

SHELTER SITE LOCATION UNDER DEMAND UNCERTAINTY: A CHANCE-CONSTRAINED MULTI-OBJECTIVE MODELING FRAMEWORK

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By
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FRAMEWORK

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We certify that we have read this thesis and that in our opinion it is fully adequate,
in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

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M.S. in Industrial Engineering

Advisor: Bahar Yetiş

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Shelters have a very critical role in disaster relief since they provide accommodation and necessary services for the disaster victims who lost their homes. The selection of their locations among many candidate points is a task that should be carried out with a proper methodology that generates applicable and fairness-based plans. Since this selection process is done before the occurrence of disasters, it is important to take demand variability into account. Motivated by this, the problem of determining shelter site locations under demand uncertainty is addressed. In particular, a chance-constrained mathematical model that takes demand as a stochastic input is developed. By using a linearization approach that utilizes special ordered set of type 2 (SOS2) variables, a mixed-integer linear programming model is formulated. Using the proposed formulation, instances of the problem using data associated with Istanbul are solved. The results indicate that capturing uncertainty in the shelter site location problem by means of chance constraints may lead to solutions that are much different from those obtained from a deterministic setting. During these computational analysis, it is observed that the single-objective model is prone to generate many alternative solutions with different characteristics of important quality measures. Motivated by this, a multi-objective framework is developed for this problem in order to have a stronger modeling approach that generates only non-dominated solutions for the selected performance measures. The ε -constraint method is used for scalarization of the model. Bi-objective and 3-objective algorithms are presented for detecting all the efficient solutions of a given setting. Unlike the single-objective configuration, the decision makers could be supplied with much richer information by reporting many non-dominated solutions and allowing them to evaluate the trade-offs based on their preferences.

Keywords: Disaster Management, Shelter Site Location, Discrete Facility Location, Stochastic Programming, Chance-Constraints, Multiple-Objective Programming, ε -constraint Method.



ÖZET

RASSAL TALEP ALTINDA BARINAK ALANI YER SEÇİMİ PROBLEMİ: OLASILIKSAL KISITLI ÇOK AMAÇLI MODELLEME YAKLAŞIMI

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Barınaklar, evlerini kaybetmiş afetzedeler için konaklama ve gerekli servisleri alabilme imkanı sunduğundan, afet yardımında önemli rol oynamaktadır. Birçok potansiyel konum arasından bu barınakların açılacağı yerleşim noktalarının seçilmesi, uygulanabilirlik ve hakkaniyet ilkelerini temel alan uygun yöntemler aracılığıyla gerçekleştirilmesi gereken bir süreçtir. Bu süreç herhangi bir afetin gerçekleşmesinden önce ele alındığından, barınaklara olan talebin değişkenliği göz önünde bulundurulması gereken önemli bir noktadır. Bu noktadan yola çıkılarak, barınak alanı yerlerinin talep değişkenliği altında belirlenmesi problemi ele alınmış ve talebi rassal bir parametre olarak kullanan, olasılıksal kısıtlı bir matematiksel model geliştirilmiştir. Bu model SOS2 tipi değişkenler kullanılarak doğrusallaştırılmış ve karışık tamsayılı doğrusal bir formülasyon elde edilmiştir. Önerilen formülasyon kullanılarak, İstanbul iline ait veri kümeleri ile hesaplama çalışmaları yapılmıştır. Yapılan analizler, talep değişkenliğini göz önünde bulundurarak barınak alanı yer seçimi problemini ele almanın, deterministik bir formülasyona kıyasla oldukça farklı sonuçlara ortaya koyabileceğini ve dolayısıyla deterministik talep varsayımı altında çalışmanın problemi olması gerekenden daha fazla basite indirgeyebileceğini göstermiştir. Yapılan tüm bu analizler sırasında tek amaç fonksiyonlu modelin farklı niteliklere sahip birçok alternatif çözüm bulmaya yatkın olduğu görülmüştür. Bu nedenle, belirlenen ölçütlerde sadece baskın sonuçlar elde etmek için bu problemin çok amaçlı bir çerçevede ele alınmasına karar verilmiştir. Belirlenen kurulumlarda bütün verimli sonuçları bulabilmek için iki ve üç amaçlı modelleri çözebilecek ε -kısıt yöntemi tabanlı algoritmalar geliştirilmiştir. Bu problem için çok amaçlı modeller kullanıldığında, karar vericiler daha zengin bir şekilde bilgilendirilebilmekte ve baskın sonuçlar arasından durum şartlarına göre en uygun olanı belirleyebilmektedir.

Anahtar sözcükler: Afet Yönetimi, Barınak Alanı Yeri Seçimi, Ayrık Tesis Yer Seçimi, Rassal Programlama, Olasılıksal Kısıtlar, Çok Amaçlı Programlama, ε -kısıt Yöntemi.



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Chapter 1

Introduction

Location analysis is defined as the field of study that uses models and techniques to provide decision makers preferable solutions to their locational decision problems. These analyses are usually evaluated as part of logistics operations.

Humanitarian logistics is a branch of logistics that deals with delivering vital supplies and services during and aftermath of a disaster. Locational decision problems also emerge as a part of humanitarian logistics efforts. A disaster may result in people losing their homes and in this case it is necessary to establish shelter areas to provide those people safe places to accommodate. Hence, determining the locations of the best possible sites is one of the important applications of location problems that is evaluated in this context.

In this thesis, the problem of determining shelter site locations under demand uncertainty is addressed. The aim is to increase disaster preparedness by developing applicable and fairness-based approaches for selecting best possible locations among many candidates. A chance-constrained mathematical model that takes demand as a stochastic input is developed, expecting that it could be a guidance to the decision makers.

In the following chapter; firstly, the core standards for humanitarian logistics operations are discussed. Next, types of disasters are defined and classified.

Turkey's seismic vulnerability is discussed by referring to geographical conditions, some historical data and studies based on anticipation of future disasters. Then, the basis of this thesis, shelter site location problem is introduced by mentioning the roles of these locations and current shelter location selection procedure in Turkey. The section is concluded by explaining the importance of capturing uncertainty and making use of multi-objective approaches to come up with a better methodology for shelter site location problem.

In Chapter 3, the most relevant literature related with this study is reviewed. Moreover, the unique characteristics of this thesis is pointed out while comparing the main characteristics of it with others.

In Chapter 4, first a chance-constrained mathematical model is developed. In particular, a maxmin probabilistic programming model that includes two types of probabilistic constraints is proposed. All technical details related to the model development process are also discussed step by step. The chapter continues with computational studies on two real data sets based on Istanbul. The aim is to see whether capturing demand uncertainty and using probabilistic constraints could lead to solutions that are much different from those obtained when a deterministic counterpart is considered.

In Chapter 5, a novel multi-objective framework for the shelter site location problem with stochastic demand is proposed. The objectives that could be used in the context of shelter site location are presented. Then, the tailored ε -constraint method is introduced and technical details of multi-objective model development are discussed. A new algorithm for solving 3-objective ε -constraint method is also introduced. Computational results for many different settings are provided and all the non-dominated solutions of each setting are listed.

The thesis ends with a conclusion chapter that is comprised of an overview of the work done along with some guidelines for future research opportunities.

Chapter 2

Problem Definition

Throughout the history of humankind, disasters, man-made or natural, had played a determinative role on human life. Especially with the start of the 20th century, in conjunction with fast and unplanned urbanization in densely populated areas, disasters seemed as more destructive than ever before. Balcik and Beamon [1] shows that the number of people affected by disasters between 2000-2004 was 33% more than 1995-1999. Moreover, in 2005, there were 7 million more people compared to 2004 who were victims of some disaster. This trend, unfortunately, has continued until today and it is estimated that about 235 million people per year had been affected since the 1990s [2]. This led to pursuit of developing approaches for at least preventing some portion of these losses and fortunately drawn notable attention towards development of humanitarian logistics and disaster management programs. Van Wassenhove [3] asserts that disaster relief is 80% logistics and for better disaster management we definitely need efficient and effective logistics operations. So that, nowadays, tools of optimization, statistical analysis and simulation started to be frequently used in order to be prepared for an upcoming disaster.

The official disaster definition by International Federation of Red Cross and Red Crescent Societies (IFRC) is as follows: “*A sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human,*

material, and economic or environmental losses that exceed the community's or society's ability to cope using its own resources" [4].

It is known that disasters can be seen in many forms. Even if they are usually caused by nature, they can also have human origins and initial classification could be done according to their causes (natural or man-made). Under the title of natural disasters, there are destructive geological (earthquakes, avalanches, landslides, volcanic eruptions), hydrological (floods, tsunamis) and meteorological (blizzards, droughts, tornadoes, storms, heat waves) events with varying characteristics about speed of occurrence, location predictability and timing predictability. Man-made disasters can be listed as political crises, terrorist or chemicals attacks and they can be classified based on their onset lengths. It should be indicated that the relevance of logistics effort is distincter for sudden onset natural disasters. Figure 2.1 summarizes this disaster categorization as a chart.

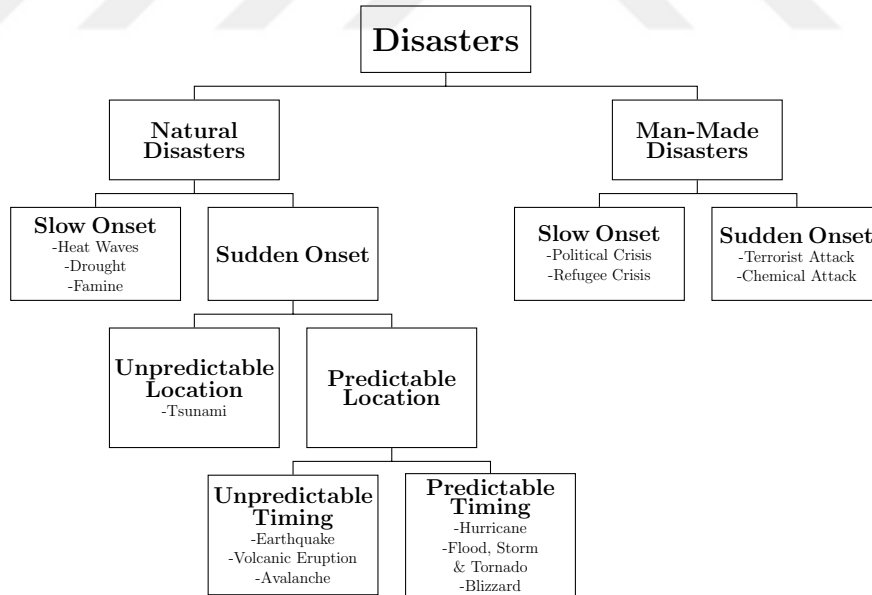


Figure 2.1: Classification of Disasters

Van Wassenhove [3] defines three main principles of humanitarian logistics and disaster management as *humanity*, *neutrality* and *impartiality*. *Humanity* expresses that anyone who is in need of assistance must be helped independently of their location. *Neutrality* hinders any actor to take a side with any bias while

conducting humanitarian operations. Lastly, *impartiality* refers that all the operations should be conducted on the basis of need without making any gender, nationality, race or class discrimination. In essence, these three principles assure that fairness is valued over anything else while making humanitarian effort.

McLoughlin [5], which is a pioneering study in the field of emergency management, is the first study that described an adequate disaster management program and its components. These components (i.e. processes) are defined as (i) mitigation; (ii) preparedness; (iii) response; and (iv) recovery and they are based on phases of disaster time-line. The pre-disaster processes are related with categories (i) and (ii) while categories (iii) and (iv) refer to post-disaster operations. In particular, mitigation refers to the actions taken in order to prevent the consequences of a disaster or reduce the long-term risk. The preparedness phase involves the elaboration of plans to provide a more efficient response when a disaster occurs. The response phase starts immediately after the event and aims to save lives in the first place and secondarily provide relief goods such as water, food, medical care, and shelter. Finally the recovery phase takes usually longer time and aims to recover all the damaged (infra)structures in order to ensure that the life of the affected population is returned to normal. The main activities of each phase is listed below.

- **Mitigation:** Risk mapping, disaster insurance, disaster-proof building, safety code assessment.
- **Preparedness:** Emergency operations plans, resource management plans, inventory prepositioning, aid agreements, warning and emergency communication systems, trainings and disaster simulation drills.
- **Response:** Emergency plan activation, search and rescue operations, medical assistance, instructions to public, relief item distribution, sheltering and evacuation.
- **Recovery:** Cleaning debris, damage assessment, control of contamination, facility and infrastructure restoration, temporary housing.

2.1 Turkey's Seismic Vulnerability

Turkey is a country much vulnerable to natural disasters. Since the beginning of the 20th century more than half-million homes have been destroyed [6] due to different kinds of disasters (e.g, earthquakes, landslides, floods). Besides this structural destruction, unfortunately, these disasters caused approximately 85,000 fatalities and 210,000 injuries [7].

The geographical region that Turkey is located is known to be a seismically active one; therefore, earthquakes are the disasters with the most severe consequences in this geography, being the direct cause of nearly 70% of the destruction stated above [7]. On Table 2.1, major earthquakes that occurred since 1990 are listed along with some statistics. Among these, the August '99 (Izmit) and October '11 (Van) are drawing the attention as being the most destructive ones. These disastrous events caused approximately 20,000 to die and 60,000 to be injured. Moreover, it is estimated that nearly 1.1 million people lost their homes as a result of these eight occurrences shown on Table 2.1.

Epicenter	Date	Death Toll	Injured Count	Homeless Count
Erzincan	March '92	653	3,850	95,000
Dinar	October '95	94	240	40,000
Ceyhan	June '98	145	1,600	88,000
Izmit	August '99	17,483	43,953	675,000
Düzce	November '99	763	4,948	35,000
Afyon (Sultandağı)	February '02	42	327	30,000
Bingöl	May '03	177	520	45,000
Van	October '11	644	4,150	175,000
TOTAL		20,001	59,588	1,183,000

Table 2.1: Major earthquakes happened in Turkey since 1990 [7], [8]

According to the statistical analysis, it is observed that, an earthquake with destructive capabilities happens in every 8 months across Turkey [9]. In addition to that, Table 2.2 demonstrates that more than 70% of the total population of Turkey is living in first or second degree threat zones which covers more than 65% of the total surface area of the country. Unfortunately, only 2% of the citizens are living in zones which do not seem to pose much threat. These threat zones are

determined based on the differentiation of estimated peak ground acceleration (PGA) value. This value indicates the approximated highest acceleration on the shaking ground during an earthquake.

Threat Degree	PGA	Population (%)	Surface Area (%)
First Degree	$\text{PGA} \geq 0.4g$	45%	42%
Second Degree	$0.3g \leq \text{PGA} \leq 0.4g$	26%	24%
Third Degree	$0.2g \leq \text{PGA} \leq 0.3g$	14%	18%
Fourth Degree	$0.1g \leq \text{PGA} \leq 0.2g$	13%	12%
Fifth Degree	$\text{PGA} \leq 0.1g$	2%	4%

Table 2.2: Earthquake Threat Zone Specifications of Turkey [10]

The Anatolian tectonic plate contains two major faults, namely the North Anatolian and the East Anatolian fault. These two faults encompass the whole country and are the main reason to have a highly earthquake-vulnerable geography. Figure 2.2 illustrates the seismic vulnerability map of Turkey and it could be observed that first degree threat zones are located along these main faults.

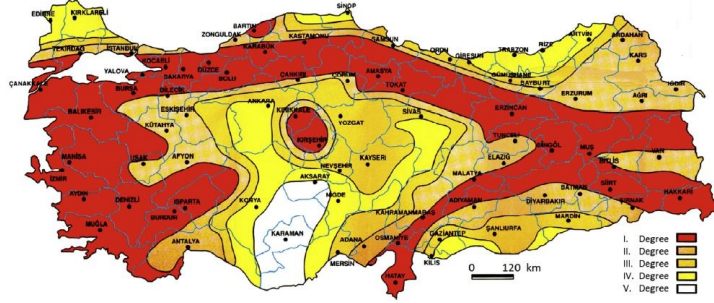


Figure 2.2: Earthquake-Prone Regions in Turkey [11]

After the earthquake with 7.4 magnitude happened in Izmit in 1999, researchers have increased focus on the movements of North Anatolian fault system. They have observed that, the northwest of this system has been getting more and more fragile as a result of seven high-magnitude earthquakes along this fault line since 1939. One of the early millennium research, Parsons et al.[12], indicates that all the recent movement on the aforementioned fault system has significantly increased the probability of occurrence of a major earthquake near Istanbul. They have shown that a highly destructive earthquake in Marmara region is inevitable.

Moreover, using an interaction-based probability calculation approach, they point out a frightening finding that Istanbul will be hit by a strong earthquake with $60 \pm 15\%$ probability within the next 30 years. As of now, 17 years of the anticipated period have passed, which implies that the occurrence probability should have been increased further.

Istanbul is known to be a metropolitan city with its nearly 15 million population and approximately $2700 \text{ people}/\text{km}^2$ population density. In fact, it is the 5^{th} most crowded and 6^{th} most densely populated city around the world. Besides its seismically vulnerable location, the population density aspect and unplanned urbanization of the city is posing as a significant threat that could lead to a catastrophe in a future disaster. Motivated by this, this study intends to contribute on improving disaster preparedness of such vulnerable countries, by developing efficient resource management plans via addressing the sheltering issues.

2.2 The Role of Shelter Sites

When a disaster results in people losing their homes, it is necessary to accommodate such people in temporary shelter areas until the disaster recovery phase is over. These shelters play a vital role in reducing the vulnerability of disaster victims and considered to be a lot more than just “accommodation” for them. In these facilities, providing food, water, medical treatment and sanitation is essential to prepare an environment for the residents where they could continue their lives with dignity. Besides, shelters also serve for preserving the personal safety of residents and protecting them from severe weather conditions.

In order to have reference points for minimum standards of disaster management operations, IFRC prepared a scheme in 1997 and named it as *The Sphere Project: Humanitarian Charter and Minimum Standards in Humanitarian Response*. They have also published a book called The Sphere Handbook [13] in which they set the principles and core standards for four main groups of subjects. These groups are itemized below.

- Nutrition, food security and food aid
- Water supply, sanitation and hygiene
- Shelter, settlement and non-food items
- Health action

This handbook [13] emphasizes that establishing shelter areas plays a very important part in recovery phase of disaster management. As these facilities are aiming to guarantee a certain level of life standard for those who try to recover from the effects of a disaster, selecting their locations is a process that should be done strategically to determine the best ones to operate; i.e. to make use of candidate locations in an efficient manner. Therefore the problem of selecting temporary shelter areas is one of the fundamental facility location problems to address for better disaster management. The problem is known in the literature as the shelter site location problem.

2.3 The Shelter Site Location Problem

Practice in Turkey

All over the world, most of the developed countries have specified methodologies for locating shelter areas and providing emergency supplies to the affected people. Next, the current practice in Turkey is analyzed.

The first step is identifying the potential sites for shelter areas in disaster prone areas and densely populated zones, i.e. the regions where the probability of a catastrophe is high (e.g. Istanbul). It should not gone unnoticed that the selection of the candidate locations is done *a priori*, which shows that this problem is a kind of a resource management plan to be established in the preparedness phase. The candidate locations can be parks, yards, school gardens or parking lots; i.e. a spot that can be characterized as “*safe*” in the event of a disastrous situation.

Then, to rank the potential sites with the aim of finding the most suitable ones, 10 criteria are used based on the basics introduced by The Sphere Handbook [13]. The elements of these criteria set are listed next.

- Reachability
- Relief items procurement
- Healthcare institutions
- Terrain structure
- Soil type
- Terrain slope
- Terrain flora
- Electrical infrastructure
- Sanitary system
- Ownership status

Each criterion defines a quality measure for a candidate shelter site location and if 10 of them are considered simultaneously, the overall suitability of this site can be assessed. The reachability criterion measures the closeness of the candidate area to the main roads to ensure transportation convenience of relief items. Secondly, as these relief items are provided from a warehouse or supermarket, relief items procurement will be less costly if an open shelter is closer to them. Distance to healthcare institutions is another important criterion; it measures the closeness of the candidate area to nearest hospital or clinic to ensure practicability of emergency medical action. There are four criteria related to the topography specifications of the land. Terrain structure identifies whether the candidate site is on a mountainside, on a stream bed, on a valley or on a savannah. Soil type evaluates the hardness of the candidate location's soil. Harder soil is more convenient to make temporary constructions on as well as being less affected by rainfall. Terrain slope is a significant performance measure for a location as flat surfaces are usually more favorable than sloping ones. Flora is also important as the vegetation cover provides natural shadows for sun protection in addition to generating oxygen-rich areas. As the aim of providing shelter sites for disaster victims is providing them an environment where they could continue their daily lives with dignity, existence of electrical infrastructure is an added value for a candidate location. Similarly, availability of sewage infrastructure and sanitary system is also substantial in these areas to assure a hygienic environment. It should not be forgotten that each criterion may have a different significance in

decision maker's perspective.

After specifying the attribute values for all 10 criteria for all candidate shelter sites according to the designated scale, a suitability rating for each location could be calculated. In this study, this rating will be referred as the *weight* of a shelter area. These *weights* are calculated as a convex combination of the normalized attribute values of the criteria and is valued between $[0, 1]$.

After determining the *weights* of each potential site, all of them can be sorted non-increasingly according to the corresponding *weights*. As a final step of this current methodology, the decision makers use the list of locations induced by the above sorting for sequentially deciding about the shelters to construct. The selection process proceeds until sufficient number of shelter sites are open for accommodating all the affected people.

Additional Aspects to Consider

At first glance, the aforementioned methodology may seem plausible. Nevertheless, considering this shelter site location selection problem from different aspects, specifically concerning fairness related issues, it could be significantly improved.

To begin with, demand point (sub-district) - shelter area assignments are neglected in the current methodology. Instinctively, the affected people who are in need for sheltering would like to reach the nearest open facility, which may be full. Therefore, this could create problems such as excessive coverage of distance or over-utilization of some of the open shelters which could be classified as an unfair situation. This could be avoided by assigning and directing the affected population to specified shelter sites.

Secondly, utilizations of shelters should also get sufficient attention while making the assignments of the affected population to shelter areas. The living conditions would be a lot more convenient in less utilized shelter areas which would result in an iniquitous situation for the ones living in fully-utilized or even over-utilized shelters. Therefore, utilization fairness should also be addressed.

Another aspect is about the travel distance of affected population. Distance between shelter sites to be opened and population centers should be considered to prevent any inconvenience about reachability; such as all open shelters being excessively far away from a single demand point.

All of these three addressed aspects of this methodology could cause fairness issues which obviously is contradictory to the essence of humanitarian operations. In order to accommodate these issues, Kılıcı et al.[14] proposed a novel approach to address this important humanitarian logistics related facility location problem. Their approach is also the main trigger and the starting point of this research. They used a single objective mixed integer linear programming formulation aiming at maximizing the minimum weight of the shelters to open while deciding about the assignment of the population areas/regions/zones to those shelters and simultaneously ensuring a minimum threshold for the utilization rate of the shelters. The authors also consider closest assignment constraints while using the demand to the shelters as a deterministic input. Their approach is analyzed in detail in the upcoming sections.

2.3.1 Importance of Capturing Uncertainty

Unfortunately, neither the occurrence of natural disasters nor its consequences can be predicted in most of the cases, particularly for the ones that are sudden onset and have predictable location and unpredictable timing (e.g. earthquakes). Moreover, their destruction level may vary significantly according to intensity, location and duration; hardly will the impact be known in advance. Consequently, the amount of sheltering needed may vary significantly as well. Since the selection of the candidate locations for the shelters is done *a priori*, it is important to take demand uncertainty into account when such selection is made. This implies that it is not favorable to work with deterministic demand assumptions for resource management plans in the preparedness phase of disaster management. As a matter of fact, it is important to evaluate variability of demand (number of people who are in need for a shelter area) as a methodological development for shelter

site selection.

2.3.2 Making Use of Multi-Objective Approaches

In humanitarian operations, using a single-objective may not be always enough to ensure overall fairness and/or better use of resources.

Maximization of the minimum weight of the open shelters is an objective that is used in the context of this problem. However, while maintaining the minimum acceptable level for the open shelter locations' *weights* at the possible maximum level, this objective cannot make sure that the best-weighted locations are utilized. Thus, the resources available may not be put to their best use by using only the single objective approach in this context. Therefore, this exemplifies a case that a side-objective is necessary to assure better use of resources to serve public welfare.

Recall that closest assignment constraints are used as a methodological development to address any reachability issues in shelter site location context. However, although these constraints aim at achieving a desirable outcome, they may not guarantee the best solution in terms of total distance traveled, which decreases their applicability. Hence, it is apparent that these constraints should be used along with a side-objective related to minimizing distance traveled to detect better solutions.

Chapter 3

Literature Review

The application of Operations Research (OR)/Management Science (MS) models and methods to disaster operations management is not new. The review papers by Altay and Green [15] and Galindo and Batta [16] show that the related works have their roots back in 1980s and the attention from scientific community augmented after the start of the 21th century. Within this field, humanitarian logistics has emerged as an important topic in which much research has been done as attested by the review papers Kovacs and Spens [17], Ortuño et al. [18], and Leiras et al.[19].

A relevant class of problems in the context of humanitarian logistics are facility location problems and a general categorization for those can be proposed as follows: (i) medical center location problems (ii) warehouse (relief material) location problems and (iii) shelter site location problems. When the aforementioned review papers are analyzed, it is observed that most of the literature covers categories (i) and (ii). In the first section of this chapter, the focus is on category (iii). In the second section, notable studies that are addressing humanitarian logistics related stochastic facility location problems (specifically, the ones utilizing chance-constraints) are discussed. In the last section of this chapter, the literature on multi-objective shelter site location problem is analyzed.

3.1 Shelter Site Location Problem Literature

As it is discussed in the problem definition section, shelters have a substantial role in disaster management since they provide accommodation and necessary services for the disaster victims who lost their homes. The selection of their location is a task that should be carried out with care and there are many quality measures that could define the “best” location for a shelter. Distinctively from conventional facility location problems, fairness related issues should not be compromised in this context.

For these type of problems, the literature is scarce compared to the other facility location problems’ on humanitarian logistics. Many of the distinguished studies are discussed next.

Sherali et al. [20] studied a problem that consists of selecting a set of shelters to open together with an evacuation plan for vehicles that altogether minimize the evacuation time. The authors developed a non-linear mixed-integer programming formulation and a heuristic alongside with an exact approach based upon a generalized Benders decomposition method. They conducted computational tests via using the network of a city in southeastern Virginia.

Kongsomsaksakul et al. [21] studied flood evacuation planning framework with shelter location decisions. The problem is modeled as a Stackelberg game where the leader (imitating the authority) determines the locations of shelters (that minimizes total evacuation time) and the follower (imitating the evacuee) chooses which shelter to go and which route to take. The proposed bi-level programming problem is solved using genetic algorithm on the data set of Logan network in Utah, United States.

Alçada-Almeida et al. [22] considered a potential disaster triggered by fire in an urban area and proposed a multi-objective model for locating p shelters together with the identification of evacuation routes. Data from the city of Coimbra, Portugal, was considered in that study. The work would be later extended by Coutinho-Rodrigues et al. [23], where a multi-objective location-routing model

was proposed for shelter site location and evacuation planning. An exogenous risk measure is considered for the evacuation paths and for the shelters to model link and node disruptions. Their model aims at identifying the number and location of shelters as well as a set of primary and secondary evacuation routes.

Anping [24] addressed a maximal covering modeling approach for shelter location problem specifically for typhoons and provided two mathematical formulations. The first one incorporates a basic maximal set covering setting where the objective is to minimize the uncovered demand. In the second one, capacity limitations of shelters are appended to the first model in order to increase applicability. The computational tests on these models are done on a randomly generated data set based on a typhoon scenario over China.

Chanta and Sangsawang [25] investigated a bi-objective model to determine the locations for at most p shelters to serve a region suffering from a flood disaster. One objective concerns the minimization of the total weighted distance from each affected area to the closest shelter; the other one aims at maximizing the population that has a shelter within a prespecified distance (max-cover objective). The proposed model is assessed using data from Bangkruai district in the central part of Thailand.

Bayram et al. [26] analyzed a shelter site location problem combined with evacuation traffic management. Their goal is to find a solution that minimizes the total evacuation time in case of a disaster. The proposed models were tested using networks available in the literature as well as the Istanbul road network.

Görmez et al. [27] did not study the shelter site location problem explicitly but adopted a more general approach that deals with locating disaster response facilities in Istanbul. Nevertheless, the authors state that so called “temporary facilities” may also serve as shelters for the disaster victims. To deal with the large-scale context of their setting, they proposed a sequential framework. Initially, an integer programming model is solved for each district to decide the locations of these temporary facilities while minimizing the demand-weighted distance. At this stage they also calculate the number of victims served from

each open facility. In the second stage, they handle a bi-criteria problem for locating new facilities for storing relief items while minimizing the average distance traveled to serve the temporary facilities (shelters) and the number these new relief item facilities (PFs) simultaneously. It should be noted that they assumed an uncapacitated setting for PFs which helps them to assure closest assignment to between temporary shelters and PFs without being required to use closest assignment constraints.

Another study that adopts a setting for locating emergency facilities (which also include shelter areas) is by Salman and Yücel [28]. Assuming that demands are deterministic withing a discrete scenario set, they developed a 2-stage stochastic program that maximizes total covered demand while handling random network damage by considering link (road) disruptions. For computational experiments randomly generated instances for Istanbul are used.

Kılçı et al. [14] proposed a mixed-integer linear programming formulation for the shelter site location problem. This is a model aiming at maximizing the minimum weight of the shelters to open while deciding about the assignment of the disaster victims to those shelters and simultaneously ensuring a minimum threshold for the utilization rate of the shelters assuming that demand is a known parameter. The authors also consider a pairwise balancing constraint for utilization of open shelters and closest assignment constraints for shelter area - demand point assignments. Their proposed methodology is used for computational studies based a real data set from Kartal district of Istanbul.

The above mentioned studies assume a deterministic setting in which the data is fully known in advance and is not subject to any type of uncertainty. However, when making resource management plans for an upcoming disaster, it is often the case that using deterministic information oversimplifies the problem. This is the case, for instance, when the consequences of a disaster may vary significantly. A quantitative approach for better hedging against such uncertainty requires its explicit consideration in a model.

Although stochastic facility location problems have been studied for many

years (the reader can refer to the book titled “Facility Location under Uncertainty” by Correia and Saldanha-da-Gama [29]), to the best of our knowledge, the first paper investigating a stochastic shelter site location problem is the one by Li et al. [30], who focused on disasters caused by hurricanes. The authors proposed a two-stage stochastic programming formulation for the problem that consists of locating a set of shelters (first-stage decision) and distributing the resources and the affected populations among the shelters (second-stage decision). Data from the Gulf Coast region of the United States was considered to test the developed solution algorithm which is a decomposition approach based upon the L-shaped method.

In late 2011, Kulshrestha et al. [31] presented a robust approach for selecting predetermined number (p) of shelter sites during evacuation planning under demand uncertainty. They proposed a scenario based stochastic programming formulation which minimizes total cost of opening and operating shelters while meeting an upper bound for maximum evacuation time and solved it by a cutting-plane scheme. The data set of Sioux Falls is used for generating hypothetical disaster scenarios and making numerical experiments using the proposed methodology.

Following that study, Li et al. [32] proposed a bi-level optimization model for selecting a set of shelter locations that is robust for a range of hurricane scenarios. In particular, the authors consider possible disruptions at the shelters. The upper-level problem is a two-stage stochastic programming problem defining the location-allocation problem related with the shelters whereas the lower-level problem focuses on the behavior of the evacuees when it comes to choose an evacuation route. With this purpose, a so-called dynamic user equilibrium model is considered. The overall goal is to minimize the total system cost. Heuristic algorithms are developed for finding feasible solutions to the problem. A case study from North Carolina, United States, is presented.

Bayram and Yaman [33] investigated a two-stage stochastic approach whose objective is the minimization of the total evacuation time. In the first stage, at most p shelters are to be located. The allocation of affected populations to the

shelters and to the routes that were not disrupted is made in the second phase. They formulated the problem as a second order conic mixed-integer programming model.

One of the most recent studies is by Cavdur et al. [34] which does not particularly focus on shelter site location problem but adopts a more general approach applicable for disaster response facilities (that includes temporary shelter establishments). A two-stage stochastic programming model developed in which in the first stage total distance traveled and number of facilities are minimized and facility allocation decisions are made; in the second stage unmet demand is minimized while performing relief item distribution decisions. To model the demand uncertainty, they use five different earthquake scenarios each having a different probability of occurrence. Their proposed methodology is tested on a real-life case study for the city Bursa, Turkey.

As it could be observed, all the studies that are using stochastic demand in shelter site location problem (except Kulshrestha et al. [31]), are using two-stage stochastic programming to deal with the multi-stage decisions (location and evacuation). In fact, there are many implementations of two-stage stochastic programming in disaster management (The reader could refer to the review study by Grass and Fischer [35] and the references therein). Typically, in these studies, pre-disaster and post-disaster decisions are handled in different levels. In this thesis, such a bi-level methodology is not adopted since we have only location decisions that could be handled in a single level (the evacuation decisions are implied by closest assignment constraints simultaneously).

3.2 The Use of Chance-Constraints in Humanitarian Logistics

If a stochastic demand setting is adopted for a given facility location problem, the use of “hard” capacity constraints (ensuring that the facility capacities should always hold for all possible scenarios) will not be practical any more. To construct

a framework that is more realistic, the use of chance-constraints (probabilistic constraints) could be the solution. By this way, each open facility is assumed handle the stochastic demand that is assigned to it with some predefined (characteristically high) probability.

Charnes and Cooper [36] first introduced chance constrained programming as a tool to solve optimization problems under uncertainty and starting from 1970s, major contributions are made by András Prékopa [37]. The integration of probabilistic programming with Location Analysis has its roots in the seminal paper by Revelle and Hogan [38] focusing on the location of emergency facilities. In fact, like in that work, most of the chance-constrained facility location literature emerges from problems consisting of locating emergency facilities.

This is the case with the study by Beraldi et al. [39] aiming at designing a robust emergency medical service network. The authors developed a chance-constrained model for determining where to locate facilities as well as the number of emergency vehicles to assign to each facility. The goal is to ensure a certain reliable level of service at minimum cost. More recently, Zhang and Li [40] proposed a model with chance-constraints for designing an emergency medical service assuming uncertain demand. The probabilistic constraints are then approximated by second order conic inequalities rendering a model tractable by an off-the-shelf solver.

In the context of a bio-terrorist attack, Murali et al. [41] studied a chance-constraint model for locating emergency facilities. By assuming a log-normal distribution for the demand the authors were able to linearize the chance-constraints. A heuristic approach was developed in that work for the approximate problem.

Hong et al. [42] proposed a model for a stochastic pre-disaster relief network design problem. The model determines the sizes and locations of the response facilities as well as the amount of emergency supplies to be stocked in order to assure some network reliability. The model includes a chance-constraint that establishes a high probability in the demand satisfaction.

Elçi et al. [43] studied a post-disaster two-echelon network design problem. In the first echelon a local distribution center receives the relief supplies and sends them to the points of distribution while in the second echelon the demand points receive the relief supplies from the points of distribution. The authors propose a model that considers equity and accessibility measures and takes into account the uncertainty associated with the demands and with the transportation network structure after a disaster. The demand satisfaction constraints are modeled as chance constraints.

Finally, the study by Lin [44] should be quoted to which some of this thesis' methodological developments are related. That author used probabilistic constraints to model service level in a single-source capacitated facility location model with stochastic demand. Two probability distributions were considered for the demand: Poisson and Normal. When the demand occurs according to a Poisson distribution the stochastic problem is equivalent to a deterministic single-source capacitated facility location problem. In turn, for Normal distributed demand, the stochastic problem becomes equivalent to a mixed-integer non-linear programming problem.

Table 3.1, pivoted on the characteristics of this study, puts together all the main aspects of the related literature discussed explicitly. What emerges clearly from observing this table is that the stochastic shelter site location problem was never considered from a chance-constrained modeling framework perspective although it seems to make much sense as explained above.

3.3 Multi-Objective Shelter Site Location Problem Literature

As shown in previous sections, most of the studies dealing with shelter site location problem have adopted a single objective framework. Most commonly used objective type is minimization and the majority of the concerns are related to

Study	Demand	Location Decisions	Closest Assignment Constraints	Chance Constraints	Service Level	Objective	Underlying Setting
Sherali et al. [20]	Deterministic	✓	✗	✗	✗	Evacuation Time (min)	Shelter Site Location & Evacuation
Beraldi et al. [39]	Stochastic	✓	✗	✓	✓	Total Cost (min)	Medical Center Location
Kongsom-saksakul et al. [21]	Deterministic	✓	✗	✗	✓	Evacuation Time (min)	Shelter Site Location
Alçada-Almeida et al. [22]	Deterministic	✓	✗	✗	✓	Distance & Risk & Time (min)	Shelter Site Location & Evacuation
Anping [24]	Deterministic	✓	✗	✗	✗	Coverage (max)	Shelter Site Location
Li et al. [30]	Stochastic	✓	✗	✗	✓	Total Cost (min)	Shelter Site Location
Görmez et al. [27]	Deterministic	✓	✗	✗	✗	Distance & Facility Count (min)	Disaster Response Facilities
Salman and Yücel [28]	Deterministic	✓	✗	✗	✗	Coverage (max)	Emergency Facility Location
Kulshrestha et al. [31]	Stochastic	✓	✗	✗	✓	Total Cost (min)	Shelter Site Location
Chanta and Sangsawang [25]	Deterministic	✓	✗	✗	✓	Coverage (max) & Total Distance (min)	Shelter Site Location & Evacuation
Coutinho-Rodrigues et al. [23]	Deterministic	✓	✗	✗	✓	Distance & Risk & Time (min)	Shelter Site Location & Evacuation
Li et al. [32]	Stochastic	✓	✗	✗	✓	Distance & Unmet Demand (min)	Shelter Site Location
Murali and Ordonez [41]	Stochastic	✓	✗	✓	✓	Coverage (max)	DC location for bio-terror attacks
Bayram and Yaman [33]	Stochastic	✓	✓	✗	✓	Evacuation Time (min)	Shelter Site Location & Evacuation
Bayram et al. [26]	Deterministic	✓	✓	✗	✓	Evacuation Time (min)	Shelter Site Location & Evacuation
Hong et al. [42]	Stochastic	✓	✗	✓	✓	Total Cost (min)	Pre-disaster Relief Network
Kılçı et al. [14]	Deterministic	✓	✓	✗	✓	Minimum Weight of Facilities (max)	Shelter Site Location
Zhang and Li [40]	Stochastic	✓	✗	✓	✗	Total Cost (min)	Medical Center Location
Cavdur et al. [34]	Stochastic	✓	✗	✗	✓	Distance & Unmet Demand (min)	Warehouse Location
Elçi et al. [43]	Stochastic	✓	✗	✓	✓	Accessibility (max)	Warehouse Location
This Thesis	Stochastic	✓	✓	✓	✓	Minimum & Average Weight of Facilities (max), Distance (min)	Shelter Site Location

Table 3.1: Related Literature Summary

total cost, travel time (or distance) or number of facilities to establish. Moreover, most of these objective are a function of the performance of evacuation processes rather than focusing on the location analysis of the shelter sites themselves. There is only a single study (e.g. Kılıcı et al. [14]) that addresses fairness issues as a primary concern and maximize the benefit of least advantaged disaster victims while selecting the shelter sites to open.

The ones that uses multi-objective methodologies are Alçada-Almeida et al. [22], Coutinho-Rodrigues et al. [23], Chanta and Sangsawang [25] and Görmez et al. [27]. The first two of these studies have attempted to deal with more than 4 objectives (all evacuation oriented) at a time for urban evacuation planning while locating shelter sites. They only provide a handful solutions by solving the models for each objective separately and applying a weighting method to scalarize their multi-objective models. Hence, it could be said that they do not aim to detect all the non-dominated solutions for their settings. The other two studies ([25],[27]) have used ε -constraint method to solve their bi-objective optimization models and detect all the non-dominated solutions.

To the best of the our knowledge, there are no studies in shelter site location problem literature that incorporates demand variability while using multi-objective approaches. Moreover, this is the first study in the literature that developed a methodology attempting to find all the non-dominated solutions in 3-objective settings of shelter site location problem. Nonetheless, all of the used objectives are either aiming to improve fairness or to eliminate any unfavorable solutions in order to improve service for the sake of public welfare.

Chapter 4

Shelter Site Location Under Demand Uncertainty

In this chapter, a chance-constrained model that takes demand variability into account for the shelter site location problem is introduced.

As a chapter prologue, a deterministic version of the problem is presented first. Then, in the upcoming sections this version is extended by hedging uncertainty in demand and by including the probabilistic constraints.

4.1 The Deterministic Problem

The starting point is a deterministic model resulting from the one proposed by Kılçı et al. [14] after making some simplifications without loss of generality.

As mentioned in the Section 2.2, in the current practice for establishing shelter sites in Turkey, each potential location is ranked according to their weight scores $\in [0, 1]$. In terms of capacity, it is assumed that at least $3.5m^2$ is allocated to each person in a shelter area. Additionally, an operating shelter must have at least $45m^2$ space to be assigned to utilities such as sanitation and nutrition. These

are, in fact, some minimum standards that are set by the Sphere Handbook [13].

In their model, Kılıcı et al. [14] assumed that people living in the same district must be all assigned to the closest open shelter. The reasons for this assumption are twofold. First, the affected people who are in need for sheltering would like to reach the nearest open facility instinctively so that they should be assigned to the closest open one; therefore, in order to “mimic” the behavior of people moving towards open facilities, closest assignment assumption is necessary. Secondly, this is a means to help keeping the social structure of the society after a disaster.

The assumptions and restrictions of the model proposed by Kılıcı et al. [14] (that are also valid for this study) are as follows:

- The set of candidate locations for the shelters is known in advance (This set only includes candidate locations such that their distance to the nearest health center and to the nearest road is below maximum values previously decided for the accessibility to those infrastructures; in other words, while eliminating constraints (5) and (6) of Kılıcı et al. [14], we make a preprocessing and only consider the feasible possibilities explicitly in the model).
- Each candidate location will remain reachable and serviceable after a disaster.
- There is a maximum capacity for each shelter location (measured in m^2).
- Each shelter location is assigned a weight score that can be previously computed (according to the criteria already mentioned in Section 2.2).
- The utilization rate of each shelter must be above a value specified in advance in order to prevent under-utilization (and promote utilization rate fairness).
- Each district must be assigned to the closest open shelter.
- The population of each district is assumed to be concentrated on its centroid.
- The objective is to maximize the minimum weight of open shelters.

Before presenting mathematical model of the deterministic problem, the following notation to be used hereafter is introduced below:

Sets:

- I Set of candidate shelter locations.
- J Set of districts.

Parameters:

- w_i : weight of candidate shelter location $i \in I$; $w_i \in [0, 1]$.
- d_j : total demand (in m^2) of district $j \in J$.
- q_i : capacity (m^2) of candidate shelter location $i \in I$.
- ℓ_{ij} : distance (km) between candidate shelter location $i \in I$ and district $j \in J$.
- β : threshold for the minimum utilization rate of a shelter (%).

For each $j \in J$, the distances ℓ_{ij} can be sorted non-decreasingly, thus providing an ordered sequence for the candidate shelter locations in terms of their distances to each district. $i_j(r)$ denotes the r -th closest candidate shelter location to district $j \in J$ ($r = 1, \dots, |I|$).

Decision Variables:

$$x_i = \begin{cases} 1 & \text{if candidate location } i \text{ is chosen as a shelter area,} \\ 0 & \text{otherwise.} \end{cases} \quad (i \in I)$$

$$y_{ij} = \begin{cases} 1 & \text{if district } j \text{ is assigned to shelter location } i, \\ 0 & \text{otherwise.} \end{cases} \quad (i \in I, j \in J)$$

$W_{\min}$ = the minimum weight of open shelters

The following optimization model can now be proposed for the deterministic shelter site location problem:

$$\text{maximize } W_{\min}, \quad (4.1)$$

$$\text{subject to } W_{\min} \leq w_i x_i + (1 - x_i), \quad i \in I \quad (4.2)$$

$$\sum_{i \in I} y_{ij} = 1, \quad j \in J \quad (4.3)$$

$$y_{i_j(1),j} \geq x_{i_j(1)}, \quad j \in J \quad (4.4)$$

$$y_{i_j(r),j} \geq x_{i_j(r)} - \sum_{s=1}^{r-1} x_{i_j(s)}, \quad j \in J, r = 2, \dots, |I| \quad (4.5)$$

$$\sum_{j \in J} d_j y_{ij} \leq q_i x_i, \quad i \in I \quad (4.6)$$

$$\sum_{j \in J} d_j y_{ij} \geq \beta q_i x_i, \quad i \in I \quad (4.7)$$

$$W_{\min} \geq 0, \quad (4.8)$$

$$x_i \in \{0, 1\}, \quad i \in I \quad (4.9)$$

$$y_{ij} \in \{0, 1\}, \quad i \in I, j \in J \quad (4.10)$$

The objective function (4.1) quantifies the minimum weight across the open shelters (to be maximized). This maxmin objective can be considered as a *Rawlsian Approach* since it targets fairness for the least advantaged victims of a disaster. These type of approaches are named after the 20th century American philosopher John Rawls and based upon his notable ideas stated in his work, titled “A Theory of Justice”, published in 1971 [45].

This maxmin non-linear objective function that can be linearized straightforwardly using constraints (4.2). Constraints (4.3) guarantee that each district is assigned to exactly one shelter area. Constraints (4.4) and (4.5) ensure that each district is assigned to the closest open shelter area. Constraints (4.6) ensure that the capacity of the opened shelter areas is not exceeded. Constraints (4.7) guarantees that each open shelter is at least $\beta\%$ utilized. Finally, constraints (4.8),(4.9) and (4.10) define the domains of the decision variables.

4.2 A Chance-Constrained Model

The stochastic version of the above problem assuming uncertainty in demands d_j ($j \in J$) is introduced in this section.

As it is stated before, since the selection of the operating shelter locations is done in the preparedness phase of a disaster, taking uncertainty into account is really important. While using the demand data as a stochastic input, one may consider uncertain demand and keep imposing “hard” capacity constraints ensuring that the established capacity should hold for all possible scenarios. In this case, we would have to plan for the worst case scenario which may be very unlikely (as it surely is in the case of disastrous events). Another possibility that emerges and that motivates this study is to consider some sort of “service level” constraints ensuring that with some high probability, each open shelter can cope with the (stochastic) demand of those districts assigned to it. In other words, we can consider a chance-constrained approach for this problem. This allows capturing a finite set of scenarios with each one calling for some (predictable) amount of sheltering. In this case, the shelter areas are selected in such a way that with prespecified probabilities, (i) the total demand does not exceed the shelters’ capacity (q_i); and (ii) the utilization rate of the shelters is not below a given threshold value ($\beta\%$).

Let $1 - \gamma_i$ denote the probability that shelter $i \in I$ has enough capacity to handle all the demand assigned to it. Then, the constraints (4.6) can be rewritten as:

$$\mathbb{P} \left[\sum_{j \in J} d_j y_{ij} \leq q_i x_i \right] \geq 1 - \gamma_i, \quad i \in I. \quad (4.11)$$

Similarly, Let δ_i denote the probability that shelter $i \in I$ does not have enough utilization to satisfy the minimum allowed minimum utilization rate of $\beta\%$. In this case, instead of constraints (4.7) , we can consider:

$$\mathbb{P} \left[\sum_{j \in J} d_j y_{ij} \leq \beta q_i x_i \right] \leq \delta_i, \quad i \in I. \quad (4.12)$$

The values γ_i and δ_i ($i \in I$) are typically small (e.g., 0.05 or 0.10) since violation of these constraints should not be highly probable.

In synthesis, we propose the following basic-form chance-constrained model for the shelter location problem under demand uncertainty:

$$\begin{aligned} & \text{maximize} && (4.1), \\ & \text{subject to} && (4.2) - (4.5), \\ & && (4.8) - (4.12). \end{aligned}$$

Throughout this thesis, it is assumed that the demand of each district is independent. In fact, events like earthquakes often have a very local effect in the sense that their destruction level depends on slope, terrain structure, soil type, urbanization planliness, etc... Hence, the consequences may vary significantly from one district to another which is close by. This situation supports that independency of demand seems to be a reasonable assumption. As a result, any demand correlation is neglected in the following developments.

In a context such as the shelter location problem, typically a solution consists of many districts to be served and a small number of shelters to be established. In the particular case of Turkey, each district, in fact, aggregates demand corresponding to many neighborhoods. Accordingly, a large number of neighborhoods is typically allocated to each open shelter. Therefore, it is safe to invoke the central limit theorem to find deterministic equivalents for the probabilistic constraints (4.11) and (4.12).

For each district ($j \in J$), let μ_j and σ_j^2 denote the expected value and variance, respectively, for its demand. The total demand that shelter $i \in I$ has to deal with is given by:

$$D_i = \sum_{j \in J} d_j y_{ij}$$

It is also known that the expected demand at shelter $i \in I$ is:

$$E[D_i] = \sum_{j \in J} \mu_j y_{ij}$$

Assuming independent demands, we could obtain:

$$\text{Var}[D_i] = \sum_{j \in J} \sigma_j^2 y_{ij}$$

When the number of terms defining D_i , i.e. number of neighborhoods, is large enough, the central limit theorem assures that

$$\frac{D_i - E[D_i]}{\sqrt{\text{Var}[D_i]}} \approx N(0, 1)$$

Let, $z_{1-\gamma_i}$ denotes the $1-\gamma_i$ quantile of a standardized normal distribution. Then, using the central limit theorem, constraints (4.11) are equivalent (approximately) to:

$$\frac{q_i x_i - E[D_i]}{\sqrt{\text{Var}[D_i]}} \geq z_{1-\gamma_i}, \quad i \in I, \quad (4.13)$$

Similarly, for the case where z_{δ_i} denotes the δ_i quantile of a standardized normal distribution, constraints (4.12) can be rewritten (approximately) as:

$$\frac{\beta q_i x_i - E[D_i]}{\sqrt{\text{Var}[D_i]}} \leq z_{\delta_i}, \quad i \in I, \quad (4.14)$$

These constraints ((4.13) and (4.14)) are non-linear due to the denominator (standard deviation) since it includes the decision variables y_{ij} ($j \in J$); thus, should be linearized in order to come up with a mixed integer programming model that could be tackled with a general-purpose solver. Lin [44] proposed handling this non-linearity using a substitution by defining a new set of variables (v_i : $0 \leq v_i \leq 1$) as follows :

$$v_i = \frac{\sqrt{\sum_{j \in J} \sigma_j^2 y_{ij}}}{\sqrt{\sum_{j \in J} \sigma_j^2}}, \quad i \in I$$

Furthermore, (4.13) and (4.14) together can now be replaced by

$$\sum_{j \in J} \left(\frac{\mu_j}{\sqrt{\sum_{k \in J} \sigma_k^2}} \right) y_{ij} + z_{1-\gamma_i} v_i \leq \frac{q_i}{\sqrt{\sum_{k \in J} \sigma_k^2}} x_i, \quad i \in I, \quad (4.15)$$

$$\sum_{j \in J} \left(\frac{\mu_j}{\sqrt{\sum_{k \in J} \sigma_k^2}} \right) y_{ij} + z_{\delta_i} v_i \geq \frac{\beta q_i}{\sqrt{\sum_{k \in J} \sigma_k^2}} x_i, \quad i \in I, \quad (4.16)$$

$$v_i^2 = \sum_{j \in J} \left(\frac{\sigma_j^2}{\sum_{k \in J} \sigma_k^2} \right) y_{ij}, \quad i \in I, \quad (4.17)$$

$$0 \leq v_i \leq 1, \quad i \in I. \quad (4.18)$$

Accordingly, the linearized deterministic equivalent for the chance-constrained model becomes the following:

$$\begin{aligned} & \text{maximize} && (4.1), \\ & \text{subject to} && (4.2) - (4.5) \\ & && (4.8) - (4.10), \\ & && (4.15) - (4.18). \end{aligned}$$

The above model is a mixed-integer non-linear model due to the left-hand side of constraints (4.17). In the next section, linearization approach for the term v_i^2 will be discussed.

4.2.1 A Mixed-Integer Linear Programming Approximation

In this section we propose the linearization of equality constraints (4.17) by approximating the value of v_i^2 using piecewise linear functions in $[0, 1]$. In fact, this can be done using integer variables (Beale and Tomlin[46], Beale and Forrest[47], and Jeroslow and Lowe [48]).

Consider a real valued function $f(v_i) = v_i^2$ that is defined on the interval $[0, 1]$. Additionally, consider a set of breakpoints inducing a partition of $[0, 1]$ with equal increments; denoted by:

$$b_1 = 0, b_2, \dots, b_{n-1}, b_n = 1$$

For every $i \in I$, taking $v_i \in [0, 1]$, there is $m \in \{0, \dots, n-1\}$ such that $v_i \in [b_m, b_{m+1}]$, i.e., v_i can be written as a convex combination of b_m and b_{m+1} : ($\lambda_{im} + \lambda_{i\ m+1} = 1$ and $\lambda_{im} \geq 0$.)

$$v_i = \lambda_{im} b_m + \lambda_{i\ m+1} b_{m+1}$$

Then, for every $i \in I$, v_i can be written as $v_i = \sum_{m=1}^n \lambda_{im} b_m$. As $v_i \in [b_m, b_{m+1}]$, then $v_i^2 \in [b_m^2, b_{m+1}^2]$. The line segment that connects (b_m, b_m^2) and (b_{m+1}, b_{m+1}^2)

determines a linear approximation of v_i^2 function. By making algebraic calculations, this function could be represented for every $m \in \{0, \dots, n-1\}$ as $\bar{f}_m(v_i) = (b_m + b_{m+1})v_i - b_m b_{m+1}$. By substituting convex combination definition of v_i into this function, it could be concluded that v_i^2 can be approximated by $\bar{f}_m(v_i) = \lambda_{im}b_m^2 + \lambda_{i,m+1}b_{m+1}^2$ which is equivalent to $\sum_{m=1}^n \lambda_{im}b_m^2$, given that λ_{im} are non-negative values satisfying the following requirements:

$$\sum_{m=1}^n \lambda_{im} = 1 \quad (4.19)$$

$$\lambda_{im} \leq t_{im}, \quad m = 1, \dots, n \quad (4.20)$$

$$\sum_{m=1}^n t_{im} \leq 2 \quad (4.21)$$

$$t_{im} + t_{im'} \leq 1, \quad m = 1, \dots, n-2; m' = m+2, \dots, n \quad (4.22)$$

$$t_{im} \in \{0, 1\}, \quad m = 1, \dots, n \quad (4.23)$$

For each $i \in I$, the binary variables t_{im} ($m = 1, \dots, n$) ensure that at most two breakpoints are used to define one value of the piecewise linear function and if two of them are used then they must be adjacent. In fact, λ_{im} 's are named as special ordered set of type 2 (SOS2) variables in this case (see Beale and Forrest [47] for further details).

While implementing this approach to the shelter site location selection context, we should consider a modification of the right hand side of constraints (4.19). The modified version is shown below as constraints (4.24).

$$\sum_{m=1}^n \lambda_{im} = x_i, \quad i \in I, \quad (4.24)$$

For some $i \in I$, if $x_i = 1$, then we have the original constraints; otherwise, if $x_i = 0$, we have $\lambda_{i1} = \dots = \lambda_{in} = 0$ which, by (4.24) together with (4.10) renders $y_{ij} = 0$, $j \in J$.

The full (approximate) deterministic equivalent model to be solved now will be referred as model (P) and is the following:

$$(P) \text{ maximize } W_{\min}, \quad (4.1)$$

$$\text{subject to } W_{\min} \leq w_i x_i + (1 - x_i), \quad i \in I, \quad (4.2)$$

$$\sum_{i \in I} y_{ij} = 1, \quad j \in J, \quad (4.3)$$

$$y_{i_j(1),j} \geq x_{i_j(1)}, \quad j \in J, \quad (4.4)$$

$$y_{i_j(r),j} \geq x_{i_j(r)} - \sum_{s=1}^{r-1} x_{i_j(s)}, \quad j \in J, r = 2, \dots, |I| \quad (4.5)$$

$$\sum_{j \in J} \left(\frac{\mu_j}{\sqrt{\sum_{k \in J} \sigma_k^2}} \right) y_{ij} + z_{1-\gamma_i} \sum_{m=1}^n \lambda_{im} b_m \leq \frac{q_i}{\sqrt{\sum_{k \in J} \sigma_k^2}} x_i, \quad i \in I, \quad (4.15)$$

$$\sum_{j \in J} \left(\frac{\mu_j}{\sqrt{\sum_{k \in J} \sigma_k^2}} \right) y_{ij} + z_{\delta_i} \sum_{m=1}^n \lambda_{im} b_m \geq \frac{\beta q_i}{\sqrt{\sum_{k \in J} \sigma_k^2}} x_i, \quad i \in I, \quad (4.16)$$

$$\sum_{j \in J} \left(\frac{\sigma_j^2}{\sum_{k \in J} \sigma_k^2} \right) y_{ij} = \sum_{m=1}^n \lambda_{im} b_m^2, \quad i \in I, \quad (4.25)$$

$$\sum_{m=1}^n \lambda_{im} = x_i, \quad i \in I, \quad (4.24)$$

$$\lambda_{im} \leq t_{im}, \quad i \in I, m = 1, \dots, n, \quad (4.26)$$

$$\sum_{m=1}^n t_{im} \leq 2, \quad i \in I, \quad (4.27)$$

$$t_{im} + t_{im'} \leq 1, \quad i \in I, m = 1, \dots, n-2; m' = m+2, \dots, n, \quad (4.28)$$

$$W_{\min} \geq 0, \quad (4.8)$$

$$x_i \in \{0, 1\}, \quad i \in I, \quad (4.9)$$

$$y_{ij} \in \{0, 1\}, \quad i \in I, j \in J, \quad (4.10)$$

$$t_{im} \in \{0, 1\}, \quad i \in I, m = 1, \dots, n, \quad (4.29)$$

$$\lambda_{im} \geq 0, \quad i \in I, m = 1, \dots, n. \quad (4.30)$$

Constraints (4.26)–(4.28) are the SOS2 constraints (Beale and Forrest [47]).

The model (P) makes use of the closest assignment constraints (4.4) and (4.5) also considered by Kılçı et al. [14]. These constraints were introduced to the literature by Rojeski and ReVelle [49] and referred to in the literature as the RR closest assignment constraints (Espejo et al. [50]). It is known that there are different alternatives of closest assignment constraints. If larger instances of the problem are to be solved, other ones which are computationally better can be considered. A candidate suggested by Espejo et al. [50] is the following:

$$\sum_{s=r+1}^{|I|} y_{i_j(s),j} + x_{i_j(r)} \leq 1, \quad j \in J, r = 1, \dots, |I| - 1 \quad (4.31)$$

Constraints (4.31) were first proposed by Wagner and Falkson [51] and referred as the WF closest assignment constraints. As shown by Espejo et al. [50], these constraints dominate the RR constraints. Their performance in the context of the shelter site location problem is tested in substitution with constraints (4.4) and (4.5) (the results are shown in Section 4.3.3, where a CPU time comparison is also presented).

4.3 Computational Experiments

In this section, the model (P), derived in the previous section, is used for assessing the relevance of considering demand variability along with chance constraints in the shelter site location problem.

First, used data sets will be introduced; there are two of them with varying sizes. Then, the results for the Kılçı et al.'s [14] deterministic model (shown on Section 4.1) are presented. This is fundamental to test the relevance of considering a stochastic approach instead of a deterministic one. Afterwards, the results of model (P) are demonstrated. Finally, the computational performance of this model will be evaluated based on its performance on a significantly larger data set.

The deterministic model and the mixed-integer approximation are coded in

Optimization Programming Language (OPL) and were solved using IBM CPLEX 12.6.1. All tests were run on a Linux OS with four AMD Opteron Interlagos 6282SE 16 Core 2.6GHz 16MB L3 cache server processors with 96 GB of RAM.

4.3.1 Data Sets

4.3.1.1 Kartal Data Set (K_{45})

Kartal is one of the 39 districts of Istanbul with an area of 38.54 km^2 and with approximately 425,000 inhabitants. The district is located near the western extension of the North Anatolian fault and considered to be a first degree earthquake threat zone which indicates its vulnerability against a future disaster. The potential shelter locations in the district are identified by Ünal [52] in his Ph.D. thesis and there are 25 of them with known capacity and *weight* parameters. In addition, it is known that there are 20 sub-districts in Kartal and the population of each is obtained from Turkish Statistical Institute. The population of each sub-district is assumed to be concentrated in its centroid and these points are referred as “demand points” of the data set. The Kartal data set was collected by Ünal [52] and has already been used in the literature by Kılıcı et al. [14]. This data set will be referred as *K45* in the upcoming sections.

The points of interest (POI) of this data set are illustrated on the Kartal map below. The stars are indicating the potential shelter locations whereas the red pins correspond to the demand points of each sub-district.

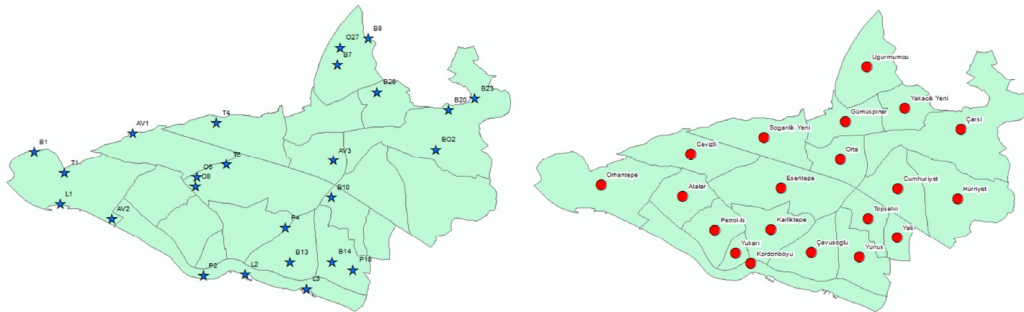


Figure 4.1: POIs in $K45$ Data Set

The specifications of the *K45* is summarized on Table 4.1 and the data set itself is provided in Appendix A.1 and A.2.

Number of potential shelter locations:	25
Number of demand points:	20
Minimum & Maximum weight:	0.674 - 0.982
Mean of weights:	0.827
Standard deviation of weights:	0.097

Table 4.1: *K45* Specifications

4.3.1.2 Istanbul Anatolian Side Data Set (*IST500*)

In order to evaluate the computational performance of model (P) for large-scale data, the Anatolian side of Istanbul is selected as another area of focus. The city has 35% of its total population located in the east side of the Bosphorus, which is known as the Anatolian (or Asian) Side and ,as indicated in Section 2.1, the latest research shows that a catastrophic earthquake will inevitably hit the city in the near future [12]. Motivated by this, the Istanbul Anatolian Side data selected as a benchmark to evaluate the practicability of model (P) for greater areas.

Naturally, this data set is significantly larger compared to *K45* and contains 270 candidate shelter locations and 230 sub-districts (demand points).The weight and capacity specifications of shelters are randomly generated whereas the demand data for districts is obtained from Turkish Statistical Institute. This data set will be referred as *IST500* in the following sections.

The major details of this data set are emphasized on Table 4.2 and the data set itself can be seen in Appendix A.3 and A.4.

Number of potential shelter locations:	270
Number of demand points:	230
Minimum & Maximum weight:	0.140633 - 0.893454
Mean of weights:	0.525810
Standard deviation of weights:	0.207899

Table 4.2: *IST500* Specifications

4.3.2 Results for *K45*

In this section, first the scenario generation and experiment configurations are discussed. Then, the results for the deterministic shelter site location problem model are provided. Following that, the results for the chance-constrained stochastic model (model *P*) are presented.

It is estimated that, approximately 12.5% of the population of Istanbul would lose their homes upon the occurrence of the most probable Istanbul earthquake scenario [52]. This so-called Percent Affected Ratio (*PAR*) value implies that 12.5% of the population is expected to be in need for a shelter after an earthquake. However, in the event of such a disaster, hardly will this parameter be known deterministically in advance; as discussed before, it may depend on different aspects. This means that when shelter locations are being decided, varying demand should not be neglected. In this work, such variability is captured via *PAR* value.

In particular, three different demand uncertainty patterns are considered (all centered around 12.5%).

- Pattern 1 — High Variability: $PAR = 0.125 \times U[0.85, 1.15]$
- Pattern 2 — Moderate Variability: $PAR = 0.125 \times U[0.90, 1.10]$
- Pattern 3 — Low Variability: $PAR = 0.125 \times U[0.95, 1.05]$

$U[a, b]$ denotes a random number generated according to a continuous uniform distribution in the interval $[a, b]$. For each pattern above, 10 values were generated for *PAR* and each one was then multiplied by the population associated with that demand point and also by $3.5m^2$ (recall that the demand is being measured in m^2). From each such demand sample, μ_j and σ_j^2 for all demand points $j \in J$ are calculated to be used in constraints (4.15), (4.16) and (4.25).

It should be noted that the expected value for *PAR* for each demand pattern is kept near 0.125. The purpose of this is keeping consistency in terms of *PAR*

with the deterministic model which the *PAR* value is set to 0.125. This is a way for understanding the effect of the variability of demand while keeping the the approaches comparable.

While modeling (P), 11 breakpoints are used in the piecewise linear approximation represented by constraints (4.25)–(4.28). Accordingly, the interval $[0, 1]$ is partitioned into 10 sub-intervals. The preliminary tests showed that this provides an excellent approximation for the value of v_i without any non-negligible errors.

Before presenting the results, it important to point out that, for a specific solution some quality measures can be developed so that we could understand features such as fairness, accessibility and efficiency. These are important aspects when it comes to analyzing a solution in the context of humanitarian operations.

Regarding fairness, the *Rawlsian* objective – maximization of the minimum weight – targets the benefits of least-advantaged disaster victims. In addition to this, for all the specific solutions found in this section, additional measures were computed, namely the average distance traveled and the maximum distance traveled. The average distance traveled gives us a measure of accessibility and efficiency. In turn, the maximum travel distance can be looked at as also an efficiency measure since it gives an indication of how far from the closest shelter is the population group that needs to walk the most. The lower this value, the more efficient the system can be looked at; in fact, a small maximum distance indicates that all the demand points have a shelter close by. Finally, concerning equity, we can compare the maximum travel distance with the average travel distance. The closer these values are to each other, the more fairness the system has.

In the following analysis for *K45* CPU time is not given since model P was always solved within a few seconds and considered as not significant enough to report.

4.3.2.1 Results for Deterministic Model

Considering the single value for the demand induced by $PAR = 0.125$, the deterministic model (4.1)–(4.10) is solved . The model is run using three different thresholds in terms of the minimum utilization rate of a shelter: 70%, 80% and 90% (i.e., $\beta = 0.7, 0.8, 0.9$, respectively).

The results are presented in Table 4.3. For instance, *Solution A* was obtained when β was set to 0.7. This led to the selection of shelters 10, 19 and 25 and to an optimal objective value ($W_{\min}$) of 0.847.

(a) $\beta = 0.70$	
Solution A	
Objective Value:	0.847
Open Shelters:	10 – 19 – 25
Avg. Distance Traveled:	3.068 km
Max Distance Traveled:	6.544 km
(b) $\beta = 0.80$	
Solution B	
Objective Value:	0.803
Open Shelters:	4 – 10 – 14
Avg. Distance Traveled:	2.566 km
Max Distance Traveled:	4.336 km
(c) $\beta = 0.90$	
Solution C	
Objective Value:	0.739
Open Shelters:	14 – 23
Avg. Distance Traveled:	3.800 km
Max Distance Traveled:	5.943 km

Table 4.3: Deterministic Model Solutions for *K45*

It could be observed from Table 4.3 that, an increase in β corresponds to a decrease in the optimal value of the problem. This is not surprising since the stricter we are in terms of the minimum utilization rate, the more flexible we must be in terms of considering alternative shelters (thus with a lower weight) and the less fair the solutions might get in terms of shelter weights.

Observing these solutions in more depth, *Solution C* turns out to have the largest average traveled distance value, indicating a smaller level of accessibility when compared with other solutions. On the other hand, the maximum travel distance is achieved in *Solution A* indicating that this solution seems not to be so efficient as the other two. When maximum travel distance is compared with the average, the smallest difference is found for *Solution B* indicating a higher equity level.

4.3.2.2 Results for Stochastic Demand Chance-Constrained Model

The next step in the computational experiments is to solve the model (P) using different setting of γ_i and δ_i options, $i \in I$. Since, the same values are considered for all potential shelter site locations $i \in I$, hereafter those probabilities will simply be denoted by γ and δ .

For both probabilities, the considered values are 0.01, 0.0275, 0.05, 0.075, and 0.1. This resulted in the values 0.990, 0.975, 0.950, 0.925, 0.9, respectively for $1 - \gamma$. The combinations of the different values for $1 - \gamma$ and δ yields 25 different instances. In turn, each combination can be considered for each of the three demand patterns. Full analysis for $\beta = 0.7, 0.8, 0.9$ will be performed.

Results for $\beta = 0.7$

The results obtained for $\beta = 0.7$ can be found in Tables 4.4, 4.6, and 4.8. Each table corresponds to solutions regarding to different levels of variability in demand.

Low Variability in Demand

It can be observed that the only solution encountered in Table 4.4a is *Solution A* — the deterministic solution obtained for $\beta = 0.7$. In other words, the dominance of *Solution A* is apparent for all tested γ - δ combinations. This indicates that model (P) could not generate any other solution for the setting where

(a) Optimal Solutions

	$\delta_{0.010}$	$\delta_{0.025}$	$\delta_{0.050}$	$\delta_{0.075}$	$\delta_{0.100}$
$\gamma_{0.010}$	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>
$\gamma_{0.025}$	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>
$\gamma_{0.050}$	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>
$\gamma_{0.075}$	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>
$\gamma_{0.100}$	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>	<i>A</i>

(b) Solution A — capacity used (%).

Open Shelters	Maximum	Average	Minimum
10	97%	92%	89%
19	77%	73%	71%
25	84%	80%	77%

Table 4.4: Results for $\beta = 0.70$ and Low Variability in Demand

$\beta = 0.7$ and demand variability is low. The *Maximum* and *Minimum* columns of the Table 4.4b corresponds to the utilization levels of open shelters for the highest and lowest *PAR* in the demand sample. As we are allowing the violation of utilization related constraints with a certain probabilities, it is not anomalous to observe values exceeding 100% or coming short of $\beta\%$. However, in this setting, it can prominently be observed that the utilization levels do not go beyond the allowed limits.

In particular, the dominance of *Solution A* decreases as we can observe in the results shown in Table 4.6 (for medium demand variability) and in Table 4.8 (for higher demand variability).

It is interesting to observe that when the chance-constrained model is considered, the quality measures we have been considering (fairness, accessibility and efficiency) improve without much deterioration in our objective, $\max W_{\min}$. This is a clear indication that a model capturing uncertainty may yield a solution that can be considered overall better than a solution ignoring uncertainty. In fact, this is a very important observation since the decision makers might be willing to slightly compromise from the objective for the sake of obtaining better values of other quality measures.

Moderate Variability in Demand

For moderate demand variability, it is observed in Table 4.6a that a new solution, *Solution D*, emerges as an optimal solution to model (*P*). The specifications of *Solution D* are depicted on Table 4.5.

Solution D	
Objective Value:	0.809
Open Shelters:	13 – 18 – 19 – 25
Avg. Distance Traveled:	2.732 km
Max Distance Traveled:	4.763 km

Table 4.5: Specifications of *Solution D*

It could be observed that, this solution is located on the left of Table 4.6a which implies that the corresponding open shelters can handle the δ -strictness better than *Solution A*. However, it should not be forgotten that this solution has a lower $W_{\min}$ value than *Solution A*.

(a) Optimal Solutions

	$\delta_{0.010}$	$\delta_{0.025}$	$\delta_{0.050}$	$\delta_{0.075}$	$\delta_{0.100}$
$\gamma_{0.010}$	<i>D</i>	<i>D</i>	<i>A</i>	<i>A</i>	<i>A</i>
$\gamma_{0.025}$	<i>D</i>	<i>D</i>	<i>A</i>	<i>A</i>	<i>A</i>
$\gamma_{0.050}$	<i>D</i>	<i>D</i>	<i>A</i>	<i>A</i>	<i>A</i>
$\gamma_{0.075}$	<i>D</i>	<i>D</i>	<i>A</i>	<i>A</i>	<i>A</i>
$\gamma_{0.100}$	<i>D</i>	<i>D</i>	<i>A</i>	<i>A</i>	<i>A</i>

(b) Solution A — capacity used (%).

Open Shelters	Maximum	Average	Minimum
10	101%	93%	85%
19	80%	74%	67%
25	88%	81%	73%

(c) Solution D — capacity used (%).

Open Shelters	Maximum	Average	Minimum
13	83%	77%	70%
18	99%	92%	83%
19	91%	84%	76%
25	88%	81%	73%

Table 4.6: Results for $\beta = 0.70$ and Moderate Variability in Demand

From the utilization rates (Tables 4.6b and 4.6c), one can conclude that *Solution D* has neither values greater than 100% nor lower than 70% whereas *Solution A* can be out of these boundaries in the extreme cases, which decreases its applicability. Specifically, for Shelter 19's utilization going beyond 70% as much as 3% is the reason for the absence of *Solution A* on the left of Table 4.6a.

High Variability in Demand

Finally, still with $\beta = 0.7$, the results are analyzed when demand exhibits the highest tested variability on Table 4.8. For this setting, two new solutions emerge, *Solution E* and *Solution F*. Nevertheless, from Table 4.7, we can see that these are alternative optimas as they have the same $W_{\min}$ value of 0.801. However, it can also be observed that despite having the same maximum walking distance value, *Solution F* is superior in terms of accessibility since it renders a better average walking distance.

Solution E	
Objective Value:	0.801
Open Shelters:	8 – 9 – 12 – 25
Avg. Distance Traveled:	2.433 km
Max Distance Traveled:	3.827 km
Solution F	
Objective Value:	0.801
Open Shelters:	4 – 8 – 9 – 12
Avg. Distance Traveled:	2.423 km
Max Distance Traveled:	3.827 km

Table 4.7: Specifications of *Solution E* & *Solution F*

Solution A does not seem to cope well with high variability; it is only valid on the left-down corner (most loose part) of δ vs γ table. This shows the importance of capturing uncertainty as the optimal solution of the deterministic model is losing its validity by the time the demand variability increases. On the other hand, *Solution D* cannot handle the γ -strictness at all. The reason for this could be understood on the capacity usage of *Shelter 18*. The table implies that the capacity of this shelter could be exceeded by more than 4% in the worst case scenario which prevents this solution to be applicable for stricter γ probability levels.

(a) Optimal Solutions

	$\delta_{0.010}$	$\delta_{0.025}$	$\delta_{0.050}$	$\delta_{0.075}$	$\delta_{0.100}$
$\gamma_{0.010}$	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>
$\gamma_{0.025}$	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>
$\gamma_{0.050}$	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>	<i>A</i>
$\gamma_{0.075}$	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>	<i>E or F</i>	<i>A</i>
$\gamma_{0.100}$	<i>E or F</i>	<i>D</i>	<i>D</i>	<i>D</i>	<i>A</i>

(b) Solution A — capacity used (%).

Open Shelters	Maximum	Average	Minimum
10	105%	94%	80%
19	84%	75%	63%
25	91%	82%	69%

(c) Solution D — capacity used (%).

Open Shelters	Maximum	Average	Minimum
13	87%	78%	66%
18	104%	93%	78%
19	95%	85%	72%
25	91%	82%	69%

(d) Solution E — capacity used (%).

Open Shelters	Maximum	Average	Minimum
8	98%	88%	74%
9	97%	87%	74%
12	92%	82%	69%
25	91%	82%	69%

(e) Solution F — capacity used (%).

Open Shelters	Maximum	Average	Minimum
4	98%	88%	74%
8	97%	87%	74%
9	99%	88%	72%
12	97%	77%	73%

Table 4.8: Results for $\beta = 0.70$ and High Variability in Demand

Results for $\beta = 0.8$

The results obtained when β is set to 0.8 can be found in Tables 4.9, 4.10 and 4.11 where each table corresponds to solutions of different demand patterns.

In these tables, we can see a behavior similar to that observed for $\beta = 0.7$. Again, the deterministic solution—now *Solution B*—dominates all through 25 combinations of optimal results of model (*P*) when the lowest variability is considered for the demand (Table 4.9a). We observe that if *Solution B* was implemented, the lower and upper limits in terms of utilization rate of the open shelters are between 82% and 100%. In other words, for the probabilities considered, the solution always stays feasible.

(a) Optimal Solutions

	$\delta_{0.010}$	$\delta_{0.025}$	$\delta_{0.050}$	$\delta_{0.075}$	$\delta_{0.100}$
$\gamma_{0.010}$	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>
$\gamma_{0.025}$	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>
$\gamma_{0.050}$	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>
$\gamma_{0.075}$	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>
$\gamma_{0.100}$	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>	<i>B</i>

(b) Solution B — capacity used (%)

Open Shelters	Maximum	Average	Minimum
4	89%	85%	82%
10	90%	86%	83%
14	100%	96%	92%

Table 4.9: Results for $\beta = 0.80$ and Low Variability in Demand

With an increase in the demand variability, *Solution B* ceases to be the optimal one and give place to *Solution C*. This solution could not meet the strict probability allowances for capacity violation and therefore is only valid on the bottom part of the Table 4.10a.

As shown in Table 4.11a, for the highest variability scenario, there is no feasible solution for any of the 25 combinations of γ and δ . This indicates that for $\beta = 0.8$ the values selected for γ and δ were too strict. In particular, a few extra computations with the data led to conclude that feasible solutions could not be obtained unless values of γ larger than 23% is considered for this setting.

(a) Optimal Solutions

	$\delta_{0.010}$	$\delta_{0.025}$	$\delta_{0.050}$	$\delta_{0.075}$	$\delta_{0.100}$
$\gamma_{0.010}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.025}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.050}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.075}$	<i>C</i>	<i>C</i>	<i>C</i>	<i>C</i>	<i>C</i>
$\gamma_{0.100}$	<i>C</i>	<i>C</i>	<i>C</i>	<i>C</i>	<i>C</i>

(b) Solution C — capacity used (%)

Open Shelters	Maximum	Average	Minimum
14	103%	95%	86%
23	101%	93%	84%

Table 4.10: Results for $\beta = 0.80$ and Moderate Variability in Demand

(a) Optimal Solutions

	$\delta_{0.010}$	$\delta_{0.025}$	$\delta_{0.050}$	$\delta_{0.075}$	$\delta_{0.100}$
$\gamma_{0.010}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.025}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.050}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.075}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.100}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>

(b) Solution C (Infeasible) — capacity used (%) if the solution was implemented

Open Shelters	Maximum	Average	Minimum
14	107%	96%	81%
23	105%	94%	78%

Table 4.11: Results for $\beta = 0.80$ and High Variability in Demand**Results for $\beta = 0.9$.**

The results obtained for $\beta = 0.9$ are depicted in Tables 4.12, 4.13 and 4.14. We observe that for moderate and high demand patterns, the values for γ and δ were too strict to allow obtaining feasible solutions. As a matter of fact, for total of 75 γ and δ combinations analyzed for $\beta = 0.9$, only 17 combinations (15 for low variability and 2 for moderate variability) turned out to be feasible. This implies that if we impose a minimum utilization rate of 90%, then we must increase the probabilities determined for γ and/or δ .

(a) Optimal Solutions

	$\delta_{0.010}$	$\delta_{0.025}$	$\delta_{0.050}$	$\delta_{0.075}$	$\delta_{0.100}$
$\gamma_{0.010}$	<i>Inf</i>	<i>Inf</i>	<i>C</i>	<i>C</i>	<i>C</i>
$\gamma_{0.025}$	<i>Inf</i>	<i>Inf</i>	<i>C</i>	<i>C</i>	<i>C</i>
$\gamma_{0.050}$	<i>Inf</i>	<i>Inf</i>	<i>C</i>	<i>C</i>	<i>C</i>
$\gamma_{0.075}$	<i>Inf</i>	<i>Inf</i>	<i>C</i>	<i>C</i>	<i>C</i>
$\gamma_{0.100}$	<i>Inf</i>	<i>Inf</i>	<i>C</i>	<i>C</i>	<i>C</i>

(b) Solution C — capacity used (%)

Open Shelters	Maximum	Average	Minimum
14	99%	94%	91%
23	97%	92%	88%

Table 4.12: Results for $\beta = 0.90$ and Low Variability in Demand

(a) Optimal Solutions

	$\delta_{0.010}$	$\delta_{0.025}$	$\delta_{0.050}$	$\delta_{0.075}$	$\delta_{0.100}$
$\gamma_{0.010}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.025}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.050}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.075}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>C</i>
$\gamma_{0.100}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>C</i>

(b) Solution C — capacity used (%)

Open Shelters	Maximum	Average	Minimum
14	103%	95%	86%
23	101%	93%	84%

Table 4.13: Results for $\beta = 0.90$ and Moderate Variability in Demand

(a) Optimal Solutions

	$\delta_{0.010}$	$\delta_{0.025}$	$\delta_{0.050}$	$\delta_{0.075}$	$\delta_{0.100}$
$\gamma_{0.010}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.025}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.050}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.075}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>
$\gamma_{0.100}$	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>	<i>Inf</i>

(b) Solution C — capacity used (%)

Open Shelters	Maximum	Average	Minimum
14	107%	96%	81%
23	105%	94%	78%

Table 4.14: Results for $\beta = 0.90$ and High Variability in Demand

4.3.3 Results for Large-Scale Data (*IST500*)

In order to evaluate the behavior of model (P) when the problem size is significantly larger, data for the whole Anatolian Side of Istanbul is considered. As introduced in Section 4.3.1.2, this data set contains 270 candidate shelter locations and 230 districts (demand points). In total, we have a 500-node instance. It should be emphasized that this section is mostly concerning with the computational performance of the model (P) and related improvements.

For the computational experiments appertaining to this data set, PAR is set to 0.125 and only demand pattern 1 (lower variability in demand) is considered. The probability allowances of service level constraints, γ and δ are set to 10%. Regarding β , it is set to 0.30, i.e., more flexibility in terms of the minimum utilization rate of the selected shelters is allowed.

Using model (P), an optimal solution is obtained in 43 hours and 48 minutes. The selected shelters as well as their weights and their utilization rates are depicted in Table 4.15. Such solution calls for opening 26 shelters whose $W_{\min}$ (objective function value) corresponds to the weight of *Shelter 46* and is equal to 0.781146. Regarding the utilization rates, it is observed that the minimum value is 38.54% and the utilization average of open shelters is equal to 71.75%.

Shelter	Weight	Utilization Rate (%)	Shelter	Weight	Utilization rate (%)
5	0.788021	98.39%	111	0.866857	71.98%
8	0.844608	89.99%	136	0.876425	65.83%
15	0.843545	64.25%	166	0.855216	91.04%
24	0.793249	42.26%	168	0.796147	93.85%
33	0.850611	51.61%	169	0.805162	38.54%
41	0.876523	96.25%	171	0.893454	55.35%
46	0.781146	47.72%	175	0.866260	56.30%
49	0.873054	97.97%	195	0.820383	86.46%
50	0.813283	98.07%	200	0.810284	65.51%
72	0.819059	83.32%	204	0.791751	86.46%
81	0.837859	90.66%	210	0.877855	50.57%
91	0.800685	41.28%	216	0.790012	54.10%
95	0.891362	90.72%	220	0.800323	56.94%

Table 4.15: Model (P) Optimal Solution for *IST500*

Since the CPU time turned out to be excessively high, ways of reducing it are investigated. Firstly, the computational effects of using another set of closest assignment constraints, constraints (4.31), instead of (4.4) and (4.5) is explored. By doing so, an alternative optima to the solution detailed presented in Table 4.16 is obtained. The CPU time turned out to be only 4 hours and 24 minutes, which represents a huge 89.9% improvement in the CPU time.

Shelter	Weight	Utilization Rate (%)	Shelter	Weight	Utilization rate (%)
8	0.844608	95.34%	125	0.837197	57.64%
15	0.843545	94.90%	136	0.876425	77.49%
24	0.793249	56.27%	166	0.855216	81.56%
33	0.850611	63.54%	168	0.796147	79.82%
41	0.876523	91.11%	169	0.805162	38.54%
46	0.781146	74.56%	175	0.866260	30.52%
49	0.873054	97.97%	177	0.792973	39.64%
50	0.813283	93.34%	195	0.820383	88.95%
72	0.819059	81.70%	200	0.810284	70.12%
81	0.837859	105.74%	204	0.791751	89.54%
91	0.800685	48.62%	210	0.877855	46.60%
95	0.891362	72.82%	216	0.790012	54.10%
110	0.859889	76.83%	220	0.800323	70.52%

Table 4.16: Alternative Solution for *IST500*

In this alternative solution, again there are 26 open shelters and the average utilization rate of turned out to be 72.01%, i.e., slightly higher than before, but a minimum utilization rate of 30.52%, which is clearly lower than before. Presumably, there are many alternative optimal solutions with the same $W_{\min}$ as a large-scale data set is used. This implies that although these solutions are called “alternative”, they are clearly different with respect to other measures apart from the minimum weight. Hence, each solution might have a different significance in decision makers’ eyes. This may call for a fine tuning in the decision making process and opens other research directions as discussed in the next chapter.

In pursuit of decreasing the CPU time even more, an additional approach is explored. As mentioned when introducing constraints (4.19)–(4.23), λ_{im} ’s are defined as special ordered set of type 2 (SOS2) variables. This feature can explicitly be set in CPLEX, thus avoiding having to use constraints (4.26)–(4.29) in model (P). In other words, using the special feature of the software, λ_{im} ’s could be

declared as SOS2 variables that enables to exclude constraints (4.26)–(4.29).

Table 4.17 summarizes the CPU time comparisons considering this alternative implementation as well as considering the closest assignment constraints (4.31) instead of (4.4) and (4.5). One can observe that defining the SOS2’s explicitly and using (4.31) as the closest assignment constraints render a prominent combination to use for obtaining the best CPU time performance. By using this combination, the CPU time could get low as 2 hours and 2 minutes.

Closest Assignment Constraints	CPU Time Using (4.26)–(4.29)	CPU Times Defining the SOS2’s
(4.4) and (4.5)	43 hours and 48 minutes	20 hours and 21 minutes
(4.31)	4 hours and 24 minutes	2 hours and 2 minutes

Table 4.17: CPU times for the two enhancements studied.

As it could be observed, an extensive analysis is not conducted for *IST500* data set as we did in the previous section based on different β values and γ - δ combinations. The main purpose of using large scale data was to improve the computational performance of model (P) and this purpose is believed to be achieved in this section. Needless to say, the computationally improved model can be used for making similar analysis that are conducted for *K45*.

4.4 Chapter in a Nutshell

In this chapter, demand uncertainty is included in the shelter site location problem, which resulted in a more realistic approach to be used in the preparedness phase of disaster management. A chance-constrained optimization model is proposed for this problem as a means for capturing uncertainty in the demand. By invoking the central limit theorem, a non-linear deterministic equivalent model is obtained, which was then reformulated in order to “isolate” the non-linear terms in a way that they can be approximated by a family of piecewise linear functions. Eventually, it was possible to obtain a mixed-integer linear programming model

that can be tackled by a conventional solver. In order to prove the value the used methodology, extensive computational studies are performed and efficacious results are observed.

In particular, it was possible to solve the stochastic shelter site location problem at hand using data from the Kartal district in Istanbul, Turkey. The results show that different combinations of (i) shelter utilization rates, (ii) demand “service level”, and (iii) demand uncertainty level, may lead to completely different solutions. This is an indication that these aspects should be involved in a modeling framework for the problem. Moreover, comparisons were performed using a deterministic counterpart model. The results obtained are encouraging in the sense that when uncertainty exists in a shelter site location problem (and it is likely that it indeed exists), considering a modeling framework such as the one proposed in this study, may render different solutions compared to the deterministic ones. This supports the claim that capturing uncertainty in the shelter site location problem by means of probabilistic constraints may lead to solutions that can better hedge against uncertainty. In fact, if we know the exact demand for sheltering, then this model is not necessary: we should directly consider a single-scenario (deterministic) mode and find the optimal solution for that scenario. However, as these type of resource management schemes are done before the occurrence of disasters, it is substantial to take the variability of demand into account. What the computational results show is that under uncertainty, a solution obtained from our model may better hedge against uncertainty, thus leading to better “expected” results than if a deterministic setting is assumed.

The data set belonging to Istanbul Anatolian Side is used to evaluate the computational performance of the developed mixed-integer linear programming model for larger instances of the problem. It is shown that by adopting different closest assignment constraints and modeling schemes for SOS2 variables, the computational times could be improved significantly.

One aspect that leads to other research directions has to do with the objective function. As it is inferred in the end of Section 4.3.3, the maxmin objective for this problem may often render alternative optimal solutions as intuition could

easily foresee. However, these alternative solutions most probably have different characteristics with respect to other quality measures and this situation should not be overlooked. This allows and even encourages a fine tuning in the decision making process via, for instance, a multi-objective approach. Motivated by this, a multi-objective framework is developed for this problem in the next chapter.



Chapter 5

A Multi-Objective Framework for the Stochastic Shelter Site Location Problem

In this chapter, a multi-objective approach is developed for the shelter site location problem under demand uncertainty.

First, the base single-objective model is provided. Consequently, the drawbacks of using a single-objective approach is discussed. Then, alternative objectives to be used in the context of shelter site location problem are introduced. These are embedded in a well-known paradigm in multi-objective optimization: the ε -constraint approach. Then, an algorithm is developed for determining non-dominated solutions for 3-objective settings. Real data from Istanbul is used for performing the numerical experiments. The results show that considering multiple objectives in these type of facility location problems leads to solutions that may better support decision making.

Based on the findings on Section 4.3.3, the single-objective model which forms a basis for this chapter is shown next.

$$(P') \text{ maximize } W_{\min}, \quad (4.1)$$

subject to,

$$W_{\min} \leq w_i x_i + (1 - x_i), \quad i \in I \quad (4.2)$$

$$\sum_{i \in I} y_{ij} = 1, \quad j \in J \quad (4.3)$$

$$\sum_{s=r+1}^{|I|} y_{i_j(s),j} + x_{i_j(r)} \leq 1, \quad j \in J, r = 1, \dots, |I| - 1 \quad (4.31)$$

$$\sum_{j \in J} \left(\frac{\mu_j}{\sqrt{\sum_{k \in J} \sigma_k^2}} \right) y_{ij} + z_{1-\gamma_i} \sum_{m=1}^n \lambda_{im} b_m \leq \frac{q_i}{\sqrt{\sum_{k \in J} \sigma_j^2}} x_i, \quad i \in I \quad (4.15)$$

$$\sum_{j \in J} \left(\frac{\mu_j}{\sqrt{\sum_{k \in J} \sigma_k^2}} \right) y_{ij} + z_{\delta_i} \sum_{m=1}^n \lambda_{im} b_m \geq \frac{\beta q_i}{\sqrt{\sum_{k \in J} \sigma_j^2}} x_i, \quad i \in I \quad (4.16)$$

$$\sum_{j \in J} \left(\frac{\sigma_j^2}{\sum_{k \in J} \sigma_k^2} \right) y_{ij} = \sum_{m=1}^n \lambda_{im} b_m^2, \quad i \in I \quad (4.25)$$

$$\sum_{m=1}^n \lambda_{im} = x_i, \quad i \in I \quad (4.24)$$

$$W_{\min} \geq 0, \quad (4.8)$$

$$\lambda_{im} \geq 0, \quad i \in I, m = 1, \dots, n \quad (4.30)$$

$$x_i \in \{0, 1\}, \quad i \in I, \quad (4.9)$$

$$y_{ij} \in \{0, 1\}, \quad i \in I, j \in J \quad (4.10)$$

The used notation was defined in Section 4.1. The *Rawlsian* objective function, (4.1), maximizes the weight of the open shelter areas where the term $W_{\min}$ is defined by constraints (4.2). Constraints (4.31) are the *WF* closest assignment constraints. Probabilistic constraints (4.15) and (4.16) are used for meeting utilization requirements of open shelters. Constraints (4.25) and (4.24) are linearization related constraints where λ_{im} 's are SOS2 variables and n denotes the number of breakpoints used. This updated single objective model will be referred by (P') in the upcoming sections.

5.1 Motivation

The maxmin objective considered in model (P') as well as the closest assignment constraints raise an interesting discussion in the context of shelter site location problem. In fact, that objective is prone in terms of producing “plateaus” in the objective function space and thus, can easily yield many alternative optimal solutions. However, in practice, decision makers may not look at these solutions as being “equally” good. Similarly, closest assignment constraints does not necessarily mean that the total traveled distance is minimized; therefore, may lead to unpreferable solutions. Accordingly, there is room for considering other objectives that may guide the decision maker when the time comes for deciding among those alternative optimas or eliminating unpreferable solutions.

5.1.1 Drawbacks of Using *Rawlsian* Objective

These type of objectives are named after the maxmin principle of philosopher John Rawls’ “Justice as Fairness” theory. This principle was originally defined by Rawls as “social and economic inequalities are to be arranged so that they are both to the greatest benefit of the least advantaged” [45]. Characteristically, this maxmin concept is convenient to be used in humanitarian applications.

In the context of shelter site location, *Rawlsian* approach could be (and is) utilized for targeting fairness for the least advantaged victims in terms of the weight of the shelter that they are assigned. In such a case, the objective function to consider (and to be maximized) is $f(\mathbf{x}, \mathbf{y}) = W_{\min} = \min_{i \in I | x_i=1} \{w_i\}$, where w_i represents the weight of location $i \in I$. While maintaining the level for the open shelter locations’ weights at the possible maximum, this objective cannot make sure that the best-weighted locations are utilized. In other words, there may possibly be other alternative solutions having the same value for the minimum weight, $W_{\min}$, but higher weight values for the rest. This shows that, by using only the *Rawlsian* objective in this context, the available resources may not be put to their best use. Therefore, often objectives are necessary to ensure the best

use of location resources to serve public welfare.

5.1.2 Drawbacks of Using Closest Assignment Constraints

When developing an optimization model for supporting decision making in the shelter site location problem, closest assignment constraints are a key aspect to be considered so that the models “mimic” the behavior of people moving towards open facilities. Although these constraints aim at achieving a desirable outcome, they may not guarantee the best solution in terms of total distance traveled, which decreases their applicability. Similarly, it is easy to show that only minimizing the distance does not guarantee the closest assignment of the victims to the open shelters (as the capacity restrictions may prevent this). Accordingly, the use of these constraints along with a distance related objective would make sense in terms of generating more preferable solutions.

5.2 Multi-Objective Approaches

Maximizing W_{avg}

In order to compensate the drawbacks of *Rawlsian* objective’s single-handed use, maximizing W_{avg} – the average weight of the open shelters – could be used. Naturally, this is an objective function that also makes use of the weights w_i , $i \in I$. It can formally be defined as:

$$Z(\mathbf{x}) = W_{avg} = \frac{\sum_{i \in I} w_i x_i}{\sum_{i \in I} x_i} \quad (\text{to be maximized})$$

Linearizing this objective is not as straightforward as for W_{min} . Nevertheless, it can be done by defining a new set of non-negative variables, τ_i , $i \in I$, such that:

$$W_{avg} \cdot \sum_{i \in I} x_i = \sum_{i \in I} \tau_i \quad (5.1)$$

We can now ensure that W_{avg} represents, in fact, the average of the weights of

the open facilities by using the following constraints ([53]):

$$\tau_i \leq \overline{W_{avg}} \cdot x_i, \quad i \in I \quad (5.2)$$

$$\tau_i \leq W_{avg}, \quad i \in I \quad (5.3)$$

$$\tau_i \geq W_{avg} - [(1 - x_i) \cdot \overline{W_{avg}}], \quad i \in I \quad (5.4)$$

$$\sum_{i \in I} \tau_i = \sum_{i \in I} w_i \cdot x_i, \quad (5.5)$$

$$\tau_i \geq 0, \quad i \in I \quad (5.6)$$

In the above constraints, $\overline{W_{avg}}$ denotes the upper bound for W_{avg} , i.e. it is a parameter. Since the weights (w_i 's) are valued between $[0, 1]$, it can be deduced that $\overline{W_{avg}}$ is 1 in this case.

Minimizing Traveled Distance

Minimizing the traveled distance is a relevant objective to consider in facility location problems that make use of the closest assignment constraints. Particularly, in this thesis, minimization of average distance traveled (ADT) to a shelter is considered as a side-objective. The purpose of this is to eliminate any possible unfavorable solutions that may be generated by unaided use of closest assignment constraints. Recall that, ℓ_{ij} denotes the distance between a candidate shelter location i and demand point j ; then the average distance traveled per person can be defined as:

$$Z(\mathbf{x}) = \text{Average Distance Traveled (ADT)} = \frac{\sum_{i \in I, j \in J} \ell_{ij} d_j y_{ij}}{\sum_{j \in J} d_j} \quad (5.7)$$

The fact that several objective functions can be considered within the context of shelter site location problem raises a query: is a single objective function selected among those ones enough to capture a decision makers' goals? If not, then, development of a multi-objective framework is obviously necessary. Next, a well-known approach in multi-objective optimization, the ε -constraint method, is introduced and tailored for the shelter site location problem context.

5.3 The ε -Constraint Method

Suppose that L objective functions, $Z_\ell(\mathbf{x})$, $\ell = 1, \dots, L$, are considered in a multi-objective optimization problem (where $\mathbf{x}$ denotes the solution vector). Then this problem can be modeled as a vectorial optimization problem generically as follows:

$$\begin{aligned} & \text{minimize (maximize)} \quad Z(\mathbf{x}) = [Z_1(\mathbf{x}), Z_2(\mathbf{x}) \dots, Z_L(\mathbf{x})] \\ & \text{subject to} \quad \mathbf{x} \in S \end{aligned}$$

with S denoting the feasibility space; i.e., the set of solution vector ($\mathbf{x}$) satisfying all of the specified constraints.

For multi-objective problems, it is well-known that in general there will be no single solution that optimizes all objectives simultaneously. This leads to replacing the concept of *optimality* by *Pareto-optimality* or *efficiency* and the target becomes determining these so-called efficient solutions [54]. Based on the graphical meaning, these efficient solutions are said to be on the Pareto-frontier. In order to obtain such solutions for vectorial optimization problems, an appropriate scalarization method (among weighting methods, constraint methods, reference point methods or direction based methods) should be adopted initially. In this thesis, the ε -constraint method is adopted. By this way, decision makers could adopt a posteriori preference articulation procedure and evaluate the efficient solutions afterwards. A generic model to be used in this method is:

$$\min (\max) \quad Z_q(\mathbf{x}) \tag{5.8}$$

$$\text{subject to} \quad Z_k(\mathbf{x}) \geq \epsilon_k, \quad k \in \text{Maximization Objective}, \quad k \neq q, a \tag{5.9}$$

$$Z_a(\mathbf{x}) \leq \epsilon_a, \quad a \in \text{Minimization Objective}, \quad a \neq q, k \tag{5.10}$$

$$\mathbf{x} \in S$$

In this method, by systematically changing the ε values and solving the given model iteratively, one can obtain non-dominated solutions. In the context of stochastic shelter site location problem, S corresponds to the feasibility space defined by constraints (4.2), (4.3), (4.8), (4.9), (4.10), (4.15), (4.16), (4.24), (4.25), (4.30), (4.31). For the settings that include W_{avg} , constraints (5.2)-(5.6) should also be considered.

5.3.1 Implementation for a Bi-Objective Framework

In order to find the non-dominated solutions of a bi-objective problem, we can make use of lexicographic optimization approach while solving the models iteratively using the ε -constraint method [55].

Let $P_1(\mathbf{x}, \epsilon_2)$ and $P_2(\mathbf{x}, \epsilon_1)$ be defined respectively as follows:

$$\begin{array}{ll} \text{maximize} & Z_1(\mathbf{x}) \\ \text{subject to} & Z_2(\mathbf{x}) \geq \epsilon_2, \\ & \mathbf{x} \in S \end{array} \qquad \begin{array}{ll} \text{maximize} & Z_2(\mathbf{x}) \\ \text{subject to} & Z_1(\mathbf{x}) = \epsilon_1 \\ & \mathbf{x} \in S \end{array}$$

Using these predefined problems of P_1 and P_2 in a simple algorithmic manner, as introduced in Algorithm 1, the efficient solutions for a bi-objective setting could be generated. Before starting this basic algorithm, an empty set for storing Pareto optimal solutions is defined and named as *Pareto*. Moreover, the terms ϵ_1 and ϵ_2 are initialized as 0. First, P_1 is solved and ϵ_1 is set to its optimal objective function value (f_1^*). Then, in step 5, P_2 is solved in order to find the best solution for the second objective among the ones having the same f_1^* value for the first objective. The resulting solution combination for Z_1 and Z_2 is then stored in the *Pareto* set. After that, the ϵ_2 value is incremented by a predefined stepsize in order to move to the next Pareto efficient solution by solving P_1 again. This procedure is repeated until the infeasibility for P_1 is reached (which implies that the bound of the Pareto-frontier is hit).

Algorithm 1 A Procedure for ε -constraint Method on Bi-Objective Problems

- 1: $Pareto := \emptyset$; $\epsilon_1 := 0$; $\epsilon_2 := 0$; $k_2 :=$ “stepsize” (small enough number)
 - 2: **while** $P_1(\mathbf{x}, \epsilon_2)$ is feasible **do**
 - 3: Solve $P_1(\mathbf{x}, \epsilon_2)$ and obtain $f_1^* := opt[P_1(\mathbf{x}, \epsilon_2)]$
 - 4: Set $\epsilon_1 := f_1^*$
 - 5: Solve $P_2(\mathbf{x}, \epsilon_1)$ and obtain $f_2^* := opt[P_2(\mathbf{x}, \epsilon_1)]$
 - 6: $X := [f_1^*, f_2^*]$
 - 7: $Pareto := Pareto \cup \{X\}$
 - 8: $\epsilon_2 := f_2^* + k_2$
 - 9: **end while**
-

It should be noted that, the given configuration for P_1 and P_2 as well as Algorithm 1 is arranged for a max-max setting; i.e. both objectives are maximized. In case, the second objective (or both) consists of minimizing the corresponding objective function, several minor changes are required. Firstly, in P_1 's formulation, the inequality sign should be reversed as in $Z_2(\mathbf{x}) \leq \epsilon_2$. Moreover, ϵ_2 value should be decremented (instead of incrementing) by k_2 on the 8th step of the algorithm ($\epsilon_2 := f_2^* - k_2$).

Algorithm 1 could straightforwardly be tailored for the shelter site location problem context. Bi-objective settings are tested in the computational experiments section of this chapter while considering different combinations of the objectives $\max W_{\min}$, $\max W_{avg}$ and $\min \text{ADT}$. The feasibility set and the objectives to be used for P_1 and P_2 will be shaped accordingly for each combination.

There is an important issue to address when $\max W_{\min}$ is selected as one of the objectives in multi-objective settings. As shown above, while using the lexicographic approach in the implementation of ε -constraint method, objective function (4.1) will be represented as an equality constraint in certain iterations ($W_{\min} = W_{\min}^*$) where the second objective is maximized (or minimized). In this case, constraint set (4.2) would only determine a lower bound value for $W_{\min}$. However, this will not be enough to ensure that the lowest weight value of the open shelters is actually equal to $W_{\min}^*$. Consequently, it may generate feasible solutions which all have strictly greater weight values than $W_{\min}^*$ for open shelters. Therefore, if this situation is not addressed, it may cause inconsistency while applying the ε -constraint method by skipping some potentially non-dominated solutions. In order to handle this, additional constraints are required.

Let a_i denote binary variables which take the value 1 when a shelter site ($i \in I$) has the minimum weight value among the open ones. Then, by using the following constraints, the model will end up with correct $W_{\min}$ value even when $\max W_{\min}$ is not declared as an objective.

$$W_{\min} = \sum_{i \in I} w_i \cdot a_i, \quad (5.11)$$

$$\sum_{i \in I} a_i = 1, \quad (5.12)$$

$$a_i \leq x_i, \quad i \in I, \quad (5.13)$$

$$a_i \in \{0, 1\}, \quad i \in I \quad (5.14)$$

It is noted here that, when dealing with the $W_{\min}$ objective, the constraints (5.11)-(5.14) and when dealing with the W_{avg} objective, the constraints (5.2)-(5.6) should be appended to the corresponding models; and therefore included in the corresponding feasibility space S . There are no special requirements for the approaches including the objective of minimizing ADT.

5.3.2 Implementation for a 3-Objective Framework

In the previous section, it is discussed that the ε -constraint method consists of solving a sequence of single objective problems considering one of the objective functions and incorporating the other one (that we call side objective) as a constraint. For 3-objective settings, applying the ε -constraint method is not as straightforward as for the bi-objective one. Thus, a more “complex” algorithmic approach is necessary for a successful and efficient implementation.

A recent study that considers 3-objective ε -constraint method is by Abounacer et al. [56], in which a multi-objective location-transportation problem for disaster response is addressed. In this study, they aimed at simultaneous minimization of the total transportation time of relief items ($Z_1(\mathbf{x})$), the number of required first-aiders ($Z_2(\mathbf{x})$), and the non-covered demand among all affected areas ($Z_3(\mathbf{x})$). They provide an exact algorithm that uses ε -constraint method to determine all the efficient solutions. In their setting, they choose the objective function to optimize as the one that can take non-integer values, namely $Z_1(\mathbf{x})$, while the other two objectives are represented in constraints (as they are integer-valued). All possible values of the side-objective $Z_2(\mathbf{x})$ are known in advance; therefore, making use of this, they set this objective to its lowest possible value as a constraint and

perform the classical ε -constraint method as if they had two objectives ($Z_1(\mathbf{x})$ and $Z_3(\mathbf{x})$) as long as the model generates feasible solutions. When infeasibility is detected, the approach continues by selecting the next value of $Z_2(\mathbf{x})$ and the same procedure is repeated until the iterations are performed for all possible values of $Z_2(\mathbf{x})$. This integrality characteristic of their objective makes it simpler to develop an iterative methodology for implementing ε -constraint method (see Abounacer et al. [56] for a more detailed description of their approach).

The above mentioned methodology can be tailored for the settings where there are no objective functions taking integer values. However, it is necessary that at least one of them is defined over a finite scale in order to be able to initialize and terminate the process. In fact, Abounacer et al.'s [56] ideas can be adapted to stochastic shelter site location problem with 3-objectives making use of the above fact.

In this context, three objective functions are determined as follows:

- $Z_1(\mathbf{x})$: ADT (minimize);
- $Z_2(\mathbf{x})$: W_{avg} (maximize);
- $Z_3(\mathbf{x})$: W_{min} (maximize).

Note that $Z_3(\mathbf{x})$ can take fractional values from a finite set of weights of shelters (of cardinality at most $|I|$) whereas the others take continuous values.

The single objective problems that we need to consider are $B_1(\epsilon_2, \epsilon_3)$ and $B_2(\epsilon_2, \epsilon_3)$; their only difference is related to the sign of the constraint concerning $Z_3(\mathbf{x})$. Their models are shown below (B_1 on the left and B_2 on the right):

$\begin{aligned} &\text{maximize} && Z_1(\mathbf{x}) \\ &\text{subject to} && Z_2(\mathbf{x}) \geq \epsilon_2, \\ &&& Z_3(\mathbf{x}) \geq \epsilon_3 \\ &&& \mathbf{x} \in S \end{aligned}$	$\begin{aligned} &\text{maximize} && Z_1(\mathbf{x}) \\ &\text{subject to} && Z_2(\mathbf{x}) \geq \epsilon_2 \\ &&& Z_3(\mathbf{x}) = \epsilon_3 \\ &&& \mathbf{x} \in S \end{aligned}$
--	--

The proposed exact algorithm for finding all the efficient solutions of multi-objective stochastic shelter site location problem consists of two main stages. In

the first one, all the non-dominated solutions are found along with some (weakly) dominated solutions. In the second stage, using a post-processing procedure the latter is iteratively eliminated.

The first stage is detailed in Algorithm 2.

Algorithm 2 A Methodology for 3-Objective ϵ -constraint Method

```

1: SolutionSet :=  $\emptyset$ ;  $\epsilon_2 := 0$ ;  $\epsilon_3 := 0$ 
2: Solve  $B_1(\epsilon_2, \epsilon_3)$  and obtain a starting  $W_{\min}$  such that:  $f^3 := Z_3(\mathbf{x})$ .
3: for  $i = 1 : |I|$  do
4:   while  $B_2(\epsilon_2, f^3)$  is feasible do
5:     Solve  $B_2(\epsilon_2, f^3)$ 
6:      $X := \text{opt}[B_2(\epsilon_2, f^3)]$ 
7:     SolutionSet := SolutionSet  $\cup \{X\}$ 
8:      $\epsilon_2 := \epsilon_2 + k_2$ 
9:   end while
10:   $\epsilon_2 := 0$  and  $\epsilon_3 := f^3 + k_3$ 
11:  if  $B_1(\epsilon_2, \epsilon_3)$  is infeasible then
12:    break for
13:  else
14:    Solve  $B_1(\epsilon_2, \epsilon_3)$  and find the next feasible  $W_{\min}$  such that:  $f^3 := Z_3(\mathbf{x})$ .
15:  end if
16: end for

```

The main steps of the first stage are as follows. First, the model $B_1(0, 0)$ is solved in order to obtain a starting $W_{\min}$. Even if $W_{\min}$ can take values from a discrete set, it is not meaningful to start our procedure from the lowest possible $W_{\min}$ value; since $B_1(0, 0)$ will yield the lowest one for a non-dominated solution (i.e., all the lower $W_{\min}$ values will result in either infeasible or dominated solutions). Between steps 4-9 of the algorithm, while fixing $W_{\min}$ the model B_2 is solved as if it is bi-objective while increasing the side objective by an increment of k_2 until infeasibility is reached. In the meantime, the results are stored in the *SolutionSet*. Afterwards, the next possible $W_{\min}$ value is determined by solving $B_1(0, \epsilon_3)$ where ϵ_3 is assured to be strictly greater than the previous $W_{\min}$. This procedure is repeated at most as the number of distinct weight values, which can be denoted by $|I|$ (in the worst case). However, the number of iterations is most probably much lower and unnecessary iterations are prevented with steps 11-13. It is also important to note here that, the used stepsize values (k_2 and k_3) are

small enough numbers ensuring that no non-dominated solutions are skipped.

Even though Algorithm 2 is well-structured, it may come up with some dominated solutions. In order to eliminate those, simple post processing operations are required. In this procedure, a solution is compared with all other solutions. If a solution has lower $W_{\min}$ and W_{avg} values and higher ADT value from another solution, then it is considered to be dominated and removed from the solution set. The procedure is fully detailed in Algorithm 3.

ParetoSet denotes the set of non-dominated solutions obtained at the end of the whole procedure. SS_ℓ is the ℓ -th solution in set *SolutionSet* (SS) and corresponding objective values for $Z_1(\mathbf{x})$, $Z_2(\mathbf{x})$ and $Z_3(\mathbf{x})$ are denoted by f^1 , f^2 and f^3 . It is observed that this simple algorithm takes negligible computational time, e.g. less than 0.5 seconds to process more than 1300 solutions.

Algorithm 3 Post Processing of Solutions to Obtain the Efficient Solutions

Require: *SolutionSet* (referred by SS) that is obtained from Algorithm 1.

```

1: ParetoSet :=  $SS$ 
2: for  $i = 1 : |SS| - 1$  do
3:   for  $j = i + 1 : |SS|$  do
4:     if  $f^1(SS_j) \leq f^1(SS_i)$  and  $f^2(SS_j) \geq f^2(SS_i)$  and  $f^3(SS_j) \geq f^3(SS_i)$ 
       then
5:        $(SS_i)$  is dominated,  $ParetoSet := ParetoSet \setminus \{SS_i\}$ 
6:     else
7:        $(SS_i)$  is a non-dominated solution.
8:     end if
9:   end for
10: end for
```

In the above specialization of the ε -constrained method the objective to optimize is chosen as the ADT (i.e., $Z_1(\mathbf{x})$: minimize ADT) but W_{avg} could also be chosen (making the necessary adjustments in Algorithm 2). However, a set of preliminary computations showed that minimizing the ADT results in significantly lower run times compared to maximizing W_{avg} .

5.4 Computational Experiments

In this section, the bi-objective and 3-objective frameworks are tested on the context of multi-objective chance-constrained stochastic demand shelter site location problem. The tests are again conducted for two varying size data sets. First, these are introduced and then the obtained results for different configurations are presented and analyzed.

The demand uncertainty is hedged into the models using the variability of PAR value (which was introduced in the previous chapter). The same demand samples which are generated for Chapter 4 are used but this time two different variability scenarios are considered.

- Scenario 1 — Low Variability: $PAR = 0.125 \times U[0.95, 1.05]$
- Scenario 2 — High Variability: $PAR = 0.125 \times U[0.85, 1.15]$

It is known that the size of the feasibility space is an aspect that can significantly affect the number of efficient solutions in a multi-objective framework. Therefore, in order to observe the behavior of our models, we consider different values of β – the minimum allowed utilization rate on a shelter site. The tested β options are 0.30, 0.50 and 0.70. These different values lead to a varying size of feasibility space, which enriches the analysis.

In addition to those, the chance constraint parameters (γ_i and δ_i) used in constraints (4.15) and (4.16) are fixed to 10% for all demand points $j \in J$.

11 breakpoints are used in the piecewise linear functions to approximate the value of v_i , i.e. $n = 11$. Again, it should be noted that partitioning the range $[0, 1]$ to 11 is more than enough to approximate the value of v_i without any error.

All of the algorithms presented in this chapter are coded in Java API and the integrated optimization models are solved using IBM CPLEX *v12.6.1* that runs on the computer whose specifications are identified in Section 4.3.

Two different data sets are used for the related computational experiments. The first one is the Kartal data set which was previously introduced in Section 4.3.2. Recall that, the basic specifications of it is presented on Table 4.1. In order to observe the behavior of multi-objective modeling approach in a medium/large scale data set which can be solved in shorter computation times, a new one is generated using *IST500* as a basis. The generation procedure of this new data set is analyzed next and the data set itself will be introduced.

5.4.1 A New Medium-Sized Data Set: *IST220*

The main idea of the generation of this new data set is based on shrinking the size of *IST500* without compromising much from the quality of data. Hence, it is aimed to aggregate nodes which are very close to each other into one and reduce the number of nodes in total. This procedure is applied for 230 demand points and 270 potential shelter locations of *IST500*.

The known parameters of *IST500* are the coordinates of the potential shelter and district locations, populations of districts and weights of potential shelters. Via using the coordinates of the nodes, distances between every candidate shelter pair are calculated and a distance matrix for shelters is generated. Similarly, a distance matrix for the districts is also formed. After doing so, a p-center problem is solved to aggregate shelters and districts, separately. The notation and mathematical formulation of this basic problem is provided below:

Sets:

R Set of nodes (Candidate shelter sites or districts)

Parameters:

ℓ_{ij} : distance (km) between nodes $i \in R$ and $j \in R$.

p : number of aggregated points.

Decision Variables:

$$m_i = \begin{cases} 1 & \text{if location } i \in R \text{ is chosen as the aggregation point,} \\ 0 & \text{otherwise.} \end{cases}$$

$$n_{ij} = \begin{cases} 1 & \text{if location } j \in R \text{ is aggregated within aggregation point } i \in R, \\ 0 & \text{otherwise.} \end{cases}$$

Ω = maximum distance between aggregated points.

The p-center model can now be formulated for node-aggregation.

$$\text{minimize } \Omega, \tag{5.15}$$

$$\text{subject to } \sum_{i \in R} m_i = p, \tag{5.16}$$

$$n_{ij} \leq m_i, \quad i \in R, j \in R \tag{5.17}$$

$$\sum_{i \in R} n_{ij} = 1, \quad j \in R \tag{5.18}$$

$$n_{ij} \cdot \ell_{ij} \leq \Omega, \quad i \in R, j \in R, \tag{5.19}$$

$$\Omega \geq 0, \tag{5.20}$$

$$m_i \in \{0, 1\}, \quad i \in R \tag{5.21}$$

$$n_{ij} \in \{0, 1\}, \quad i \in R, j \in R \tag{5.22}$$

In this p-center model, it is aimed to aggregate the closest nodes; therefore the the maximum of the distances between each aggregated node pair is minimized in the objective function. Number of aggregation points is set to a known value (p) and it is ensured that all nodes are assigned to a selected point. In order to determine the final p value, this model is solved multiple times for different p values until an acceptable Ω value is obtained. 230 potential shelter location nodes in *IST500* are aggregated into 100 nodes, within a maximum radius of 875 meters. On the other hand, 230 demand points in *IST500* are aggregated into 120 nodes, within a radius of 1.30 kilometers. As a result, a data set with 220 nodes is generated, which will be referred as *IST220* in the rest of the thesis.

After determining 100 alternative shelter locations, the capacities of the aggregated points are summed up for each aggregation point and this sum is assigned as the capacity value. As the weight data is already randomly generated, when associating a weight value to these 100 points, the aggregation points' weights are preserved. For the demand points, same procedure is used for calculating the population of aggregation points as it is done for capacities of shelters.

The major specifications of this data set are summarized on Table 5.1 and the data set can be found in in Appendix A.5 and A.6. It could be said that this data set is more of an artificial one compared to others.

Number of candidate shelter areas:	100
Number of demand points:	120
Minimum & Maximum weight:	0.140633 - 0.893454
Mean of weights:	0.575811
Standard deviation of weights:	0.202467

Table 5.1: *IST220* Specifications

Stepsize values should also be determined strategically to make transitions between iterations while not leaving any non-dominated solutions behind. Based on the used data, selected stepsize values for each objective type is shown below. It should also be noted that, in order not to skip any non-dominated solutions, the optimality tolerance of CPLEX should be adjusted based on the stepsize of the objective that remains on the objective function.

Objective Type	Stepsize for <i>K45</i>	Stepsize for <i>IST220</i>
$W_{\min}$	10^{-3}	10^{-6}
W_{avg}	10^{-5}	10^{-5}
ADT	10^{-3}	10^{-3}

Table 5.2: Stepsize Values for Different Data Set & Objective Configurations

5.4.2 Results for *K45*

The results for this data set is provided in two parts. In the first one, two different bi-objective settings are evaluated. Afterwards, an analysis on a 3-objective

framework is presented.

Results for Bi-Objective Settings

The Pareto-optimal solutions of $K45$ will be examined in two different bi-objective settings. In the first one, W_{avg} is maximized alongside W_{min} . In the following one, W_{min} is maximized and ADT is minimized simultaneously.

W_{min} vs. W_{avg}

The computational results of maximizing both W_{min} and W_{avg} can be found in Table 5.3. This solution table contains two sub-tables, each of which for a different variability level. In each sub-table, settings of all three β levels presented. For each such value, we present a first line corresponding to the single objective model's solution (model (P')). In this line, we observe the values obtained for both of the objective functions, in this case W_{min} and W_{avg} . Following this, all the Pareto optimal solutions are presented.

Low Variability				High Variability			
		W_{min}	W_{avg}			W_{min}	W_{avg}
$\beta = 0.3$	max W_{min}	0.847	0.89825	$\beta = 0.3$	max W_{min}	0.847	0.89825
	Pareto Optimal 1	0.847	0.89825		Pareto Optimal 1	0.847	0.89825
	Pareto Optimal 2	0.827	0.93740		Pareto Optimal 2	0.827	0.91360
$\beta = 0.5$	max W_{min}	0.847	0.88167	$\beta = 0.5$	max W_{min}	0.847	0.88167
	Pareto Optimal 1	0.847	0.88167		Pareto Optimal 1	0.847	0.88167
	Pareto Optimal 2	0.827	0.9374		Pareto Optimal 2	0.803	0.91560
$\beta = 0.7$	max W_{min}	0.847	0.88167	$\beta = 0.7$	max W_{min}	0.847	0.88167
	Pareto Optimal 1	0.847	0.88167		Pareto Optimal 1	0.847	0.88167

Table 5.3: Results for $K45 - W_{min}$ vs. W_{avg} .

As it could be observed, in all of the 6 combinations of β and demand variability levels, the optimal solution to the single objective problem (max W_{min}) provides directly an efficient solutions, i.e. it always coincides with the Pareto Optimal 1. This can be explained by the fact that the data set under consideration is small and thus the number of Pareto optimal solutions is small and not much “rich”.

This is confirmed by the fact that for the setting where the feasibility space is the smallest ($\beta = 0.7$), we only have one Pareto optimal solution which is also provided by the single-objective problem.

$W_{\min}$ vs. ADT

For the second objective pairing, $W_{\min}$ and ADT, the results are provided in Table 5.4.

Low Variability				High Variability			
		$W_{\min}$ ADT				$W_{\min}$ ADT	
$\beta = 0.3$	max $W_{\min}$	0.847	2.983	$\beta = 0.3$	max $W_{\min}$	0.847	3.068
	Pareto Optimal 1	0.847	2.911		Pareto Optimal 1	0.847	2.911
	Pareto Optimal 2	0.827	1.698		Pareto Optimal 2	0.809	2.077
	Pareto Optimal 3	0.801	1.572		Pareto Optimal 3	0.803	1.990
	Pareto Optimal 4	0.694	1.500		Pareto Optimal 4	0.801	1.532
$\beta = 0.5$	max $W_{\min}$	0.847	3.068	$\beta = 0.5$	max $W_{\min}$	0.847	3.068
	Pareto Optimal 1	0.847	3.068		Pareto Optimal 1	0.847	3.068
	Pareto Optimal 2	0.827	1.728		Pareto Optimal 2	0.809	2.435
	Pareto Optimal 3	0.694	1.671		Pareto Optimal 3	0.803	1.211
					Pareto Optimal 4	0.801	1.974
$\beta = 0.7$	max $W_{\min}$	0.847	3.068	$\beta = 0.7$	max $W_{\min}$	0.847	3.068
	Pareto Optimal 1	0.847	3.068		Pareto Optimal 1	0.847	3.068
	Pareto Optimal 2	0.827	1.789		Pareto Optimal 2	0.809	2.732
					Pareto Optimal 3	0.801	2.424
					Pareto Optimal 4	0.674	2.217

Table 5.4: Results for $K45 - W_{\min}$ vs. ADT.

Here we observe that not all the Pareto optimal solutions obtained for the low variability setting are efficient in the high variability one and vice versa. This indicates that capturing uncertainty (i.e., taking demand variability into account) is relevant since different solutions may be obtained when the variability increases.

Another interesting aspect is that, for $\beta = 0.3$ (the most loose setting in terms of β), the single objective solution corresponding to maximizing $W_{\min}$ is weakly dominated by the first Pareto optimal solution in both variability scenarios. This shows the ability of the multi-objective framework to look for the best alternative solution in terms of $W_{\min}$ that minimizes ADT.

Moreover, observing Table 5.4, we conclude that significant improvements can be achieved in ADT if we allow deteriorating from the single objective solution's base $W_{\min}$ value. Those improvements range between 28% and 50%. Taking into account that ADT is an average value (per person), such improvements mean that the total distance traveled by all disaster victims can be significantly reduced in some cases.

Accordingly, by using such an approach and obtaining many efficient solutions, we can provide the decision makers with deeper information for evaluating the trade-offs between different objectives and this way select a solution that best fits a particular setting.

Results for the 3-Objective Setting

On Table 5.5 we can observe the computational specifications related to the implementation of the ε -constraint based exact algorithm that finds the non-dominated solutions in 3-objective frameworks.

		Number of Solutions Found	Number of Efficient Solutions	Total Solution Time
Low Variability	$\beta = 0.3$	15	10	3.2 sec
	$\beta = 0.5$	7	4	1.5 sec
	$\beta = 0.7$	2	2	0.6 sec
High Variability	$\beta = 0.3$	19	17	4.9 sec
	$\beta = 0.5$	5	5	1.6 sec
	$\beta = 0.7$	4	4	1.6 sec

Table 5.5: 3-Objective Setting's Computational Overview for *K45*

For this 45-node instance, it can easily be noticed that the run times are short. It is also apparent that the number of non-dominated solutions is slightly larger for the high variability scenario setting. In addition, the effect of the feasibility space size is observed on the gradual decrease in terms of number of efficient solutions when we observe the increase of β . The algorithm's rate of yield of non-dominated solutions seems satisfying.

The non-dominated solutions for each β setting and demand variability level of 3-objective framework of *K45* data set is shown on Table 5.6.

Low Variability					High Variability				
$\beta = 0.3$		$W_{\min}$	W_{avg}	ADT		$W_{\min}$	W_{avg}	ADT	
	Pareto Optimal 1	0.694	0.86100	1.500	Pareto Optimal 1	0.694	0.86400	1.505	
	Pareto Optimal 2	0.694	0.86400	1.505	Pareto Optimal 2	0.801	0.90757	1.532	
	Pareto Optimal 3	0.801	0.90414	1.527	Pareto Optimal 3	0.801	0.91467	1.623	
	Pareto Optimal 4	0.801	0.90757	1.532	Pareto Optimal 4	0.801	0.92100	1.801	
	Pareto Optimal 5	0.801	0.91067	1.618	Pareto Optimal 5	0.801	0.93220	1.893	
	Pareto Optimal 6	0.801	0.91467	1.623	Pareto Optimal 6	0.803	0.87950	1.990	
	Pareto Optimal 7	0.827	0.92533	1.698	Pareto Optimal 7	0.803	0.89883	2.004	
	Pareto Optimal 8	0.827	0.93740	1.789	Pareto Optimal 8	0.803	0.90450	2.026	
	Pareto Optimal 9	0.847	0.89160	2.911	Pareto Optimal 9	0.803	0.90560	2.096	
	Pareto Optimal 10	0.847	0.89825	2.921	Pareto Optimal 10	0.803	0.91240	2.117	
$\beta = 0.3$									
	Pareto Optimal 11	0.809	0.88050	2.077	Pareto Optimal 11	0.809	0.88050	2.077	
	Pareto Optimal 12	0.809	0.89983	2.091	Pareto Optimal 12	0.809	0.89983	2.091	
	Pareto Optimal 13	0.809	0.90550	2.112	Pareto Optimal 13	0.809	0.90550	2.112	
	Pareto Optimal 14	0.809	0.90680	2.182	Pareto Optimal 14	0.809	0.90680	2.182	
	Pareto Optimal 15	0.809	0.91360	2.204	Pareto Optimal 15	0.809	0.91360	2.204	
	Pareto Optimal 16	0.847	0.89160	2.911	Pareto Optimal 16	0.847	0.89160	2.911	
	Pareto Optimal 17	0.847	0.89825	2.921	Pareto Optimal 17	0.847	0.89825	2.921	
$\beta = 0.5$					$\beta = 0.5$				
	Pareto Optimal 1	0.694	0.87300	1.671		Pareto Optimal 1	0.801	0.85400	1.974
	Pareto Optimal 2	0.827	0.89983	1.728		Pareto Optimal 2	0.801	0.91560	2.060
	Pareto Optimal 3	0.827	0.93740	1.789		Pareto Optimal 3	0.803	0.91240	2.117
$\beta = 0.5$					$\beta = 0.5$				
	Pareto Optimal 4	0.847	0.88167	3.068		Pareto Optimal 4	0.809	0.86350	2.435
	Pareto Optimal 5					Pareto Optimal 5	0.847	0.88167	3.068
$\beta = 0.7$					$\beta = 0.7$				
	Pareto Optimal 1	0.827	0.93740	1.789		Pareto Optimal 1	0.674	0.85040	2.217
	Pareto Optimal 2	0.847	0.88167	3.068		Pareto Optimal 2	0.801	0.86075	2.423
						Pareto Optimal 3	0.809	0.85825	2.732
$\beta = 0.7$					$\beta = 0.7$				
						Pareto Optimal 4	0.847	0.88167	3.068

Table 5.6: Results for K45 – 3-Objective Framework

There are many solutions that are only valid for one of the scenarios; however, it could be analyzed that some solutions of low variability one dominates some of the high variability's Pareto optimal solutions. It could also be observed that, there are always more non-dominated solutions for high variability scenario compared to the low variability one. This is, in fact, an important indication that shows the affect of capturing different levels of demand uncertainty on yielding different solutions.

5.4.3 Results for *IST220*

The same scheme applied for *K45* was also used for *IST220* with the results reported next. This is a much larger data set and thus, we expect to observe the benefits of applying a multi-objective optimization framework more explicitly.

Results for Bi-Objective Settings

$W_{\min}$ vs. W_{avg}

The most prominent characteristic in this setting turns out to be the small number of non-dominated solutions found. Naturally, it is hard to improve average of the weights while decreasing the lowest value. However, maximizing $W_{\min}$ or W_{avg} individually does not necessarily lead to the same solution. This can be observed in the settings which yield more than one efficient solution (We recall that, the last Pareto optimal solution maximizes W_{avg} for each setting). Even though the number of efficient solutions is considerably small, unlike *K45* data set, among the 5 settings out of 6, the first Pareto optimal solution immediately improve the objective function W_{avg} value significantly and therefore each one dominates the solution yielded by the single objective model (P'). This shows the importance of adopting a multi-objective framework in order to get rid of unpreferable solutions.

The corresponding results are shown on the following table.

Low Variability				High Variability			
$\beta = 0.3$		$W_{\min}$	W_{avg}	$\beta = 0.3$		$W_{\min}$	W_{avg}
	max $W_{\min}$	0.595974	0.73458		max $W_{\min}$	0.595974	0.74888
$\beta = 0.5$	Pareto Optimal 1	0.595974	0.82540	$\beta = 0.5$	Pareto Optimal 1	0.595974	0.82243
	max $W_{\min}$	0.595974	0.74345		max $W_{\min}$	0.595974	0.72726
$\beta = 0.7$	Pareto Optimal 1	0.595974	0.80902	$\beta = 0.7$	Pareto Optimal 1	0.595974	0.80902
	Pareto Optimal 2	0.580393	0.80996		max $W_{\min}$	0.595974	0.75822
$\beta = 0.9$	max $W_{\min}$	0.595974	0.74225	$\beta = 0.9$	Pareto Optimal 1	0.595974	0.75822
	Pareto Optimal 1	0.595974	0.75822		Pareto Optimal 2	0.580393	0.78775

Table 5.7: Results for *IST220* – $W_{\min}$ vs. W_{avg} .

$W_{\min}$ vs. ADT

The results obtained when the objective functions considered are $W_{\min}$ and ADT for *IST220* data set are depicted in two tables; namely in Table 5.8 and Table 5.9. These tables are read as the previous ones but each one is associated with a single demand variability level (small and high, respectively). Since the

number of Pareto optimal solutions is considerably higher than before, graphical representations of the results are also provided on the bottom of the tables.

For low variability scenario, when β is 0.3 and 0.5 the average distance is improved more than 50% when we move from the single objective solution to the first Pareto optimal one. On the other hand, when β is 0.7 the feasibility space seems to be considerably reduced and such changes are not immediately observed or else they are not so significant. Also, for this value of β in the low variability setting, less number of efficient solutions are observed. The corresponding results are depicted on Table 5.8.

Low Variability			Low Variability			Low Variability		
$\beta = 0.3$		$W_{\min}$ ADT	$\beta = 0.5$		$W_{\min}$ ADT	$\beta = 0.7$		$W_{\min}$ ADT
	max $W_{\min}$	0.595974 4.864		max $W_{\min}$	0.595974 4.494		max $W_{\min}$	0.595974 2.342
	Pareto Optimal 1	0.595974 2.143		Pareto Optimal 1	0.595974 2.247		Pareto Optimal 1	0.595974 2.342
	Pareto Optimal 2	0.587395 1.837		Pareto Optimal 2	0.580393 1.995		Pareto Optimal 2	0.572222 1.869
	Pareto Optimal 3	0.580393 1.784		Pareto Optimal 3	0.572222 1.739		Pareto Optimal 3	0.502137 1.814
	Pareto Optimal 4	0.577434 1.455		Pareto Optimal 4	0.502137 1.636		Pareto Optimal 4	0.471939 1.680
	Pareto Optimal 5	0.572222 1.416		Pareto Optimal 5	0.471939 1.620		Pareto Optimal 5	0.417498 1.372
	Pareto Optimal 6	0.502137 1.372		Pareto Optimal 6	0.462376 1.575		Pareto Optimal 6	0.268146 1.185
	Pareto Optimal 7	0.462376 1.370		Pareto Optimal 7	0.417498 1.326			
	Pareto Optimal 8	0.417498 1.325		Pareto Optimal 8	0.347547 1.135			
	Pareto Optimal 9	0.376080 1.266		Pareto Optimal 9	0.268146 1.026			
	Pareto Optimal 10	0.347547 0.989						

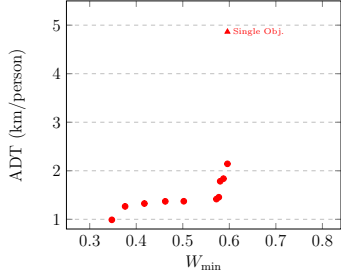
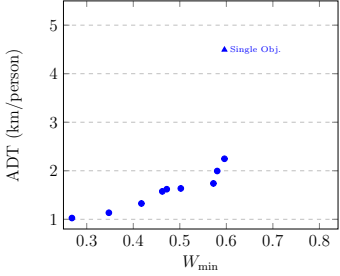
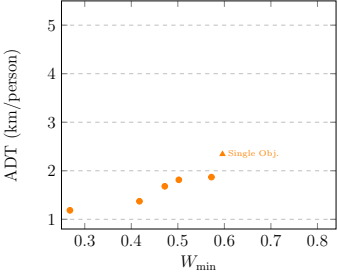




Table 5.8: Results for *IST220* – $W_{\min}$ vs. ADT (Low Variability Demand)

For the high variability setting, a similar pattern can be observed in terms of number of Pareto optimal solutions whilst β is increasing. However, the stochasticity effects are significant on the average distance values, specifically in the earlier iterations. Therefore, this is again another major indication that efficient solutions can be highly affected by the demand variability and shows the value of capturing such uncertainty. Additionally, the higher demand variability results in increased number of efficient solutions. Although we can observe improvements in terms of ADT in the initial iterations of three β levels, the improvement rates

are not as significant as the low variability scenario. The results are presented on Table 5.9.

High Variability			High Variability			High Variability		
$\beta = 0.3$		$W_{\min}$ ADT	$\beta = 0.5$		$W_{\min}$ ADT	$\beta = 0.7$		$W_{\min}$ ADT
	max $W_{\min}$	0.595974 4.483		max $W_{\min}$	0.595974 5.232		max $W_{\min}$	0.595974 5.533
	Pareto Optimal 1	0.595974 3.881		Pareto Optimal 1	0.595974 4.307		Pareto Optimal 1	0.595974 5.387
	Pareto Optimal 2	0.574319 3.830		Pareto Optimal 2	0.574319 4.286		Pareto Optimal 2	0.574319 5.235
	Pareto Optimal 3	0.556093 3.784		Pareto Optimal 3	0.556093 4.249		Pareto Optimal 3	0.502137 4.296
	Pareto Optimal 4	0.545592 2.908		Pareto Optimal 4	0.546913 4.234		Pareto Optimal 4	0.485232 4.193
	Pareto Optimal 5	0.510776 2.859		Pareto Optimal 5	0.502137 3.296		Pareto Optimal 5	0.471939 4.136
	Pareto Optimal 6	0.502137 2.507		Pareto Optimal 6	0.456578 3.285		Pareto Optimal 6	0.440460 3.893
	Pareto Optimal 7	0.485232 2.475		Pareto Optimal 7	0.453114 3.169		Pareto Optimal 7	0.417498 3.881
	Pareto Optimal 8	0.471939 2.464		Pareto Optimal 8	0.434373 3.131		Pareto Optimal 8	0.410607 3.578
	Pareto Optimal 9	0.456579 2.451		Pareto Optimal 9	0.410607 2.882		Pareto Optimal 9	0.376080 3.366
	Pareto Optimal 10	0.433190 2.447		Pareto Optimal 10	0.405868 2.852		Pareto Optimal 10	0.140633 3.349
	Pareto Optimal 11	0.417498 2.403		Pareto Optimal 11	0.376080 2.598			
	Pareto Optimal 12	0.410607 2.359		Pareto Optimal 12	0.335560 2.536			
	Pareto Optimal 13	0.376080 2.254		Pareto Optimal 13	0.253225 2.486			
	Pareto Optimal 14	0.347547 2.226		Pareto Optimal 14	0.241292 2.218			
	Pareto Optimal 15	0.335902 2.220						
	Pareto Optimal 16	0.335560 2.193						
	Pareto Optimal 17	0.284405 2.165						
	Pareto Optimal 18	0.253225 2.111						
	Pareto Optimal 19	0.241292 1.903						
	Pareto Optimal 20	0.215851 1.780						

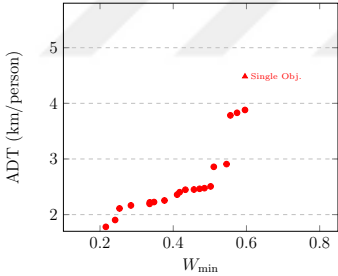
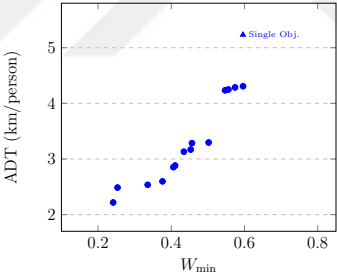
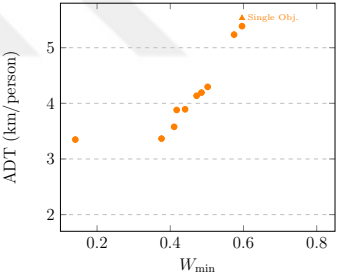




Table 5.9: Results for *IST220* – $W_{\min}$ vs. ADT (High Variability Demand)

For both low and high variability solutions, the bi-objective framework’s results explicitly show the benefits of this approach in *IST220* data set.

Results for the 3-Objective Setting

As expected, the number of iterations observed for *IST220* is significantly higher than for *K45*. Table 5.10 provides an overview in terms of the obtained computational results. We note that for the particular case where $\beta = 0.3$, the number of iterations turns out to be more than 1000 along with the total solution time slightly exceeding 4 hours for each demand uncertainty scenario. With an increase of β to 0.5, we observe a decrease of more than 60% in the number of solutions while the number of non-dominated solutions is dramatically decreased

for high variability scenario as opposed to the nearly halved state of low variability one.

		Number of Solutions Found	Number of Efficient Solutions	Total Solution time
Low Variability	$\beta = 0.3$	1323	416	4h 1m
	$\beta = 0.5$	462	209	3h 8m
	$\beta = 0.7$	89	62	22m
High Variability	$\beta = 0.3$	1168	476	4h 3m
	$\beta = 0.5$	287	153	58m
	$\beta = 0.7$	40	28	8m

Table 5.10: 3-Objective Setting's Computational Overview for *IST220*

Since the number of solutions on the Pareto frontier is quite large, a tabular identification of them is not meaningful. Hence, solutions are only depicted graphically.

Figures 5.1–5.3 shows the non-dominated solutions for the three β levels and for low uncertainty scenario. Similarly, Figures 5.4–5.6 illustrate the Pareto-frontier for the high variability scenario for each β level. For better understanding of the field of view in the 3-dimensional figures, front and side-views of the graphs are also provided. Besides this reasoning, these views also provide a practical perspective for pairwise comparison of objectives.

Looking into these figures we observe that all the solutions define a “cascade” pattern. The main reason behind this is the accumulation of solutions around a single value of $W_{\min}$. Moreover, we can observe more scattered solutions when β increases. As the number of non-dominated solutions scaled up for this 3-criteria setting (for *IST220*), it could be easily said that selection of a solutions among these will not be as easy as in other settings for a decision maker. However, the cascaded structure of solutions would make it easy to detect the highest shift in values. Nevertheless, a decision maker would certainly have a deeper insight in terms of the possible trade-off between the different objectives considered using this approach.

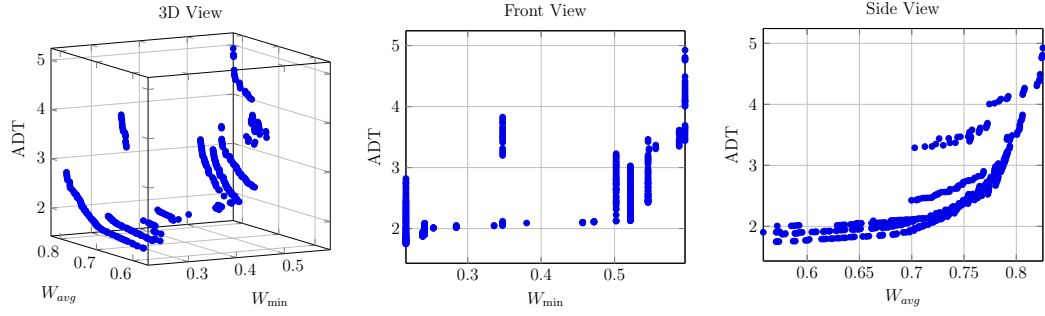


Figure 5.1: 3-Objective *IST220* Solutions (Low Variability & $\beta=0.3$)

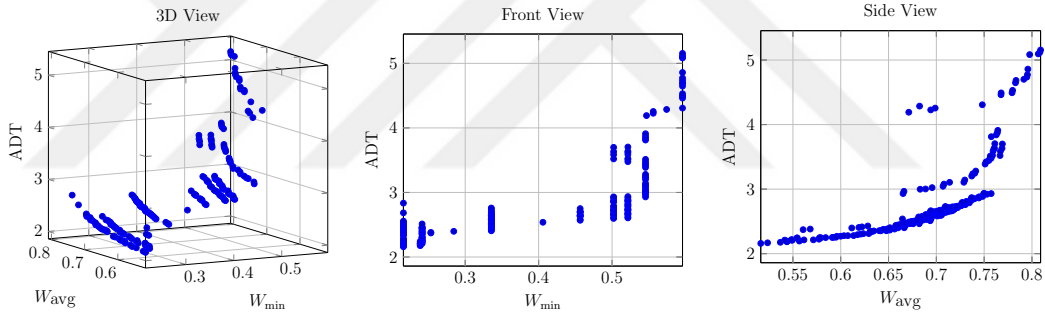


Figure 5.2: 3-Objective *IST220* Solutions (Low variability & $\beta=0.5$)

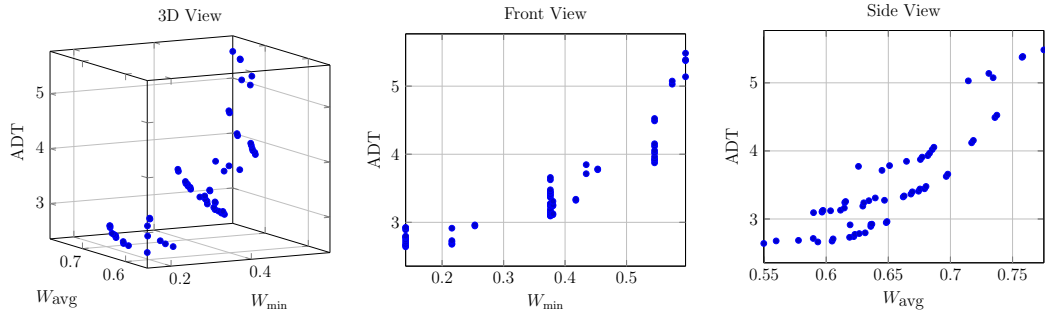


Figure 5.3: 3-Objective *IST220* Solutions (Low variability & $\beta=0.7$)

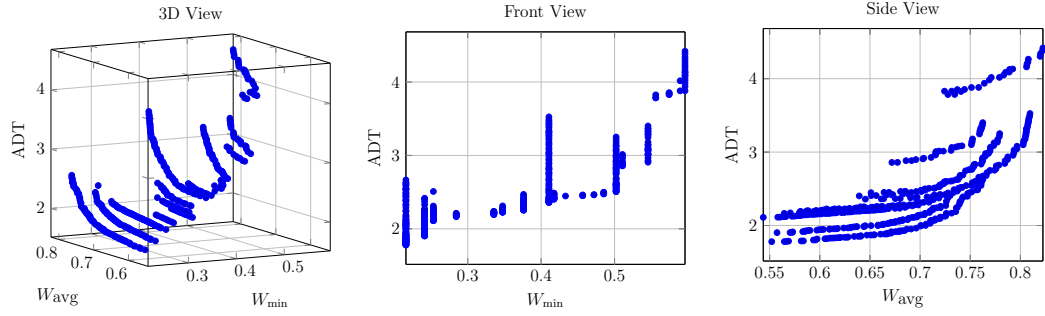


Figure 5.4: 3-Objective *IST220* Solutions (High Variability & $\beta=0.3$)

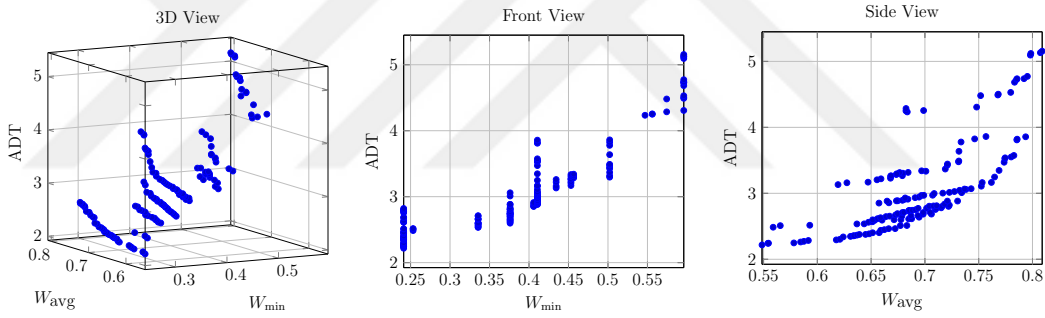


Figure 5.5: 3-Objective *IST220* Solutions (High Variability & $\beta=0.5$)

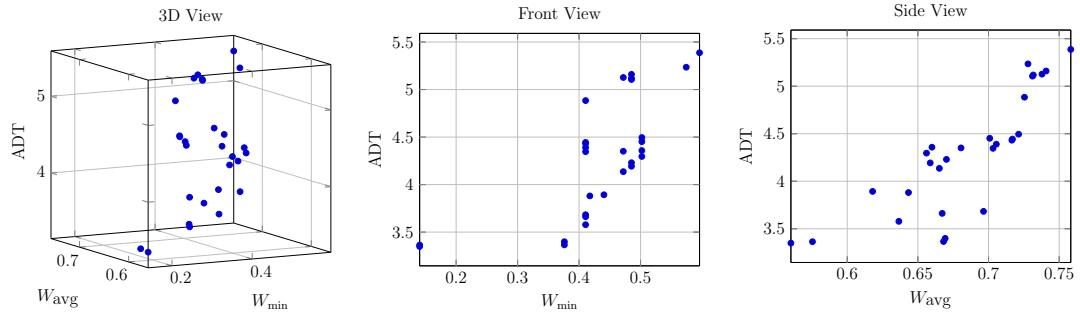


Figure 5.6: 3-Objective *IST220* Solutions (High Variability & $\beta=0.7$)

5.5 Chapter in a Nutshell

In this chapter, multi-objective optimization methods are embedded to the shelter site location problem in order to have a stronger modeling approach that generates only non-dominated solutions for the selected performance measures. By using the ε -constraint method, bi-objective and 3-objective frameworks for shelter site location context are developed. An existing algorithm for 3-objective settings is tailored so that the modified version could be used for the situations where all 3-objectives may take non-integer values.

In bi-objective configurations, while maximizing W_{avg} alongside W_{min} , the drawbacks of using only the *Rawlsian* approach could be compensated as the dominated alternative solutions will no longer come forward any more. Similarly, maximizing W_{min} while minimizing ADT ensures that the closest assignment constraints do not generate any solutions that yields more distance than necessary to be traversed by the disaster victims. For 3-objective framework, both advantages are gained simultaneously, i.e., the dominated alternative solutions yielded by the maxmin objective are eliminated and the closest assignment constraints are supported to provide best possible results.

Throughout the computational experiments, the importance of capturing uncertainty is unfolded again. For the results of nearly every tested setting, it is observed that the number of efficient solutions differs based on the level of demand variability. Besides that, the efficient solutions for low variability configurations are generally no longer valid when the variability level increases. These are strong indications implying that the variation of demand should definitely be considered in the decision making process in order to develop well-prepared resource management plans in pre-disaster phase.

In addition to that, the computational studies show the effect of the feasibility space size on the significance of the benefits of multi-objective framework explicitly. Particularly, the significance is highest when large-scale data sets are used

with “looser” constraint settings (e.g. service level constraints with lower β values). Accordingly, by obtaining many efficient solutions, the decision makers can be provided with deeper information for evaluating the trade-offs between different objectives and select the one that is the most suitable for them. However, for cases where the number of efficient solutions is excessively high, the selection process for the decision makers would be rather difficult. Complementarily, based on their preferences a utility function could be defined to rank these efficient solutions in a preference order which would help them to select one of these solutions without complications. Nevertheless, it should be noted that defining an applicable utility function is not a very easy process itself as it would require many reliable input from the decision makers.

Chapter 6

Conclusions and Future Research Directions

In this thesis, one of the crucial problems in disaster management, the shelter site location problem, is addressed. The selection of the locations for these facilities is done before the occurrence of disasters; hence, it is important to take uncertainty into account when making resource management plans in the preparedness phase of disaster management. Motivated by this, a new methodology for shelter site location problem is developed by taking demand variability into consideration.

In the second chapter, the principles of humanitarian operations are presented and the role of shelter sites in disaster response and relief is emphasized. In Chapter 3, we present the related literature to the so-called shelter site location problem together with the studies that utilize chance-constraints and multi-objective frameworks in similar contexts. In Chapter 4, a stochastic programming model is proposed for this problem as a tool for capturing uncertainty in the demand. In Chapter 5, bi-objective and 3-objective schemes are implemented in the stochastic shelter site location problem.

In the proposed stochastic programming model in Chapter 4, chance-constraints are utilized for capacity related constraints in order to construct a

framework that is more realistic while capturing uncertainty in shelter demand. These deterministic equivalents of chance-constraints are derived using the Central Limit Theorem assuming that the demand of each district is independent. The resulting non-linearity of these deterministically-equivalent constraints is resolved using an approximation approach that uses SOS2 variables. As a result, a mixed-integer linear programming formulation is obtained that can be tackled by an off-the-shelf solver. Computational experiments generated encouraging results that implies the value of stochastic optimization over a deterministic one by showing that uncertain demand scheme may render different solutions compared to the deterministic one. Thus, it is not wrong to conclude that using a deterministic approach may oversimplify this problem especially if the demand variability is not low and cannot generate robust solutions. A large-scale data set is used for evaluating and improving the computational performance of the stochastic optimization model on larger instances and different modeling techniques are adopted based on the findings of the experiments.

Multi-objective optimization methods are developed for shelter site location problem context in Chapter 5. The method for scalarizing the generic multi-objective vectorial optimization model is selected as the ε -constraint method. For bi-objective settings, two models are solved in a lexicographic manner and all the efficient solutions are obtained. A new algorithm, that does not have a requirement to have any of the objectives as integer-valued, is developed and specifically tailored for 3-objective ε -constraint method to be applied for shelter site location problem. Unlike the single-objective settings, we are able to provide the decision makers with much richer information by reporting many non-dominated solutions and allowing them to evaluate the trade-offs and eventually select the “best one fitting their preferences. The computational experiments again showed the importance of capturing uncertainty explicitly and yielded efficacious results for multi-objective settings of many different configurations.

Certainly, as of a future research direction, different fairness-oriented objective configurations could also be tested in multi-objective settings, such as maximum distance traveled (minimize), pairwise utilization difference (minimize), range of weights (minimize). Besides that, the use of multi-criteria decision analysis

tools (such as analytical hierarchy process or multi-attribute value theory) could be developed for this context to select the best-fitting efficient solution among many. This would help the decision makers in the decision making process for finding the solutions that is closest to their ideal preferences.



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Appendix A

Data

A.1 *K45* - Candidate Shelter Sites

<i>Shelter Number</i>	<i>Capacity</i>	<i>Weight</i>	<i>Shelter Number</i>	<i>Capacity</i>	<i>Weight</i>
1	24000	0.865	14	50000	0.803
2	45000	0.795	15	30625	0.827
3	25000	0.781	16	30000	0.982
4	60000	0.948	17	75000	0.982
5	60000	0.948	18	45000	0.829
6	25000	0.674	19	60000	0.847
7	30000	0.674	20	30000	0.865
8	75000	0.801	21	25000	0.689
9	25600	0.847	22	25000	0.689
10	100000	0.850	23	150000	0.739
11	30000	0.694	24	30000	0.948
12	62500	0.847	25	60000	0.948
13	60000	0.809			

A.2 *K45* - Demand Points

<i>District Number</i>	<i>Population</i>	<i>District Number</i>	<i>Population</i>
1	14242	11	14827
2	30003	12	11720
3	10302	13	13718
4	22978	14	43433
5	22380	15	27568
6	17390	16	28591
7	25261	17	37144
8	29124	18	8093
9	14366	19	30147
10	13744	20	11649

A.3 *IST500* - Candidate Shelter Sites

<i>#</i>	<i>Capacity</i>	<i>Weight</i>	<i>#</i>	<i>Capacity</i>	<i>Weight</i>
1	90101	0.70408	16	98915	0.417498
2	86635	0.392633	17	130607	0.68507
3	97336	0.282347	18	112782	0.577434
4	61781	0.573696	19	128514	0.74029
5	70106	0.788021	20	70588	0.579393
6	63062	0.471939	21	147791	0.467642
7	240000	0.394369	22	61716	0.413235
8	119450	0.844608	23	130961	0.268146
9	70789	0.587395	24	120620	0.793249
10	80396	0.44716	25	85518	0.251144
11	88409	0.63416	26	63023	0.209982
12	66136	0.694403	27	80966	0.599873
13	77758	0.33493	28	62903	0.572222
14	131570	0.459644	29	77650	0.462376
15	77221	0.843545	30	74300	0.39872

#	<i>Capacity</i>	<i>Weight</i>	#	<i>Capacity</i>	<i>Weight</i>
31	56467	0.219115	71	104464	0.265126
32	137440	0.630426	72	144742	0.819059
33	115253	0.850611	73	84607	0.507915
34	60064	0.402083	74	70106	0.43319
35	104981	0.693027	75	62171	0.54234
36	105282	0.347547	76	69785	0.552217
37	84667	0.275141	77	92612	0.350627
38	147419	0.733194	78	81154	0.324364
39	81887	0.498412	79	105584	0.380253
40	104218	0.322426	80	129549	0.379376
41	83209	0.876523	81	104100	0.837859
42	147940	0.556093	82	117319	0.603678
43	86227	0.337936	83	83249	0.26464
44	116984	0.677054	84	92365	0.699879
45	444460	0.752814	85	113842	0.650643
46	88225	0.781146	86	72799	0.635516
47	136945	0.267742	87	79885	0.52156
48	81793	0.231084	88	122393	0.733447
49	57109	0.873054	89	118156	0.360272
50	114292	0.813283	90	111532	0.588019
51	103127	0.550223	91	145844	0.800685
52	138898	0.406158	92	135092	0.345058
53	124844	0.211374	93	140189	0.720678
54	64777	0.322147	94	56177	0.70158
55	132402	0.417943	95	125483	0.891362
56	71383	0.264064	96	83299	0.780623
57	67687	0.335902	97	80360	0.510776
58	62790	0.557601	98	82453	0.241883
59	72450	0.493685	99	97854	0.250533
60	90876	0.668144	100	106758	0.780655
61	98687	0.373562	101	108494	0.685416
62	145448	0.666293	102	94615	0.284405
63	99420	0.57276	103	145253	0.441329
64	84300	0.869223	104	70661	0.467304
65	106274	0.618329	105	124705	0.221543
66	58063	0.481999	106	99298	0.574319
67	86977	0.404926	107	65459	0.637573
68	72367	0.227318	108	110380	0.360731
69	71119	0.837535	109	139241	0.49457
70	141212	0.548599	110	96805	0.859889

#	<i>Capacity</i>	<i>Weight</i>	#	<i>Capacity</i>	<i>Weight</i>
111	103990	0.866857	151	105108	0.241292
112	137129	0.224548	152	7671210	0.673552
113	119207	0.546913	153	129834	0.209692
114	143605	0.405868	154	59663	0.406742
115	127000	0.28479	155	96527	0.377874
116	57092	0.317195	156	121691	0.420029
117	62490	0.863612	157	87133	0.707786
118	60074	0.387725	158	127402	0.589418
119	123001	0.27454	159	106969	0.655986
120	95174	0.519523	160	130362	0.649808
121	115286	0.554462	161	105139	0.698594
122	141462	0.41886	162	112334	0.224388
123	73999	0.38488	163	78403	0.659275
124	57662	0.206167	164	69100	0.301764
125	142534	0.837197	165	86942	0.215851
126	91793	0.543763	166	118332	0.855216
127	138568	0.217289	167	131886	0.341633
128	113074	0.401731	168	72668	0.796147
129	56440	0.358362	169	88034	0.805162
130	59470	0.68529	170	57020	0.778936
131	129866	0.758436	171	91888	0.893454
132	70206	0.380882	172	85118	0.203004
133	68099	0.771772	173	97360	0.205178
134	90054	0.370518	174	61513	0.612295
135	70360	0.457265	175	58012	0.86626
136	142188	0.876425	176	124505	0.595974
137	87780	0.224919	177	104304	0.792973
138	90586	0.702316	178	84924	0.37608
139	68942	0.238716	179	116348	0.499711
140	129406	0.339003	180	58462	0.237836
141	105737	0.44046	181	92929	0.653351
142	66468	0.266206	182	67348	0.253225
143	63422	0.268336	183	110606	0.670365
144	116453	0.502137	184	83482	0.228036
145	73175	0.88716	185	101584	0.75544
146	142666	0.580393	186	128354	0.618098
147	82586	0.729141	187	87419	0.33556
148	141686	0.685121	188	84779	0.652191
149	117749	0.521222	189	116366	0.205077
150	84906	0.747721	190	71033	0.802445

#	<i>Capacity</i>	<i>Weight</i>	#	<i>Capacity</i>	<i>Weight</i>
191	101302	0.30624	211	104891	0.588874
192	71290	0.676241	212	104153	0.25293
193	82638	0.247876	213	79024	0.652326
194	98040	0.646462	214	121861	0.239518
195	118178	0.820383	215	90090	0.589301
196	66271	0.822575	216	127620	0.790012
197	136694	0.444251	217	105067	0.329613
198	144886	0.691889	218	96977	0.410607
199	146614	0.140633	219	57674	0.376865
200	129054	0.810284	220	97093	0.800323
201	62711	0.581978	221	146750	0.533132
202	58387	0.607958	222	144412	0.504517
203	62518	0.74377	223	101996	0.545592
204	107669	0.791751	224	121128	0.236415
205	118772	0.256848	225	109229	0.337031
206	116804	0.434373	226	91578	0.634925
207	96792	0.725173	227	57655	0.380602
208	75601	0.835689	228	126212	0.20788
209	77194	0.649347	229	88232	0.485232
210	87940	0.877855	230	74818	0.459037

A.4 *IST500* - Demand Points

#	<i>Population</i>	#	<i>Population</i>	#	<i>Population</i>
1	23589	11	12088	21	4038
2	20018	12	14779	22	2622
3	24549	13	11199	23	7643
4	22107	14	20168	24	15427
5	11204	15	18408	25	4343
6	32379	16	72907	26	21597
7	23152	17	5766	27	6168
8	19129	18	2769	28	8452
9	10194	19	1334	29	4512
10	14508	20	2909	30	8229

#	<i>Population</i>	#	<i>Population</i>	#	<i>Population</i>
31	10531	71	30147	111	12024
32	15245	72	14366	112	26441
33	5541	73	29124	113	4721
34	4237	74	22380	114	55394
35	19236	75	11720	115	43230
36	6424	76	37144	116	14372
37	4495	77	14242	117	23827
38	4901	78	10302	118	5437
39	12112	79	8093	119	3376
40	22577	80	14827	120	3700
41	18900	81	13718	121	9841
42	33795	82	13744	122	19589
43	33961	83	28011	123	24712
44	37952	84	31916	124	8705
45	20810	85	14126	125	13951
46	23595	86	41435	126	33056
47	25333	87	18384	127	5144
48	36591	88	5075	128	7096
49	16604	89	31833	129	32152
50	20774	90	23146	130	18915
51	27161	91	20265	131	11099
52	20024	92	33133	132	15509
53	39609	93	14400	133	18044
54	15585	94	16883	134	13241
55	37416	95	16816	135	10094
56	6952	96	25843	136	12837
57	41793	97	12885	137	5368
58	7502	98	51994	138	12226
59	13791	99	19823	139	16548
60	33775	100	21073	140	13764
61	27836	101	16358	141	11358
62	8332	102	10820	142	24758
63	30003	103	14611	143	7154
64	28591	104	15934	144	15633
65	17390	105	22317	145	13404
66	25261	106	16512	146	16481
67	22978	107	21232	147	7668
68	43433	108	11847	148	10989
69	27568	109	17620	149	14530
70	11649	110	34452	150	27779

#	<i>Population</i>	#	<i>Population</i>	#	<i>Population</i>
151	10690	191	6900	231	25949
152	26008	192	4596	232	42411
153	11366	193	5754	233	3108
154	26838	194	6207	234	22420
155	20409	195	7259	235	9881
156	23987	196	3080	236	14099
157	17179	197	15291	237	9631
158	20911	198	3800	238	21176
159	26355	199	15363	239	19531
160	13780	200	25170	240	5952
161	12969	201	25556	241	29924
162	12860	202	21307	242	16478
163	18327	203	24139	243	31138
164	17164	204	10539	244	16713
165	873	205	22182	245	13233
166	26991	206	14169	246	1574
167	17037	207	20869	247	13837
168	4760	208	21017	248	2255
169	9456	209	14936	249	4873
170	688	210	2508	250	18257
171	2465	211	8688	251	8864
172	3978	212	10241	252	17621
173	17097	213	16384	253	18696
174	2083	214	18277	254	21692
175	4458	215	8907	255	12647
176	14979	216	13000	256	14339
177	3598	217	26542	257	10479
178	22584	218	20975	258	13079
179	15769	219	12454	259	7595
180	11841	220	851	260	12564
181	22991	221	19038	261	22561
182	6658	222	8327	262	35081
183	4145	223	11057	263	13775
184	4623	224	12806	264	14885
185	6748	225	16698	265	31915
186	19229	226	11213	266	17614
187	18071	227	11606	267	2126
188	11359	228	17087	268	2349
189	17411	229	25469	269	1109
190	8011	230	14422	270	339

A.5 *IST220* - Candidate Shelter Sites

#	<i>Capacity</i>	<i>Weight</i>	#	<i>Capacity</i>	<i>Weight</i>
1	90101	0.70408	31	530121	0.57276
2	271701	0.392633	32	697400	0.869223
3	435398	0.635457	33	86977	0.404926
4	97336	0.282347	34	460327	0.227318
5	211318	0.788021	35	159344	0.837535
6	63062	0.471939	36	144742	0.819059
7	240000	0.394369	37	70106	0.43319
8	119450	0.844608	38	69785	0.552217
9	427401	0.587395	39	228070	0.324364
10	80396	0.44716	40	105584	0.380253
11	139311	0.694403	41	475687	0.453114
12	77221	0.843545	42	92365	0.699879
13	397027	0.417498	43	79885	0.52156
14	130607	0.68507	44	499939	0.588019
15	900569	0.577434	45	804120	0.345058
16	128514	0.74029	46	586968	0.891362
17	415074	0.268146	47	153960	0.780623
18	120620	0.793249	48	283910	0.510776
19	593862	0.572222	49	94615	0.284405
20	77650	0.462376	50	501614	0.441329
21	130767	0.39872	51	457762	0.574319
22	332360	0.630426	52	96805	0.859889
23	115253	0.850611	53	103990	0.866857
24	104981	0.693027	54	119207	0.546913
25	380675	0.347547	55	143605	0.405868
26	234167	0.556093	56	62490	0.863612
27	292581	0.873054	57	317945	0.206167
28	185843	0.335902	58	68942	0.238716
29	62790	0.557601	59	105737	0.44046
30	72450	0.493685	60	199702	0.502137

#	<i>Capacity</i>	<i>Weight</i>	#	<i>Capacity</i>	<i>Weight</i>
61	518324	0.580393	81	148201	0.652191
62	105108	0.241292	82	71033	0.802445
63	420128	0.209692	83	118178	0.820383
64	557460	0.406742	84	66271	0.822575
65	130362	0.649808	85	146614	0.140633
66	363316	0.698594	86	129054	0.810284
67	78403	0.659275	87	107669	0.791751
68	86942	0.215851	88	201411	0.434373
69	72668	0.796147	89	146891	0.835689
70	618116	0.805162	90	104891	0.588874
71	57020	0.778936	91	265662	0.652326
72	91888	0.893454	92	90090	0.589301
73	61513	0.612295	93	54317	0.424028
74	58012	0.86626	94	136842	0.456578
75	781668	0.595974	95	453461	0.410607
76	195304	0.37608	96	348024	0.800323
77	209034	0.253225	97	101996	0.545592
78	429888	0.670365	98	149233	0.634925
79	199737	0.618098	99	368588	0.485232
80	180031	0.33556	100	220388	0.83901

A.6 *IST220* - Demand Points

#	<i>Population</i>	#	<i>Population</i>	#	<i>Population</i>
1	20018	11	4038	21	56498
2	96364	12	48476	22	107284
3	96059	13	21595	23	45710
4	44102	14	20417	24	94938
5	60074	15	8229	25	102212
6	46686	16	29431	26	52483
7	5766	17	4237	27	99826
8	9734	18	4495	28	64427
9	16579	19	4901	29	87718
10	2909	20	39201	30	39412

#	<i>Population</i>	#	<i>Population</i>	#	<i>Population</i>
31	37344	71	45137	111	56413
32	61054	72	40618	112	70986
33	61980	73	42314	113	21450
34	47641	74	100551	114	54524
35	37144	75	30133	115	74197
36	14242	76	873	116	104561
37	13718	77	26991	117	2126
38	104111	78	4760	118	2349
39	18384	79	9456	119	1109
40	5075	80	688	120	339
41	51541	81	2465		
42	108839	82	3978		
43	12885	83	40088		
44	80865	84	2083		
45	46142	85	4458		
46	16512	86	14979		
47	67708	87	3598		
48	86689	88	22584		
49	26441	89	15769		
50	4721	90	11841		
51	55394	91	6658		
52	43230	92	4145		
53	14372	93	4623		
54	14475	94	6748		
55	3700	95	63618		
56	44423	96	11359		
57	35390	97	32973		
58	24712	98	3800		
59	33056	99	50976		
60	32152	100	58076		
61	84665	101	122288		
62	10094	102	41755		
63	12837	103	66383		
64	46273	104	74636		
65	44219	105	32023		
66	27715	106	2508		
67	24758	107	11606		
68	49169	108	93575		
69	50554	109	45077		
70	10690	110	14099		