reliability is 0.5.

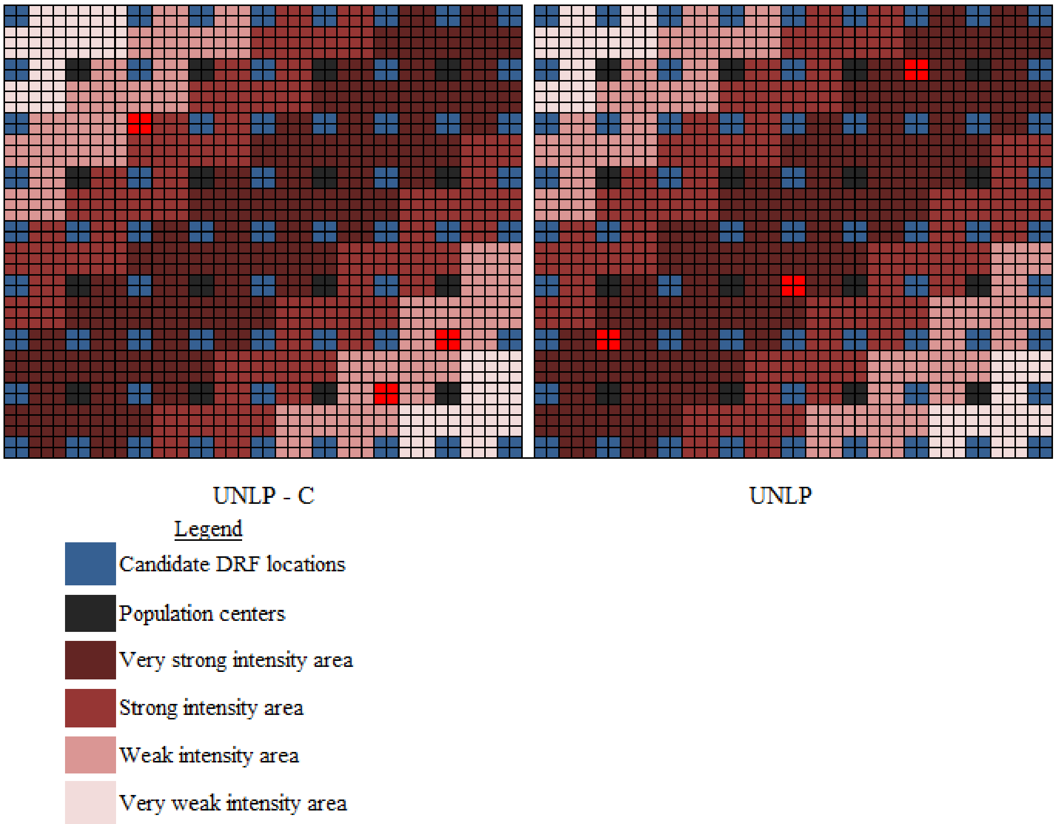


Figure 4.5: Optimal DRF locations under Scenario 2

The average distance is 1420 meters in UNLP-C and it is 620 meters when the chance constraints are not used. This time, expected unsatisfied demand percentage increases from 43 % of the total demand to 66 %.

One more scenario is the Scenario 3 which consists of the progression scheme 2 with intensity level 4. Figure 4.6 shows the optimal locations of DRFs when the total number of DRFs to be opened is two and the minimum service reliability is 0.7.

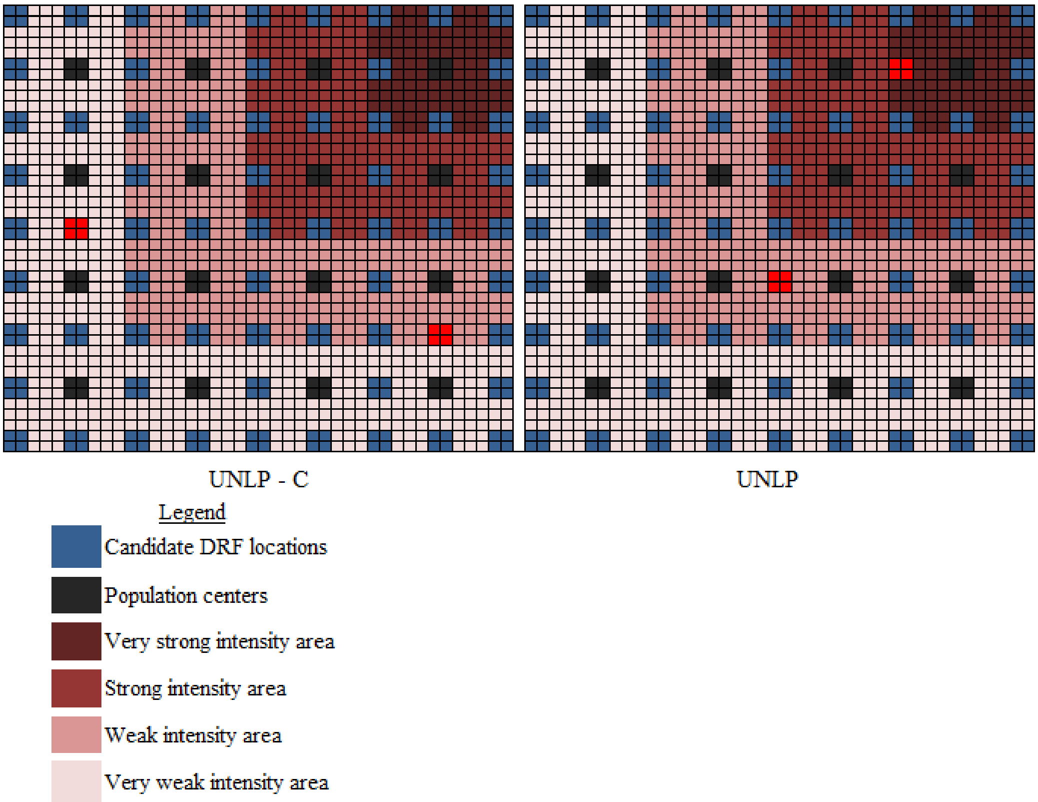


Figure 4.6: Optimal DRF locations under Scenario 3

The average distance is 1845 meters in chance-constrained formulation and it drops to 1293 meters when UNLP is used. Similar to the previous scenarios, expected unsatisfied demand percentage is increased, from 23.3 % of the total demand to 51.4 %.

The solutions of the other 13 scenarios are similar to the ones of the three example scenarios. Actually, we have shown that results in the four-location example, too. Chance constraints chooses locations that are safer, although they are more distant from the affected areas, than the chosen locations of UNLP; therefore, average distance is increased whereas expected unsatisfied demand percentage decreases. Minimizing distance means minimizing the time of relief arrival and using weighted distance, more importance is given to transportation of more items. On the other side, the main purpose is sending relief, so expected loss of demand should be as small as possible. Chance constraints serve this purpose by decreasing the expected unsatisfied demand percentage and providing a pre-specified service reliability for the affected areas. Using different minimum service reliability values, tradeoff between the weighted distance and expected loss may be analysed. As an example, the Tables 4.7 shows the results of progression scheme 3 with intensity level 2, named as Scenario 4, for different minimum service reliability values, 0.5 and 0.7, respectively.

Table4.7: Results obtained under Scenario 4

α = 0.5	Results of UNLP		Results of UNLP-C		Difference(%)	
# of DRFs	A.D.	E.U.(%)	A.D.	E.U.(%)	A.D.	E.U.(%)
1	2500	34.19	1750	54.12	42.86	-36.84
2	1406	37.97	1250	52.63	12.5	-27.85
3	1156	38.37	1000	54.31	15.63	-29.34
4	1000	38.41	750	54	33.33	-28.88
5	875	38.38	688	52.75	27.27	-27.25
6	750	39.25	625	51.5	20	-23.79
7	688	39.44	563	45.19	22.22	-12.72
8	641	39.47	500	47.34	28.13	-16.63
9	609	38.69	500	47.06	21.88	-17.8
10	594	38.19	500	48.5	18.75	-21.26
α = 0.7	Results of UNLP		Results of UNLP-C		Difference(%)	
# of DRFs	A.D.	E.U.(%)	A.D.	E.U.(%)	A.D.	E.U.(%)
1	infeasible	infeasible	1750	54.13		
2	2250	26.38	1250	52.63	80.00	-49.88
3	2000	26.38	1000	54.31	100.00	-51.44
4	1750	26.38	750	54.00	133.33	-51.16
5	1688	26.57	688	52.75	145.45	-49.64
6	1625	26.75	625	51.50	160.00	-48.06
7	1594	26.75	563	45.18	183.33	-40.80
8	1563	26.75	500	47.34	212.50	-43.50
9	1547	26.84	500	47.06	209.38	-42.96
10	1531	27.00	500	48.50	206.25	-44.33

* A.D. : average distance

* E.U. : expected unsatisfied demand

As it can be seen, if minimum service reliability increases the increase in the weighted distance and the decrease in the expected unsatisfied demand percentage increases. The result is the same for the other scenarios for all intensity levels. Therefore, chance constraints might be used for decreasing expected unsatisfied demand percentage and the tradeoff can be calculated by manipulating the minimum service reliability.

Without chance constraints, the damage on relief item transportation is not taken into account. We mention that the literature is mostly lack of the attention on this damage and scenario-based formulations are frequently takes place. Scenario-based formulations are used because there exists uncertainty in occurrence of a disaster. Therefore, possible scenarios are derived and their occurrence probabilities are used to optimize expectation of an objective. Most of the scenario-based formulations proposed in the literature do not include reliability constraints. However, uncertainty does not only exist between the occurrences of scenarios, it exists in those scenarios, also. Using the chance constraints, reliability is provided against the uncertainty in the scenarios. Main difference here is the existence of the reliability concept through the chance constraints. In this section, the comparison between scenario-based models and chance-constrained formulation is made. An example scenario combination is to be used for this purpose.

Let us assume that the dissemination of the disaster is predicted as in progression scheme 2 introduced before. However, the intensity level of the earthquake is not predicted exactly and there are four possible scenarios; scenario 5, 6, 7 and 8. The results of the four possible scenarios can be seen in Table 4.8 when the total number of DRFs goes to five. This number is selected because the larger numbers gives very similar solutions.

Table4.8: Results under scenarios 5, 6, 7, and 8

Scenario 5	UNLP-C,α = 0.5		UNLP-C,α = 0.7		UNLP	
# of DRFs	A.D.	E.U(%)	A.D.	E.U(%)	A.D.	E.U(%)
1	2633	25.9	infeasible	infeasible	1800	49
2	1500	34.03	1867	23.17	1267	52.33
3	1333	31.7	1767	23.7	1067	47.97
4	1233	32.43	1767	25.03	867	45.3
5	1167	33	1767	25.03	700	45.4
Scenario 6	UNLP-C,α = 0.5		UNLP-C,α = 0.7		UNLP	
# of DRFs	A.D.	E.U(%)	A.D.	E.U(%)	A.D.	E.U(%)
1	1881	24.3	2786	22.67	1881	24.33
2	1357	33.4	1643	20	1357	35.19
3	1071	30.1	1405	20.76	1071	37.14
4	881	30.5	1262	21.14	881	30.81
5	786	33.1	1214	21.52	786	34
Scenario 7	UNLP-C,α = 0.5		UNLP-C,α = 0.7		UNLP	
# of DRFs	A.D.	E.U(%)	A.D.	E.U(%)	A.D.	E.U(%)
1	1864	25.27	infeasible	infeasible	1864	25.27
2	1318	34.32	1682	21.45	1318	47.45
3	1045	30.95	1455	21.45	1045	43.68
4	864	32.82	1318	21.45	864	34.45
5	773	30.77	1273	21.45	773	34
Scenario 8	UNLP-C,α = 0.5		UNLP-C,α = 0.7		UNLP	
# of DRFs	A.D.	E.U(%)	A.D.	E.U(%)	A.D.	E.U(%)
1	2638	25.9	infeasible	infeasible	1776	47.93
2	1466	33.93	1845	23.28	1293	51.41
3	1190	36.93	1741	23.83	1052	44.48
4	1086	36.21	1741	24.86	879	45.1
5	1017	36.31	1741	24.86	707	49.66

* A.D. : average distance

* E.U. : expected unsatisfied demand

We can see that the chance constraints are redundant when the minimum service reliability is 0.5 for scenarios 6 and 7. Moreover, the expected percentage of unsatisfied demand is decreased when α increases from 0.5 to 0.7 which is consistent with previously obtained results.

In order to compare the results, we solve the problem with SBP, SBP-C when $\alpha = 0.5$ and SBP-C when $\alpha = 0.7$ assuming that occurrence probabilities are the same. Table 4.9 presents the results.

Table4.9: Results of scenario based formulations

SBP	All scenarios		Scenario 5		Scenario 6		Scenario 7		Scenario 8	
# of DRFs	E.	O.E.U (%)	A.D.	E.U. (%)	A.D.	E.U. (%)	A.D.	E.U. (%)	A.D.	E.U. (%)
1	1865	28.04	1800	49	1929	30.81	1955	32.36	1776	47.93
2	1309	31.37	1267	54.23	1357	35.19	1318	36.05	1293	53.38
3	1084	33.32	1100	53.7	1071	35.9	1045	43.68	1121	50.28
4	890	29.61	900	51.13	881	32.86	864	34.45	914	49.93
5	741	29.47	700	50.17	786	33.52	773	34.18	707	49.14
SBP-C (α = 0.5)	All scenarios		Scenario 5		Scenario 6		Scenario 7		Scenario 8	
# of DRFs	E.	O.E.U (%)	A.D.	E.U. (%)	A.D.	E.U. (%)	A.D.	E.U. (%)	A.D.	E.U. (%)
1	2661	17.38	2633	25.9	2690	21.71	2682	21.91	2638	25.9
2	1573	20.76	1500	33.5	1643	24.1	1682	25.45	1466	33.93
3	1241	20.94	1333	33.6	1214	24.62	1227	25.55	1190	36.93
4	1113	22.21	1333	33.6	976	27.14	955	28.09	1190	36.93
5	986	23.1	1267	34.2	786	28.67	773	29.55	1121	36.72
SBP-C (α = 0.7)	All scenarios		Scenario 5		Scenario 6		Scenario 7		Scenario 8	
# of DRFs	E.	O.E.U (%)	A.D.	E.U. (%)	A.D.	E.U. (%)	A.D.	E.U. (%)	A.D.	E.U. (%)
2	1852	15.85	1867	23.17	1833	20	1864	20.23	1845	23.28
3	1643	16.6	1867	23.43	1405	21.52	1455	21.45	1845	23.55
4	1569	16.62	1767	23.5	1357	21.52	1409	21.45	1741	23.62
5	1522	16.62	1767	23.5	1262	21.52	1318	21.45	1741	23.62

* E.A.D. : expected average distance with respect to scenarios

* O.E.U. : overall expected unsatisfied demand with respect to scenarios

* A.D. : average distance

* E.U. : expected unsatisfied demand

We can say that Scenario 6 is the worst in terms of average distance. Results show that the solutions of UNLP under the Scenario 6 and SBP are the same except the case of only one DRF. So, using UNLP-C with $\alpha = 0.7$ increases the average distance and decreases expected unsatisfied demand percentage for Scenario 6 which is an expected results considering previous analyses. Actually, this is not only valid for Scenario 6, it is for all scenarios.

When the results of SBP-C with $\alpha = 0.5$ and SBP-C with $\alpha = 0.7$ are compared to UNLP-C with $\alpha = 0.5$ and UNLP-C with $\alpha = 0.7$, respectively, it can be seen that scenario-based formulations give the same solutions with the worst case scenario, which is Scenario 5, in terms of the objective function value. Therefore, in this example, using scenario-based formulations increases the problem size, only.

Previously, the scenarios differs only in disaster intensity; their progression schemes are the same. Now, we construct new scenarios which have the same intensity level but different progression schemes.

Let us assume that the intensity level of the earthquake is predicted as level 4 introduced before. However, the center of the earthquake is not predicted exactly and there are four progression schemes; 1, 2, 3 and 4. Therefore, we name the scenarios including intensity level 4 with progression schemes 1,2,3 and 4 as Scenario 9, Scenario 10, Scenario 11 and Scenario 12, respectively.

Same problem is solved using four different formulations which are UNLP-C, UNLP, SBP and SBP-C. The figures below show the optimal locations of DRFs in each scenario according to the results of different formulations when the total number of DRFs to be opened is four.

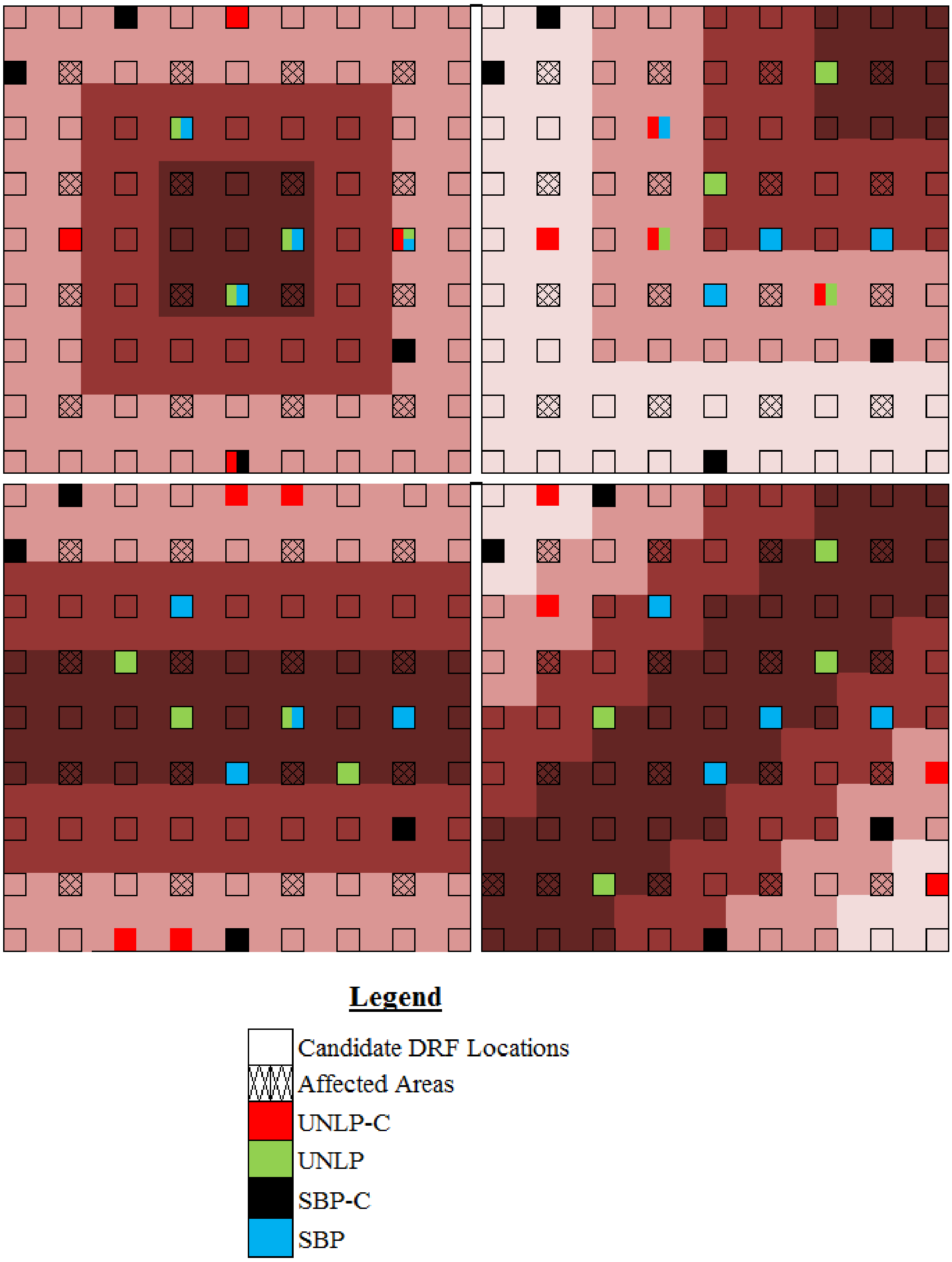


Figure 4.7: Optimal DRF locations when *w* is four

It can be seen that locations of formulations UNLP and SBP are more centred than the solutions of UNLP-C and SBP-C. Even the locations of SBP-C are more dispersed than the locations of UNLP-C in each scenario. This is because, the progression schemes are different and there is no obvious worst case scenario. When SBP-C utilized chance constraints for all of the scenarios, safer locations are chosen and thus expected unsatisfied percentage of demand is decreased.

In short, if chance constraints are not included to scenario-based formulation, although it considers all possible scenarios, it does not capture the risk of relief transportation blockage. Chance constraints result in small expected unsatisfied percentage and relatively high average distance in all formulations. They help observing the tradeoff between the time and reliability concepts while providing a minimum requirement on the reliability of relief transportation.

4.2 Numerical Study

4.2.1 Data Related to Istanbul Region

Proposed model in the previous section is applied to the European Side of Istanbul. All data are obtained from The Study on A Disaster Prevention / Mitigation Basic Plan in Istanbul Including Seismic Microzonation in the Republic of Turkey prepared by Japan International Cooperation Agency (JICA) and Istanbul Metropolitan Municipality (IMM) [33]. In that research,four possible earthquake models are proposed namely Model A, Model B, Model C and Model D. They stated that Model D resembles Model A and Model B resembles Model C; so, they estimate damages for only two of the models: Model A and Model C. Because Model C is the worst case, in this thesis estimations for Model C is used.

There are 18 districts of Istanbul at the European Side. Weighted population centers of the districts are used as demand points (affected areas) in the model. Since two of the districts, Şişli and Avcılar, are divided into two due to their geographical shapes, there are 20 affected areas in need of relief items. Table 4.10 shows the districts of the affected areas and Figure 4.8 presents the population center of the districts (affected areas).

Table4.10: Affected areas and their districts

Affected area	District	Affected area	District
1	Şişli 1	11	Zeytinburnu
2	Beşiktaş	12	Bağcılar
3	Şişli 2	13	Güngören
4	Kağıthane	14	Bakırköy
5	Beyoğlu	15	Bahçelievler
6	Eminönü	16	Avcılar 1
7	Gaziosmanpaşa	17	Küçükçekmece
8	Eyüp	18	Avcılar 2
9	Bayrampaşa	19	Büyükçekmece
10	Fatih	20	Sarıyer

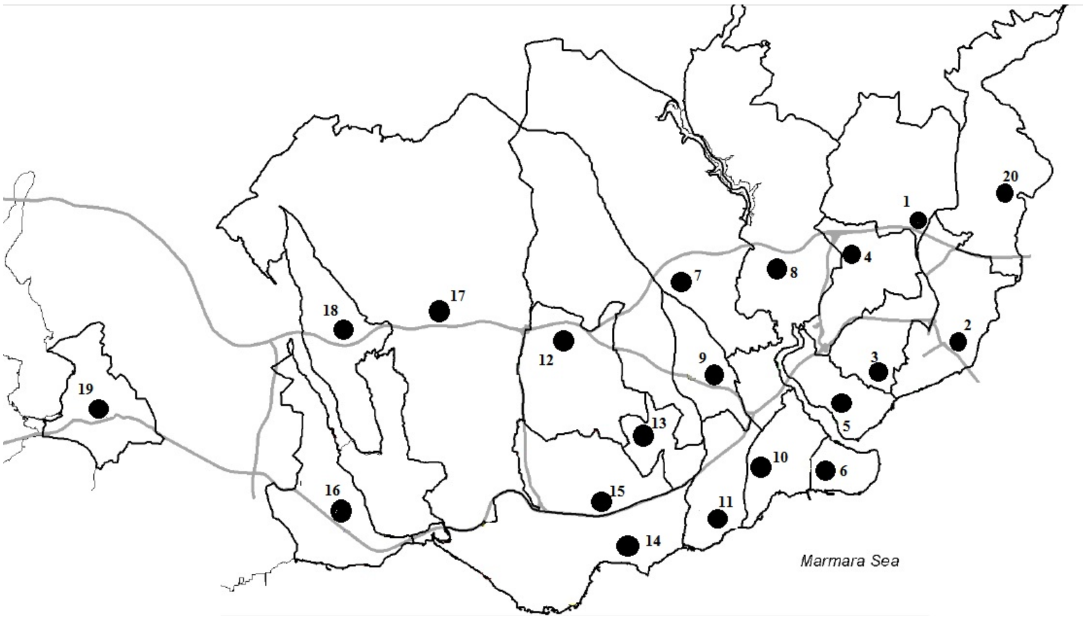


Figure 4.8: Demand Centers of the Affected Areas

Amounts of relief items needed by the affected areas are estimated based on the JICA and IMM report [35]. Most notable cause of damage is claimed to be building collapse. They evaluate buildings located at each district in terms of their construction year, floor number and structure; and they group the buildings into three: heavily damaged buildings, moderately damaged buildings and partly damaged buildings. Heavily and moderately damaged buildings are not usable for living until they are repaired or rebuilded. Therefore, people living in those type of buildings will need certain items like tent, hygiene kits, food and water supply. Additionally, need for medical equipment kits can be estimated using number of people living in these type of buildings. The JICA report provides number and percentage of heavily, moderately and partly damaged buildings in each district together with population data of them. In this study, need for the five types of relief items are estimated for each district by multiplying district population with the total percentage of heavily and moderately damaged buildings in that district. Using CARE International's specifications, demand for relief items for all districts are calculated. According to CARE's specifications, one tent is for 5 people, one medical equipment kit is for 50 people, one food kit is for 8 people, one hygiene kit is for 8 people and a person needs 3 liters of waters daily. The estimations can be seen in Table 4.11.

Table4.11: Need by affected areas for five relief item types

Affected areas	Need for relief items					% of total demand
	Med. Eq. kit (units)	Hygiene kit (units)	Food kit (units)	Tent (units)	Water (liters)	
Avcılar 1	777	4,854	4,854	7,766	116,480	3.19
Avcılar 2	777	4,854	4,854	7,766	116,480	3.19
Bahçelievler	3,233	20,204	20,204	32,326	484,881	13.27
Bakırköy	1,685	10,530	10,530	16,848	252,708	6.92
Bağcılar	2,153	13,452	13,452	21,523	322,845	8.84
Beyoğlu	978	6,110	6,110	9,775	146,619	4.01
Beşiktaş	417	2,603	2,603	4,165	62,472	1.71
Büyükçekmece	190	1,186	1,186	1,897	28,452	0.78
Bayrampaşa	1,304	8,148	8,148	13,036	195,534	5.35
Eminönü	317	1,977	1,977	3,163	47,433	1.30
Eyüp	799	4,991	4,991	7,985	119,766	3.28
Fatih	2,712	16,944	16,944	27,111	406,653	11.13
Güngören	1,724	10,774	10,774	17,237	258,555	7.08
Gaziosmanpaşa	1,336	8,348	8,348	13,357	200,343	5.48
Kağıthane	754	4,710	4,710	7,535	113,019	3.09
Küçükçekmece	2,652	16,570	16,570	26,512	397,671	10.88
Sarıyer	175	1,092	1,092	1,747	26,199	0.72
Şişli 1	269	1,677	1,677	2,683	40,245	1.10
Şişli 2	269	1,677	1,677	2,683	40,245	1.10
Zeytinburnu	1,848	11,547	11,547	18,475	277,116	7.58

We assume that the DRFs are not damaged by an earthquake because they can be built as disaster-resisting buildings. However, they can be isolated due to the fact that the paths linking them to affected areas can be destroyed. Therefore, candidate DRF locations are chosen considering isolation risk caused by road blockage after an earthquake. There are 25 candidate DRF locations and they are presented on a map provided by JICA & IMM [35] showing the isolation risk of areas in Figure 4.9.

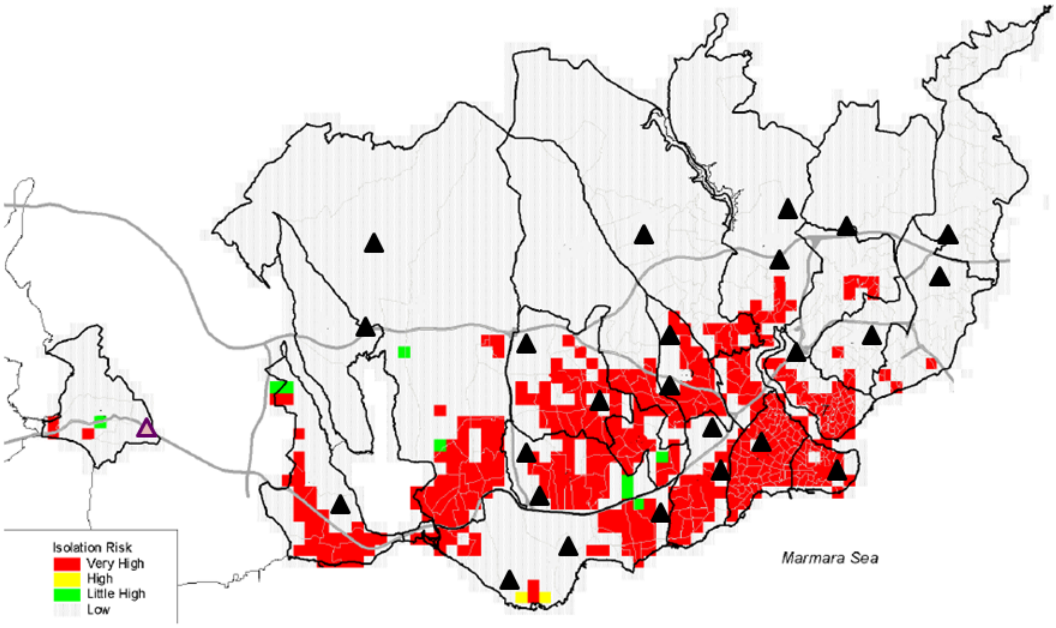


Figure 4.9: Candidate DRF Locations

In the report of JICA and IMM [35], a proposed emergency road map is presented and that road map can be seen in Figure 4.10. Roads are evaluated according to route division, connection, factor on traffic characteristics, building collapse risk and crossing large bridges and viaducts in order to propose most suitable road map to be used in emergency situations. Using the proposed emergency road map, distances of shortest paths between candidate DRF locations and affected areas are found and presented in Appendix A. In this thesis, we use shortest paths and maximum reliable paths. In a real situation, when a path is blocked, an alternative path is used for relief transportation. However, the solutions are obtained according to shortest paths or maximum reliable paths in this thesis. As a simplifying assumption, alternative paths are not considered.

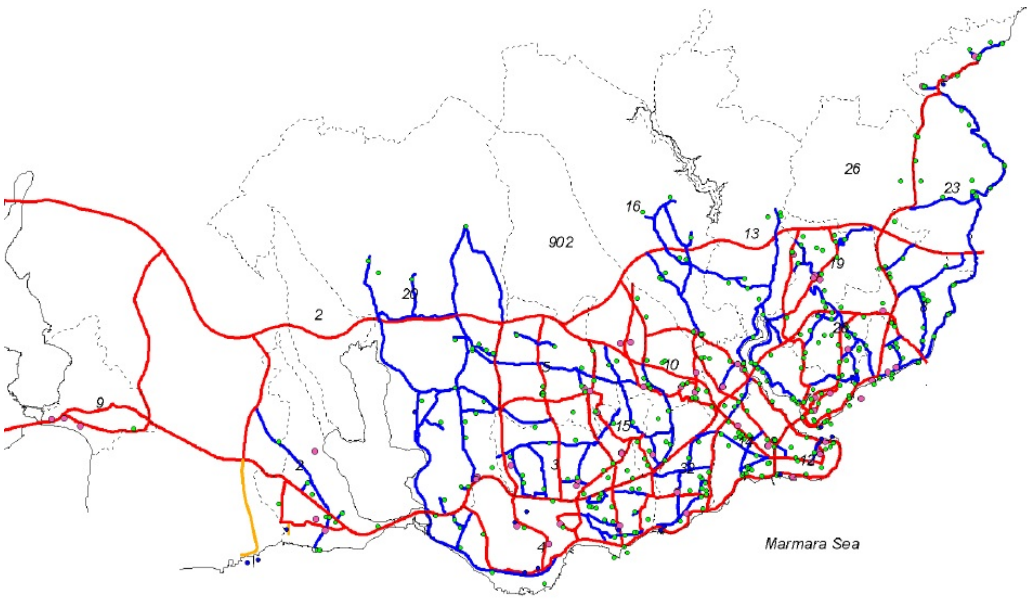


Figure 4.10: Proposed Emergency Road Network (JICA & IMM, 2002)

In the report of JICA and IMM [35], blockage probabilities of the roads in the proposed road network are determined considering width of roads and building collapse risk. Roads are categorized into three groups: wide width roads (16 meters and over), medium width roads (7 - 15 meters) and narrow width roads (2-6 meters) and for three types of roads, bloackage probabilities are presented. As an example, a map including medium width roads can be seen in Figure 4.11. Areas are colored according to building collapse risk; red for 0.5 and over, orange for the range of 0.3-0.5; yellow for the range of 0.2-0.3; green for the range of 0.1-0.2; blue for the range of 0.05-0.1;and grey for the range of 0-0.05. Average value of a range is used as building collapse risk of a road passing through an area. Maps of wide width and narrow width roads are given in Appendix B.

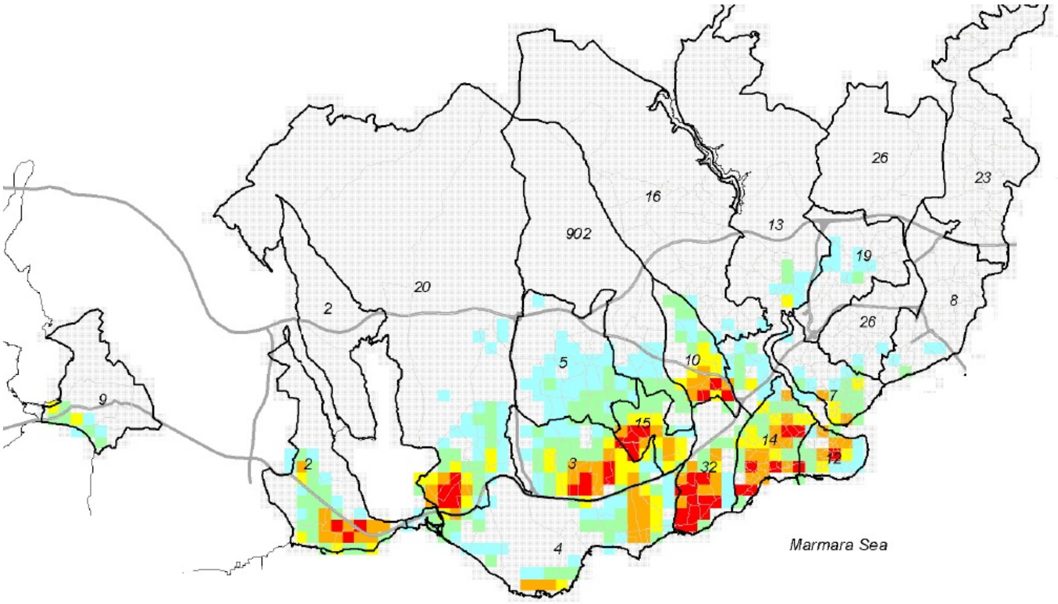


Figure 4.11: Building Collapse Risk for Medium Width Roads (JICA & IMM, 2002)

In Figure 4.11, the probability of road blockage due to building collapse is presented for areas. However, a path between a DRF location and an affected area can pass through the areas with different blockage probabilities. As explained in Chapter 3 numerical examples part, an average probability of blockage for the path is calculated. We multiply distance that the path takes in an area and the blockage probability of that area. After taking the sum of the multiplication over all areas that the path goes thorough, the sum is divided by the total distance of the path giving us the average blockage probability for the path. All probabilities are less than 1 in Istanbul problem, which means there is no path which is definitely blocked. This is why the explained calculation of blockage probabilities, finding an average probability, is reasonable. However, it is possible to calculate blockage probabilities of the paths in another way. Again, we separate the path into the parts passing through the areas with different blockage probabilities. Then, we multiply the probabilities of the parts not being blocked and extract the multiplication from 1. By this way, we find the probability that at least one of the parts is blocked, which is named as overall blockage probability in the thesis. Therefore, two different calculations are possible for finding blockage probabilities; we can use average probabilities or overall probabilities. Disadvantage of using average probabilities is that if there are parts that will definitely be blocked, then the path will definitely be blocked. We ignore this fact using distance weights and decreasing the blockage probability. Using overall probability has also a disadvantage because it ignores the distances of the parts. However, finding an appropriate calculation is not the main concern of this thesis; discussion on the appropriate calculation is another topic of study. Therefore, because in Istanbul problem, we do not have any parts that will definitely be blocked, we prefer to use average probabilities. In addition, we also present solutions when overall probabilities are used. Appendix C shows the average blockage probabilities of the paths between the locations and Appendix D shows the overall probabilities.

4.2.2 Numerical Results

Using data of European Side of Istanbul, problem of finding the locations for pre-positioning DRFs and relief items a priori to a large-scale earthquake is solved. The formulation without the chance constraints (UNLP) is used first. Then, chance-constrained formulation (UNLP-C) is used in order to obtain results with less expected unsatisfied percentage of demand than those of UNLP. In these formulations, demand of affected areas is satisfied fully; however, they are modified in order to solve with problem with unsatisfied demand. Even though the JICA & IMM report [35] does not include any data about capacities of the candidate sites and costs to open them, using simulated data the problem is also solved with capacitated DRFs and fixed costs. After obtaining the results with minimizing the total average distance, the problem is solved minimizing unsatisfied percentage of demand and results are examined. Shortest paths between the locations are used unless it is stated otherwise. Lastly, maximum reliable paths are used and the solutions are discussed. Moreover, solutions that are proposed in the thesis of Gormez [34] mentioned in the Chapter 2 are presented and they are compared and commented in terms of the risk of infrastructure being destroyed.

At the end of the previous section, it is said that average blockage probabilities are preferred in this thesis but the solutions obtained using overall probabilities are also presented. Table 4.12 shows the results of UNLP and UNLP-C when overall probabilities are used. Minimum service reliabilities of relief items are 0.5, 0.5, 0.4, 0.4 and 0.3 for medical equipment, food supply, water supply, hygiene kits and tents, respectively.

Table4.12: Results of UNLP and UNLP-C when overall probabilities are used

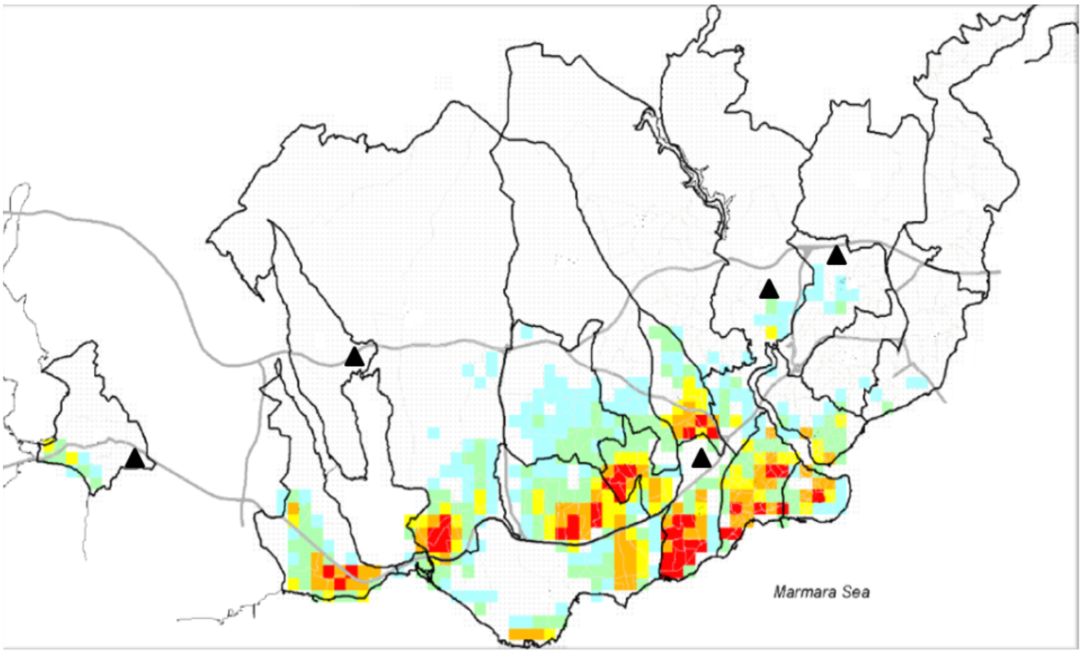
	UNLP		UNLP-C		Difference	
# of DRFs	A.D.	E.U.	A.D.	E.U	A.D.	E.U
1	infeasible	infeasible	0	0		
2	infeasible	infeasible	7082	39		
3	infeasible	infeasible	4909	33		
4	8395	20	3985	30	111	-31
5	5586	19	3508	29	59	-35
6	5001	18	3095	24	62	-27
7	4567	18	2719	23	68	-24
8	4174	17	2469	25	69	-30
9	3943	18	2324	25	70	-30

* A.D. : average distance

* E.U. : expected unsatisfied demand

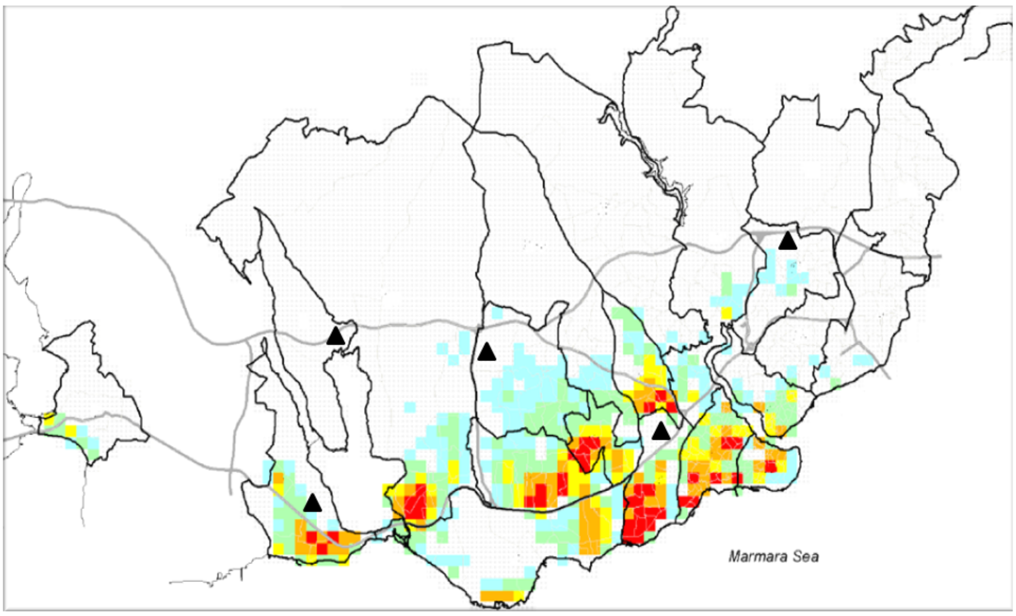
We can say that average distance increases by 70% and expected unsatisfied demand percentage decreases by 30%, approximately. This is because when the chance constraints are used

DRFs are opened at less risky locations even though they are more distant to affected areas. Figure 4.12 and Figure 4.13 show the optimal DRF locations of the formulations with and without chance constraints, respectively, when total number of DRFs to be located is five.



UNLP-C

Figure 4.12: Optimal DRF locations



UNLP

Figure 4.13: Optimal DRF locations

As we can see from the figures, optimal DRF locations are getting out of risky areas when chance constraints are used. This is why average distance increases and expected unsatisfied demand decreases. If average blockage probabilities are used in the same setting, chance constraints are redundant because average probabilities are less than overall probabilities.

After presenting the results when overall blockage probabilities are used, we use average probabilities in the remainder of the thesis. In addition, we set minimum service reliabilities of relief items to 0.9, 0.85, 0.85, 0.7 and 0.7 for medical equipment, water, food, hygiene kits and tents, respectively. Results of UNLP and UNLP-C are presented at Table 4.13.

Table4.13: Results of UNLP and UNLP-C

	UNLP		UNLP-C		Difference	
# of DRFs	A.D.	E.U.	A.D.	E.U	A.D.	E.U
1	infeasible	infeasible	infeasible	infeasible	-	-
2	infeasible	infeasible	7082	0.1011	-	-
3	infeasible	infeasible	4909	0.0925	-	-
4	6155	0.0418	3985	0.0932	54%	-55%
5	4950	0.0519	3508	0.0925	41%	-44%
6	4357	0.0511	3095	0.0812	41%	-37%
7	3777	0.0504	2719	0.1408	39%	-64%
8	3403	0.0549	2469	0.1879	38%	-71%
9	3064	0.052	2324	0.2023	32%	-74%
10	2919	0.0587	2227	0.2081	31%	-72%
11	2821	0.0491	2144	0.2073	32%	-76%
12	2773	0.053	2101	0.2065	32%	-74%

* A.D. : average distance

* E.U. : expected unsatisfied demand

These results are expected considering the analysis done on the simulated data. The chance constraints cause the average distance to increase and the expected loss of demand to decrease. This is why DRFs are opened at safer but more distant locations from their assigned affected areas than those of the formulation without the chance constraints. As an illustration, Figure 4.14 and Figure 4.15 below show their optimal locations when the number of total DRFs is six.

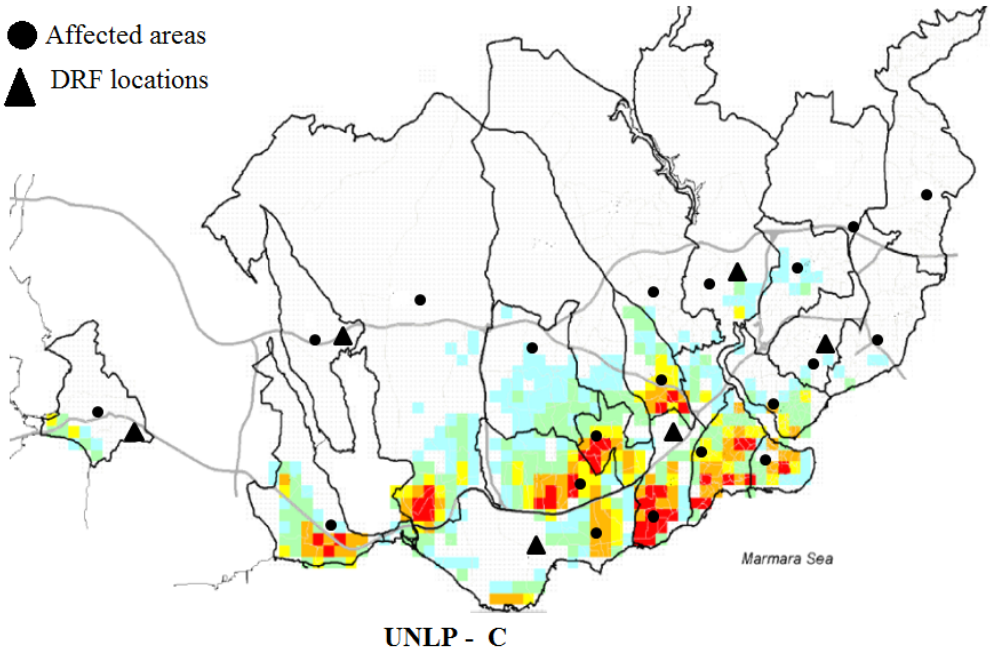


Figure 4.14: Optimal DRF locations

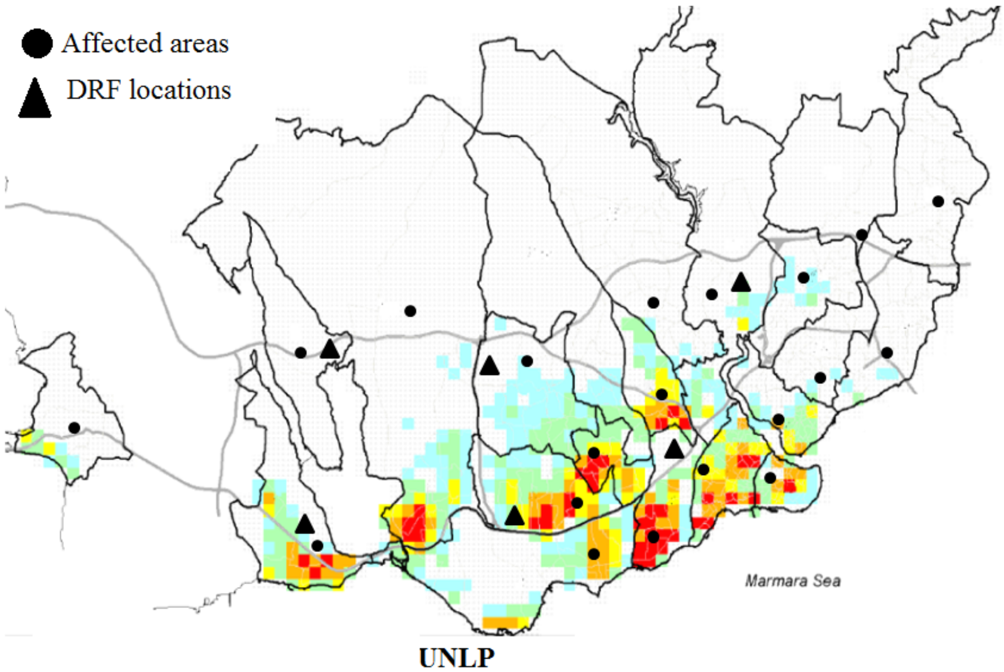


Figure 4.15: Optimal DRF locations

In addition Table 4.14 shows the expected unsatisfied demand percentage of all relief items individually when the total no of DRFs to be opened is six.

Table4.14: Expected unsatisfied demand percentage of all relief items

	Relief Items				
	1	2	3	4	5
UNLP-C	3.2912	4.9338	4.9338	6.9681	6.9681
UNLP	8.119289	8.120332	8.120397	8.120285	8.120397

It can be seen that expected unsatisfied demand percentage of more critical items are in less amounts than the less critical ones when the chance constraints are used. UNLP treats as if all items have the same importance.

The results are presented when the total demand is satisfied. However, that might not be possible due to budget limitations and some portion of the demand might be left to the public relief agencies to be satisfied. Therefore, we also obtain the solutions when only a portion of the total demand is satisfied. There are two possibilities; either some portion of the overall demand is satisfied or some portion of the individual relief items is satisfied. In order to do this, we made some modifications on UNLP and UNLP-C.

New Parameter

m		unsatisfied portion of the demand

New Variable

o_{jk}	$i \in I$	positive variable that denotes the unsatisfied amount of demand of affected area j for relief item k; 0, otherwise

Additionally, Constraint set (3.2) is modified;

$$\sum_{i \in I} x_{ijk} \geq n_{jk} - o_{jk} \tag{4.1}$$

If some portion of the overall demand is not satisfied then the constraint below is added to the model.

$$\sum_{j \in J} \sum_{k \in K} o_{jk} \leq m * \sum_{j \in J} \sum_{k \in K} n_{jk} \qquad \forall j \in J, k \in K \tag{4.2}$$

The formulations involving UNLP and UNLP-C together with the Constraint Sets (4.1) and (4.2) are called uncapacitated location problem with unsatisfied total demand UNLPU and uncapacitated location problem with unsatisfied demand and chance constraints (UNLPU-C), respectively.

If portions of the individual demand of relief items are not satisfied then the constraint below is added to the model.

$$\sum_{k \in K} o_{jk} \leq m * \sum_{k \in K} n_{jk} \qquad \forall k \in K \qquad (4.3)$$

The formulations involving UNLP and UNLP-C together with the Constraint Sets (4.2) and (4.3) are called uncapacitated location problem with unsatisfied demand of individual items (UNLPI) and uncapacitated location problem with unsatisfied demand of individual items and chance constraints (UNLPI-C), respectively.

Table 4.15 shows the solutions when the total number of DRFs is six and the chance constraints are not used. It shows the average distance, overall unsatisfied demand percentage and unsatisfied demand percentages of the relief items separately.

Table4.15: Results obtained when chance constraints are not involved

			Unsatisfied demand percentage of relief items				
	A.D.	E.U.	1	2	3	4	5
UNLP	3095	0.0812	8.1193	8.1203	8.1204	8.1203	8.1204
UNLPI, $o = 0.75$	1451	0.1792	17.9182	17.9219	17.9216	17.9217	17.9216
UNLPI, $o = 0.5$	572	0.1762	17.6132	17.6159	17.6157	17.6158	17.6157
UNLPU, $o = 0.75$	1451	0.1792	18.0369	17.9228	17.9101	17.9102	17.9101
UNLPU, $o = 0.5$	572	0.1762	18.0000	17.6520	17.3578	17.3579	17.3578

When the chance constraints are not used, unsatisfied demand percentage of all the relief items are either equal or very close to each other.

Table 4.16 shows the solutions when the total number of DRFs is six also and the chance constraints are involved. It shows the average distance, overall unsatisfied demand percentage and unsatisfied demand percentages of the relief items separately.

Table4.16: Results obtained when chance constraints are involved

			Unsatisfied demand percentage of relief items				
	A.D.	E.U.	1	2	3	4	5
UNLP-C	6155	0.04178	3.83712	4.14012	4.14012	4.56574	4.56575
UNLPI-C, $o = 0.75$	1972	0.04065	1.77576	3.95950	3.95945	5.21541	5.21537
UNLPI-C, $o = 0.5$	853	0.04183	2.24341	4.06061	4.06075	5.47612	5.47614
UNLPU-C, $o = 0.75$	1968	0.03684	2.02946	3.37626	3.35380	6.75372	6.75373
UNLPU-C, $o = 0.5$	843	0.04147	2.38012	3.98951	3.54687	5.94475	5.94477

The chance constraints provide that unsatisfied demand percentage of more critical items is less than the others. In addition, when the overall demand is limited, more importance is given to the critical items due to the chance constraints.

When the DRFs are capacitated, the problem is solved again. Because real data about the capacities are not reached, they are generated. Total demand is divided among the candidate DRFs according to the blockage probabilities of their outgoing paths. The risky sites have less capacity than the other sites. The results are presented in Table 4.17.

Table4.17: Results of CLP and CLP-C

	CLP		CLP-C		Difference	
# of DRFs	A.D.	E.U.	A.D.	E.U	A.D.	E.U
6	5188	0.0521	4383	0.0837	18%	-38%
7	4204	0.0491	3361	0.154	25%	-68%
8	3644	0.0508	2855	0.1557	28%	-67%
9	3305	0.0479	2500	0.1833	32%	-74%
10	2997	0.0419	2352	0.2007	27%	-79%
11	2851	0.0491	2213	0.2073	29%	-76%
12	2803	0.053	2130	0.2065	32%	-74%

* A.D. : average distance

* E.U. : expected unsatisfied demand

When the total number of DRFs to be positioned is seven, Table 4.18 shows the expected percentage of unsatisfied demand of all relief items individually.

Table4.18: Expected percentage of unsatisfied demand of relief items of capacitated formulations

	Relief Items				
	1	2	3	4	5
CLP-C	3.4008	4.5598	4.4385	8.4053	8.4095
CLP	16.0694	15.3279	15.6324	16.1898	15.6324

The result is similar. The chance constraints both provide that the losses are decreased and the items are lost according to their criticality.

After the capacitated problem is solved, fixed costs are generated in order to see the functioning of the proposed model. Fixed costs of risky places are higher than the others. Total budget is taken as 20%, 25%, 30%, and 35% of the total opening costs and the results with different budgets are presented in Table 4.19.

Table4.19: Results of fix-CLP and fix-CLP-C

	fix-CLP-C			fix-CLP		
# of DRFs	A.D.	E.U.	A.D.	E.U	A.D.	E.U
Budget	# of DRFs	A.D.	E.U.	# of DRFs	A.D.	E.U.
20% of total	6	5187.939	0.052005	6	4647.417	0.074959
25% of total	7	4396.946	0.051726	7	3684.367	0.069728
30% of total	9	3790.717	0.048245	8	2952.526	0.1593
35% of total	9	3305.902	0.053693	9	2717.717	0.147087

* A.D. : average distance

* E.U. : expected unsatisfied demand

When the chance constraints are involved, more DRFs could be opened with the same budget because opening DRFs to the risky places are more costly. When the minimum reliability is not required to be served, risky, costly but more centered locations can be selected in order to minimize total weighted distance.

So far, minimizing the total average distance is used as the objective of the problem. However, minimizing the expected unsatisfied percentage of demand is another important objective. Results of UNLP-C using both of the objectives are presented in Table 4.20.

Table4.20: Results of UNLP-C with two different objectives

	Min. A.D		Min E.U.		Difference	
# of DRFs	A.D	E.U.	A.D	E.U.	A.D	E.U.
4	6155	0.0418	18581.15	0.040335	202%	-4%
5	4950	0.0519	18588.51	0.040451	276%	-22%
6	4357	0.0511	18019.63	0.039187	314%	-23%
7	3777	0.0504	18015.77	0.039185	377%	-22%
8	3403	0.0549	18016.55	0.039183	429%	-29%

* A.D. : average distance

* E.U. : expected unsatisfied demand

Percent increase in the average distance is much higher than the percent decrease in the expected unsatisfied percentage of demand when the objective is minimizing the expected loss. However, in this case, total demand is 4,551,415 items and, for example, 20% of the total demand is 910,283 items. Expected losses of all items are calculated individually and they can be seen in Table 4.21 when the number of DRFs is five.

Table4.21: Expected unsatisfied demand of relief items

	Relief Items				
	1	2	3	4	5
Minimizing the weighted distance	4.140229	5.173651	5.173651	5.380448	5.380488
Minimizing expected unsatisfied demand	2.2289	3.9279	3.9279	5.2833	5.2834
Total demand	26,244	3,934,907	163,964	262,336	163,964
Expected number of items that are gained when the expected unsatistied demand is minimized	502	49019	2043	255	159

Although the chance constraints decrease the expected unsatisfied demand minimizing the average distance, it does not drop to its minimum value. There is a tradeoff between the average distance and the expected loss which means there is a tradeoff between the risk and time. Therefore, the gain on the critical items might be considered in making the decisions. If the capacities are involved in the formulations results are as follows:

Table4.22: Results of CLP-C using two different objectives

	Min A.D.		Min E.U.	
# of DRFs	A.D	E.U.	A.D	E.U.
6	5188	0.0521	14765.37	0.053697
7	4204	0.0491	10687.16	0.011681
8	3644	0.0508	11467.8	0.013488
9	3305	0.0479	11579.25	0.058053
10	2997	0.0419	12874.85	0.077649

* A.D. : average distance

* E.U. : expected unsatisfied demand

The results are similar to the uncapacitated case.

So far, we use the shortest paths between the candidate locations and the affected areas. Now, we use the maximum reliable paths between the locations and present the results. Maximum reliable paths are found using linear programming and its formulation can be found in Appendix E and the distances and blockage probabilities of maximum reliable paths can be found in Appendix F and Appendix G. Table 4.23 shows the solutions of the formulation without the chance constraints.

Table4.23: Results of UNLP using both shortest paths and maximum reliable paths

	Shortest paths		Max. reliable paths		Difference	
# of DRFs	A.D.	E.U.	A.D.	E.U.	A.D.	E.U.
1	infeasible	infeasible	infeasible	infeasible	-	-
2	7082	0.1011	infeasible	infeasible	-	-
3	4909	0.0925	8489	0.000287	73%	-99.69%
4	3985	0.0932	5929	0.00017	49%	-99.82%
5	3508	0.0925	4939	0.00024	41%	-99.74%
6	3095	0.0812	4355	0.000157	41%	-99.81%
7	2719	0.1408	3855	0.000145	42%	-99.90%
8	2469	0.1879	3565	0.000115	44%	-99.94%
9	2324	0.2023	3345	0.000115	44%	-99.94%
10	2227	0.2081	3146	0.000115	41%	-99.94%
11	2144	0.2073	3019	0.000115	41%	-99.94%
12	2101	0.2065	2951	0.000115	40%	-99.94%

* A.D. : average distance

* E.U. : expected unsatisfied demand

Table 4.24 shows the results of the chance-constrained formulation.

Table4.24: Results of UNLP-C using both shortest paths and maximum reliable paths

	Shortest paths		Max. reliable paths		Difference	
# of DRFs	A.D.	E.U.	A.D.	E.U.	A.D.	E.U.
1	infeasible	infeasible	infeasible	infeasible	-	-
2	infeasible	infeasible	infeasible	infeasible	-	-
3	infeasible	infeasible	8489	0.000287	-	-
4	6155	0.0418	5929	0.00017	-3.67%	-99.59%
5	4950	0.0519	4939	0.00024	-0.22%	-99.54%
6	4357	0.0511	4355	0.000157	-0.05%	-99.69%
7	3777	0.0504	3855	0.000145	2.07%	-99.71%
8	3403	0.0549	3565	0.000115	4.76%	-99.79%
9	3064	0.052	3345	0.000115	9.17%	-99.78%
10	2919	0.0587	3146	0.000115	7.78%	-99.80%
11	2821	0.0491	3019	0.000115	7.02%	-99.77%
12	2773	0.053	2951	0.000115	6.42%	-99.78%

* A.D. : average distance

* E.U. : expected unsatisfied demand

Chance constraints are redundant when the maximum reliable paths are used because the vulnerabilities of the paths are very small in the Istanbul problem. Comparing to the results of UNLP, using maximum reliable paths increases the weighted distance approximately by 46 % whereas it decreases the expected loss of demand to its half. However, comparing to the results of UNLP-C, differences between the weighted distances are very small and again, the expected unsatisfied demand of demand drops to its half approximately.

Let us analyze the expected unsatisfied demand of relief items individually when the total number of DRFs is five.

Table4.25: Expected unsatisfied demand of relief items using UNLP-C

	Relief Items				
	1	2	3	4	5
Using the shortest paths (%)	4.140229	5.173651	5.173651	5.380448	5.380488
Using the shortest paths (units)	1087	203578	8483	14115	8822
Using the maximum reliable paths (%)	0.023955	0.023958	0.023958	0.023958	0.023958
Using the maximum reliable paths (units)	6	943	39	63	39
Total demand	26,244	3,934,907	163,964	262,336	163,964
Expected number of items that are gained when the expected loss is minimized	1081	202635	8444	14052	8783

UNLP-C ignores the criticality of relief items due to the redundancy of chance constraints. Despite this fact, using maximum reliable paths decreases the unsatisfied percentage in significant amount in the Istanbul problem.

In the thesis of Gormez [34], the euclidean distances between the locations are used and usage of the real paths is given as a future study. Additionally, the data obtained from the report of JICA & IMM [35] is utilized differently. Therefore, in order to compare, the four optimal locations proposed in that thesis are taken and average distance and expected unsatisfied demand percentage are calculated. Figure 4.16 shows the optimal locations proposed in the study of Gormez and in this thesis when the total number of DRFs is four.

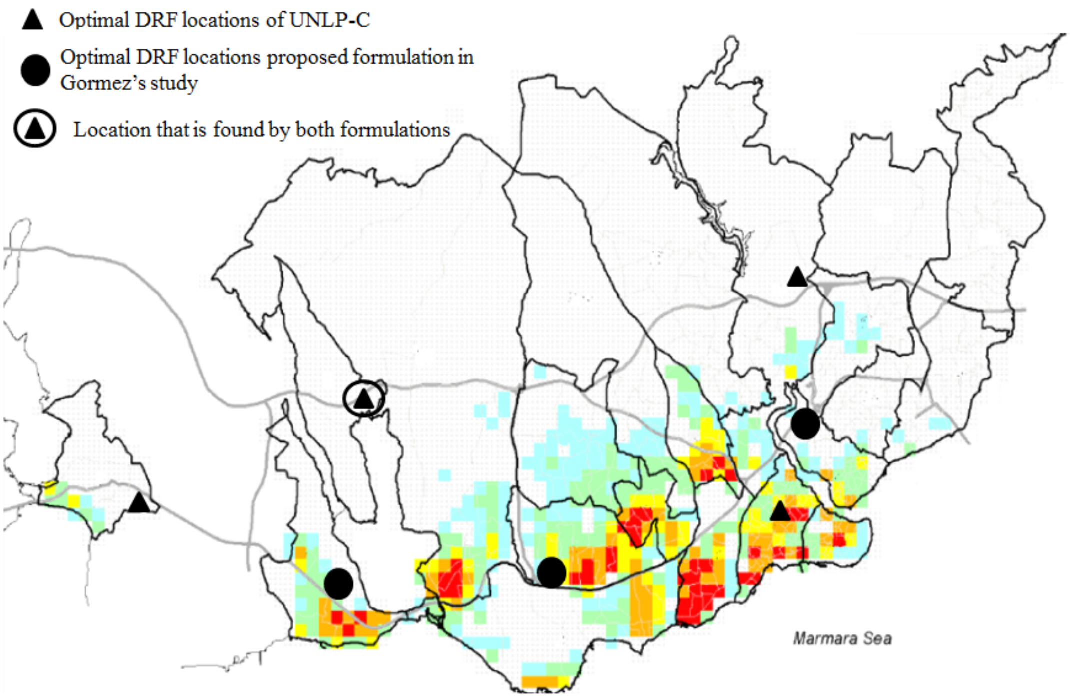


Figure 4.16: Optimal DRF locations of both formulations

Due to the lack of reliability constraints, optimal locations found by the proposed formulation in the study of Gormez [34] are more centred that the ones found bu UNLP-C. Table 4.26 shows the average distance, expected unsatisfied demand percentage in total and in individual relief item demands according to the solutions of both formulations.

Table4.26: Results of both formulations

			E. U. Relief Items (%)				
	A.D.	E.U.	1	2	3	4	5
UNLP-C	6155	0.042	3.837	4.14	4.14	4.566	4.566
Formulation proposed by Gormez [34]	4702	0.151	15.056	15.059	15.058	15.059	15.058

Average distance of the formulation proposed by Gormez [34] is 76% of the one found by UNLP-C. However, when UNLP-C is used expected percentage of the total demand drops from 15.1% to 4.2%. In addition, the criticality of different relief items is not captured in that formulation whereas UNLP-C provides that unsatisfied percentage of demand of critical items is less than the others.

CHAPTER 5

CONCLUSION

Preparation stage of humanitarian logistics is a critical stage for reducing human suffering and minimizing damage caused by disasters. In this thesis, literature on location problems and preparation stage of humanitarian logistics are reviewed. So far, in the literature, mathematical models proposed handle the stochastic features of disasters by using expected values with respect to possible disaster scenarios. In the proposed model, stochasticity is included to the model using probabilistic constraints.

First, the a mixed-integer mathematical model is introduced without chance constraints. Then, the reasoning of chance constraints are explained and they are formulated. Additionally, the formulations including capacitated disaster response facilities and opening costs of facilities are introduced. Moreover, a scenario-based formulation is presented to make a comparison.

The main objective function used in this thesis is minimizing the average distance between the locations. However, considering humanitarian purposes, a different objective function, minimizing expected percentage of unsatisfied demand, is also used.

Formulations are used to solve numerical examples. Two different settings are presented as numerical examples and the solutions of the formulations are commented. In addition to numerical examples, a numerical study is conducted on a real life problem of Istanbul city. Data obtained from the report of JICA & IMM [35] are utilized and the problem is solved using different formulations.

In all experiments, the results are similar. The main effect of chance constraints on the results is that optimal disaster response facility locations are getting out of risky areas; thus, chance constraints, reliability constraints, provide a minimum reliability for relief item transportation and gives better results in terms of expected unsatisfied demand than the formulations without chance constraints. However, they increase average distance. Therefore, there is a tradeoff between minimizing average distance and minimizing expected unsatisfied demand which can be interpreted as the tradeoff between the response time and the risk.

As a future study, a risk averse objective function, which is suitable for humanitarian purposed, can be formulated and used. In addition, for the cases in which it is impossible to satisfy all demand, a variation of maximal coverage problem together with the probabilistic constraints can be developed.

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APPENDIX A

DISTANCES (IN METERS) OF SHORTEST PATHS BETWEEN CANDIDATE DRF LOCATIONS AND AFFECTED AREAS

TableA.1: Distances (in meters) of Shortest Paths between Candidate DRF Locations and Affected Areas (1-10)

	Affected Areas (1-10)									
DRF #	1	2	3	4	5	6	7	8	9	10
1	1534	5125	7911	8080	9656	9110	10858	10391	5245	9811
2	4346	2764	5550	7254	7816	8284	12223	12570	8057	10587
3	8364	5118	523	5600	2584	4275	10182	10916	9614	6880
4	4805	10115	9363	4263	9296	5293	6967	4052	6868	7596
5	9060	5876	4592	4723	2959	5753	9910	6291	10135	8056
6	9017	14327	14531	10427	12953	11457	3826	4551	7992	11582
7	9330	12405	11121	7627	9723	8657	4092	473	8258	10248
8	4521	9831	11140	9419	9562	10078	4245	7864	3625	8191
9	8815	7137	5892	10969	5825	1822	8427	10446	5379	2037
10	8372	12453	9986	12167	8675	5916	9102	12358	4936	2583
11	6616	11926	12286	11514	10975	8216	10377	13825	6211	4883
12	2058	7368	10154	6956	10700	7986	5819	9267	1653	6219
13	8978	14288	16757	11657	16690	12687	15207	13968	11041	11845
14	7473	12783	14837	12045	14579	10767	11234	14356	7068	7434
15	4714	10024	12290	7190	12223	8220	10943	9501	6777	8392
16	4928	10238	12504	7404	12437	8434	11157	9715	6991	8912
17	13322	18632	19501	17796	18190	15431	17083	20107	12917	12098
18	9866	15176	17442	12342	17375	13372	16095	14653	11929	12291
19	15606	20916	23182	18082	23115	19112	21835	20393	17669	18031
20	16836	22146	24615	19515	24548	20545	23065	21826	18899	19438
21	19389	24699	27168	22068	27101	23098	25618	24379	21452	21991
22	26277	31587	33853	28753	33786	29783	32506	31064	28340	28702
23	3090	8400	10666	5566	10599	6596	9319	7877	5153	7145
24	7033	9892	8647	11870	8389	4577	7763	11019	3597	1244
25	10465	7419	6174	11251	6107	4418	11019	13038	10451	7717

TableA.2: Distances of Shortest Paths between Candidate DRF Locations and Affected Areas (11-20)

	Affected Areas (11-20)									
DRF #	11	12	13	14	15	16	17	18	19	20
1	8909	10774	7890	7153	6499	17908	18478	18950	30456	6626
2	11721	13586	10702	9965	9311	20720	21290	21762	33268	6515
3	11975	17519	14432	13695	13041	24450	25020	25492	36998	10236
4	8110	10178	7091	6354	5700	17109	17679	18151	29657	8528
5	12946	15014	11927	11190	10536	21945	22515	22987	34493	12429
6	13989	16342	13255	12518	11864	23273	23843	24315	35821	12740
7	12635	14703	11616	10879	10225	21634	22204	22676	34182	13053
8	9493	12113	9229	8492	7838	19247	19817	20289	31795	8244
9	7132	14142	10519	9782	11460	21857	22427	22899	34405	12255
10	2512	11272	7649	6873	7535	21348	19685	18603	32019	13065
11	1377	8890	5267	3191	4133	17946	17303	16221	28617	11309
12	6338	9650	6465	6029	5375	16784	17354	17826	29332	5781
13	10005	1068	5461	10209	6455	18844	11369	13364	31392	12701
14	5594	4673	1050	6676	5359	17920	13086	14144	30468	11196
15	5532	8136	4513	3762	3499	13025	13595	14067	25573	8437
16	6123	6151	2528	4367	877	15122	14564	15622	27670	8651
17	9238	7207	4799	7848	3728	13956	11495	10413	24627	18015
18	9431	12035	8412	7644	8651	9085	14110	14582	21633	13589
19	15171	17775	14152	13384	14391	0	19084	16832	13327	19329
20	17598	11486	13054	16924	13170	14692	4545	2140	20778	20559
21	20151	14039	15607	19477	15723	17245	7098	4693	23331	23112
22	25842	28446	24823	24055	25062	11450	23446	16761	1877	30000
23	4285	6889	3266	2529	1875	13284	13854	14326	25832	6813
24	3851	10861	7238	6501	8179	18576	19146	19618	31124	10756
25	12812	19822	16199	15462	17140	27537	28107	28579	40085	12537

APPENDIX B

BUILDING COLLAPSE RISK OF THE PATHS

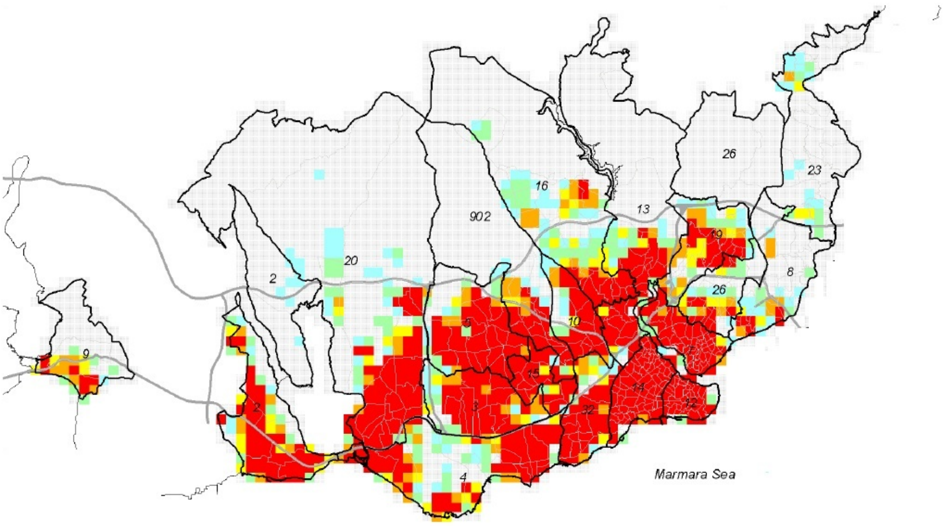

Figure B.1: Building Collapse Risk for Narrow Width Roads (JICA & IMM, 2002)

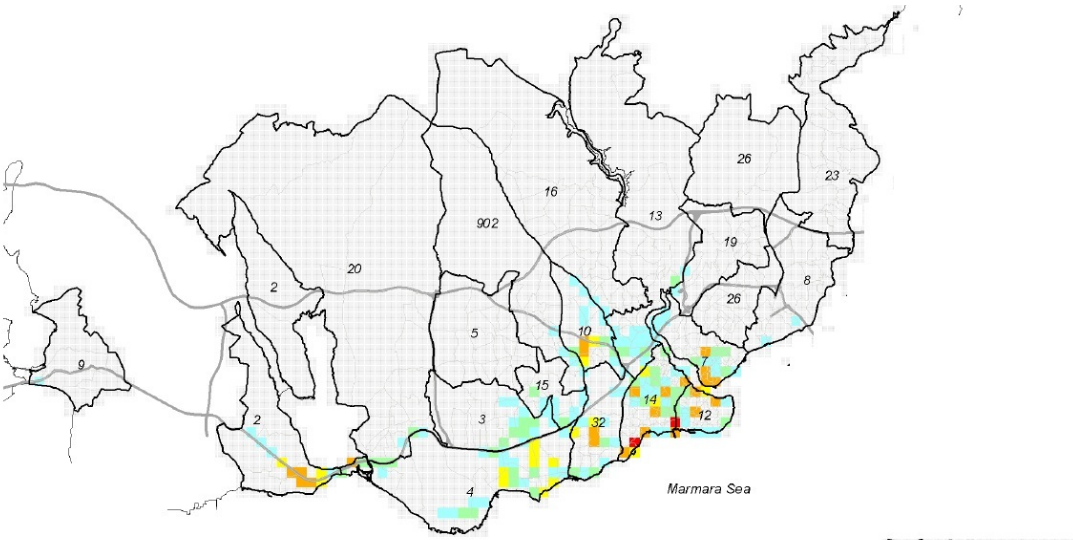

Figure B.2: Building Collapse Risk for Wide Width Roads (JICA & IMM, 2002)

TableB.1: Building Collapse Risks corresponding the Colors in Figure B.1 and Figure B.2

Color	Corresponding building collapse risk in Figure B.1	Corresponding building collapse risk in Figure B.2
Red	0.5 and over	0.01 and over
Orange	0.3 - 0.5	0.004 - 0.01
Yellow	0.2 - 0.3	0.003 - 0.004
Green	0.1 - 0.2	0.002 - 0.003
Blue	0.05 - 0.1	0.001 - 0.002
Grey	0 - 0.05	0 - 0.001

APPENDIX C

AVERAGE BLOCKAGE PROBABILITIES OF THE SHORTEST PATHS

TableC.1: Probability that the Shortest Path Between a Candidate DRF Location and an Affected Area (1-10) is Blocked

	Affected Areas (1-10)									
DRF #	1	2	3	4	5	6	7	8	9	10
1	0.00	0.00	0.01	0.02	0.04	0.02	0.14	0.01	0.22	0.22
2	0.01	0.01	0.01	0.00	0.03	0.00	0.13	0.12	0.14	0.00
3	0.01	0.02	0.08	0.02	0.09	0.06	0.18	0.15	0.28	0.04
4	0.00	0.00	0.04	0.05	0.04	0.04	0.00	0.01	0.17	0.03
5	0.01	0.01	0.03	0.01	0.00	0.01	0.15	0.24	0.23	0.01
6	0.01	0.01	0.13	0.02	0.15	0.02	0.01	0.01	0.06	0.08
7	0.01	0.12	0.14	0.09	0.16	0.08	0.00	0.00	0.05	0.16
8	0.02	0.01	0.31	0.03	0.37	0.32	0.45	0.24	0.27	0.30
9	0.30	0.00	0.03	0.02	0.04	0.00	0.13	0.18	0.32	0.06
10	0.32	0.06	0.08	0.09	0.07	0.09	0.24	0.18	0.36	0.21
11	0.08	0.05	0.04	0.07	0.02	0.03	0.18	0.04	0.24	0.04
12	0.05	0.02	0.02	0.04	0.34	0.04	0.25	0.02	0.62	0.33
13	0.03	0.02	0.03	0.03	0.03	0.03	0.12	0.02	0.12	0.16
14	0.11	0.07	0.11	0.14	0.23	0.14	0.20	0.11	0.25	0.19
15	0.01	0.00	0.03	0.03	0.04	0.03	0.15	0.01	0.17	0.01
16	0.01	0.00	0.03	0.03	0.03	0.03	0.14	0.01	0.17	0.16
17	0.14	0.10	0.08	0.06	0.07	0.09	0.19	0.04	0.21	0.11
18	0.07	0.05	0.06	0.07	0.07	0.07	0.14	0.05	0.16	0.06
19	0.02	0.02	0.03	0.03	0.03	0.03	0.09	0.02	0.08	0.02
20	0.02	0.02	0.03	0.03	0.03	0.02	0.08	0.02	0.08	0.11
21	0.02	0.02	0.03	0.03	0.03	0.02	0.08	0.02	0.07	0.10
22	0.07	0.06	0.07	0.07	0.07	0.07	0.11	0.06	0.11	0.07
23	0.01	0.00	0.04	0.04	0.04	0.03	0.17	0.01	0.23	0.00
24	0.31	0.00	0.02	0.02	0.22	0.00	0.21	0.15	0.34	0.00
25	0.00	0.00	0.03	0.02	0.03	0.46	0.15	0.19	0.24	0.00

TableC.2: Probability that the Shortest Path Between a Candidate DRF Location and an Affected Area (11-20) is Blocked

	Affected Areas (11-20)									
DRF #	11	12	13	14	15	16	17	18	19	20
1	0.16	0.03	0.02	0.04	0.07	0.02	0.04	0.03	0.06	0.01
2	0.13	0.02	0.02	0.03	0.05	0.02	0.04	0.03	0.06	0.02
3	0.07	0.03	0.03	0.04	0.06	0.03	0.04	0.04	0.06	0.04
4	0.18	0.02	0.03	0.04	0.08	0.02	0.04	0.04	0.06	0.01
5	0.11	0.01	0.02	0.03	0.04	0.02	0.04	0.03	0.06	0.02
6	0.11	0.01	0.01	0.02	0.04	0.01	0.03	0.03	0.05	0.01
7	0.12	0.02	0.02	0.03	0.05	0.02	0.04	0.03	0.06	0.01
8	0.16	0.03	0.03	0.05	0.07	0.02	0.04	0.04	0.06	0.02
9	0.10	0.04	0.03	0.04	0.05	0.02	0.04	0.04	0.06	0.02
10	0.00	0.17	0.21	0.00	0.06	0.02	0.11	0.11	0.06	0.21
11	0.75	0.24	0.34	0.13	0.20	0.04	0.14	0.14	0.08	0.06
12	0.23	0.04	0.14	0.07	0.10	0.03	0.05	0.04	0.07	0.03
13	0.31	0.06	0.10	0.17	0.16	0.12	0.03	0.02	0.12	0.02
14	0.48	0.10	0.15	0.25	0.25	0.13	0.05	0.05	0.13	0.08
15	0.27	0.06	0.05	0.26	0.12	0.02	0.06	0.04	0.07	0.01
16	0.23	0.07	0.06	0.06	0.75	0.02	0.05	0.04	0.07	0.01
17	0.30	0.10	0.17	0.17	0.25	0.03	0.03	0.02	0.08	0.11
18	0.23	0.10	0.10	0.15	0.13	0.10	0.07	0.06	0.12	0.06
19	0.12	0.04	0.03	0.06	0.05	0.03	0.11	0.11	0.11	0.02
20	0.19	0.02	0.06	0.11	0.08	0.13	0.01	0.00	0.00	0.02
21	0.17	0.02	0.06	0.10	0.08	0.11	0.02	0.01	0.00	0.02
22	0.13	0.08	0.08	0.10	0.09	0.12	0.00	0.00	0.00	0.07
23	0.33	0.07	0.05	0.10	0.22	0.02	0.05	0.04	0.07	0.02
24	0.14	0.04	0.02	0.04	0.05	0.02	0.04	0.04	0.06	0.21
25	0.04	0.02	0.01	0.02	0.03	0.02	0.03	0.03	0.05	0.02
23	0.75	0.15	0.15	0.40	0.15	0.15	0.25	0.25	0.75	0.03
24	0.40	0.15	0.15	0.40	0.03	0.25	0.25	0.25	0.75	0.75
25	0.40	0.15	0.15	0.40	0.75	0.25	0.25	0.25	0.75	0.15

APPENDIX D

OVERALL BLOCKAGE PROBABILITIES OF THE SHORTEST PATHS

TableD.1: Probability that the Shortest Path Between a Candidate DRF Location and an Affected Area (1-10) is Blocked

	Affected Areas (1-10)									
DRF #	1	2	3	4	5	6	7	8	9	10
1	0.00	0.00	0.03	0.10	0.43	0.10	0.91	0.03	0.87	0.87
2	0.03	0.03	0.05	0.03	0.33	0.03	0.91	0.82	0.88	0.03
3	0.10	0.08	0.08	0.10	0.31	0.31	0.67	0.84	0.90	0.32
4	0.00	0.00	0.17	0.10	0.38	0.10	0.00	0.03	0.87	0.10
5	0.03	0.03	0.03	0.03	0.01	0.03	0.82	0.82	0.94	0.03
6	0.15	0.15	0.57	0.10	0.54	0.10	0.03	0.03	0.32	0.58
7	0.03	0.82	0.82	0.32	0.82	0.32	0.00	0.00	0.31	0.59
8	0.15	0.15	0.88	0.23	0.87	0.87	0.77	0.77	0.40	0.88
9	0.97	0.01	0.09	0.11	0.32	0.01	0.82	0.83	0.94	0.26
10	0.92	0.59	0.59	0.70	0.41	0.40	0.90	0.75	0.85	0.40
11	0.46	0.46	0.49	0.51	0.27	0.26	0.93	0.47	0.90	0.25
12	0.15	0.15	0.17	0.23	0.92	0.23	0.90	0.17	0.85	0.85
13	0.12	0.12	0.21	0.14	0.41	0.14	0.92	0.07	0.89	0.81
14	0.89	0.89	0.77	0.78	0.92	0.75	0.99	0.76	0.98	0.75
15	0.03	0.03	0.19	0.12	0.40	0.12	0.91	0.05	0.88	0.25
16	0.03	0.03	0.19	0.12	0.40	0.12	0.91	0.05	0.88	0.75
17	0.96	0.96	0.92	0.51	0.88	0.88	0.99	0.47	0.99	0.88
18	0.17	0.17	0.32	0.26	0.49	0.26	0.93	0.19	0.89	0.15
19	0.24	0.24	0.37	0.32	0.53	0.32	0.93	0.26	0.90	0.22
20	0.21	0.21	0.29	0.23	0.47	0.23	0.93	0.16	0.90	0.81
21	0.23	0.23	0.31	0.25	0.48	0.25	0.93	0.18	0.90	0.81
22	0.89	0.89	0.91	0.90	0.93	0.90	0.99	0.89	0.99	0.89
23	0.03	0.03	0.19	0.12	0.40	0.12	0.91	0.05	0.88	0.00
24	0.87	0.01	0.09	0.12	0.67	0.01	0.83	0.59	0.75	0.00
25	0.00	0.00	0.08	0.10	0.31	0.75	0.53	0.55	0.86	0.01

TableD.2: Probability that the Shortest Path Between a Candidate DRF Location and an Affected Area (11-20) is Blocked

	Affected Areas (11-20)									
DRF #	11	12	13	14	15	16	17	18	19	20
1	0.82	0.19	0.17	0.46	0.76	0.24	0.37	0.29	0.89	0.03
2	0.82	0.21	0.19	0.47	0.76	0.26	0.39	0.30	0.89	0.05
3	0.59	0.28	0.33	0.56	0.80	0.38	0.49	0.42	0.91	0.23
4	0.82	0.12	0.17	0.46	0.76	0.24	0.37	0.29	0.89	0.03
5	0.82	0.14	0.19	0.47	0.76	0.26	0.39	0.31	0.89	0.18
6	0.84	0.12	0.17	0.46	0.76	0.24	0.37	0.29	0.89	0.17
7	0.82	0.14	0.19	0.47	0.76	0.26	0.39	0.30	0.89	0.05
8	0.84	0.31	0.30	0.54	0.79	0.35	0.47	0.39	0.91	0.17
9	0.56	0.42	0.37	0.59	0.81	0.57	0.64	0.59	0.94	0.18
10	0.01	0.80	0.79	0.00	0.75	0.22	0.85	0.81	0.89	0.93
11	0.75	0.85	0.84	0.25	0.81	0.42	0.89	0.86	0.91	0.47
12	0.84	0.31	0.89	0.54	0.79	0.35	0.47	0.39	0.91	0.17
13	0.96	0.10	0.23	0.94	0.57	0.53	0.16	0.14	0.93	0.14
14	0.95	0.21	0.15	0.86	0.69	0.59	0.41	0.23	0.94	0.89
15	0.86	0.41	0.36	0.55	0.75	0.22	0.36	0.27	0.89	0.05
16	0.81	0.21	0.15	0.45	0.75	0.22	0.41	0.23	0.89	0.05
17	0.98	0.43	0.53	0.88	0.53	0.28	0.31	0.10	0.89	0.96
18	0.84	0.33	0.28	0.49	0.79	0.37	0.41	0.32	0.91	0.19
19	0.85	0.39	0.34	0.53	0.81	0.00	0.54	0.42	0.85	0.26
20	0.96	0.21	0.23	0.92	0.46	0.42	0.03	0.00	0.00	0.23
21	0.96	0.23	0.23	0.92	0.46	0.42	0.05	0.03	0.03	0.25
22	0.98	0.91	0.90	0.93	0.97	0.85	0.03	0.00	0.00	0.89
23	0.81	0.21	0.15	0.45	0.75	0.22	0.36	0.27	0.89	0.05
24	0.41	0.22	0.15	0.45	0.75	0.42	0.52	0.45	0.91	0.88
25	0.41	0.23	0.16	0.45	0.75	0.42	0.53	0.46	0.92	0.17

APPENDIX E

FORMULATION USED FOR FINDING MAXIMUM RELIABLE PATHS

Sets		
I, J		nodes
Parameters		
d_{ij}	$i \in I, j \in J$	distance between the nodes
p_{ij}	$j \in J, k \in K$	blockage probabilities of the paths between the nodes
$initial$		initial node
$destination$		destination node
Variables		
$y_i j$	$i \in I$	1, if the path between node i and j is used; 0, otherwise

Objective function

$$\text{Minimize} \quad z = \frac{\sum_{i \in I} \sum_{j \in J} d_{ij} p_{ij} y_{ij}}{\sum_{i \in I} \sum_{j \in J} d_{ij}} \tag{E.1}$$

$$\tag{E.2}$$

$$\text{subject to :} \sum_{j \in J} y_{initial,j} - \sum_{j \in J} y_{j,initial} = 1 \tag{E.3}$$

$$\sum_{j \in J} y_{destination,j} - \sum_{j \in J} y_{j,destination} = -1 \tag{E.4}$$

$$\sum_{j \in J} \sum_{k \in K} t_{ijk} \leq M_1 y_i \qquad \forall i \in I \tag{E.5}$$

$$\sum_{j \in J} y_{i,j} - \sum_{j \in J} y_{j,i} = 0 \forall j \in J \neq destination, \forall i \in I \neq initial \tag{E.6}$$

$$\tag{E.7}$$

$$\sum_{j \in J} y_{ij} \leq 1 \forall j \in J \tag{E.8}$$

APPENDIX F

DISTANCES (IN METERS) OF MAXIMUM RELIABLE PATHS BETWEEN CANDIDATE DRF LOCATIONS AND AFFECTED AREAS

TableF.1: Distances (in meters) of Maximum Reliable Paths between Candidate DRF Locations and Affected Areas (1-10)

	Affected Areas (1-10)									
DRF #	1	2	3	4	5	6	7	8	9	10
1	1534	5125	15086	9615	13381	13910	14655	15380	16812	21599
2	4346	2764	12725	7254	11020	11549	16807	16183	20973	19238
3	15794	12610	523	11112	3980	21395	28255	27631	32421	18146
4	4805	10115	20076	14605	18371	18900	6307	7032	10473	27938
5	10607	7423	4664	5925	2959	16208	23068	23793	27234	12959
6	10969	16279	26240	20769	24535	25064	4059	4784	8225	34102
7	12310	18969	28930	23459	25876	26405	4092	473	8258	35443
8	15465	20775	30736	25265	29031	29560	8555	9280	12721	38598
9	15431	11703	22208	16737	4581	1822	26543	27268	32058	6950
10	26561	23377	22400	21879	16308	13549	37673	38398	43188	7265
11	24179	20995	20018	19497	13926	11167	35291	36016	40806	4883
12	18620	23930	33891	28420	32186	32715	11710	12435	15876	41753
13	40946	37762	36785	36264	30693	27934	52058	52783	56224	21650
14	37929	34745	33768	33247	27676	24917	49041	49766	54556	18633
15	29128	25944	24967	24446	18875	16116	40240	40965	44406	9832
16	28279	25095	24118	23597	18026	15267	39391	40116	43557	8983
17	32338	29154	28177	27656	22085	15431	43450	44175	48965	13042
18	36281	33097	32120	31599	26028	23269	47393	48118	52908	16985
19	41479	38295	37318	36797	31226	28467	53940	54665	58106	22183
20	42712	39528	38551	38030	32459	29700	53824	54549	59339	23416
21	45265	42081	41104	40583	35012	32253	56377	57102	61892	25969
22	61613	58429	57452	56931	51360	48601	74074	73450	76891	42317
23	3090	8400	18361	12890	16656	17185	10132	10857	14298	24874
24	20540	17356	16379	15858	10287	7528	31652	32377	37167	1244
25	13449	8683	20226	14755	3143	3694	24561	25286	29271	11436

TableF.2: Distances of Maximum Reliable Paths between Candidate DRF Locations and Affected Areas (11-20)

	Affected Areas (11-20)									
DRF #	11	12	13	14	15	16	17	18	19	20
1	26000	41023	38794	26819	27481	41294	42672	42527	61907	5656
2	23639	38662	36433	24458	25120	38933	40311	40166	59546	9817
3	22547	37570	35341	23366	24028	37841	39219	39074	58454	21265
4	30990	46013	43784	31809	32471	46284	47662	47517	66897	11995
5	17360	32383	30154	18179	18841	32654	34032	33887	53267	16078
6	37154	52177	49948	37973	38635	52448	53826	53681	73061	18159
7	39844	54867	52638	40663	39976	55138	56516	55022	75751	19500
8	41650	56673	54444	42469	43131	56944	58322	58177	77557	22655
9	11351	26374	24145	12170	12832	26645	28023	27878	47258	20358
10	2512	21077	18848	6873	7535	21348	22726	22581	41961	32032
11	3672	18695	16466	4491	5153	18966	20344	20199	39579	29650
12	44805	59828	57599	45624	46286	60099	61477	61332	80712	25810
13	20439	1068	5461	17400	14378	22609	16234	16089	35469	46417
14	17422	4673	1050	14383	11361	19592	19839	19694	39074	43400
15	8621	17454	15225	5582	3912	17725	19103	18958	38338	34599
16	7772	16605	14376	4733	3063	16876	18254	18109	37489	33750
17	11831	9846	7617	8792	5770	14001	11495	11350	30730	37809
18	15774	17673	15444	12735	9713	10484	19322	19177	38557	41752
19	20972	22871	20642	17933	14911	0	24520	24375	43755	46950
20	22205	16351	20744	19166	16144	24375	4545	2140	19380	48183
21	24758	18904	23297	21719	18697	26928	7098	2553	21933	50736
22	41106	35252	39645	38067	35045	43276	23446	18901	1877	67084
23	29275	44298	42069	30094	30756	44569	45947	45802	65182	10280
24	5645	20668	18439	6464	7126	20939	22317	22172	41552	26011
25	15837	30860	28631	16656	17318	31131	32509	32364	51744	20639

APPENDIX G

AVERAGE BLOCKAGE PROBABILITIES OF THE MAXIMUM RELIABLE PATHS

TableG.1: Probability that the Maximum Reliable Paths Between a Candidate DRF Location and an Affected Area (1-5) is Blocked

	Affected Areas (1-5)				
DRF #	1	2	3	4	5
1	0.000000	0.000000	0.000000	0.000000	0.000007
2	0.000025	0.000025	0.000025	0.000025	0.000032
3	0.000044	0.000044	0.000044	0.000044	0.000050
4	0.000000	0.000000	0.000000	0.000000	0.000007
5	0.000000	0.000000	0.000000	0.000000	0.000007
6	0.000000	0.000000	0.000000	0.000000	0.000007
7	0.000000	0.000000	0.000000	0.000000	0.000007
8	0.000000	0.000000	0.000000	0.000000	0.000007
9	0.000017	0.000017	0.000017	0.000017	0.000017
10	0.000043	0.000043	0.000043	0.000043	0.000048
11	0.000262	0.000262	0.000262	0.000262	0.000266
12	0.000000	0.000000	0.000000	0.000000	0.000007
13	0.000158	0.000158	0.000158	0.000158	0.000162
14	0.000534	0.000534	0.000534	0.000534	0.000539
15	0.000031	0.000031	0.000031	0.000031	0.000035
16	0.000082	0.000082	0.000082	0.000082	0.000086
17	0.000071	0.000071	0.000071	0.000071	0.000076
18	0.000294	0.000294	0.000294	0.000294	0.000298
19	0.000391	0.000391	0.000391	0.000391	0.000395
20	0.000244	0.000244	0.000244	0.000244	0.000249
21	0.000315	0.000315	0.000315	0.000315	0.000320
22	0.000244	0.000244	0.000244	0.000244	0.000249
23	0.000029	0.000029	0.000029	0.000029	0.000036
24	0.000029	0.000029	0.000029	0.000029	0.000033
25	0.000006	0.000006	0.000006	0.000006	0.000007

TableG.2: Probability that the Maximum Reliable Paths Between a Candidate DRF Location and an Affected Area (6-10) is Blocked

	Affected Areas (6-10)				
DRF #	6	7	8	9	10
1	0.000015	0.000000	0.000000	0.000477	0.000029
2	0.000040	0.000025	0.000025	0.000502	0.000054
3	0.000058	0.000044	0.000044	0.000520	0.000072
4	0.000015	0.000000	0.000000	0.000477	0.000029
5	0.000015	0.000000	0.000000	0.000477	0.000029
6	0.000015	0.000000	0.000000	0.000477	0.000029
7	0.000015	0.000000	0.000000	0.000477	0.000029
8	0.000015	0.000000	0.000000	0.000477	0.000029
9	0.000002	0.000017	0.000017	0.000494	0.000016
10	0.000032	0.000043	0.000043	0.000520	0.000014
11	0.000251	0.000262	0.000262	0.000739	0.000233
12	0.000015	0.000000	0.000000	0.000477	0.000029
13	0.000147	0.000158	0.000158	0.000635	0.000129
14	0.000524	0.000534	0.000534	0.001011	0.000506
15	0.000020	0.000031	0.000031	0.000507	0.000002
16	0.000071	0.000082	0.000082	0.000558	0.000053
17	0.000060	0.000071	0.000071	0.000548	0.000043
18	0.000283	0.000294	0.000294	0.000771	0.000265
19	0.000380	0.000391	0.000391	0.000868	0.000362
20	0.000234	0.000244	0.000244	0.000721	0.000216
21	0.000304	0.000315	0.000315	0.000792	0.000287
22	0.000234	0.000244	0.000244	0.000721	0.000216
23	0.000044	0.000029	0.000029	0.000506	0.000058
24	0.000018	0.000029	0.000029	0.000505	0.000000
25	0.000008	0.000006	0.000006	0.000483	0.000026

TableG.3: Probability that the Maximum Reliable Paths Between a Candidate DRF Location and an Affected Area (11-15) is Blocked

	Affected Areas (11-15)				
DRF #	11	12	13	14	15
1	0.000046	0.000202	0.000709	0.000031	0.000488
2	0.000071	0.000227	0.000734	0.000056	0.000513
3	0.000089	0.000246	0.000753	0.000074	0.000531
4	0.000046	0.000202	0.000709	0.000031	0.000488
5	0.000046	0.000202	0.000709	0.000031	0.000488
6	0.000046	0.000202	0.000709	0.000031	0.000488
7	0.000046	0.000202	0.000709	0.000031	0.000488
8	0.000046	0.000202	0.000709	0.000031	0.000488
9	0.000033	0.000189	0.000696	0.000018	0.000475
10	0.000014	0.000184	0.000691	0.000012	0.000470
11	0.000246	0.000403	0.000910	0.000231	0.000689
12	0.000046	0.000202	0.000709	0.000031	0.000488
13	0.000143	0.000067	0.000629	0.000127	0.000585
14	0.000519	0.000499	0.000175	0.000504	0.000961
15	0.000015	0.000172	0.000679	0.000000	0.000457
16	0.000066	0.000223	0.000730	0.000051	0.000508
17	0.000056	0.000212	0.000719	0.000041	0.000498
18	0.000278	0.000435	0.000942	0.000263	0.000720
19	0.000376	0.000532	0.001039	0.000360	0.000818
20	0.000229	0.000226	0.000788	0.000214	0.000671
21	0.000300	0.000296	0.000859	0.000285	0.000742
22	0.000229	0.000226	0.000788	0.000214	0.000671
23	0.000075	0.000231	0.000739	0.000060	0.000517
24	0.000017	0.000174	0.000681	0.000002	0.000459
25	0.000043	0.000200	0.000707	0.000028	0.000485

TableG.4: Probability that the Maximum Reliable Paths Between a Candidate DRF Location and an Affected Area (16-20) is Blocked

	Affected Areas (16-20)				
DRF #	16	17	18	19	20
1	0.000391	0.000309	0.000244	0.000244	0.000080
2	0.000416	0.000334	0.000269	0.000269	0.000105
3	0.000434	0.000353	0.000288	0.000288	0.000123
4	0.000391	0.000309	0.000244	0.000244	0.000080
5	0.000391	0.000309	0.000244	0.000244	0.000080
6	0.000391	0.000309	0.000244	0.000244	0.000080
7	0.000391	0.000309	0.000244	0.000244	0.000080
8	0.000391	0.000309	0.000244	0.000244	0.000080
9	0.000378	0.000297	0.000231	0.000231	0.000097
10	0.000373	0.000291	0.000226	0.000226	0.000123
11	0.000592	0.000510	0.000445	0.000445	0.000342
12	0.000391	0.000309	0.000244	0.000244	0.000080
13	0.000488	0.000246	0.000181	0.000181	0.000238
14	0.000864	0.000679	0.000613	0.000613	0.000614
15	0.000360	0.000279	0.000214	0.000214	0.000110
16	0.000411	0.000330	0.000265	0.000265	0.000161
17	0.000401	0.000320	0.000254	0.000254	0.000151
18	0.000537	0.000542	0.000477	0.000477	0.000373
19	0.000000	0.000639	0.000574	0.000574	0.000471
20	0.000574	0.000065	0.000000	0.000000	0.000324
21	0.000645	0.000136	0.000071	0.000071	0.000395
22	0.000574	0.000065	0.000000	0.000000	0.000324
23	0.000420	0.000339	0.000274	0.000274	0.000109
24	0.000362	0.000281	0.000216	0.000216	0.000108
25	0.000388	0.000307	0.000242	0.000242	0.000086