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SUPPLIER SELECTION AND COLLABORATION FOR DETERMINING JOINT FACILITY LOCATION FOR HUMANITARIAN RELIEF DISTRIBUTION

PHD DISSERTATION

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DECLARATION

I declare that this thesis my own work and has not been submitted in any form for another degree or diploma at any university or institution. Information derived from the published or unpublished work of others has been acknowledged in the text and a list of references is given.

Eren ŞALLI

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ABSTRACT

Humanitarian logistics activity is essentially made up of three main stage in the disaster life cycle: (pre-disaster) mitigation stage, (post-disaster) response stage, and recovery stage. Relief vendor selection and cooperation is a very significant section of the pre-disaster phase in order to get through to eliminate the troubles in the response phase that the government cannot handle on its own. The primary aim of this thesis is to choose the most suitable relief vendors in the mitigation phase according to determined criteria. In order to accomplish this aim;

First, the criteria are determined as a result of literature review, brain storming, and face-to-face surveys. Then, Interpretive Structural Modeling (ISM) is applied to clasify and sort the criteria and discover the mutual effects between them. Among 15 (fifteen) determined criteria, 7 (seven) of them are evaluated to be more significant and affecting the other criteria.

Second, Analytic Network Process (ANP) is applied to obtain the weights of the criteria, which are choosen through the Interpretive Structural Modeling (ISM). Then, the potential candidate relief vendors are determined. In this study, Asian side of Istanbul is assumed as the affected zone in the case study. Whereupon candidate relief suppliers are evaluated and ranked thanks to weighted criteria by means of the Rating technique.

Third, mathematical model is constructed with four objective functions comprising of minimizing the impact of over and under supply in the affected zones, maximizing satisfied demand rate, minimizing joint facility location, and minimizing the distance between the joint facility locations and the other relief suppliers who have not been selected as joint facility locations. Whereupon, Non Sorting Genetic Algorithm (NSGA-II) is applied so as to solve this mathematical model, whereupon the solutions obtained after using NSGA-II are clustered using *k*-means algorithm.

Ultimately, the proposed model's solution that is obtained as a result of multi-criteria decision making, and Pareto optimal solutions, which are obtained after using NSGA-II and *k*-means algorithm, respectively are compared.

In this respect, if the host government collaborates with only highly collaborative relief suppliers under determined circumstances, our proposed model's solution lies among the Pareto optimal frontiers as a result of the NSGA-II. On the other hand, if host

government collaborates with not only highly collaborative relief suppliers but also with normal collaborative relief suppliers, our propose model's solution is not situated within Pareto optimal frontiers.

Keywords – *Analytic Network Process (ANP), Humanitarian logistics, Interpretive Structural Modeling (ISM), Supplier selection, Non- Sorting Genetic Algorithm II (NSGA-II), k-means algorithm.*

ÖZET

Doğal afet lojistiği, afet döngüsü içerisinde temel olarak üç safhadan oluşmaktadır. Bunlar sırası ile afet öncesi, afet sırası ve afet sonrası safhalardır. Tedarikçi seçimi ve işbirliği, afet sırasında ortaya çıkabilecek zorlukların aşılması için afet öncesi safhada yapılması gereken en önemli faaliyetlerden bir tanesidir. Geçmiş tecrübelerin de gösterdiği gibi bu süreç içerisinde hükümetler afet lojistiğinde tek başına başarı gösterememişlerdir. Bu çalışmanın ana amacı, belirlenmiş kriterlere göre afet öncesi safhada en uygun tedarikçinin seçilmesidir. Bu çalışmada en uygun tedarikçinin seçilmesinde İstanbul Anadolu yakası vaka çalışmasına esas bölge olarak incelenmiştir. Bu çalışma esas olarak üç bölümden oluşmaktadır.

Birinci bölümde, Türkiye Cumhuriyeti Afet ve Acil Durum Yönetimi Başkanlığının ana yüklenicisi durumunda bulunan Alternatif Lojistik firmasının farklı pozisyonlarında görev alan personelin katılımı ile doğal afet lojistiğinde görev alabilecek tedarikçileri seçmek için kriterler belirlenmiştir. Kriterler, literatür tarama, yüz yüze görüşme, beyin fırtınası yöntemleri kullanılarak seçilmiştir. Yapılan değerlendirme sonucunda 15 (on beş) adet kriter tespit edilmiştir. Kriterler arasındaki ilişkiyi tespit etmek ve önem sırasını belirlemek maksadı ile Yorumlayıcı Yapısal Modelleme (ISM) uygulanmış, 7 (yedi) adet kriterin diğer kriterler arasında daha önemli olduğu ve diğer kriterlere daha çok etki ettiği gözlemlenmiştir.

İkinci bölümde, ilk bölümde görev alan personelin katılımı ile belirlenen 7 (yedi) kriterin tedarikçi seçiminde ağırlıklarını tespit etmek maksadıyla Analitik Ağ Süreci (ANP) yöntemi uygulanmış ve kriterlerin ağırlıkları tespit edilmiştir. Daha sonra aynı ekip tarafından çalışmaya esas olmak üzere vaka çalışmasının yapıldığı İstanbul Anadolu yakasında muhtemel 20 (yirmi) adet tedarikçi belirlenmiş, bu tedarikçiler, Analitik Ağ Süreci (ANP) yöntemi sonucunda belirlenmiş olan kriter ağırlıklarına göre puanlanmıştır. Puanlamanın sonucunda muhtemel tedarikçilerin seçim sıralaması tespit edilmiştir.

Son bölümde, doğal afet lojistiği kapsamında tedarikçi seçimi ve iş birliği, matematiksel model kurulmak sureti ile çözülmüştür. Modelde 4 (dört) adet amaç fonksiyonu kullanılmıştır. Bunlar; Afet bölgesine ulaşan fazla/eksik yardım malzemelerinin etkisinin minimize edilmesi, afet bölgesinin kapsama alanının maksimize edilmesi, afet anında iş birliği yapılacak tedarikçiler ile birlikte açılacak olan ortak tesis yeri sayısının minimize edilmesi ve iş birliği yapılan tedarikçiler ile seçilmeyen diğer

tedarikçilerin arasındaki mesafenin minimize edilmesidir. Oluşturulan matematiksel model Çok Amaçlı Genetik Algoritması (NSGA-II) uygulanarak çözülmüştür. Vaka çalışmasında çeşitli senaryolar ele alınmış, Çok Amaçlı Genetik Algoritması (NSGA-II) uygulanarak elde edilen ve Pareto optimumda bulunan sonuçlar, *k* ortalama ve kümeleme yöntemi uygulanarak kümeyi temsil edecek şekilde azaltılmıştır. Daha sonra ilk iki bölümde Çok Kriterli Karar Verme yöntemi ile elde edilen sonuçlar ile Çok Amaçlı Genetik Algoritması (NSGA-II) sonucunda çıkan sonuçlar belirlenen senaryolar kapsamında karşılaştırılmıştır.

Bu kapsamda, Yorumlayıcı Yapısal Modelleme ve Analitik Ağ Süreci yöntemi sonucunda ortaya çıkan tedarikçi sıralamasında ilk 8 (sekiz) tedarikçi yüksek seviyede iş birliğine uyumlu, diğer 12 (on iki) tedarikçi ise normal seviyede iş birliğine uyumlu olarak kıymetlendirilmiştir. Senaryolar kapsamında Çok Amaçlı Genetik Algoritması (NSGA-II) uygulanarak elde edilen sonuçlar değerlendirildiğinde; doğal afetlere müdahale sırasında sadece yüksek seviyede iş birliğine uyumlu tedarikçiler seçilmesi durumunda bulunan sonuçlar Pareto optimumda yer almış, bunun dışındaki bütün senaryolarda bulunan değerler Pareto optimumda yer alamamıştır.

Anahtar Kelimeler – *Analitik Ağ Süreci (ANP), Doğal afet lojistiği, Yorumlayıcı Yapısal Modelleme (ISM), Tedarikçi seçimi, Çok Amaçlı Genetik Algoritması (NSGA-II), k ortalama kümeleme yöntemi.*

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1. INTRODUCTION

“It is necessary to take into account the preventive and protective measures prior to the disaster. It is no use to bewail aftermath the disaster.” (Mustafa Kemal Atatürk)

Day by day, our world is becoming more and more affected by exacerbated natural and human-driven disasters. The current situation has become a threat for communities when it comes to living in a safe environment. The best to deal with this threat is to detect the perils and hazards linked within all aspects of life, and then to take the required precautions against them. A society’s quality of living can always be raised in this way.

Strategic policies and preparations must be made for the unforeseen circumstance by considering disasters caused by global climate change and instability. In order to not to struggle with any kind of disasters, be they man-made or natural, emergency logistics activities should be planned in detail.

Emergency logistics (EL) activities have uncertain and dynamic features: both the supply side (i.e. relief resources and relief suppliers) and demand side (i.e. relief demand and people who are affected) may go through uncertain events. These uncertain events are rather unstable in case of a disaster. The Emergency logistics for such large-scale disasters cannot be managed by organization – not even by a government without collaborating with others due to the complicated and varying nature of these operational environments (Waugh & Streib, 2006).

Notably, relief supply collaboration is very important for conducting EL throughout natural disasters (Waugh & Streib, 2006; Balcik et al., 2010). Given that host Governments cannot run EL activities on their own during and post disaster, but rather search for relief suppliers with whom cross functional relief activities and joint action can be organized so that effectiveness can be increased. Collaboration may improve the stabilization of impact and service level of the supply chain performance (Fu & Piplani, 2004). Nonetheless, many domestic NGOs do not collaborate with host government when distributing relief items, which thus leads to an imbalance in the distribution. Moreover, undersupply and/or oversupply may occur in terms of relief materials in the areas getting affected. Relief undersupply in the affected areas is mainly related to shortage of relief resources that are made up of crews and commodities. These kinds of shortages may lead to an increase mortality rate and may also deteriorate social balance, thus leading to things such as looting. For example, most of people who are affected those effected by the 1999 Kocaeli earthquake affecting Turkey's Marmara region had to live in temporary shelter areas for up to seven months. Approximately 91,000 people were forced to reside in tents in Kocaeli, Düzce, Yalova, Bolu, and Sakarya. Table 1.1 displays the population residing in the shelter zones of every region and their rate of use (Kılıcı, et al., 2015).

Table 1.1 Usage and population of shelter areas in five cities in March 2000

City	Number of people	Utilization (percentage)
Kocaeli	18.450	100
Sakarya	904	21
Yalova	2.545	73
Bolu	16.645	99
Düzce	53.050	92

Another similar example was the undersupply of relief materials after Typhoon Haiyan devastated the Philippine Islands in 2013. Looting became deadly, and had people who are affected panicking over shortage of food, potable water, and medicine to the point that many people unearthed subterranean water conduit and shattered them open, whereas others stormed shopping malls, stole relief materials, and destroyed their surroundings in search of more relief materials from the stores (Reuters, 2013). Similarly, relief oversupply could happen in other impact zones in the aftermath of man-made or natural disasters. The distribution of an outnumbered inventory of relief materials may bring about abundancy, the over consumption of relief sources, and even congestion within the system (Russel, 2005). For example, five months the Van earthquake in 2011, a number of the villages close to city center received an overabundance of tents for people who are affected, and thus not all were used up. While other villages away from city center were deprived of a sufficient number of tents. As a result, many people suffered from freezing. At the time of response period following the 1999 Taiwan earthquake, refuge centers containing relief supplies were at an excessive level of accumulation (Sheu, 2007).

Turkey is one such country, which has been the affected most by disasters because of its s topographic, seismic, tectonic, and climactic structure. Whilst earthquakes have the most devastating impact on Turkey, disasters such as landslides, avalanches, fires, and floods are also common as well.

Turkey ranks nine in the world in terms of human losses due to earthquakes, and the fifty-one in terms of the total number of people who get affected. Each year, an average of one earthquake at magnitude of 5 to 6 takes place in Turkey. 70% of Turkey’s land and 76% of its industrial facilities are located in first and second-degree seismic risky zones according to a seismic zone map. Each year, nearly 1,000 people losing their lives, and 9,000 residences become damaged due to disasters on average (AFAD, 2012).

Since 1950, nearly 34,000 people have lost their lives to earthquakes in Turkey. Statistics from the past 60 years reveal that disasters have caused direct and indirect economic losses, to as much as 3% of the GNP. Therefore, disaster management is rather important for Turkey (AFAD, 2012).

Due to both the complex situation as well as limited sources both during and after disasters, distribution of relief supplies remains a very important problem in emergency response. It has been proven that coordinating operations within supply chain players and centralized decision making is both effective as well as capable of offering higher operational efficiency in such scenarios (Balcik et al., 2010).

After a large-scale disaster, a government can or cannot deal with problems related to disasters. Remaining functional is fundamental issue after the any kind of disaster. For example, Haiti earthquake, which occurred in 2011, brought about very critical devastation, and to many official buildings either collapsing or becoming heavily damaged. On the other hand, in the wake of the aftermaths of the 2013 Lushan earthquake alongside 2011 Van earthquake, each country’s host governments remained functional and conducted emergency logistics activities. Furthermore, governments act as both the coordinator for relief supply collaboration, and also as the most powerful relief supplier. According to this study, the host government is effective with regards to the aftermath of a large-scale disaster only to a certain degree.

Pre-event and post-event responses are the two phases of emergency response efforts. Pre-event tasks aim to foresee and analyze possible dangers, as well as to make action plans required for alleviation of impacts. Post-event response takes place during the progress of the disaster. It is difficult for available resources to be managed, located, coordinated, and allocated at this stage. Both stages must be integrated in line with the objective of the emergency response plan in order to be effective. What is more, dividing pre- and post-loss objectives may bring about suboptimal solutions to the overall problem (Tüfekçi & Wallace, 1998).

Comprehensive humanitarian logistics management consists of four main phases, which are mitigation, preparedness, response, and recovery according to common descriptions in Turkey. (Green, 2002; Waugh, 2000; Godschalk, 1991; Waugh & Hy, 1990). On the other hand, Sheu & Pan (2016) divide the phases of disaster management into three main sections, including mitigation, response, recovery, and reconstruction.

Decreasing or eliminating the probability of loss, or lightening its intensity by means of risk evaluations, are among the objectives of mitigation phase. This phase also covers research activities, as well as the development of policies and strategies according to needs and priorities, the development of organizational structures and legislation implemented prior to and following the disasters, and the raising public awareness concerning disaster risk. The basis of mitigation activities is established according the following output Within this phase:

• Standards of disaster and emergency services,

• International exchange of information,

• Principles of in-kind, in-cash and humanitarian aid,

• Plans, projects, and zoning principles for areas probably to suffer damages,

• Information and evaluation reports on disasters and emergencies taking place both at the national level and abroad,

• The determination of possible disaster and emergency zones, and the announcement of hindering precautions,

• National Disaster Management Strategy and Action Plans,

• Arrangements oriented around informing, education, and raising awareness of the public on disasters and emergencies, and

• Risk management and mitigation plans based on disaster and emergency studies implemented at a national level.

Preparation and training activities take place during the preparation phase in order to intervene disasters by means of collaboration with people and institutions. Within this phase essential aim is to make certain large-scale preparedness against disasters. The basis of disaster preparedness activities is established according to the following output:

• Making sure that standards of disaster and emergency management centers' general communication and information systems are in unison,

• Exercises regarding disasters,

• Ensuring conformity of NGOs to disaster-related service standards,

• International cooperation,

• Generalizing insurance services,

• The training of response teams,

• Emergency aid and logistics service plans,

• Risk maps,

• Research and development activities,

• Resource management system, and

• Arrangements oriented around informing, education, and raising awareness of the public on disasters and emergencies.

The response phase covers activities that determine and meet all necessities that may arise as a result of disasters and emergencies, in a fast a manner as possible. Within this phase, the following services have vital importance for the host government in order to guarantee coordination and effective job distribution in order to facilitate rapid delivery:

• Information management,

• Infrastructure reparation,

• Logistics and maintenance,

• Safety and traffic,

• Nutrition,

• Emergency aid funding,

• Protection from fire and perilious items,

• Debris removal,

• Safety of food, agriculture as well as animal,

• Health and sanitation,

• Interment,

• Emergency shelter,

• Social support,

• Search and rescue,

• Transportation, and

• Damage assessment.

Recovery phase aims to make normal and, if possible, further develop all life systems that have been disturbed by either disaster or emergency as in as fast and precise a manner as possible. In order to normalize social life as well as to increase disaster resilience, the following output and services are crucial within this phase there includes;

• Safe site selection,

• Zoning, planning as well as project arrangements for disaster prone zones,

• Disaster housing,

• Post-disaster safe re-building,

• Measures to normalize life after disaster and emergency,

• Credit to those re-building their homes.

In Turkey, the management of potential disasters and emergencies whose impact may be local, regional, national, or international in the globalization process is the duty of the Disaster and Emergency Management Authority (AFAD). However, AFAD or the host government cannot overcome all the problems caused by disasters effectively and in a timely manner by itself. Therefore, they both should collaborate with non-governmental organizations (NGO) as relief suppliers. However, in order to accomplish this, the host government must first solve the problems outlined below.

Problem 1: The willingness to engage in emergency logistics activities such as relief suppliers varies among NGOs. Given that each NGO has its own structure that affect collaboration, some NGOs are eager to collaborate with government, whilst others may carry out these activities independently (Waugh & Streib, 2006).

Problem 2: Relief resources provided by NGOs vary in terms of quantity and quality, including relief materials and work force. Each NGO should take part in emergency logistics activities by its relief resources. For example, hospitals could provide doctors and nurses, shopping malls could provide food, potable water, medicine, cleaning kits, and non-consumable supplies (Sheu & Pan, 2016).

Problem 3: The number of relief suppliers who take part in emergency logistic activities varies over time. Many suppliers take part in relief supply tasks in the aftermath of the disasters (Waugh & Streib, 2006). However, within in the response phase, relief supply distribution varies among suppliers. The emergency, continuum, and initial recovery response period, as given in Figure 1.1, are the parts of response phase.

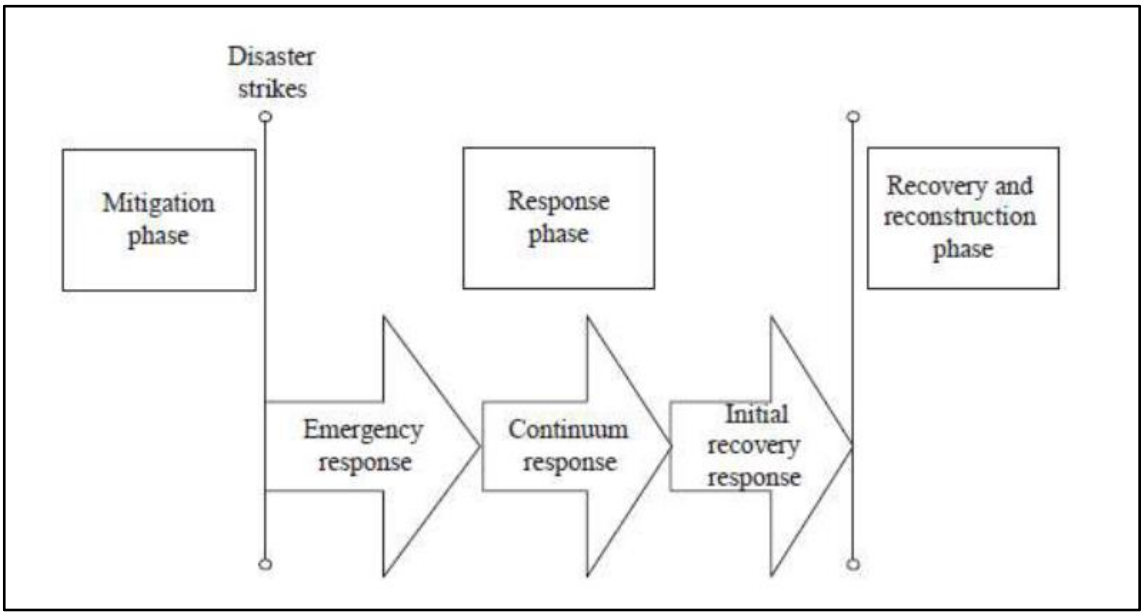

Figure 1.1 Response phase in disaster management (Sheu & Pan, 2016).

Problem 4: In Istanbul, only one logistics support center has been established on the European/Thracian side of the city, and it is executed by Istanbul Metropolitan

Municipality. AFAD is also responsible for storing certain relief supplies such as tents, blanket, and first aid kits in warehouses by means of contractors. However, these places are not sufficient when it comes to supporting those people who are affected living on the Asian/Anatolian side of Istanbul in the aftermath of possible large-scale disasters. In order to tackle this problem, a joint facility center location should be established during the pre-disaster period. Additionally, the host government must make a decision as to which suppliers are the best choices in terms of the criteria determined in the pre-disaster period.

Humanitarian Logistics activities are increasingly drawing the attention of scholars. Unfortunately, most published studies focus on facility location, resource allocation, and relief distribution. Only one study takes a closer look at relief supply collaboration (Sheu & Pan, 2016). The objective function in many former studies is to minimize total cost or unsatisfied demand. Only one study is aiming at minimizing the effect of an unbalanced relief supply-demand (Sheu & Pan, 2016).

This thesis aims to choose suppliers who are most appropriate in the pre-disaster period, and then to establish joint facility centers with selected suppliers at the locations of the suppliers, as presented in Figure 1.2. The four objectives if this study include (a) to minimize the impact of undersupply or oversupply on the affected area; (b) to maximize the overall satisfied demand rate; (c) to minimize the number of joint facility locations; and (d) to minimize the distance between the joint facility locations and the other relief suppliers who have not been selected as joint facility locations.

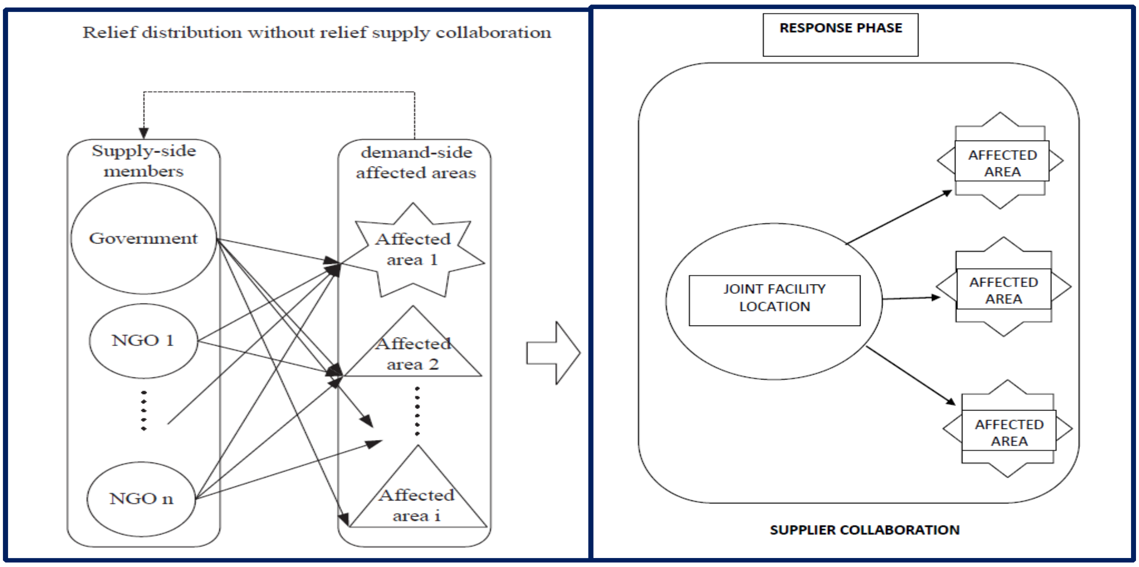

Figure 1.2 Relief distribution with and without relief supply collaboration.

Emergency logistics activities have very dynamic and stochastic patterns related to NGOs as well as to demand sites. In order to overcome these uncertainties, as well as in order to decrease their possible impacts, this study proposes a novel supplier selection and collaboration approach in order to determine joint facility locations for distributing relief supplies to the people who are affected aftermath of people during a large-scale disaster, i.e., response phase.

This study distinguishes itself in the following manner:

1. In order to choose the optimum suppliers, a face-to-face survey is employed in order to determine the criteria for selecting the supplier. A questionnaire including the potential selection criteria was prepared for the survey. The people responding to the survey are chosen at random from different functional positions of the *Alternatif Logistics Company*, which conducted emergency logistics activities on the behalf of AFAD from 2014 till 2017. Post and Telegraph Corporation takeover the mission from *Alternatif Lojistics Company* as of 2017. Depending upon the survey carried out, the major influencing criteria are selected as the supplier selection criteria used in this study. The aim is to determine and class the criteria utilized for selecting the relief supplier, as well as to find the interactions between the criteria through the Interpretive Structural Modelling (ISM) for supplier selection and collaboration for humanitarian logistics activities.
2. Upon determining the criteria using ISM, Analytic Network process (ANP) is conducted in order to determine the weights of criteria.
3. The rating process is conducted among the potential candidate suppliers using the weighted criteria.
4. The problem is formulated as a mathematical model using four objective functions. The model is solved using the Non Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2000), upon which a set of Pareto-optimal solutions is obtained. Then, by applying the *k*-means clustering algorithm in order to find the representative solutions, the number of candidate solutions in the pareto-optimal set is reduced.

One of the other distinctive features of this study is to compare the results of multi criteria decision-making algorithm with multi-objective optimization algorithm-based using NSGA-II, whereby this is the first study in which ISM, ANP, and NSGA-II are applied together in one study. In addition, in order to reduce the candidate solution in the Pareto-optimal set after applying NSGA II, *k*-means clustering algorithm is applied.

The organization of this study is as follows: It is presented a review of the relevant literature in Section 2. Methodological framework is presented in Section 3. The mathematical model formulation is given in Section 4. The case study and the results are presented in Section 5. Finally, concluding remarks are emphasized in Section 6.

2. LITERATURE REVIEW

This study concentrates on the literature in three parts. The literature on phase of disaster in humanitarian activities is reviewed in the first part. Then, the literature on facility location problem is reviewed in the second part. These are followed by literature review on multi objective optimization related to emergency logistics.

2.1 Phase of Disaster

There are several studies about humanitarian logistics activities in the literature. These studies are divided into three phases in terms of stage of disasters, including the pre-disaster, response, and recovery periods.

2.1.1 Pre-disaster period

It has been observed that the recurrence, type, number, and impact areas of disasters increases along with the change in the climactic, social, environmental, and economic conditions in a given country. In order to mitigate effects of disasters, preparedness, planning, as well as risk prevention action should be ensured. Furthermore, relief items and inventories, which are essential for people who are affected aftermath of the large-scale disasters, should be deployed. Sheu & Pan (2015) proposed an approach of relief supply cooperation for tackling the problem of post-disaster relief supply-demand imbalance in humanitarian logistics avtivities, whereby two stages relief suppliers clustering mechanism for the variance in time, as well as for the multi-source relief suppliers are applied. Then, in order to identify a multi-source relief supply diminishing the effect of relief supply–demand imbalance during emergency logistics response to the minimum, a stochastic dynamic programming model is employed. Pre-disaster models are stochastic in general due to ambiguity. Mete and Zabinsky proposed an approach of scholastic optimization (2010) in order for the optimal stock level and distribution issue of medical relief items utilized in emergency logistics management activities in the aftermath of catastrophes at various magnitudes. They develop stochastic programming model so as to identify the most suitable place of medical relief supplies at the pre-disaster period and inventory stages in terms of each type of medical supply. They present case study of stochastic programming model for potential earthquake scenarios in the district of Seattle. A model of logistics was presented by Lin et al. (2011) in order for the distribution of prioritized supplies in the disaster relief managements. It takes into account the multi-periods, a split-delivery strategy scenario, soft time windows, multi-vehicles, and multi-items, and is formulated as a multi-objective integer-programming model. There are two heuristic approaches which are applied for this objective. While the first approach decomposes the original problem, the second approach uses a genetic algorithm. A computational study compares these two approaches. Finally, they present case study for illustrating applicability of their model. Monopinives and Irohara (2016) focus on a stochastic linear mixed-integer programming model for integrated decisions in the mitigation and response stages in pre- and post-disaster activities, respectively. Furthermore, they developed a model to integrated decisions in which the following three key areas of emergency logistics were kept in mind: relief vehicle planning, evacuation planning, facility, and stock prepositioning. Both a cost-based and equity-based solution approach is considered in their multiple objective models in order to establish a framework for effective relief operations. Then, a normalized weighted sum method is employed so that their multiple objective-programming model can be parameterized. In their study, they proposed a compromise between the cost and the equity of relief casualties, whereupon they displayed through the experiments how time restrictions and the availability of relief vehicles affect the two objective functions. The strategic problem which arises when designing emergency supply networks is the focus in the study of Klibi, W. (2017) so that disaster relief is supported over a planning horizon. The problem presents decisions on the location, as well as the number of distribution centers required, their capacity, and the quantity of each relief substance to keep in stock. A case study that was inspired by real-world data gathered from the North Carolina Emergency Management Division (NCEM) and the Federal Emergency Management Agency (FEMA) was taken as a basis. The approach involves the following three phases and is based on a scenario aimed at handling the problem: disaster scenario generation, design generation, and design evaluation. In order to create plausible catastrophic scenarios, stochastic processes were adapted to model disasters, and a Monte Carlo procedure was derived. In order to construct the emergency supply network, the authors presented a multi-phase modelling framework based on this comprehensive representation of disasters. They employed a sample average approximation method to propose the two-stage stochastic programming model which they solved, and a scenario-based solution approach was used to the case study to form reasonable scenarios so that alternative designs can be obtained, as well as in order to evaluate them according to a set of performance measures to choose the best design.

People living in disaster zones experience tremendous damage. It is a critical issue in order to supply relief items rapidly to the affected area as well as to people in terms of helping them recover from the effects of a disaster. When it comes to decreasing the arrival time of relief supplies to the areas affected and allocating them efficiently, pre-disaster planning is critically important. A mixed integer-programming model was suggested by Renkli and Duran (2014) so that the warehouses can be pre-positioned in all over a potential affected area, and in order to determine the amount of relief substances which could be kept in those warehouses. The authors aimed to drop the period between the hit of the disaster and arrival of relief supplies to a minimum in the affected areas. Furthermore, using probabilistic constraints, relief items could arrive to the affected areas within a fixed period of time with certain reliability thanks to the model. This proposed model is employed in the case of Istanbul so as to pre-position distribution centers prior to the potential predicted large-scale earthquake as the city sits on an unstable fault line.

Hong, X et al (2014) introduced an approach of risk-averse stochastic modeling in response to an issue about pre-disaster relief network design under unpredictable demand and transportation capacities. While ensuring network reliability at a certain level, the capacity and area of the facilities were determined, whereby relief supplies were to be at inventory levels at each facility. They introduced probabilistic constraint on the existence of a feasible flow so that they could ensure satisfying the demand for relief items throughout the network with a specified high possibility. Describing multiple locations within the network and introducing local possible constraints on satisfying each location's demand was also accounted for responsiveness. These local constraints guarantee the self-sufficiency of each region regarding its capacity to provide its own with a large likelihood. The Gale-Hoffman inequalities are employed in order to express the conditions on the presence of a feasible network flow, and whereby the solution method is based on two pillars. A preprocessing algorithm is utilized by eliminating redundant ones among the inequalities of Gale–Hoffman, and then proposed models are formulated as mixed-integer linear programs that are computationally efficient through using a method based on combinatorial patterns.

The efficiency of the models and the solution method are demonstrated using the computational results of a case study and randomly generated problem instances.

Uster and Dalal (2016) considered the integration of rapid evacuation and cost-effective relief distribution objectives, as well as the two critical aspects of emergency management in order to design a strategic emergency preparedness network for foreseen disasters such as hurricanes. For this purpose, they introduced the design of a three-tier system involving the evacuation source, shelters, and distribution centers, all of which integrate the relief (supply) and evacuation (demand) sides of an emergency preparedness network. Their motivation was the realization that the shelters are shared facilities at the interface of the supply and demand sides. Although primarily intended for strategic decision-making, their model can also make tactical decisions, thus spanning two separate periods before a disaster occurs. In order to solve models for large-scale instances, they adopted a Benders Decomposition-based approach with an implementation that solves only one instance of the master problem. They also determined that, within this framework, the tuning of the master tree search parameters along with the strengthening of Benders cuts significantly impact convergence. They conduct an extensive computational study in order to examine the impact of algorithmic improvements, as well as to further consider a realistic case study based on geographic information system (GIS) data from coastal Texas, and thus to examine the effects of changing problem parameters. By comparing their approach with current practice, they illustrated that a proactive strategic integration of evacuation and distribution can relieve the resource constrained large urban areas traditionally considered to be to be shelter locations.

In order to distribute emergency supplies, a model of three-echelon network was presented by Mutlu et al (2016) for integrated emergency preparedness and response planning. The model reduces the social cost to the minimum in determining a set of potential supply points (SPs) at the highest echelon, whereby consolidates the supply substances and sends them to the prepositioning facilities. One is to regard this model's cost as being the total costs of logistics and deprivation incurred by the population due to the lack of access to supplies or services, and then to presume that the deprivation cost increases exponentially with the deprivation time. Pre-disaster and post-disaster purchasing decisions at the SPs need also to be taken into account with this model, thus allowing the SPs and prepositioned facilities to make direct deliveries to the demand points. One can ensure that supplies are efficiently distributed, and can reduce the deprivation costs through multiple supply sources according to numerical analysis. One can slow down the shortage in emergency supplies using partial prepositioning and post-disaster purchasing, as the results demonstrate.

During the disaster phase, the pre-disaster period is very crucial for reducing impacts of disasters. However, precaution against damages taken in pre-disaster phase is very costly as well. A central element to reduce the impact of disasters is disaster preparedness, according to Kunz et al (2014). The standard methods of preparedness are problematic due to the requirement of high investment in various locations of these methods, such as pre-positioning relief stocks in countries prone to disasters, given that the next disaster can neither be timed nor located with great certainly. One can overcome this constraint by investing in disaster management capabilities, for example adapting import procedures with local customs clearance procedures, pre-negotiating customs agreements with countries prone to disasters, and training staff. The authors analyzed the performance of different preparedness scenarios and propose the delivery process model of ready-to-use therapeutic food supplies during the immediate response period of a disaster by way of system dynamics modeling. According to their findings, the beneficiaries get positive results from pre-positioning inventory, however the costs are extremely high. With the reduction of lead-time reductions of up to 67% (18 days) compared to a scenario without preparedness because investment in disaster management capabilities, one can consider this to be an interesting alternative at significantly lower costs than pre-positioning inventory. When one combines both preparedness strategies, allocating part of the available funding to disaster management capabilities and pre-positioning inventory, they can achieve the best performance. The authors analyzed 2,828 scenarios that were combined this way, so that they could determine the best mix of preparedness strategies for different levels of available funding. Relief organizations get recommendations from them based on their findings when it comes to how to set their preparedness budget.

In order to make sure that the given service after a large-scale emergency is of the highest quality, selection of disaster response facilities plays a vital role for the storage of emergency items. The effect that a disaster could have on the disaster response facilities and the population centers in surrounding zones have been taken into account in two location models put forth by Verma and Gaukler (2015). In the first model, distance-dependent damages are incorporated to disaster response facilities and population centers and it is a deterministic model. In the second model, which is a stochastic programming model, the first is extended by directly taking into consideration the damage intensity as a random variable. The authors accordingly developed a novel solution method for this second model based on Benders Decomposition, which is also applicable for other two-stage stochastic programming problems.

So as to prepare an earthquake response plan in which they integrated pre-and post-disaster decisions, multi-objective stochastic programming model had been presented by Mohommadi, Ghomi and Jolai (2016). The purpose of this three-objective model is to optimize the total expected demand coverage, and to drop the total expected cost and the difference in the satisfaction rates between nodes to a minimum. Moreover, new multi-objective particle swarm optimization (MOPSO) algorithm was developed by them in order to solve this model. They also designed a genotype-phenotype-based binary particle swarm optimization (PSO) and continuous PSO so that they can tackle with the binary location and other continuous decision variables, respectively.

2.1.2 Response period

Response phase logistics models generally consist of relief delivery, casualty transport models, and mass evacuation models. In terms of disaster response planning, Rennemo et al. (2014) presented a three-stage mixed-integer stochastic programming model regarding the establishing of local distribution warehouses, the initial allocation of items, and last mile distribution of aid, whereupon they considered the vehicles available for transportation, the state of the infrastructure, and the demand of the potential beneficiaries are to be stochastic elements. The solutions of a deterministic expected value approach are significantly worse than those of the stochastic programming model according to extensive computational testing on realistic instances.

A greedy-search-based, multi-objective, genetic algorithm was presented by Chang et al. (2014) in order to provide the immediate and efficient dispatch of relief to people who are affected those affected following a disaster. With this algorithm, the distribution of available supplies can be regulated, and also a variety of feasible emergency logistics schedules can automatically be generated for decision-makers. So as to decrease unmet demand for supplies, delivery time, and transportation costs to a minimum, one would dynamically adjust distribution schedules from various supply nodes by the proposed algorithm according to the requirements at demand nodes. So as to demonstrate its performance, the proposed algorithm was used to the case of the Chi–Chi earthquake in Taiwan. Simulation results shows that the proposed algorithm surpassed the MOGA and standard greedy algorithm in terms of 'time to delivery' with an average of 63.57% and 46.15%, respectively, based on 10,000 iterations under conditions of a limited/unlimited number of available vehicles.

A mathematical model was proposed by Liu and Yu (2012) for evacuation planning in densely populated urban zones in which a potentially large number of pedestrians depend on public transportation to evacuate. The proposed model's capacity to simultaneously operate the dynamic processes of evacuee guidance (i.e. from buildings or parking lots to pick up points) and bus routing (i.e. from pick up points to shelters) is what makes it unique. The routing of transit's performance will improve significantly with such integration in response to the evacuee demand variation. This integration will also increase the utilization of number of available buses to a maximum by dynamically adjusting the demand distribution of evacuees at different pick up points. The model was formulated as a combined vehicle routing and assignment problem and the authors solved it through a two-stage Tabu-based heuristic in order to come up with meta-optimal solutions. The proposed model's feasibility and applicability was demonstrated with a numerical example solved for optimality. According to the results, the proposed model can guide evacuees validly and in a detailed way. Furthermore, the model can yield transit routing plans during the evacuation within a reasonable period. The proposed model is robust and insensitive to the weight variations as indicated in the senility analysis of the effect of objective function weights. It also provides guidelines for evacuation operators on best customizing the objectives in order to achieve expected evacuation operational performance.

Taking into consideration network failure, multiple vehicle use, and standard relief time, a multi-depot location-routing model was presented by Ahmadi et al. (2015). The local warehouses are located with this model and it also identifies routing for last mile distribution after a disaster. The model is upgraded by the authors to a two-stage stochastic program including random travel time in order to locate the distribution centers. GAMS was employed to solve small instances for optimality. A variable neighborhood search algorithm designed by the authors was employed to solve the deterministic model. It is possible for unsatisfied demands to decrease significantly at the cost of a higher number of local warehouses and vehicles according to the computational results in their case study.

One of the most essential aspects of a relief activity in disaster management is humanitarian relief logistics during post-disaster period. A multi-objective robust stochastic programming approach was illustrated by Amiri et al. (2011) for disaster relief logistics under uncertainty. They regarded demand sides as being the uncertain parameters in their approach, as well as the goods and the cost of procurement and transportation. Furthermore, they take into consideration uncertainty into account in this model for areas where those demands might arise, and where there was a possibility that the disaster would destroy some of the pre-positioned resources in the relief distribution facility or supplier. While penalizing the solution’s infeasibility because of parameter uncertainty, the multi-objective model of Amiri et al. (2011) ensures to decrease the sum of the desired value and the variance of the total cost of the relief chain to a minimum. Moreover, increasing the satisfaction levels of the impact areas to a maximum by means of decreasing the sum of the maximum shortages to a minimum is the purpose of the model. The authors devised a compromise-programming model and modified it in order to obtain a non-dominating compromise solution, considering the global evaluation of two objectives. They then presented a case study for disaster planning concerning disaster scenarios in one of the Iran’s regions. According to their findings, one can make decisions about both the facility location and supply allocation in cases of disaster relief efforts thanks to the proposed model.

After an earthquake or any kind of other disaster, decision-makers have to make decisions regardıng the location of distribution centers as well as the roads that are to be used in order to distribute relief supplies. A lack of information regarding the road conditions increases relief effort uncertainty after a disaster. Xu et al. (2016) presented a two-tier model under a random fuzzy environment in order to overcome this problem. The Rescue Control Center is the upper level decision-maker, and it is the center’s responsibility to select the location from the available list of candidates. On the other hand, logistics companies serve as lower level decision-maker and are required to select the optimum routes so as to minimize the possible transportation time. In order to manage the uncertainties, the authors had employed random fuzzy variables. A random fuzzy interactive genetic algorithm based on simulation was designed so that optimum solutions could be found there within the two-tier model. Finally, the model's practicality and efficiency was demonstrated in a case study about the emergency logistics concerning the Lushan earthquake.

Following a disaster, too many people who are affected should be evacuated from affected area to temporary shelters. However, due a lack of evacuation capacity, many are forced to wait in the disaster regions, and many of those who have been evacuated to shelters zone still have to wait for resources due to insufficient relief supplies. Hu et al. (2014), had proposed novel mathematical programs which were developed concerning the multi-step evacuation and protect under the minimization of monetary and psychological penalty costs. By developing typical scenarios, they investigated the resource scarcity and psychological severity. The authors assessed Wenchuan County (i.e. the epicenter of the 2008 Sichuan earthquake) as a test case, and looked at the influence and the sensitivity of parameters, the tradeoff between monetary and psychological costs, and the effects of various scenarios using six experiments, whereby they applied the proposed models to the post-disaster evacuation and sheltering so as to better obtain information about its complexity and managerial insight.

It is the duty of earthquake disaster management to select the location of shelters as well as to guide the evacuees to them; therefore, establishing shelters plays a vital role in this management. Xu et al. (2018) again developed a multi-objective mathematical model involving four groups of objectives, allied with a modified particle swarm optimization algorithm, in order to solve the location–allocation problem for the earthquake shelter. The four objective groups include: TSN and total weighted evaluation time (TWET), TSA and TWET, total shelter number (TSN) and total evacuation distance (TED), and total shelter area (TSA), and TED. The solutions of the models include determining shelters from the candidates and how to allocate population. The authors then employed the case study of Chaoyang, China to use the solutions of the presented model and they compared them by means of a safety, capacity, and investment evaluation index. In order to help decide how suitable establishing shelters is, and how to allocate the affected population, the optimum model solutions can be chosen in relation to government's choices and future city planning.

Kulsrestha et al. (2011) presented a robust approach in order to identify the most suitable areas of public shelters and their capacities based on a given set of potential sites at the time of evacuation planning under demand uncertainty. They used demand uncertainty in their article to address the uncertainty concerning the number of people using the public shelters in the course of the evacuation. They estimated the number of shelters, their locations, and capacities by a planning authority, and whereby select a shelter in order to evacuate and the paths to access it. The proposed model was devised as a mathematical program with complementarity constraints and a cutting-plane scheme was utilized to solve the model. According to a numerical example in reference to the Sioux Falls network, robust plans can obtain approximately the exact level of performance with a cost significantly lower than a conservative plan, which deems the highest demand of each origin point.

In order to handle the bad effects of disasters in post-disaster period, precautions related to disasters such as determining temporary the site of shelters, allocation plans, and preventive measures ought to be taken during the pre-disaster period. A two-stage stochastic programming model is proposed by Hu, Han and Meng (2017) in order to integrate supplier selection in humanitarian relief with decisions concerning pre-disaster inventory level and post-disaster procurement quantity. Three features including lead-time discount, return price, and equity are taken into consideration in the model. They applied a scenario-based approach so that the uncertain demand can be represented, given the uncertainty concerning the disaster type and location of appearance. In order to measure risk at different confidence levels, they employed a conditional Value-at-Risk. Based on a real-world example whereby a surge in demand was incurred by the snowstorm, earthquake, flood and typhoon that took place China in 2008, they presented a case study in order to investigate the applicability of the proposed model, and discussed its implications are based on numerical studies.

Hung et al (2015) illustrated the humanitarian goals of allocating relief supply and distribution in disaster response activities. They expressed the humanitarian principles as three objective functions, including fairness, cost of delay, and utility of lifesaving, and then developed an integrated multi-objective optimization model integrating resource allocation with emergency distribution, whereby they used a time space network in order to incorporate the frequent information and decision updates in a rolling horizonapproach.

2.1.3 Recovery period

Proper damage assessment, an effective reverse logistics system for debris disposal and recycling, and infrastructure rebuilding with minimum cost and time duration are dealt with by the planning issues in the recovery phase. The recovery phase is made up of two areas: road and other infrastructure restoration, along with debris management, including removal, disposal, and recycling. The purpose of the novel model presented by Yan and Shih (2009) is to decrease the length of time required for both roadway repair and relief items distribution to a minimum, and because of operating constraints, they illustrate model planning emergency repair and relief distribution routes and schedules within a limited time. Their model is a multi-objective, mixed-integer, multiple commodity network flow problem.

The problem of allocating scarce resources is taken into consideration by Duque and Sörensen (2011) in order that a rural road network is repaired aftermath of disasters. They propose novel approach based on the both Greedy Randomized Adaptive Search Procedure (GRASP) and Variable Neighborhood Search (VNS) metaheuristics, which purposes to maximize the accessibility of as many people as possible to the main cities or regional centers where the economic and social infrastructure is usually located. When their approach is applied to a set of small and medium size instances as well as to large real-life motivated instance, its efficiency comes forward.

Debris generated by disasters could hamper relief efforts as well as emergency logistics activities, thus resulting in devastating economic, environmental, and health problems, and even increasing the death toll. A decision-support tool which uses analytical models was presented by Lorca et al. (2017) in order to provide disaster and waste management officials assistance with decisions regarding the recycling, reduction, transportation, collection, and disposal of debris. Landfill usage, the duration of the collection and disposal operations, the financial and environmental costs, and the volume of recycled materials is optimized and balanced thanks to the tool. The challenging task of developing strategic plans for disaster preparedness, along with the operational decisions aftermath of a disaster, is supported with this tool.

A constructive heuristic algorithm is presented by Özdanur, Aksu and Ergüneş (2014). This algorithm develops roadside debris cleanup plans in the event that the equipment in the post-disaster road recovery process is restricted. Travel times between cleanup tasks are not certain beforehand, but they are rather based upon the entire road network's blockage status at the time of travel. The authors developed a novel mathematical model that maximizes cumulative network accessibility throughout the cleanup operation and minimizes make span. Furthermore, planning road restoration efforts at the time of disaster response and recovery was the main focus of the study of Aksu and Özdamar (2014). In order to evacuate the survivors and to remove roadside debris immediately, the main purpose was to increasing network accessibility to a maximum for all places in the area in the course of the restoration process. A dynamic path based mathematical model, thus identifying blockages criticality, and clearing them using limited resources is proposed in order to handle this problem.

The model presented by Furuta et al. (2008) ensures that the lifeline systems are restored early following earthquake disasters. According to the former researches, it is powerful to optimize the restoration schedule by means of a genetic algorithm (GA). However, the uncertain environment in the aftermath of earthquake disasters is not taken into consideration. Secondary disasters including bad weather, aftershock, and fire considerably change the level of damage at the devastated areas. In addition, unexpected accidents may delay the restoration work. Therefore, a robust restoration schedule is a must, taking into consideration that the actual restoration work could not develop smoothly under the uncertain environment. Various involved uncertainties can be treated by GA considering uncertainty (GACU), but a robust schedule is hard to obtain.

In order to distribute emergency supplies to disaster areas which are identified beforehand, Sahin, Kara and Karasan (2016) conducted a study developing a solution methodology which takes into consideration the blockages on the transportation network. The proposed methodology's capability to distribute disaster-relief supplies to affected zones as immediate as possible is its main contribution. Therefore, this methodology saves lives and defuse the chaotic post-disaster condition. The problem characteristics imply both a node-routing aspect, thus requiring the vehicle to visit predetermined disaster zones, and an arc-routing aspect, whereby it might be necessary to unblock some of the arcs on travel path of the vehicle.

Disasters can bring about a high risk of casualties and fundamental damages. There is a tremendous amount of disaster waste caused by destructive disasters including earthquakes, which requires to be controlled. In order to reduce the necessity of reconstruction resources, one can reuse and recycle materials in the debris. A model built around a framework is presented by Onan et al. (2015) in order to locate temporary storage facilities, and moreover, they include planning for the collection and transportation of disaster waste for managing it in a sustainable way in terms of environment. In this study, a multi-objective optimization model was developed and a Non Sorting Genetic Algorithm (NSGA-II) was employed to solve it. Istanbul which is a city under a high risk of earthquake damage has been selected for the illustration of the proposed framework. Minimizing the cost and risk from hazardous waste exposure are the aims of this model.

2.2 Facility Location Problem

Most of the facility location optimization problems in humanitarian logistics activities mainly focus on constructing new facilities, such as a distribution location or selecting among existing ones so as to distribute relief items aftermath of the disasters in time. Best location selection for relief distribution is among the most important issues in facility location with regard to emergency operations of large scale of disasters. Golabi et al. (2017) investigated a combined mobile and immobile pre-earthquake facility location problem. In their study, a set of potential candidate locations was taken as basis to select a determined number of locations. Each facility was to be employed in the relief distribution operation. Collapse of some network edges and accessibility loss of corresponding areas are inevitable because of earthquakes. So as to receive the relief, the place of the distribution centers is preferred by people on intact and accessible edges according to the assumptions of the authors. In the relief distribution operation, the medium-scale unmanned aerial vehicle (UAV) helicopters are used for those located on collapsed or inaccessible network edges. The objective of the current study is to create a mathematical model reducing the aggregate traveling time to a minimum in terms of both people and UAVs over a set of feasible scenarios. In order to solve the proposed model, certain metaheuristic algorithms have been developed taking into consideration the NP-hard aspect of the network problems.

Gözaydın and Can (2013) put forth a model selecting logistics center for earthquake help stations using P-Median and Maximum Covering Location Problem. The position of a city on the earthquake zone defines the frequency and the magnitude of the earthquakes faced by that city, whereby its population, the number of the buildings, and the number of residences/houses all define vulnerability and the size of possible losses during earthquakes, whereby these numbers are accepted as being leading factors, which thus were used as weights in their model.

Both macro- (country, region) and micro-(the immediate locality) aspects of pre-warehouse positioning in terms of humanitarian relief organizations were contemplated by Roh et al. (2015), and they analyzed the managerial implications of those decisions. First, managerial level officers were being interviewed so that data can be obtained to analyze the positioning of warehouses at a regional level. Then, specific location was identified in the Dubai area in which discussions and interviews are participated by stakeholders from different organizations. The Analytic Hierarchy Process reveals that individual criteria is relatively important. Furthermore, they employed the fuzzy-TOPSIS method in order to obtain the final ranking of locations, whereby the vagueness and subjectivity of decisions were handled by linguistic.

A network flow model was recommended by Khayal et al. (2015) to select the temporary distribution facilities dynamically, and to allocate the resources for emergency response planning. In order to reduce deprivation, the transfer between temporary facilities which operate at different periods in terms of excess resources was analyzed by the model. The temporary facilities were located by the demand and supply points according to the numerical analysis. The research of Khayal et al. contributed to the emergency response planning, thus requiring a quick response for the supply of relief materials immediately after a disaster hits a particular area.

The general facility location problems were addressed by Jia et al. (2007) in a study of them, and they identified models which are employed to underline comprehensive emergency conditions, e.g. house fires and regular health care needs, etc. Whereupon, the features of large-scale emergencies were analyzed, and a general facility location model was presented for large-scale emergencies. This general facility location model could be cast as a covering model, a P-median model or a P-center model, all of which are suitable for different needs at the course of a large-scale emergency. They gave examples which demonstrate how to utilize proposed model so that the locations of facilities can be optimized for medical supplies in order to address large-scale emergencies in Los Angeles, California. The focus of Carson and Batta (1990) was the location of ambulance for emergency situations and in order to find the dynamic ambulance positioning strategy on behalf of a campus emergency service, a P-median model was recommended. With the aim to reduce the average response time in the service calls to a minimum, the model utilizes scenarios to represent the demand conditions at different times, whereby the ambulances are relocated in different scenarios. Two P-median problems were investigated by Berlin et al. (1976) so as to locate the hospitals and ambulances. The main focus of the first problem is the needs of patient, and to reduce the average distance between the hospitals and the demand nodes to a minimum, and also minimize the average ambulance response time from ambulance bases to demand nodes. In order to enhance the performance of the system, a new purpose is added in the second problem which minimizes the average distance between ambulance bases and hospitals. The p-center problem was examined closely by Huang et al. (2010), and according to their assumption, the facility located at a point responds to demands originating from the point in this problem. This assumption is also applicable to emergency and health care services. However, it is not valid for large-scale emergencies due to the possibility of most facilities in a whole city to lose their ability of outright function. Therefore, the closest facilities may not be relied on by the residents in certain areas cannot. These observations thus bring about the improvement of a variation of the p-center problem with an additional assumption that the facility at a node fails to respond to demands from the node. The dynamic programming approach was employed by the authors in order to locate on a path network, and an efficient algorithm was further developed to optimize the locations on a general network.

Man-made such as terrorist attacks also occur alongside natural disasters. In case of a catastrophic bio-terror attack, large amounts of medicine must be efficiently provided by major urban centers to the population. In order to identify the locations to distribute medicine to the population in a large city, a facility location problem was addressed by Murali et al. (2012). In order to increase coverage to a maximum, they thought locating authorized facilities, considering both a distance-dependent coverage function along with demand uncertainty. A special case of the maximal covering location problem (MCLP) with a loss function was formulated by them so as to explain the distance-sensitive demand, and they also looked at chance-constraints in order to address the demand uncertainty.

The main aim of selecting appropriate facility for distributing relief items aftermath of large scale of disasters is to determine pre-positioning emergency inventory for potential disaster threats. Ni, Shu, and Song (2017) recommended a model that optimizes the decisions of facility location, emergency inventory pre-positioning, and relief delivery operations within a single-commodity disaster relief network. In order to capture the uncertainties on both the left and right hand side parameters within the constraints, they proposed a min-max robust model. The former corresponds to the proportions of the pre-positioned inventories were deemed usable after a disaster attack, whereas the latter represents the demands of the inventories and the road capacities in the disaster affected areas. The main purpose of the researches was to efficiently solve the robust model, and they analyzed a special case which reduces the deprivation cost to a minimum. A case study of the 2010 earthquake in Yushu, Qinghai, China is employed to demonstrate the application of this model is illustrated.

In order to mitigate the effects of large-scale emergencies, Celik, Aydın, and Gumus (2017) had focused on deciding upon the number of facilities and their locations, on procurement for pre and post-disaster, and on allocation. A two-stage stochastic mixed integer-programming model was recommended by them. This model, along with providing emergency supplies to many demand locations in the aftermath of large-scale emergencies with uncertainty in demand, combines facility location-prepositioning decisions on pre-stocking levels for emergency supplies, and allocation of located distribution centers (DCs) to affected locations. Also, a case study involving prepositioning of supplies in probable large-scale emergencies in eastern and southeastern Anatolia was employed before to demonstrate the use of this model.

There are a great number of studies regarding facility location problem for emergency response. Li et al. (2011) compiled covering models and optimization techniques for emergency response facility location and planning that were found in the literature over the past few decades, whilst emphasizing recent developments. They introduced several typical covering models, and their extensions ordered from simple to complex, including Location Set Covering Problem (LSCP), Maximal Covering Location Problem (MCLP), Double Standard Model (DSM), Maximum Expected Covering Location Problem (MEXCLP), and Maximum Availability Location Problem (MALP) models. Furthermore, recent developments on hypercube queuing models, dynamic allocation models, gradual covering models, and cooperative covering models were also presented in the study. Rawls and Turnquist (2010) developed an emergency response planning tool that determines the facility location and quantities of various types of relief supplies to be pre-positioned, under uncertainty about if, or where, a natural disaster will occur. They present a two-stage stochastic mixed integer program (SMIP) that provides an emergency response pre-positioning strategy for hurricanes and other disaster threats. The SMIP is a robust model that considers uncertainty in demand for the stocked supplies as well as uncertainty regarding transportation network availability after an event. Due to the computational complexity of the problem, a heuristic algorithm referred to as the Lagrangian L-shaped method (LLSM) was developed to solve large-scale instances of the problem. Paul et al. (2017) formulated a multi-objective hierarchical extension of the maximal covering location problem in the search to maximize coverage of the population within a rapid response aftermath of large-scale emergency situations whilst minimizing modifications to the existing structure.

2.3 Multi Objective Optimization Related to Emergency Logistics

Optimization problems related to humanitarian relief distribution are made up of the simultaneous consideration of multiple objective functions as well as criteria. Complex situations at times undergo objectives such that improvement in one can only be received through at the expense of the others. Therefore, no single solution ensures the best performance across these objectives. The aim of the algorithm is to help decision makers in order to find acceptable solutions. Trivedi and Singh (2017) presented a hybrid algorithm for efficiently managing location and relocation projects by proposing a hybrid multi-objective decision model based on an analytic hierarchy process (AHP), fuzzy set theory and goal programming approach. The objectives of proposition were to minimize distance, risk, the number of sites, and the uncovered demand, all the while maximize suitability based on qualitative factors, taking into consideration demand, capacity, utilization and budgetary constraints. They chose to solve this problem by converting all objectives into a single objective function by means of using goal a programming approach. Cao et al. (2018) set out to devise the strategies of relief distribution concerning beneficiary perspective on sustainability. This problem was formulated as a multi-objective mixed-integer nonlinear programming model in order to maximize the lowest victims perceived satisfaction, and in order to minimize respectively the largest deviation on victims perceived satisfaction for all demand points and sub-phases. Then, a genetic algorithm was conducted to solve this mathematical model.

Jha et al. (2017) developed models a humanitarian relief chain, comprising of a relief items supply chain and an evacuation chain in the case of a natural disaster. Optimum network flow was analyzed for both the chains means of considering three main objectives: demand satisfaction in relief chain, demand satisfaction in evacuation chain, and overall logistics cost. The relief items supply chain also comprises of three echelons: suppliers, relief camps and affected zones. The evacuation chain consists of two echelons: evacuation camps and affected areas. The Mixed Integer Programming problem has been solved using a Non Sorting Genetic Algorithm-III (NSGA-III). Haghi et al. (2017) developed multi-objective programming model for locating relief items distribution locations and health centers, alongside distributing relief items, and transferring the victims to health centers, with pre/post-disaster budget constraints for items and victims' logistics. In order to illustrate a model in reality, the uncertainties in demand, supply, and cost parameters are included in the model. Moreover, facility failure (e.g. relief distribution locations, health centers, hospitals, and supply nodes failure) because of earthquakes were considered. The proposed model maximized the response level to medical needs of the victims whilst targeting the justly distribution of relief items and minimizing the total costs of mitigation and response phases, and was solved using the ε-constraint method. For a large sized form, the researchers proposed using the MOGASA algorithm, and compared the results with those of the NSGA-II algorithm. A study by Tavana et al. (2017) developed a multi-echelon humanitarian logistics network that takes into consideration the location of facility locations, the managing of the stock of consumable relief materials in the mitigation phase, and the routing the relief vehicles following a disaster. An epsilon-constraint method, a non-dominated sorting genetic algorithm (NSGA-II), and a modified NSGA-II called reference point based non-dominated sorting genetic algorithm-II (RPBNSGA-II) were proposed to solve this mixed integer linear programming (MILP) problem. Hu et al. (2014) aimed to address the selection of earthquake shelter locations, and the districting planning of service areas jointly. They proposed a bi-objective model in order to minimize the total evacuation distance and the overall cost, subject to capacity and contiguity constraints. A non-dominated sorting genetic algorithm (NSGA) was proposed to handle the bi-objective model involving a multitude of decision variables. In order to fit the model, the chromosome structure, initialization process and genetic operators in the algorithm were specifically designed in order to maintain the contiguity of the service area. Additionally, a hybrid strategy of bidirectional multi-point crossover and bidirectional single-point crossover helped to promote the diversity of the solutions and accelerate the convergence.

Along with the facility location problems, multi objective algorithms are also used for vehicle routing problem in humanitarian logistics activities. Molina et al. (2018) considered a problem based on real-world conditions in emergency logistics, whereby the main features are the lack of available vehicles and the compulsory need of a quick evacuation of all the affected by a disaster, but within the minimum possible travel cost. These aspects will be considered within a Multi-Objective Capacitated Vehicle Routing Problem with Multiple Trips. The main objectives are to minimize number of vehicles and total travel cost as well as the maximum latency. They considered the maximum latency to be more relevant than classic latency criteria given that the decreasing of the waiting time of the last affected is very critical for survival when disaster strikes. For the aim of generate high-quality solutions, a Multi-Start Algorithm with Intelligent Neighborhood Selection was specifically designed, and then compared with one of the most competitive references in the literature, NSGA-II, in order to prove its superiority.

In order to solve a post-disaster emergency logistics problem in which medical assistance teams are dispatched, and in which the relief items are distributed among demand nodes. Wang et al. (2018) proposed a mixed integer-programming model and a two-stage hybrid metaheuristic method developed in order to solve a problem, whereby a numerical example sourced from on the Kyushu Earthquake in Japan, which occurred in 2016, were used in order to test the proposed model and algorithm. According to Nolz et al. (2010), distribution is very crucial for people who are affected in affected zone aftermath of large-scale of disasters. To this end, the researchers proposed an operations research (OR) model for planning water distribution tours in disaster relief, especially in situations after a disaster occurrence which are instability and the immediate need of help in which high-quality decisions need to be made fast. For this reason, it is very useful if planning decisions can be alleviated by a decision support system (DSS) using an efficient multi-objective metaheuristic as its algorithmic core. In response to this, the researchers developed a metaheuristic search technique based on evolutionary concepts for a real-world extension of a multi-objective covering tour problem.

Singh et al. (2017) developed a post-disaster multi-objective two-stage transportation model in order to define the distributions of relief substances from supply sides to affected points. In their proposed model, they classified the disaster affected areas into three zones according to degree of devastation. The study aimed to minimize the overall shipment cost, as well as to maximize the safety in the routes of the transportation under the budget and desired safety level constraints, respectively. Finally, the problem was solved using the Global Criteria Method via the Lingo 13.0 optimizer solver and a Genetic Algorithm.

Zhao and Liu (2018) designed a user-friendly decision support tool in order to facilitate the process of optimizing urban emergency rescue facility locations in large-scale urban areas. The authors defined the design, architecture, and implementation of the tool and its core optimization component. Based on a hypothetical case study, they described its functionalities as well as the decision-making workflow. The results ensure evidence that the tool can successfully generate Pareto-optimal frontier, and capture a set of alternative solutions for the decision maker for trade-off. This work offers new insights on promoting future urban emergency logistics management with the use of a Geographic Information System and emerging artificial intelligence technologies, and makes contributions in integrating multi-objective optimization algorithm with GIS for solving geospatial multi-objective optimization problem. Javadin et al. (2017) considered a emergency logistics network design problem that include local distribution centers (LDCs) and multiple central warehouses (CWs), and developed a scenario-based stochastic programming (SBSP) approach. Moreover, the uncertainty associated with demand and supply information as well as the availability of the transportation network's routes level after an earthquake were considered by employing stochastic optimization. Whilst the proposed model attempts to minimize the overall costs of the relief chain, it implicitly minimizes the maximum travel time between each pair of facility location and the demand nodes of the goods. Additionally, the authors derived a data set from a real disaster case study surrounding the region of Iran, and extracted and applied a constraint in low dimension alongside other well-known evolutionary algorithms in order to solve the proposed model. According to Hu et al. (2016), emergency resource allocation constitutes is one of the most crucial problems in humanitarian logistics activities. In order to handle this issue, they formulated the bi-objective robust emergency resource allocation (BRERA) model in the attempt to maximize both efficiency, as well as fairness under different uncertainties. In order to obtain the allocation policy most preferred by decision-makers, a novel emergency resource allocation decision method consisting of three steps was proposed: (1) developing a bi-objective heuristic particle swarm optimization algorithm in order to search for the Pareto frontier of the BRERA model; (2) selecting a coefficient to measure fairness; and (3) establishing a decision method based on decision-makers' preference restricted by the fairness coefficient.

Ransikarbun (2015) presents a multi-objective, integrated network optimization model for making strategic decisions in the relief distribution and network restoration phases of emergency logistics activities. Their model ensures an equity- or fairness- based solution under constrained capacity, budget, and resource problems in post-disaster logistics management. The researches then generated efficient Pareto frontiers in order to better understand the trade- off between the objectives of interest, whereupon they constructed a goal programming-based multiple-objective integrated response and recovery model. Finally, they adapted the well-known Non-dominated Sorting Genetic Algorithm II (NSGA-II) by integrating an evolutionary heuristic using the Hybrid NSGA-II or optimization-based techniques for this NP-hard problem.

3. METHODOLOGICAL FRAMEWORK

This study mainly makes up of three different phases. In the first phase, Interpretive Structural Modelling (ISM), is conducted to define correlation and relationship between the determined selection criteria. In the second phase, Analytic Network Process (ANP), is applied to determine the weights of criteria, whereby a rating process is conducted so as to evaluate the candidate suppliers based on these criteria. The third part features the construction of a mathematical model using four objective functions, as well as the application of a Non Sorting Genetic Algorithm (NSGA-II) in order to solving this model. Figure 3.1 summarizes methodological framework of this study.

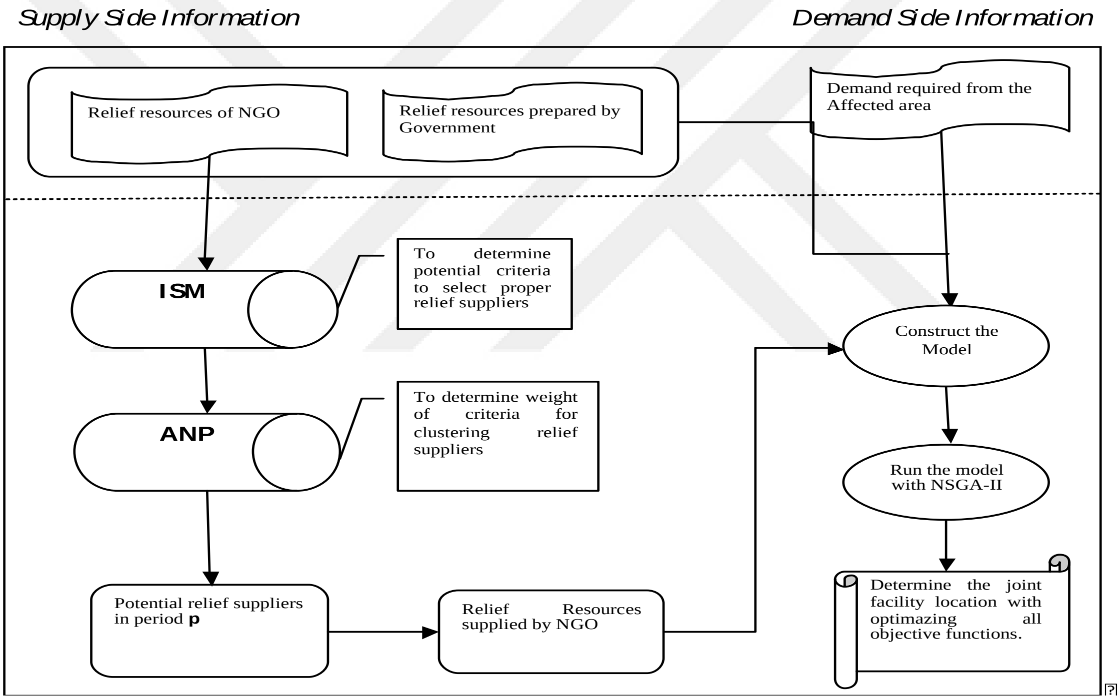

Figure 3.1 Framework of the study

The methods applied in the thesis are described in detail below.

3.1 Interpretive Structural Modeling (ISM)

Interpretive Structural Modelling (ISM) is a method, which is applied in order to analyze as well as define the relationships among certain pre-determined criteria (Warfield, 1974). According to Jain and Banwet (2013), ISM is an innovative and interactive learning process that provides a systematic and comprehensive model of wide range of directly and indirectly related variables with respect to any problem defined. In the ISM method, the decisions concerning the interdependencies among the variables depend upon expert opinion. Therefore, ISM is subjective and interpretive naturally (Muduli et al., 2013). The main objective of using the ISM method is to analyze the complicated and complex problems by applying systematical and plausible thinking, as supported by expert opinion (Barve et al., 2007). One of the distinctive features of ISM compared to other techniques such as the Delphi and Structural Equation Modelling is that it requires fewer expert opinions in order to evaluate the criteria. In conducting the Delphi technique, most researchers face difficulties in terms of collecting a sufficient number of responses through expert surveys (Barve et al., 2007). Through the ability to develop the initial model using group creativity technique such as brainstorming, ISM transforms both inexplicit as well as poorly articulated models of systems into clear and understandable forms (Talip et al., 2011). ISM methodology is made up of various steps, which are define below (Kanan & Haq, 2007).

Phase 1. Criteria thought for the system under consideration are compiled.

Phase 2. From the criteria determined in Phase 1, a contextual relationship is set up between criteria with regard to which pairs of criteria would be examined.

Phase 3. A structural self-interaction matrix (SSIM) is formed for criteria that denotes pair-wise relationships amongst criteria of the system under consideration.

Phase 4. Reachability matrix is formed from the SSIM and the matrix is controlled for transitivity. The transitivity of the contextual relation is a basic assumption made in ISM, which states that if variable X is related to Y and Y is related to Z, then X is necessarily related to Z.

Phase 5. The reachability matrix obtained in Phase 4 is separated into different levels.

Phase 6. Based on the relationships obtained above in the reachability matrix, a directed graph is drawn, and the transitive links are removed.

Phase 7. The resultant digraph is transformed into an ISM by replacing criteria nodes with statements.

Phase 8. The ISM model formed in Phase 7 is checked for conceptual inconsistency, and necessary modifications are made. All the steps mentioned are illustrated in Figure 3.2.

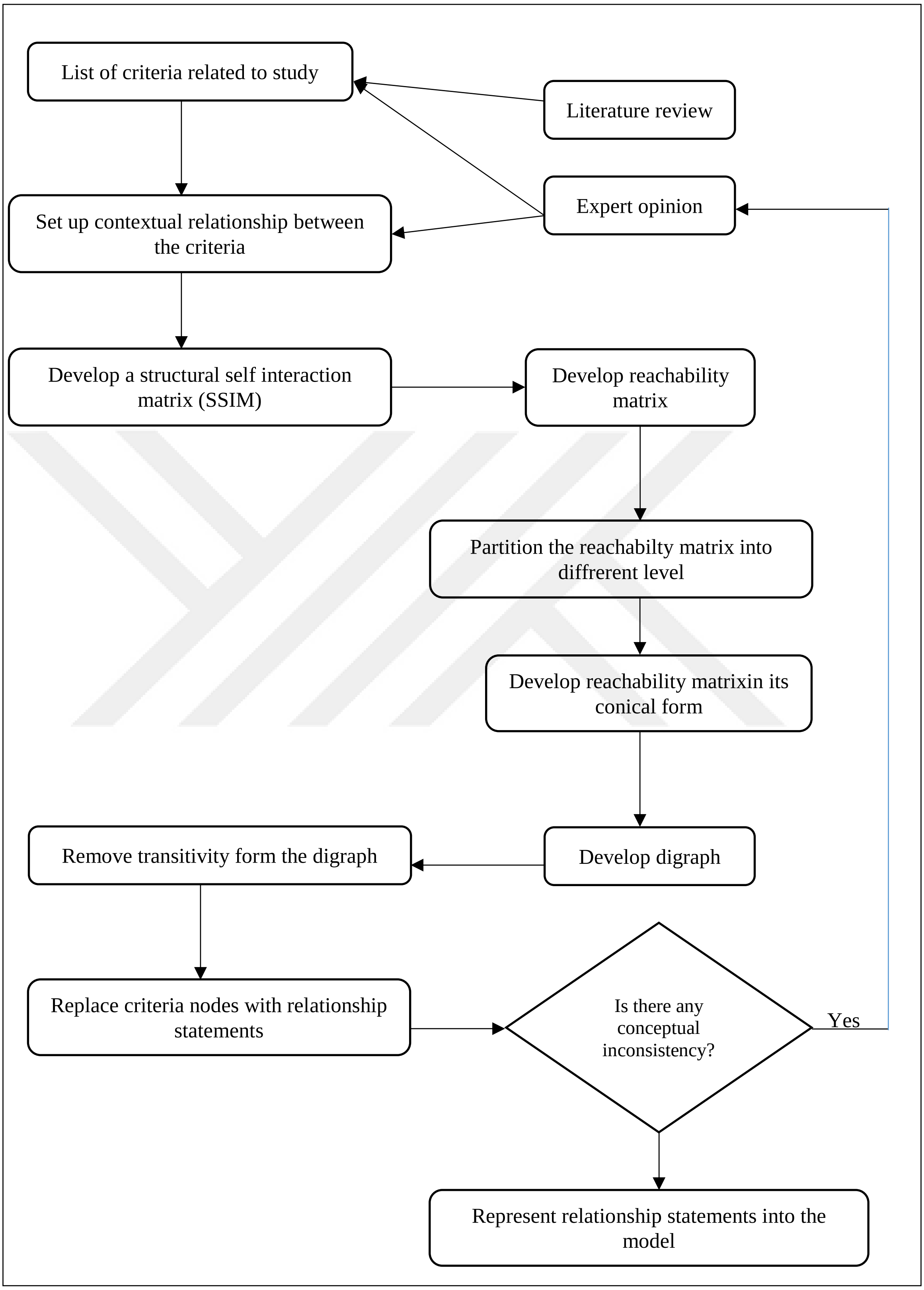

Figure 3.2 The ISM Methodology

3.2 Analytic Network Process (ANP)

There are several methods applied for multi-criteria decision-making problems in the literature, two of which include Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP), with both having been introduced by Saaty (1996). AHP attempts to solve a multi-criteria decision-making problem by modeling it in a hierarchy system ANP is used when the problem is too complicated to solve in a hierarchical manner. Many decision-making problems could not be formed hierarchically given that they involve interaction and dependencies between elements. According to Saaty (1996), not only does the importance of the criteria determine the importance of the alternatives, but also the importance of the alternatives themselves determines the importance of the criteria. The differences between ANP and AHP are given in Figure 3.3.

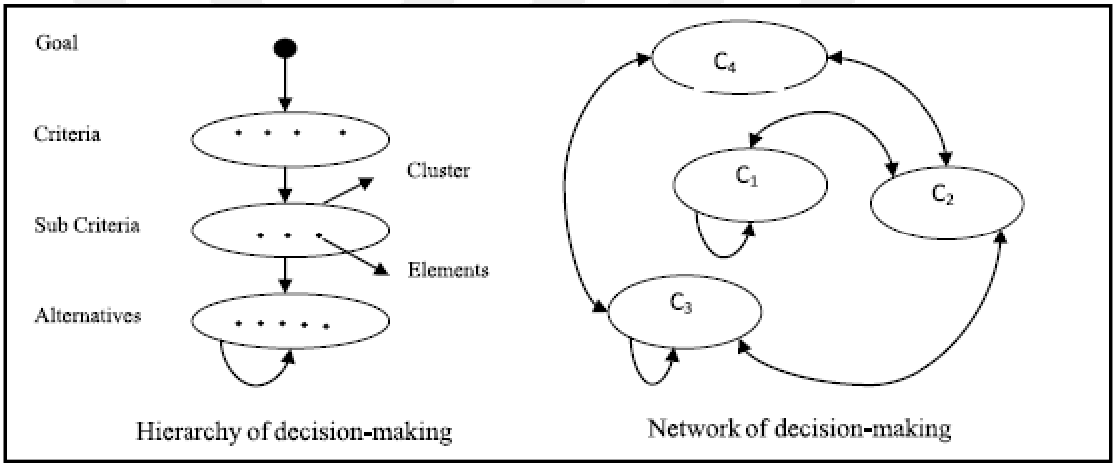

Figure 3.3 Comparison of AHP and ANP

According to Saaty (1996) as well as Meade and Sarkis (1999), ANP consists of four main steps outlined as follows, and depicted Figure 3.4.

Step 1: Define the multi criteria decision problem thoroughly comprising all objective elements, criteria, sub-criteria, actors and expected outcome of that decision.

Step 2: Form pairwise comparisons within the calculation of the eigenvalues of the corresponding matrix.

Step 3: Constitute super matrix.

Step 4: Sort and evaluate the best alternatives according to outcomes.

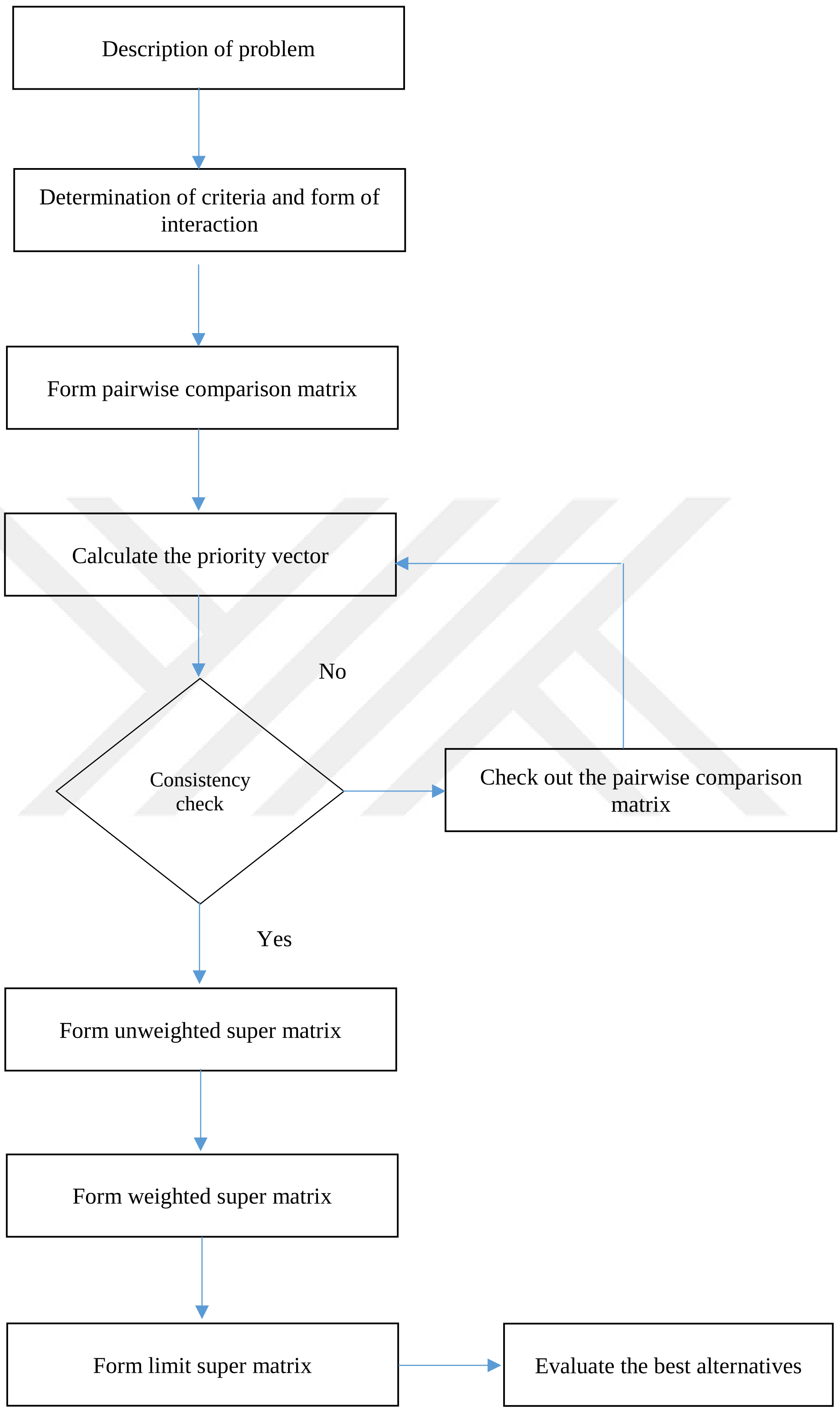

Figure 3.4. The ANP Methodology

Upon determining the goal, criteria, sub-criteria and alternatives, one ought to form the pairwise matrix in order to determine priority vector. The elements are then compared using the Saaty scale given in Table 3.1.

Table 3.1 Ratio scale for pairwise comparisons (Saaty, 1990)

Intensity of importance	Definition	Verbal expression/explanation
1	Equal importance	'Two alternatives/criteria contribute equally to the superordinate criterion, to the objective'
3	Moderate importance	'Alternative/criterion *x* is slightly more important/contributing than alternative/criterion *y*'
5	Strong importance	'Alternative/criterion *x* is strongly more important/contributing than alternative/criterion *y*'
7	Very strong importance	'Alternative/criterion *x* is very strongly more important/contributing than alternative/criterion *y*'
9	Extreme importance	'Alternative/criterion *x* is extremely more important/contributing than alternative/criterion *y*'
2, 4, 6, 8	Intermediate values between two judgements	To indicate compromises between two judgements
Reciprocals	To indicate the inverse intensity of importance	If alternative/criterion *x* received a certain judgement when compared with alternative/criterion *y*, then *y* has the reciprocal value when compared with x

As a result, one obtains the pairwise comparison matrices through these comparisons. Afterwards, one is to check the inconsistency ratios for every matrix so as to determine the misevaluation of comparisons. Inconsistency ratios are generally acceptable up to a limit of 0.10, while some scholars offer a limit of up to 0.20 (Cox et al., 2000; Soma, 2003). If all matrices are consistent, the process can proceed to the next step. If not, inconsistent matrices ought to be reassessed in order to provide consistency for all matrixes. The developed super matrix method calculates all interaction between all elements given the determination of priority among the elements including criteria, sub-criteria, as well as alternatives. Finally, after obtaining the limit super matrix, weights of elements are determined. Decision-makers sort all alternatives with respect to their weight and select the best alternatives.

3.3 Non-Sorting Genetic Algorithm II (NSGA-II)

Multi-objective problems lead to a set of optimal solution. That is, Pareto optimal solutions, rather than single optimal solutions. One of the important characteristics of Pareto optimal solution is that one of these solutions cannot be superior to the other. The classical optimization method, which includes multi-criteria decision-making methods, proposes transforming multi-objective optimization problem into a single optimization problem in order to solve in easy way. Were the other method used in order to find multiple solutions, it would have to be applied many times in order to obtain a different set of solutions at each process. Multiple objective algorithms have the ability to optimize objective functions at the same time and with multiple Pareto optimal solutions (Deb et al., 2002).

Non-Sorting Genetics Algorithm II (NSGA-II) is an evolutionary algorithm that has multi objective functions, as developed by Deb et al., (2002). NSGA-II was developed in order to tackle the drawbacks of NSGA, such as high computational complexity of non-dominated sorting, a lack of elitism, and the need for specifying the sharing parameter. NSGA-II had been designed based on a genetic algorithm so as to seek the best set of Pareto solutions. In addition to the steps of the genetic algorithm, other steps are taken into consideration in order to calculate a fast non-dominated sorting approach and diversity preservation. The workflow of the NSGA II is illustrated in Figure 3.5.

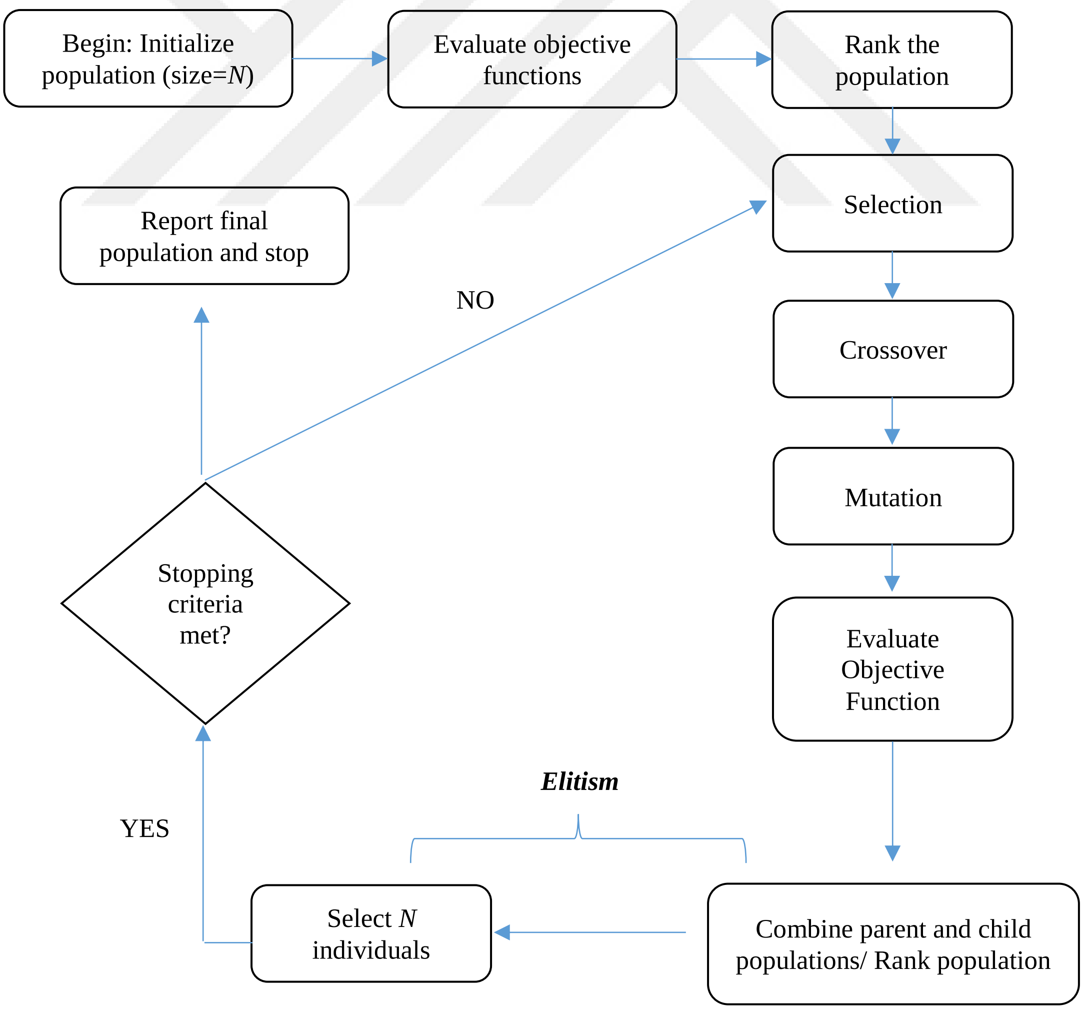

Figure 3.5 Workflow of NSGA-II

Fast non dominated sorting approach: Non sorting genetic algorithm (NSGA) has a computational complexity of $O(MN^3)$, in which M is number of objective functions and N is population size. This complexity makes the problem computationally too expensive for a large population size. In comparison to NSGA, NSGA-II offers a fast non dominated sorting approach with computational complexity of $O(MN^2)$ using below computation (Figure 3.6).

```
fast-non-dominated-sort(P)
for each p ∈ P
   S_p = ∅
   n_p = 0
   for each q ∈ P
      if (p ≺ q) then                 If p dominates q
         S_p = S_p ∪ {q}              Add q to the set of solutions dominated by p
      else if (q ≺ p) then
         n_p = n_p + 1                Increment the domination counter of p
   if n_p = 0 then                    p belongs to the first front
      p_rank = 1
      F_1 = F_1 ∪ {p}
i = 1                                 Initialize the front counter
while F_i ≠ ∅
   Q = ∅                              Used to store the members of the next front
   for each p ∈ F_i
      for each q ∈ S_p
         n_q = n_q − 1
         if n_q = 0 then              q belongs to the next front
            q_rank = i + 1
            Q = Q ∪ {q}
   i = i + 1
   F_i = Q
```

Figure 3.6 Computation of the fast non-dominated sorting approach (NSGA-II)

Diversity Preservation: Schaffer (1987), as well as Zitzler and Thiele (1998) both emphasize that elitism could accelerate the performance of genetic algorithm notably, and that it ensures to prevent loosing good solutions. In order to reach good spread of solutions in obtained set of Pareto solutions, NSGA use sharing function approach ensure to maintain sustainable diversity in a population with appropriate setting of its associated parameters. The sharing method includes a sharing parameter related to distance metric selected in order to reckon the proximity distance between two members of the population, in which mostly users give this parameter. The performance of sharing function approach in terms of spread of solution heavily depends upon selected value as determined by users. As for NSGA-II, sharing function approach is replaced with the crowded-comparison approach in order to eliminate the drawbacks of sharing function approach. NSGA-II does not require any given parameter in order to maintain diversity among the population members. The other superior feature of NSGA-II compare to NSGA has a better computational complexity. So as to obtain an estimate of the density of solutions surrounding a particular solution in the population one must calculate the average distance of two points on either side of this point along each of the objectives. This is known as crowding distance, and is determined using cuboid form. Figure 3.7 and 3.8, respectively, show the crowding distance calculation and algorithm. In Figure 9 considers only two objective functions. Using more than two objective functions is also applicable, as well.

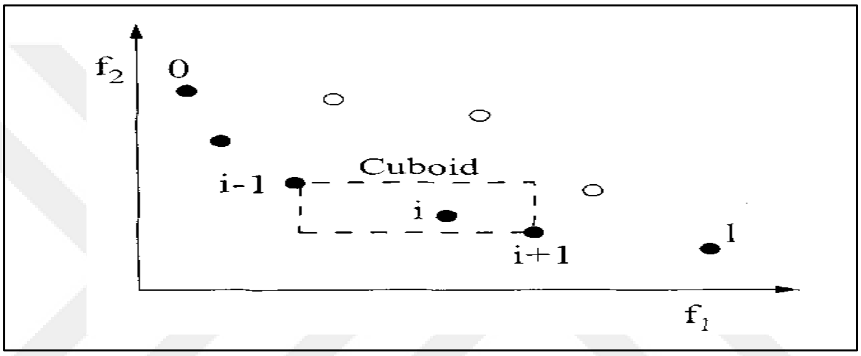

Figure 3.7 Calculation of crowding distance.

crowding-distance-assignment($\mathcal{I}$)

$l = \lvert\mathcal{I}\rvert$	number of solutions in $\mathcal{I}$
for each i, set $\mathcal{I}[i]_{\text{distance}} = 0$	initialize distance
for each objective m	
$\quad \mathcal{I} = \text{sort}(\mathcal{I}, m)$	sort using each objective value
$\quad \mathcal{I}[1]_{\text{distance}} = \mathcal{I}[l]_{\text{distance}} = \infty$	so that boundary points are always selected
$\quad$ for $i = 2$ to $(l-1)$	for all other points
$\quad\quad \mathcal{I}[i]_{\text{distance}} = \mathcal{I}[i]_{\text{distance}} + (\mathcal{I}[i+1].m - \mathcal{I}[i-1].m)/(f_m^{\max} - f_m^{\min})$	

Figure 3.8 Crowding distance algorithm.

NSGA-II uses a crowding-comparison operator in order to optimize the selection process at various steps of the algorithm to get better set of Pareto optimal solutions. It is assumed that every individual has two features, as is given in Figure 3.9.

1) nondomination rank (i_{rank});
2) crowding distance (i_{distance}).
We now define a partial order $\prec_n$ as

$$
\begin{aligned}
i \prec_n j \quad & \text{if } (i_{\text{rank}} < j_{\text{rank}}) \\
& \text{or } ((i_{\text{rank}} = j_{\text{rank}}) \\
& \text{and } (i_{\text{distance}} > j_{\text{distance}}))
\end{aligned}
$$

Figure 3.9 Features of individuals.

If two solutions with different non-domination are obtained because of algorithm, one should prefer to select the lower one for the minimization problem. On the other hand, if both solutions are in same front, one should prefer to choose the solution located in lesser-crowded section.

These features are (1) a fast non-dominated sorting procedure, (2) a fast crowded distance estimation procedure, and (3) a simple crowded comparison operator. Figure 3.10 illustrates the main algorithm of the NSGA-II, whereas Figure 3.11 shows the NSGA-II procedure, respectively.

$R_t = P_t \cup Q_t$	combine parent and offspring population
$\mathcal{F} = \texttt{fast-non-dominated-sort}(R_t)$	$\mathcal{F} = (\mathcal{F}_1, \mathcal{F}_2, \ldots)$, all nondominated fronts of R_t
$P_{t+1} = \emptyset$ and $i = 1$	
until $\lvert P_{t+1}\rvert + \lvert\mathcal{F}_i\rvert \leq N$	until the parent population is filled
$\quad\texttt{crowding-distance-assignment}(\mathcal{F}_i)$	calculate crowding-distance in $\mathcal{F}_i$
$\quad P_{t+1} = P_{t+1} \cup \mathcal{F}_i$	include ith nondominated front in the parent pop
$\quad i = i + 1$	check the next front for inclusion
$\text{Sort}(\mathcal{F}_i, \prec_n)$	sort in descending order using $\prec_n$
$P_{t+1} = P_{t+1} \cup \mathcal{F}_i[1 : (N - \lvert P_{t+1}\rvert)]$	choose the first $(N - \lvert P_{t+1}\rvert)$ elements of $\mathcal{F}_i$
$Q_{t+1} = \texttt{make-new-pop}(P_{t+1})$	use selection, crossover and mutation to create a new population Q_{t+1}
$t = t + 1$	increment the generation counter

Figure 3.10 Main loop of NSGA-II

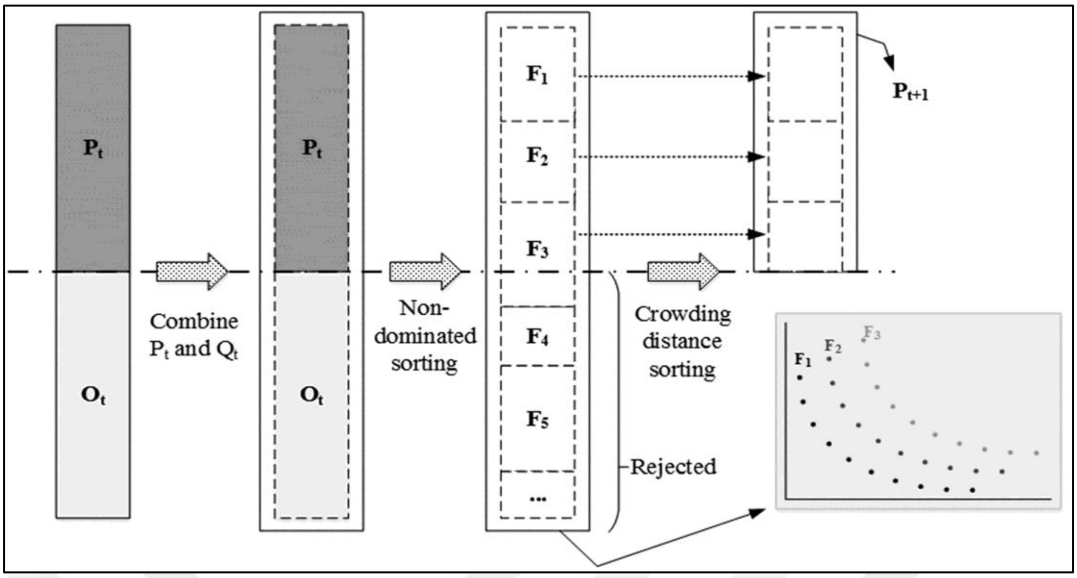

Figure 3.11 Procedure of NSGA-II

Upon describing the methods featured in the study, in the following section, a mathematical model formulation has been constructed based on real scenarios, as well as on actors such as governments, NGOs and potential relief suppliers.

4. MATHEMATICAL MODEL FORMULATION

A comparison of constructed mathematical model using both the Non Sorting Genetic Algorithm II (NSGA-II) as well as multi-criteria decision methods thus results in subjectivity. In order to identify joint facility locations for distributing relief supplies, one must form a mathematical model. Given that the relief suppliers determined may not deliver exact quantities of supplies required for affected an area, one must generate real quantities of relief supplies provided by relief suppliers, alongside an expected quantity of relief supplies assigned based on size of population residing in affected areas. Although the capacities of relief suppliers are known in terms of resource size and type, real quantities of relief supply from relief suppliers are uncertain, they fluctuate, and they take on a dynamic form during the response period of disasters. Therefore, this model is a stochastic dynamic programming model. So as to ensure the minimizing toll of victims, of an unsatisfied demand ratio, and of the time needed for replenishment for victims in the affected area, different objectives are put forward, and are defined in detail in this section. The main purpose of constructing a mathematical model with these objective functions is to provide the right types and quantities of supplies to the impact zones at the right time.

4.1 Assumptions of the Study

The host government owns relief supplies in which information about the types of and quantities of that relief are publically available. This study considers that the Turkish government as a host government is thus partly functional aftermath of a large-scale earthquake that is likely to occur in Istanbul. Information regarding this can be obtained through Alternatif Logistics, which serves as the main contractor for Disaster and Emergency Management Presidency (AFAD). The contractor is responsible for stocking supplies as determined by host government for humanitarian logistics activities, and more over is responsible for conducting all activities regarding emergency logistics on behalf of AFAD. All other data is obtained via Istanbul Metropolitan Municipality.

Time varying relief demand is also given. In order to simplify this study, one must roughly estimate the time varying relief demand based on last census of Istanbul. Within the proposed model, Istanbul is divided into two sections in accordance with earthquake information data of Istanbul Metropolitan Municipality.

Notations used in mathematical model are shown below.

4.2 Notation of Model

<u>Parameters:</u>

F**:** The maximum number of joint facility location selected among all relief suppliers.

I**:** Set of impact zones, **i** =1, …., ***m*.**

J**:** Set of relief suppliers location, **j** = 1, …., ***n*.**

K**:** Set of people who are affected,

$$k = \begin{cases} 1, helpless\ people(childeren\ and\ elderly\ people) \\ 2, young\ or\ middle\ age\ people \end{cases}$$

L**:** The set of nodes covered by ***j*** but not equal to ***s*** nodes.

P**:** Period of response phase

$$P = \begin{cases} 1, the\ emergency\ response\ phase \\ 2, the\ continuum\ response\ phase \\ 3, the\ initial\ recovery\ response\ phase \end{cases}$$

R**:** Set of relief resources, where

r_1 : Non-consumable commodities,

r_2 : Consumable commodities.

S: Set of nodes that are selected as a joint facility location, ***s*** = 1, …., ***p*.**

$\boldsymbol{t}$: Time interval $\boldsymbol{t} = 1, ..., \boldsymbol{T}$

$\boldsymbol{T_p}$: Time of period of response phase, where

$\mathbf{P}=1, \boldsymbol{t_{p_1}} = 1, ..., \mathrm{T}_1$

$\mathbf{P}=2, \boldsymbol{t_{p_2}} = \mathrm{T}_1 + 1, ..., \mathrm{T}_2$

$\mathbf{P}=3, \boldsymbol{t_{p_3}} = \mathrm{T}_2 + 1, ..., \mathrm{T} = \left(\mathrm{t}_1 \bigcup \mathrm{t}_2 \bigcup \mathrm{t}_3\right)$

$\boldsymbol{h}$: Highly collaborative group.

$\boldsymbol{m}$: Normal collaborative group.

$\boldsymbol{D_{i,r,k}(t_p)}$: Quantity of relief items $\boldsymbol{r}$, needed for people who are affected $\boldsymbol{k}$, in the impact zone $\boldsymbol{i}$, at time $\boldsymbol{t}$, in period $\boldsymbol{p}$.

$\boldsymbol{C_{i,r,k}(t_p)}$ **:** Rate of coverage provided by relief suppliers related to resources $\boldsymbol{r}$, required for people who are affected $\boldsymbol{k}$, in the impact zone $\boldsymbol{i}$, at time $\boldsymbol{t}$, in period $\boldsymbol{p}$.

$\boldsymbol{\Omega_{i,r,k}(t_p)}$: Quantity of relief items $\boldsymbol{r}$, provided by the government for people who are affected $\boldsymbol{k}$, at time $\boldsymbol{t}$ of the impact zone $\boldsymbol{i}$, in period $\boldsymbol{p}$.

$\boldsymbol{\phi_r^{p,h}}$: Capacity of highly collaborative group supply relief resources $\boldsymbol{r}$, in period $\boldsymbol{p}$.

$\boldsymbol{\phi_r^{p,m}}$: Capacity of normal collaborative group supply relief resources $\boldsymbol{r}$, in period $\boldsymbol{p}$.

$c^h(t_p)$: Average relief feed rate of highly collaborative group at time ***t***, in period ***p***.

$c^m(t_p)$: Average relief feed rate of normal collaborative group at time ***t***, in period ***p***.

$\tau_{i,r,k}$ **:** Degree of urgency of providing people who are affected ***k*** with relief resources ***r*** , in the impact zone ***i***.

$v_{i,r}$: Degree of risk given relief resources ***r*** stocks in the affected area ***i***.

$U_{i,r,k}(t_p)$: Relief under supply impact of relief resource **r** required from people who are affected ***k*** in the impact zone ***i*** at time ***t*** in period ***p***.

$O_{i,r,k}(t_p)$: Relief over supply impact of relief resources ***r*** required from people who are affected ***k*** in the impact zone ***i*** at time ***t*** in period ***p***.

$w_{i,r,k}(t_p)$: Weight of undersupply of received relief resources ***r*** for people who are affected ***k*** in the impact zone ***i*** at time ***t*** in period ***p***.

$\delta_{i,r,k}(t_p)$: Weight of oversupply of received relief resources ***r*** for people who are affected ***k*** in the impact zone ***i*** at time ***t*** in period ***p***.

$\psi^h_{irk}(t_p)$: Amount of relief resources ***r*** required from highly collaborative group for people who are affected ***k*** in a given zone ***i*** at time ***t*** in period ***p***.

$\psi^m_{irk}(t_p)$: Amount of relief resources ***r*** required from normally collaborative group for people who are affected ***k*** in a given zone ***i*** at time **t** in period ***p***.

$\boldsymbol{I^{+}_{i,r,k}(t_p)}$: Positive inventory of relief resources $\boldsymbol{r}$ for people who are affected $\boldsymbol{k}$ in the impact zone $\boldsymbol{i}$ at time $\boldsymbol{t}$ in period $\boldsymbol{p}$.

$\boldsymbol{I^{-}_{i,r,k}(t_p)}$: Negative inventory of relief resources $\boldsymbol{r}$ for people who are affected $\boldsymbol{k}$ in the impact zone $\boldsymbol{i}$ at time $\boldsymbol{t}$ in period $\boldsymbol{p}$.

$\boldsymbol{\Gamma_{i,r,k}(t_p)}$: Amount of relief items $\boldsymbol{r}$ provided by te government as well as relief suppliers to people who are affected $\boldsymbol{k}$ in the impact zone $\boldsymbol{i}$ at time $\boldsymbol{t}$ in period $\boldsymbol{p}$.

$\boldsymbol{Cap_j}$: Physical capacity of joint facility location.

$\boldsymbol{\eta(t_p)}$: Time differences between the present time $\boldsymbol{t}$ and the time of the last negative inventory in period $\boldsymbol{p}$.

$\boldsymbol{\varphi(t_p)}$: Time differences between the present time $\boldsymbol{t}$ and the time of the last positive inventory in period $\boldsymbol{p}$.

$\boldsymbol{d_{lj}}$**:** Distance from node $\boldsymbol{j}$ which refer to selected suppliers as a joint facility location to node $\boldsymbol{l}$ which refer to suppliers are not selected.

<u>Decision Variables:</u>

$$X_j = \begin{cases} 1, If\ the\ candidate\ point\ j\ selected\ as\ a\ joint\ facility\ location \\ 0, Otherwise \end{cases}$$

4.3. Objective Functions

$$Minimize\ Z1 = \sum_{tp}\sum_{i}\sum_{r}\sum_{k}(U_{irk}(tp)\ +\ O_{irk}(tp)) \tag{1}$$

$$Maksimize\ Z2 = \sum_{t_p}\sum_{i}\sum_{r}\sum_{k}\ C_{irk}(t_p) \tag{2}$$

$$Minimize\ Z3 = \sum_{j\in J} X_j \tag{3}$$

$$Minimize\ Z4 = \sum_{l\in L}\sum_{s\in S} d_{ls} \tag{4}$$

Objective function (1) was inspired by Sheu & Pan (2016), is used for minimizing the impact of undersupply or oversupply to the affected area, and mainly comprises of two sections: relief oversupply impact $(\boldsymbol{O_{i,r,k}(t_p)})$ and relief undersupply impact $(\boldsymbol{U_{i,r,k}(t_p)})$.

(a) $\boldsymbol{U_{i,r,k}(t_p)}$ stands for the impact of the disaster on people who are affected ***k*** in the affected area ***i*** caused by an increase in negative inventory of relief items ***r*** at time ***t*** in period ***p*,** and is given by

$$\boldsymbol{U_{i,r,k}(t_p)} = \boldsymbol{I^{-}_{i,r,k}(t_p)}\ x\ \boldsymbol{w_{i,r,k}(t_p)}\ \ \forall (i, k, r, tp)$$

$$\boldsymbol{w_{i,r,k}(t_p)} = \Delta\,(\boldsymbol{\tau_{i,r,k}}\,, \boldsymbol{\eta(tp)})\ \forall (i, k, r, tp)$$

whereby $w_{i,r,k}(t_p)$ refers to the weight of the undersupplied relief item $\boldsymbol{r}$ for those affected $\boldsymbol{k}$ in the affected area $\boldsymbol{i}$ at time $\boldsymbol{t}$ in period $\boldsymbol{p}$. When relief undersupply happens in an affected area, the weight is conducted. $\eta(tp)$ indicates the time difference between the present time $\boldsymbol{t}$ and the time of the last negative inventory in period $\boldsymbol{p}$; $\tau_{i,r,k}$ indicates the degree of urgency ('urgent degree') of providing people who are affected $\boldsymbol{k}$ with relief item $\boldsymbol{r}$ in the affected area $\boldsymbol{i}$, which is a given parameter. $\eta(\eta(tp))$and $\tau_{i,r,k}$ takes into account the components of $w_{i,r,k}(t_p)$. Additionally, because various disasters generate different situations, Δ does not have a unique form and ought to be based on the conditions of a disaster.

(b) $O_{i,r,k}(t_p)$ represents the impact of a disaster on the people who are affected $\boldsymbol{k}$ in the affected area $\boldsymbol{i}$ caused by an increase in positive inventory during the response phase, and is given by

$$O_{i,r,k}(t_p) = I^{+}_{i,r,k}(t_p) \times \delta_{i,r,k}(t_p) \quad \forall (i, k, r, tp)$$

$$\delta_{i,r,k}(t_p) = \oslash(v_{i,r}, \varphi(tp)) \; \forall (i, k, r, tp)$$

$\delta_{i,r,k}(t_p)$ stands for the weight of the oversupplied relief resource $\boldsymbol{r}$ for those affected $\boldsymbol{k}$ in the affected area $\boldsymbol{i}$ at time $\boldsymbol{t}$ in period $\boldsymbol{p}$. $\delta_{i,r,k}(t_p)$ is similar to $w_{i,r,k}(t_p)$, and is applicable when relief oversupply occurs in an affected area; thereafter, the weight added. $\delta_{i,r,k}(t_p)$ comprises two components – stock-time lag ($\varphi(tp)$) and stock-risk degree($v_{i,r}$). $\varphi(tp)$ indicates the time difference between the present time $\boldsymbol{t}$ and the time of the last positive inventory in period $\boldsymbol{p}$; $v_{i,r}$ is a given parameter that presents to the degree of risk given relief resource $\boldsymbol{r}$ stocks in the affected area $\boldsymbol{i}$. The form of $\oslash$ also determines the current condition following a disaster.

Objective function (2) is used for maximizing coverage rate of remained demand after supplied by the government in terms of relief resource ***r*** for those affected ***k*** in the affected area ***i*** at time ***t*** in period ***p,*** and is given by

$$C_{irk}(t_p) = \left\{c^m(t_p)\ * \psi^m_{irk}(t_p)\right\} + \left\{c^h(t_p)\ * \psi^h_{irk}(t_p)\ \right\} / \left\{D_{irk}(t_p) - \ \Omega_{irk}(t_p)\right\}$$

Here $c^h(t_p)$ and $c^m(t_p)$ represent average relief feed rate of highly and normal collaborative group at time ***t***, in period ***p,*** respectively. These parameters are stochastic and dynamic with respect to supplier's collaboration attribute. $\psi^h_{irk}(t_p)$ and $\psi^m_{irk}(t_p)$ represents the amount of relief resources **r** required from highly and normal collaborative groups for people who are affected ***k*** in a given area ***i*** at time ***t*** in period ***p,*** respectively.

The objective function (3) ensures to minimize the number of joint facility locations in order to increase the coordination between affected areas, suppliers, as well as government; and to decrease the total cost including the cost of transportation, investment, personnel, etc.

One should use the objective function (4) in order to minimize the distances between suppliers chosen as a joint facility location, and other relief suppliers not selected as a joint facility location in order to easily replenish relief substances from other relief suppliers.

4.4 Constraints of the Study

Constraints and its definitions used in the thesis are presented below:

$$\psi^h_{irk}(t_p)\ + \psi^m_{irk}(t_p)\ \geq D_{irk}(t_p)\ - \Omega_{irk}(t_p)\ - \left\{I^+_{irk}(t_p - 1) - I^-_{irk}(t_p - 1)\right\} \forall\, i, r, k, t_p \tag{1}$$

$$\sum_{t_p}\sum_{i}\sum_{r}\ c^h(t_p)\ * \psi^h_{irk}(t_p)\ \leq \phi^{p,h}_r \tag{2}$$

$$\sum_{t_p}\sum_{i}\sum_{r} c^m(t_p) * \psi_{irk}^m(t_p) \le \phi_r^{p,m} \tag{3}$$

$$I_{irk}^{+} - I_{irk}^{-} = \{I_{irk}^{+}(t_p - 1) - I_{irk}^{-}(t_p - 1)\} + \Gamma_{irk}(t_p) - D_{irk}(t_p) \forall\, i, r, k, t_p \tag{4}$$

$$\sum_{j\in J} X_j \le F \tag{5}$$

$$\sum_{j\in J} X_j \ge 1 \tag{6}$$

$$\sum_{t_p}\sum_{i}\sum_{r}\sum_{k}\{D_{i,r,k}(t_p) - \Omega_{i,r,k}(t_p)\} \le \sum_{j\in J} Cap_j * X_j \tag{7}$$

$$\psi_{irk}^h(t_p), \psi_{irk}^m(t_p), I_{irk}^{+}, I_{irk}^{-} \ge 0 \,\forall\, i, r, k, t_p \tag{8}$$

Constraint (1) ensures that the total relief items provided by the collaborative groups $\psi_{irk}^h(t_p) + \psi_{irk}^m(t_p)$ are greater than or equal to the differences between the government-prepared resources and the demands from the affected areas. Given that relief missions are ultimately the duty of the government; its relief items should therefore be determined before those of the collaborative groups. These constraints also denote the lower bound the total amount of relief resources that provided by the collaborative groups. Shortages of the relief resources, $D_{i,r,k}(t_p) - \Omega_{i,r,k}(t_p)$, if $D_{i,r,k}(t_p) - \Omega_{i,r,k}(t_p)$ >0, signify that the government could not satisfy the demands from the affected areas by itself. Thus, the relief materials provided by the collaborative groups must reduce the shortages of relief resources. This study assumes this situation as mentioned in the assumptions. In contrast, $D_{i,r,k}(t_p) - \Omega_{i,r,k}(t_p) \le 0$ means that the government could satisfy the demands of the affected areas by itself, thus rendering relief supply collaboration unnecessary. However, this situation is a rare in the case of large-scale disasters.

Notably, $I_{irk}^{+}(t_p)$ and $I_{irk}^{-}(t_p)$ are included in the proposed mathematical model, considering that either undersupply or oversupply may occur in an affected area. Both are non-negative variables. Accordingly, if $I_{irk}^{+}(t_p)$ >0, then $I_{irk}^{-}(t_p)$ must equal zero, meaning that the relief resource ***r*** for people who are affected ***k*** is oversupplied to the affected area ***i*** at time ***t*** in period ***p***. In contrast, if $I^{-}_{irk}(t_p)$ >0, then $I^{+}_{irk}(t_p)$ must be zero, and thus undersupply occurs.

Constraints (2) and (3) ensure that total quantities of relief materials provided by the collaborative groups do not exceed their resource capacities, respectively. Particularly, $c^h(t_p) \ * \psi^h_{irk}(t_p)$ and $c^m(t_p) \ * \psi^m_{irk}(t_p)$ denote the 'real' quantities of relief resource ***r*** for those people ***k*** supplied by the highly and normal collaborative groups in the affected area ***i*** at time ***t*** in period ***p***, respectively. $c^h(t_p)$ and $c^h(t_p)$ represent the average relief feet rate of highly and normal collaborative groups, respectively. Relief feed rate equals that the 'real' average quantity of the relief resource supplied from collaborative groups divided by the 'expected' quantity assigned in joint decision-making. Hence, the values of relief feed rate of collaborative groups are stochastic and dynamic in the proposed mathematical model.

Constraints (4) underline the relationships upon ending inventory $I^{+}_{irk}(t_p) - I^{-}_{irk}(t_p)$, total relief supply $\Gamma_{irk}(t_p)$, and relief demand $D_{i,r,k}(t_p)$ between current time ***t*** and previous time ***t* − *1*** in period ***p***. $\Gamma_{irk}(t_p)$ represents the amount of relief resource ***r*** supplied to people affected ***k*** in the affected area ***i*** at time ***t*** in period ***p***, and is given by

$$\Gamma_{irk}(t_p) = \Omega_{irk}(t_p) + \{c^m(t_p) \ * \psi^m_{irk}(t_p)\} + \{c^h(t_p) \ * \psi^h_{irk}(t_p) \ \} \ \forall \ (i, r, k, t_p)$$

Constraints (5) and (6) specify both the upper bound and lower bound of the number of the Joint facility location, respectively. ***F*** represents number of suppliers assigned as a joint facility location. ***F*** is being tested while NSGA-II is being conducted.

Constraints (7) are capacity constraints that ensure that the capacities of suppliers selected as a joint facility location, and are larger than the demand of affected area ***i.***

Constraints (8) are non-negativity constraints, which ensure that variables the listed in those constraints are positive.

5. CASE STUDY

The essential purpose of the case study is to analyze efficiency of proposed model with regard to a numeric solution. The case study concerns large scale of earthquake that may hit the Marmara region. The Marmara region is more prone to earthquakes in accordance than other regions in Turkey. The earthquakes that hit the Marmara Region in 1999 was, by far, the most catastrophic disasters experienced in Turkey. What set these earthquakes apart from their predecessors were their main characteristics, such as how they hit zones with large populations, and how they devastated numerous buildings. For this reason, we are mainly focus on Istanbul and, in particular, the Anatolian or Asian side of Istanbul.

The Anatolian side of Istanbul has 14 districts, alongside a population of nearly 6 million people in order to simplify this case study, the demand side consists of two affected areas according to the Kandilli Observatory and Earthquake Research Institute. Figure 5.1 shows an earthquake risk map. It is understood that coastline of the city is located at first degree risk zone, whereas the other side is located at second degree risk zone.

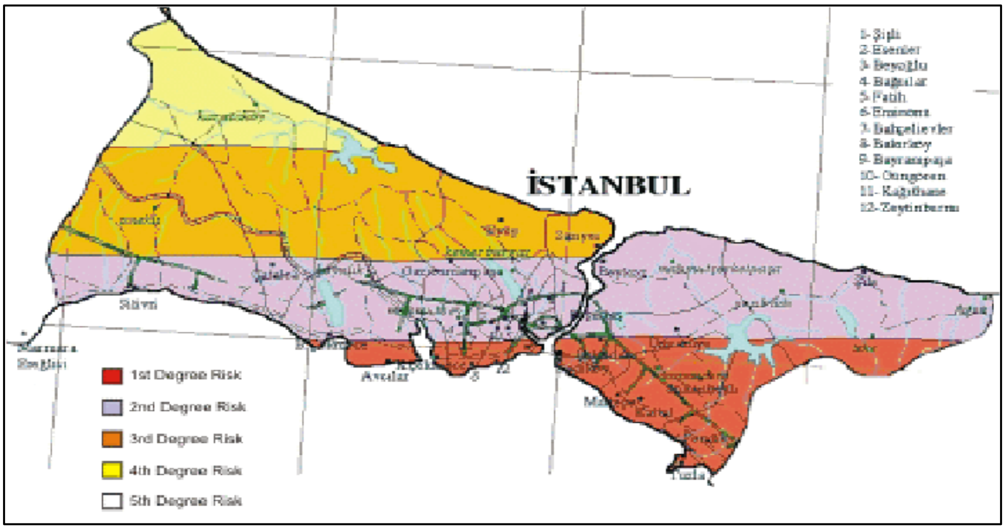

Figure 5.1 Earthquake risk map of Istanbul

The host government and relief suppliers comprise of the supply side. Given that the host government is assumed to be partly functional, main supplier of this case study is the host government. In order to determine relief suppliers as being joint facility locations, first the ISM method was used to select the selection criteria, and then the suppliers were rated using ANP. Two types of relief supplies are required for the affected zones. Those affected have been separated into two categories: helpless people including children and the elderly. and those who are middle-aged. Finally, potential earthquake consists of 3 main phases mentioned in former sections.

5.1 Interpretive Structural Modeling

The researcher chose the criteria involved in the supplier selection a face-to-face survey, whereupon they then designed a questionnaire consisting of these factors for the survey. The respondents for the survey are selected randomly from different functional positions of Alternatif Logistics, which conducts emergency logistics activities on behalf of AFAD. Based on the survey, the main influencing criteria involved in supplier selection were presented in Table 5.1. The objective was to determine and classify the criteria utilized for the supplier selection, as well as to find the interactions between the criteria by using ISM for the supplier selection, and collaboration for humanitarian logistics activities.

Table 5.1 Supplier selection criteria for humanitarian logistics activities

Number	Criteria
1	Collaboration attribute
2	Resource size
3	Quality improvement
4	Cost minimization
5	Flexibility
6	Trust development
7	Lead time reduction
8	Long-term strategic goals
9	Capability
10	Relational orientation

11	Resource and information sharing
12	Evaluation and certification system
13	Geographic position
14	Using information technology tools
15	Data accuracy

5.1.1 Structural self interaction matrix

ISM methodology proposes the use of expert opinions based on various management techniques such as brainstorming and the nominal technique. in in order to develop the contextual relationship among the variables. Thus, in this study, in order to identify, we consulted the contextual relationship among the interactions for the supplier selection criteria: four experts, two from the Alternative Logistics, one from academia and one from AKOM. Keeping in mind the contextual relationship for each element, we also questioned the existence of a relation between any two criteria (q and z) and the associated direction of the relation. Four symbols have been used in order to indicate the direction of the relationship between the criteria (q and z):

(1) V – criteria q will help alleviate criteria z;
(2) A – criteria z will be alleviated by criteria q;
(3) X – criteria q and z will help achieve each other; and
(4) O – criteria q and z are unrelated.

The relationship between the criteria are shown in Table 5.2 as a result of experts' opinion.

Table 5.2 Structural self interaction matrix

	Criteria	**15**	**14**	**13**	**12**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
1	Collaboration attribute	V	V	V	V	V	V	V	V	V	V	V	X	V	V	
2	Resource size	O	A	A	O	A	A	A	X	V	A	X	O	V		
3	Quality improvement	A	A	A	X	A	X	X	A	A	V	O	O			
4	Cost minimization	A	A	A	O	A	A	A	A	A	O	A				
5	Flexibility	A	A	O	O	A	A	X	A	V	A					
6	Trust development	X	A	O	X	A	A	V	A	V						
7	Lead time reduction	A	A	A	O	A	A	X	A							
8	Long-term strategic goals	V	V	X	A	V	A	X								
9	Capability	A	A	A	A	A	X									
10	Relational orientetion	X	A	O	V	V										
11	Resource and information sharing	V	A	A	A											
12	Evaluation and certification system	V	V	O												
13	Geopraphic position	O	O													
14	Using information technology tools	V														
15	Data accuracy															

5.1.2 Initial reachability matrix

The Structural Self Interaction Matrix (SSIM) is converted into a binary matrix known as the initial reachability matrix by superseding V, A, X, O by 1 and 0 as per the case. The rules for the substitution of 1 and 0 are as follows:

(1) If the (q, z) entry in the SSIM is V, then the (q, z) entry in the reachability matrix becomes 1 and the (z, q) entry becomes 0.

(2) If the (q, z) entry in the SSIM is A, then the (q, z) entry in the reachability matrix becomes 0 and the (z, q) entry becomes 1.

(3) If the (q, z) entry in the SSIM is X, then the (q, z) entry in the reachability matrix becomes I and the (z, q) entry also becomes 1.

(4) If the (q, z) entry in the SSIM is 0, then the (q, z) entry in the reachability matrix becomes 0 and the (z, q) entry also becomes 0. After the transformation of SSIM, Initial reachability matrix is formed, as is shown in Table 5.3.

Table 5.3 Initial reachability matrix

Criteria	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	0	1	1	0	1	0	1	1	0	0	0	0	0	0	0
3	0	0	1	0	0	1	0	0	1	1	0	1	0	0	0
4	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
5	0	1	0	1	1	0	1	0	1	0	0	0	0	0	0
6	0	1	0	0	1	1	1	0	1	0	0	1	0	0	1
7	0	0	1	1	0	0	1	0	1	0	0	0	0	0	0
8	0	1	1	1	1	1	1	1	1	0	1	0	1	1	1
9	0	1	1	1	1	0	1	1	1	1	0	0	0	0	0
10	0	1	1	1	1	1	1	1	1	1	1	1	0	0	1
11	0	1	1	1	1	1	1	0	1	0	1	0	0	0	1
12	0	0	1	0	0	1	0	1	1	0	1	1	0	1	1
13	0	1	1	1	0	0	1	1	1	0	1	0	1	0	0
14	0	1	1	1	1	1	1	0	1	1	1	0	0	1	1
15	0	0	1	1	1	1	1	0	1	1	0	0	0	0	1

5.1.3 Final reachability matrix

The final reachability matrix for the criteria was obtained by incorporating the transitivity. The transitivity of the contextual relation is a basic assumption made in the ISM. It states that if the criterion number 1 is related to number 2, and criterion number 2 is related to number 3, then criterion number 1 is necessarily related to number 3. Table 5.4 denotes the final reachability matrix.

Table 5.4 Final reachability matrix with driving power and dependence

Criteria	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Driving Power	Rank
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15	1
2	0	1	1	1*	1	1*	1	1	1*	1*	1*	1*	1*	1*	1*	14	2
3	0	1*	1	1*	1*	1	1*	1*	1	1	1*	1	0	1*	1*	13	3
4	1	1*	1*	1	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	1*	15	1
5	1*	1	1*	1	1	0	1	1*	1	1*	0	0	0	0	0	9	5
6	0	1	1*	1*	1	1	1	1*	1	1*	1*	1	0	1*	1	13	3
7	1*	1*	1	1	1*	1*	1	1*	1	1*	0	1*	0	0	0	11	4
8	1*	1	1	1	1	1	1	1	1	1*	1	1*	1	1	1	15	1
9	1*	1	1	1	1	1*	1	1	1	1	1*	1*	1*	1*	1*	15	1
10	1*	1	1	1	1	1	1	1	1	1	1	1	1*	1*	1	15	1
11	1*	1	1	1	1	1	1	1*	1	1*	1	1*	0	0	1	13	3
12	0	1*	1	1*	1*	1	1*	1	1	1*	1	1	1*	1	1	14	2
13	1*	1	1	1	1*	1*	1	1	1	1*	1	1*	1	1*	1*	15	1
14	1*	1	1	1	1	1	1	1*	1	1	1	1*	0	1	1	14	2
15	1*	1*	1	1	1	1	1	1*	1	1	1*	1*	0	0	1	13	3
Dependence	11	15	15	15	15	14	15	15	15	15	13	14	8	11	13		
Rank	4	1	1	1	1	2	1	1	1	1	3	2	5	4	3		

* Values after transitivity

5.1.4 Level partitions

The reachability and antecedent sets for each criterion were acquired from final reachability matrix. The reachability set for a particular criterion consists of the criteria itself and the other criteria, which it might help achieve. The antecedent set comprises of the criteria itself and the other criteria, which might help in achieve them. Subsequently, the intersection of these sets has been derived for all criteria.

The criteria for which the reachability and the intersection sets are the same is given the top-level variable in the ISM hierarchy, which would not help achieve any other criteria above their own level. After the identification of the top-level element, it is eliminated from the other remaining criteria. Table 5.5 gives all of the iterations of the level partitions.

Table 5.5 Level partition (All Iterations)

Level Partitation
Iteration-1

Criteria	Reachability Set															Antecedent Set															Intersection Set															Level
1	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	-	-	4	5	-	7	8	9	10	11	-	13	14	15	1	-	-	4	5	-	7	8	9	10	11	-	13	14	15	-
2	-	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	-	2	3	4	5	6	7	8	9	10	11	12	13	14	15	I
3	-	2	3	4	5	6	7	8	9	10	11	12	-	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	-	2	3	4	5	6	7	8	9	10	11	12	-	14	15	I
4	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	I
5	1	2	3	4	5	-	7	8	9	10	-	-	-	-	-	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	-	7	8	9	10	-	-	-	-	-	I
6	-	2	3	4	5	6	7	8	9	10	11	12	-	14	15	1	2	3	4	-	6	7	8	9	10	11	12	13	14	15	-	2	3	4	-	6	7	8	9	10	11	12	-	14	15	-
7	1	2	3	4	5	6	7	8	9	10	-	12	-	-	-	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	-	12	-	-	-	I
8	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	I
9	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	I
10	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	I
11	1	2	3	4	5	6	7	8	9	10	11	12	-	-	15	1	2	3	4	-	6	-	8	9	10	11	12	13	14	15	1	2	3	4	-	6	-	8	9	10	11	12	-	-	15	-
12	-	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	-	6	7	8	9	10	11	12	13	14	15	-	2	3	4	-	6	7	8	9	10	11	12	13	14	15	-
13	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	-	4	-	-	-	8	9	10	-	12	13	-	-	1	2	-	4	-	-	-	8	9	10	-	12	13	-	-	-
14	1	2	3	4	5	6	7	8	9	10	11	12	-	14	15	1	2	3	4	-	6	-	8	9	10	-	12	13	14	-	1	2	3	4	-	6	-	8	9	10	-	12	-	14	-	-
15	1	2	3	4	5	6	7	8	9	10	11	12	-	-	15	1	2	3	4	-	6	-	8	9	10	11	12	13	14	15	1	2	3	4	-	6	-	8	9	10	11	12	-	-	15	-

Level Partitation
Iteration-2

Criteria	Reachability Set															Antecedent Set															Intersection Set															Level
1	1	-	-	-	-	6	-	-	-	-	11	12	13	14	15	1	-	-	-	-	-	-	-	-	-	11	-	13	14	15	1	-	-	-	-	-	-	-	-	-	11	-	13	14	15	-
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6	-	-	-	-	-	6	-	-	-	-	11	12	-	14	15	1	-	-	-	-	6	-	-	-	-	11	12	13	14	15	-	-	-	-	-	6	-	-	-	-	11	12	-	14	15	II
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Criteria	Reachability Set															Antecedent Set															Intersection Set															Level
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Level Partitation
Iteration-3

Criteria	Reachability Set															Antecedent Set															Intersection Set															Level
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Level Partition
Iteration-4

Criteria	Reachability Set															Antecedent Set															Intersection Set															Level
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5.1.5 MICMAC analysis

The main aim of the MICMAC analysis is to determine the driver power and the dependence power of the criteria. The criteria are classified into four clusters. The first cluster comprises of the autonomous criteria that have both weak driver power and weak dependence. These criteria are relatively disconnected from the system, with which they have only few links that have the potential of being strong. The second cluster comprises of the dependent criteria, which have weak driver power but strong dependence. The third cluster has the linkage criteria, which have strong driving power and also strong dependence. These criteria are unstable in the fact that any action on these criteria will have an effect on others as well as a feedback on themselves. The fourth cluster includes the independent criteria, and has strong driving power but weak dependence. Here, one observes that a variable with a very strong driving power called the key variables falls into the category of independent or linkage criteria. The driving power and the dependence of each of these criteria are shown in Figure 5.2.

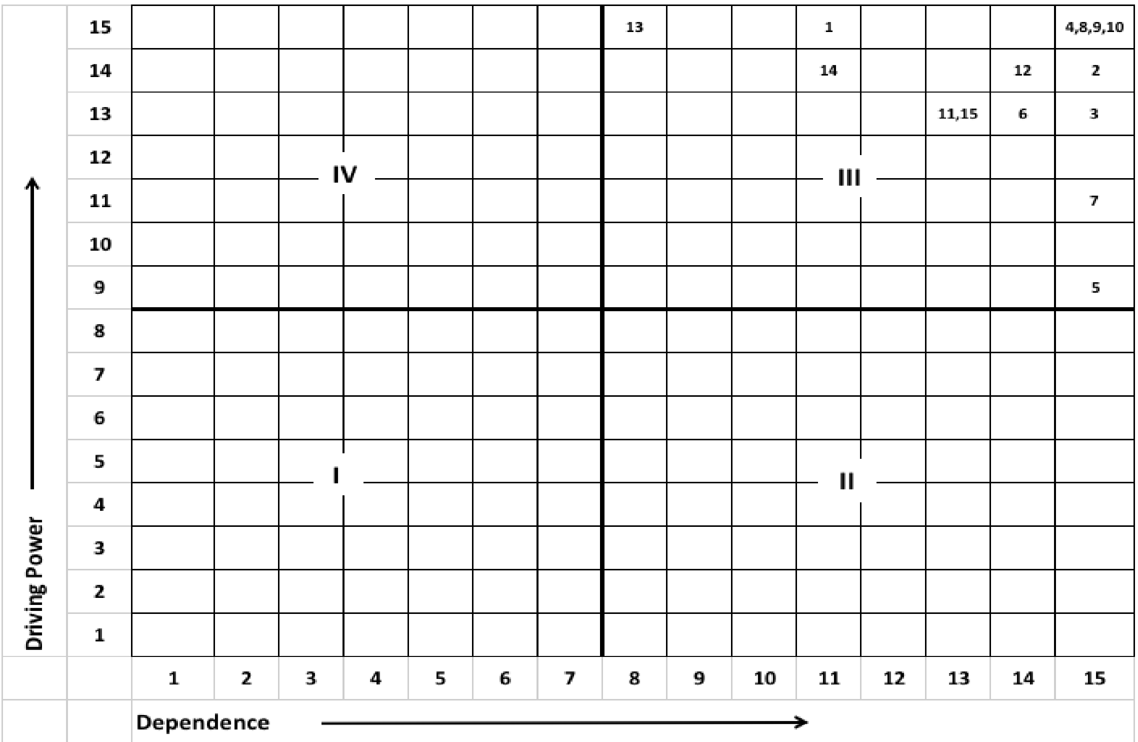


Figure 5.2 Driving and dependence power diagram for criteria.

5.1.6 Result and analysis

The criteria hampering the supplier selection pose considerable challenges for both managers and policymakers in humanitarian logistics activities. Here, we have underscored the major criteria, and put into an ISM model in order to analyze the interaction among the criteria.

These criteria need to be improved for the success in supplier selection. The driver-dependence diagram is given in Figure 5.2 gives some invaluable insights about the relative importance and the interdependencies between the criteria. This could give better insights to the decision-makers so that they can proactively tackle with these criteria. Some of the observations from the ISM model, which give important managerial implications, are discussed below.

It is observed from Figure 5.2 that there are not any autonomous criteria in driver-dependence diagram. For this reason, all of these criteria influence the supplier selection process in humanitarian logistics activities. One can also observe from the ISM model that the Geographic position has strong driving power and less dependence power in comparison with the other criteria. Thus, it can be inferred that Geographic position is the main cause of remaining criteria.

It is observed from Figure 5.3 that ***Geographic position*** (criterion 13) is a very significant factor for the supplier selection process, so it forms the base of the hierarchy. ***Resource size*** (criterion 2), ***Quality improvement*** (criterion 3), ***Cost minimization*** (criterion 4), ***Flexibility*** (criterion 5), ***Lead time reduction*** (criterion 7), ***Long term strategic goals*** (criterion 8), ***Capability*** (criterion 9), and ***Relational orientation*** (criterion 10) depict the successful supplier selection process. These criteria have appeared at the top of the hierarchy. The ***Geographic position*** criterion leads to the following criteria: ***collaboration attribute***, ***Using information and technology tools***. These two criteria lead to ***Trust development, Resource and information sharing, Evaluation and certification system, Data accuracy*** criteria.

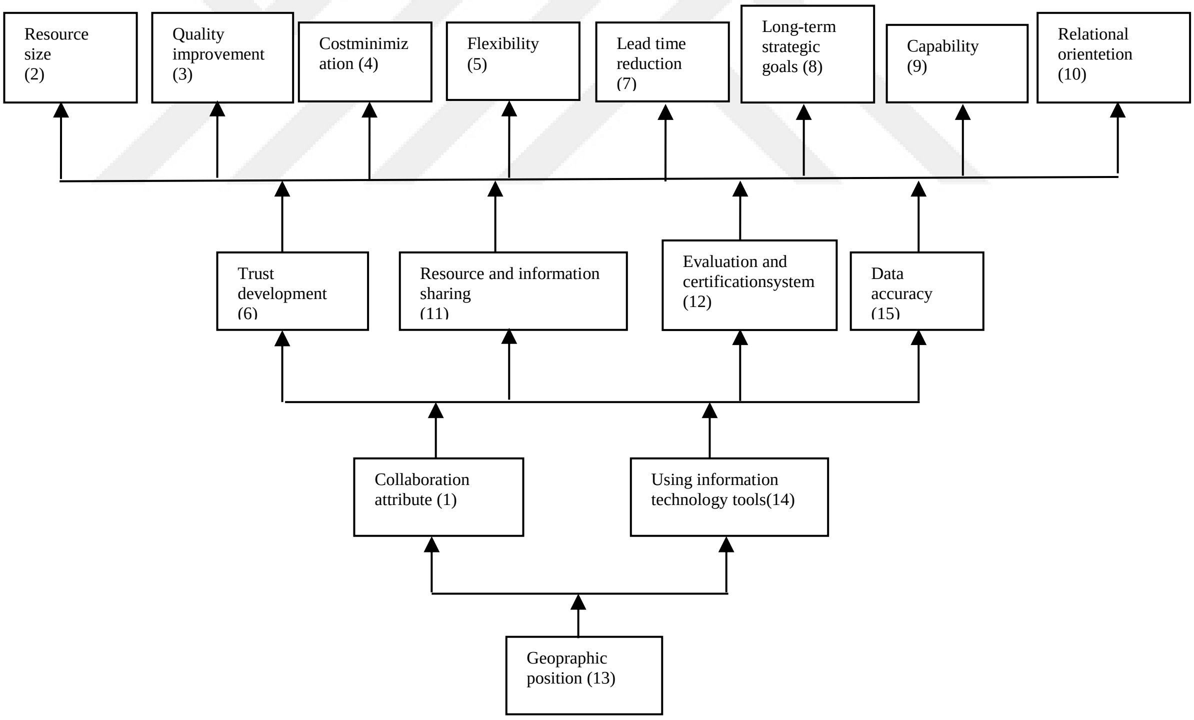


Figure 5.3 ISM-based supplier selection criteria model

5.2 Analytic Network Process (ANP)

Among fifteen criteria selected by both the literature review and face-to-face surveys with experts, seven (i.e. the first three levels) are found to be more significant, and affect the others after using ISM. These criteria include geographic position, collaboration attribute, using information technology tools, data accuracy, evaluation and certification system, resource and information sharing, and trust development. Then, the Analytic Network Process is conducted with the same group in which the ISM conducted on**.** Several steps implement the ANP-based model. First, pairwise comparison matrices are formed in order to determine inner dependencies in the criteria cluster as based on Saaty's scale. During the assessment process, problems may occur in terms of consistency. Therefore, inconsistency ratios for every matrix must be controlled so as to determine the misevaluation of comparisons. Inconsistency ratios are generally acceptable up to the limit of 0.10, whereas several experts offer a limit of up to 0.20 (Cox et al., 2000). If all matrices are consistent, the process can proceed to the next step. If not, inconsistent matrices should be reassessed in order to ensure consistency for all matrices. Considering the Saaty's scale, in this case there is no problem in terms of the consistency value, which is under the limit. Second, the super matrix is formed consisting of an unweighted super matrix, a weighted super matrix, and a limit super matrix, which are respectively formed one after the other through proper computation. Finally, the limit super matrix ensures priorities of criteria. In fact, values of the limit super matrix represent the overall priorities, which embrace the cumulative influence of each criteria of the network on every other criteria, in which it interacts. In particular, the computations related to ANP application have been conducted using Super Decisions. The weighted super matrix, limit super matrix and priorities of criteria are given Table 5.6, Table 5.7 and Table 5.8 respectively.

Table 5.6 Weighted super matrix

CRITERIA	1.Collaboration attribute	6.Trust Development	11. Resource and information sharing	12. Evaluation and certification system	13. Geoprahic position	14.Using information technology tools	15. Data accuracy
1.Collaboration attribute	0	0,14577	0,105103	0,129695	0,8	0,289751	0,161977
6.Trust Development	0	0	0,08858	0,063239	0	0,152004	0,119545
11. Resource and information sharing	0,338015	0,335612	0	0,134024	0	0	0,167986
12. Evaluation and certification system	0	0,041726	0,063316	0	0,2	0,117061	0,041979
13. Geoprahic position	0,444329	0,126675	0,383725	0,145097	0	0,441184	0,104296
14.Using information technology tools	0,162196	0,202875	0,206062	0,29002	0	0	0,404217
15. Data accuracy	0,05546	0,147341	0,153214	0,237926	0	0	0

Table 5.7 Limit super matrix

CRITERIA	1.Collaboration attribute	6.Trust Development	11. Resource and information sharing	12. Evaluation and certification system	13. Geoprahic position	14.Using information technology tools	15. Data accuracy
1.Collaboration attribute	0,287652	0,287652	0,287652	0,287652	0,287652	0,287652	0,287652
6.Trust Development	0,044303	0,044303	0,044303	0,044303	0,044303	0,044303	0,044303
11. Resource and information sharing	0,133302	0,133302	0,133302	0,133302	0,133302	0,133302	0,133302
12. Evaluation and certification system	0,080438	0,080438	0,080438	0,080438	0,080438	0,080438	0,080438
13. Geoprahic position	0,260742	0,260742	0,260742	0,260742	0,260742	0,260742	0,260742
14.Using information technology tools	0,13152	0,13152	0,13152	0,13152	0,13152	0,13152	0,13152
15. Data accuracy	0,062043	0,062043	0,062043	0,062043	0,062043	0,062043	0,062043

Table 5.8 Priorities of criteria

CRITERIA	1.Collaboration attribute	6.Trust Development	11. Resource and information sharing	12. Evaluation and certification system	13. Geographic position	14.Using information technology tools	15. Data accuracy
Limiting value	0.29	0.05	0.13	0.08	0.26	0.13	0.06
Normalized value	0.29	0.05	0.13	0.08	0.26	0.13	0.06

As it is seen in Table 5.8, the collaboration attribute is the most important criteria among the seven criteria according to weighted values as a result of the ANP. The other criteria are sorted in terms of Geographic position, Resource and information sharing, Using information technology tools, Data accuracy, Trust development, respectively.

5.2.1 Evaluation of suppliers

In this part, we tried to determine the potential relief suppliers, located on the Anatolian side of Istanbul, and that might be involved in humanitarian logistics activities. This investigation includes charitable organizations and private companies. Twenty suppliers were evaluated in terms of determined and weighted criteria. These potential relief suppliers are given in Table 5.9, alongside the location of these suppliers in Figure 5.4.

Table 5.9 Potential suppliers list

Number	NGOs	Region
1	World Atlantis Shopping Mall	Pendik
2	Asyapark Outlet Shopping Mall	Ümraniye
3	Beşyıldız Shopping Mall	Ümraniye
4	Kardiyum Shopping Mall	Çekmeköy
5	Neomarin Shopping Mall	Pendik
6	Plato Shopping Mall	Sultanbeyli
7	Rings Shopping Mall	Sancaktepe
8	Capitol Shopping Mall	Üsküdar
9	Buyaka Shopping Mall	Ümraniye
10	Tepe Nautilus Shopping Mall	Kadıköy
11	Cevahir Hotel	Maltepe
12	Brandium Shopping Mall	Ataşehir
13	Palladium Shopping Mall	Ataşehir
14	Akasya Shopping Mall	Acıbadem
15	Optimum Outlet Shopping Mall	Yenisahra
16	Via/Port Outlet Shopping Mall	Pendik
17	Real Shopping Mall	Kartal
18	Carrefoursa Shopping Mall	Kozyatağı
19	Maltepe Park Shopping Mall	Maltepe
20	Metro Shopping Mall	Yenisahra

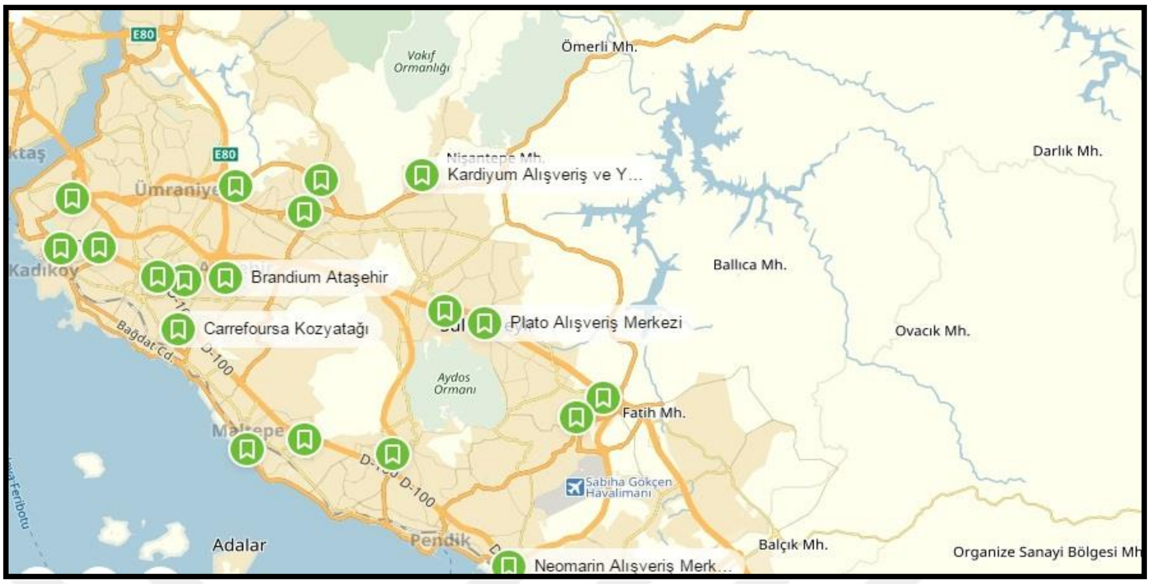


Figure 5.4 Location of potential relief suppliers

This study surveys experienced official personnel working in Emergency Logistics (EL), who are in charge of emergency response training during normal times and for collecting the relief items provided through the government and manager of Alternative Logistics, who is conducting emergency logistics activities on behalf of AFAD. These members measure all of the corresponding criteria of the NGO. The survey responses through these personnel are thus the data used for the rating technique. Here, it is established rating categories for each covering criterion and prioritize the categories by pairwise comparing them for preference. Alternatives are evaluated by selecting the appropriate rating category on each criterion, as given in Table 5.10. The rating categories for the criterion are very good, good, average, bad, and very bad. The criteria are compared for preference using a pair-wise comparison matrix. In order to obtain the idealized priorities, we normalize by dividing the largest of the priorities. The idealized priorities are used as rating values. Table 5.11 gives the verbal rating of the twenty alternatives for each of the criterion being covered, and Table 5.12 gives their corresponding numerical ratings from Table 5.11, with their totals and group rate.

Table 5.10 The prioritized ratings categories for all of the criteria

CRITERIA	**1.Collaboration attribute**	**6.Trust Development**	**11. Resource and information sharing**	**12. Evaluation and certification system**	**13. Geoprahic position**	**14.Using information technology tools**	**15. Data accuracy**
very good	1	1	1	1	1	1	1
Good	0,63	0,65	0,53	0,71	0,54	0,68	0,59
avarage	0,38	0,41	0,37	0,31	0,34	0,42	0,27
bad	0,12	0,14	0,11	0,18	0,17	0,13	0,1
very bad	0,02	0,04	0,02	0,09	0,04	0,03	0,02

Table 5.11 Ratings for the alternatives on each criterion

Criteria	**Geoprahic Position**	**Collaboration attribute**	**Using information technology tools**	**Trust development**	**Resources and information sharing**	**Evaluation and certification system**	**Data accuracy**
Suppliers	**0,26**	**0,29**	**0,13**	**0,05**	**0,13**	**0,08**	**0,06**
1.World Atlantis Shopping Mall	*Average*	*Good*	*Good*	*Bad*	*Average*	*Bad*	*Bad*
2.Asyapark Outlet Shopping Mall	*Average*	*Average*	*Good*	*Average*	*Average*	*Bad*	*Average*
3.Beşyıldız Shopping Mall	*Average*	*Good*	*Good*	*Verybad*	*Average*	*Average*	*Average*
4.Kardiyum Shopping Mall	*Average*	*Good*	*Average*	*Bad*	*Average*	*Average*	*Bad*
5.Neomarin Shopping Mall	*Good*	*Very good*	*Good*	*Good*	*Very good*	*Very good*	*Very good*
6.Plato Shopping Mall	*Average*	*Average*	*Average*	*Bad*	*Bad*	*Average*	*Average*
7.Rings Shopping Mall	*Bad*	*Average*	*Average*	*Bad*	*Average*	*Bad*	*Bad*
8.Capitol Shopping Mall	*Good*	*Good*	*Very good*	*Average*	*Good*	*Very good*	*Very good*
9.Buyaka Shopping Mall	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*
10.Tepe Nautilus Shopping Mall	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*
11.Cevahir Hotel	*Very good*	*Average*	*Bad*	*Verybed*	*Good*	*Good*	*Bad*
12.Brandium Shopping Mall	*Very good*	*Very good*	*Very good*	*Average*	*Very good*	*Very good*	*Very good*
13.Palladium Shopping Mall	*Very good*	*Very good*	*Very good*	*Good*	*Very good*	*Very good*	*Very good*
14.Akasya Shopping Mall	*Good*	Bad	*Very good*	*Average*	*Average*	*Very good*	*Very good*
15.Optimum Outlet Shopping Mall	*Bad*	*Average*	*Good*	*Average*	*Good*	*Good*	*Average*
16.Via/Port Outlet Shopping Mall	*Very good*	*Average*	*Good*	*Very good*	*Good*	*Very good*	*Good*
17.Real Shopping Mall	*Good*	*Very good*	*Average*	*Good*	*Good*	*Good*	*Average*
18.Carrefoursa Shopping Mall	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*
19.Maltepe Park Shopping Mall	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*
20.Metro Shopping Mall	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*	*Very good*

Table 5.12 Numerical values for ratings given in Table 5.11

Criteria	Geopraphic Position	Collaboration attribute	Using information technology tools	Trust development	Resources and information sharing	Evaluation and certification system	Data accuracy	TOTAL WEIGHT	RANK
Suppliers	**0,26**	**0,29**	**0,13**	**0,05**	**0,13**	**0,08**	**0,06**		
1.World Atlantis Shopping Mall	0,34	0,63	0,68	0,11	0,37	0,18	0,1	0,4335	**15**
2.Asyapark Outlet Shopping Mall	0,34	0,38	0,68	0,41	0,37	0,18	0,27	0,3862	**18**
3.Beşyıldız Shopping Mall	0,34	0,63	0,68	0,04	0,37	0,31	0,27	0,4506	**14**
4.Kardiyum Shopping Mall	0,34	0,63	0,42	0,11	0,37	0,31	0,1	0,4101	**16**
5.Neomarin Shopping Mall	0,54	1	0,68	0,65	1	1	1	0,8213	**8**
6.Plato Shopping Mall	0,34	0,38	0,42	0,11	0,11	0,31	0,27	0,314	**19**
7.Rings Shopping Mall	0,17	0,38	0,42	0,11	0,37	0,18	0,1	0,283	**20**
8.Capitol Shopping Mall	0,54	0,63	1	0,41	0,53	1	1	0,6825	**10**
9.Buyaka Shopping Mall	1	1	1	1	1	1	1	1	**4**
10.Tepe Nautilus Shopping Mall	1	1	1	1	1	1	1	1	**5**
11.Cevahir Hotel	1	0,38	0,13	0,04	0,53	0,71	0,1	0,5208	**12**
12.Brandium Shopping Mall	1	1	1	0,41	1	1	1	0,9705	**7**
13.Palladium Shopping Mall	1	1	1	0,65	1	1	1	0,9825	**6**
14.Akasya Shopping Mall	0,54	0,12	1	0,41	0,37	1	1	0,5138	**13**
15.Optimum Outlet Shopping Mall	0,17	0,38	0,68	0,41	0,53	0,71	0,27	0,4052	**17**
16.Via/Port Outlet Shopping Mall	1	0,38	0,68	1	0,53	1	0,59	0,6929	**9**
17.Real Shopping Mall	0,54	1	0,42	0,65	0,53	0,71	0,27	0,6594	**11**
18.Carrefoursa Shopping Mall	1	1	1	1	1	1	1	1	**1**
19.Maltepe Park Shopping Mall	1	1	1	1	1	1	1	1	**2**
20.Metro Shopping Mall	1	1	1	1	1	1	1	1	**3**

As a result of final evaluation of potential relief suppliers in terms of the rating categories, the final ranking is formed as given in Table 5.13.

Table 5.13 Final ranking of suppliers

Number	Suppliers	Rank	Weight
1	Carrefoursa Shopping Mall	1	1
2	Maltepe Park Shopping Mall	2	1
3	Metro Shopping Mall	3	1
4	Buyaka Shopping Mall	4	1
5	Tepe Nautilus Shopping Mall	5	1
6	Palladium Shopping Mall	6	0,9825
7	Brandium Shopping Mall	7	0,9705
8	Neomarin Shopping Mall	8	0,8213
9	Via/Port Outlet Shopping Mall	9	0,6929
10	Capitol Shopping Mall	10	0,6825
11	Real Shopping Mall	11	0,6594
12	Cevahir Hotel	12	0,5208
13	Akasya Shopping Mall	13	0,5138
14	Beşyıldız Shopping Mall	14	0,4506
15	World Atlantis Shopping Mall	15	0,4335
16	Kardiyum Shopping Mall	16	0,4101
17	Optimum Outlet Shopping Mall	17	0,4052
18	Asyapark Outlet Shopping Mall	18	0,3862
19	Plato Shopping Mall	19	0,314
20	Rings Shopping Mall	20	0,283

The evaluation made so far are based on subjective criteria as a result of ISM, ANP, and Rating. In the next section, mathematical model is constructed with four objective functions and it is solved using NSGA-II. Then, performances of subjectives' solutions and performances of mathematical models' solutions are compared.

5.3 Non Sorting Genetic Algorithm

5.3.1 Parameter setting

The parameter setting presented in this study is developed from the parameter setting study outlined by Sheu & Pan (2014). They put forth only one objective function, and used a mix integer programming in order to solve the mathematical model. Contrary to the study, we propose a mathematical model with four objective functions, and then solved it using a non-sorting genetic algorithm (NSGA-II) with Visual Studio 13 software.

After the applied ISM and ANP, we can rank all relief suppliers with regard to scores given by an expert opinion. First, the mathematical model is solved based on relief supplier ranking as a result of the rating. It then is solved using NSGA-II. Finally, the performance of solutions is compared. Table 5.14 summarizes the parameters concerning the study, which are described as follows

(1) The quantities of relief supplies provided by host government ($\boldsymbol{\Omega_{i,r,k}(t_p)}$): In accordance with assumptions of this study, the host government is a partly functional aftermath of the large scale of the disaster. In this study, $\boldsymbol{\Omega_{i,r,k}(t_p)}$ is assumed to be between %50 and %95 of $\boldsymbol{D_{i,r,k}(tp)}$.

(2) Probability density function (*pdf*) for the average relief feed rate of group *h/m* (($\boldsymbol{c^h(t_p), c^m(t_p)}$): The relief feed rate of relief suppliers might differ, based on disaster conditions and supplier attributes, such as collaborative attributes. In this study, we referred to certain reliability studies by Warren (1996) and Nowak and Collins (2012), and assume that, in this case, the relief rates follow a normal distribution. The rate of a relief supplier in group *h* at time *t* in period *p* follows a normal distribution where the mean = 1 and the standard deviation = 0.1 ($N(1, 0.1^2)$), while the rate of a relief supplier in group *m* follows $N(1,0.3^2)$. In this study, it is assumed that first eight suppliers because of the rating process with regard to scores are highly collaborative group, the others are

a normal collaborative group of suppliers.

(3) Resource capacity ($\boldsymbol{\phi_r^{p,h}}$, $\boldsymbol{\phi_r^{p,m}}$): Relief suppliers resource capacity is gathered based on interviews with managers of suppliers.

(4) Degree of urgency ($\boldsymbol{\tau_{i,r,k}}$): For commodities, the degree of urgency of those who are helpless is assumed to be 0.7. and that of middle-aged people is assumed to be 0.5.

(5) Degree of inventory risk ($\boldsymbol{v_{i,r}}$): $v_{i,1}$ and $v_{i,2}$ are assumed to be 0.5 and 0.3, respectively.

(6) Delay time lag (***η(tp))*** and stock time lag **($\oslash$*(tp)):*** According to definition of delay time lag and stock time lag, ***η(tp)*** and ***$\oslash$(tp)*** are set up.

(7) The weight of relief undersupply ($\omega_{i,r,k}$(tp)) and of relief oversupply ($\delta_{i,r,k}$(tp)): Based on the weights of relief undersupply and oversupply, mentioned in former section, and the concept of 'compound interest', which varies with the time lag, the corresponding functions are assumed to be $(1 + \tau_{i,r,k})^{\eta(tp)}$ and $(1 + v_{i,r})^{\oslash(tp)}$, respectively.

(8) The distances between the joint facility location and other relief suppliers ($\boldsymbol{d_{l,j}}$) are calculated in accordance with Google Maps, which is given in Appendix.

Table 5.14 Summary of parameter setting

Parameter	Relief resource	Setting
$\boldsymbol{\Omega_{i,r,k}(t_p)}$	*Commodity (kg)*	*X x* $\boldsymbol{D_{i,r,k}(tp)}$ $\forall(i \in I, k \in K, r \in R, t_p \in T)$
$\boldsymbol{c^h(t_p)}$ and $\boldsymbol{c^m(t_p)}$	*Commodity (kg)*	$C^h(t_p) \sim N(1, 0.1^2/N_p^h)$ $\forall(t_p \in T)$ $C^m(t_p) \sim N(1, 0.3^2/N_p^m)$ $\forall(t_p \in T)$
$\boldsymbol{\phi_r^{p,h}}$ and $\boldsymbol{\phi_r^{p,m}}$	*Commodity (kg)*	*Given in Appendix*
$\boldsymbol{\tau_{i,r,k}}$	*Commodity (kg)*	$\tau_{i,r,1} = 0.5; \tau_{i,r,2} = 0.7$ $\forall(i \in I, k \in K)$
$\boldsymbol{v_{i,r}}$	*Commodity (kg)*	$v_{i,1} = 0.5; v_{i,3} = 0.3$ $\forall(i \in I)$

Table 5.14 Summary of parameter setting (continued)

Parameter	Relief resource	Setting
$\eta(tp)$	*Commodity (kg)*	*If* $I^{-}(t_p - 1) > 0$, *then* $\eta(t_p) = \eta(t_p - 1) + 1$; *Otherwise* $\eta(tp)=0$
$\varphi(tp)$	*Commodity (kg)*	*If* $I^{+}(t_p - 1) > 0$, *then* $\varphi(t_p) = \varphi(t_p - 1) + 1$; *Otherwise* $\varphi(t_p) =0$
$\omega_{i,r,k}(tp)$	*Commodity (kg)*	$(1 + \tau_{i,r,k})^{\eta(t_p)}\ \forall(i \in I, k \in K, r \in R, t_p \in T)$
$\delta_{i,r,k}(tp)$	*Commodity (kg)*	$(1 + v_{i,r})^{\varphi(t_p)}\ \forall(i \in I, k \in K, r \in R, t_p \in T)$

5.3.2 Model testing

In this study, NSGA-II was utilized to the solve multi objective model. In order to determine the most appropriate values of the parameters, experimental design was first generated, and then operated. The algorithm was run using several different parameter configurations including iteration (number of generations), population (number of individuals in a generation), crossover rate, and mutation probability. These parameters are given in Table 5.15.

Table 5.15 Parameters used for running NSGA-II

Parameter	**Values**
Mutation probability	0,1 – 0,01
Crossover rate	0,75 – 0,90
Population	30 – 50 – 100 – 150
Iteration	500 – 1.000 – 5.000 – 10.000

In order to determine which option is most appropriate for the iteration number, iteration number value is being changed among the options while other parameters are constant. After obtaining all solutions, a single set of solution is created and non-dominated solutions are determined. Total number of non-dominated solutions formed by a combination is considered to what measures its performance. Table 5.16 outlines the most favorable solution, its' number of non-dominated solution, and run time for the iteration.

Table 5.16 Determination of iteration value

Iteration number	**Number of solutions in the first frontier**	**Run time (second)**
500	8	63
1000	8	113
5000	**9**	**383**
10000	9	510

Note: *Population number= 30, Crossover rate=0.75, Mutation probability=0.1*

Among these combinations, the best result of iteration number is 5,000. Same process is also carried out for the other parameters. Table 5.17, Table 5.18, Table 5.19 denote the best of configurations for number of population, crossover rate and mutation probability, respectively.

Table 5.17 Determination of number of population

Population number	**Number of solutions in the first frontier**	**Run time (second)**
30	9	383
50	10	407
100	**11**	**487**
150	10	523

Note: *Iteration number= 5,000, Crossover rate=0.75, Mutation probability=0.1*

Table 5.18 Determination of crossover rate

Crossover rate	Number of Solution in the first frontier	Run time (second)
0.75	**11**	**487**
0.90	10	447

Note: *Iteration number= 5,000, Population number=100, Mutation probability=0.1*

Table 5.19 Determination of mutation probability

Mutation prob.	Number of Solution in the first frontier	Run time (second)
0.1	**10**	**487**
0.01	6	481

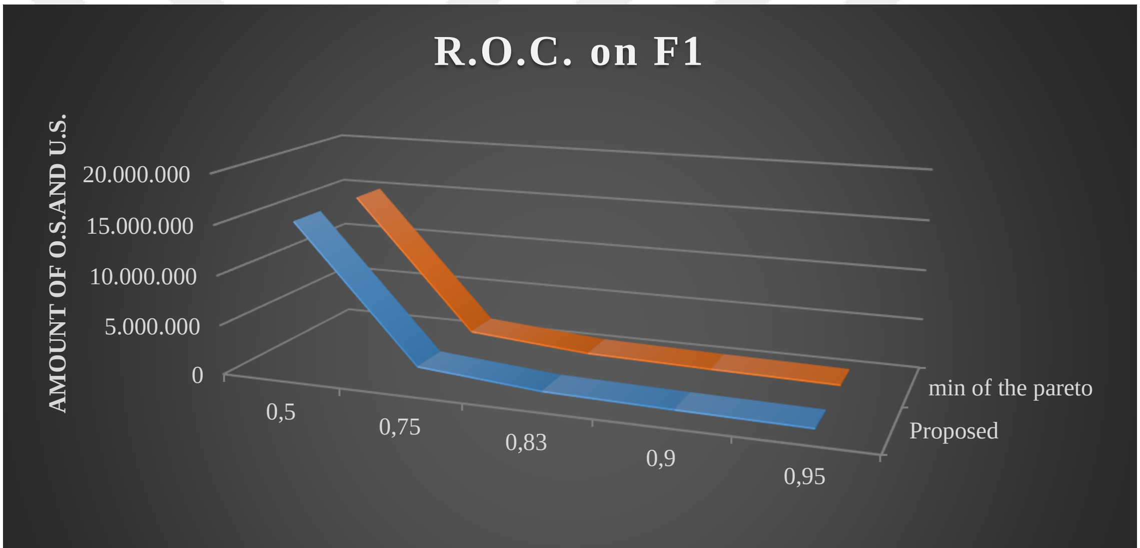
Note: *Iteration number= 5,000, Population number=100, Crossover rate=0.75*

Among these combinations, the results of the first one contains 5,000 generations; a population size of 100 individuals; a crossover rate of 0.75; and a mutation probability of 0.10 are all determined as a result of experimental analysis.

5.3.3 Scenario analysis

In this section, we have generated many scenarios and compared their outcomes. This is mainly focused on a government assistance rate of the supply side. (1) First, resource capacity of host government was adjusted in order to observe impact over objective functions one by one. (2) Second, the number of relief suppliers was changed in order observe impact over the objective functions' values. For example, if host government collaborates with only highly collaborative groups, one then observes whether the objective values are high compared to normal collaborative group. (3) Finally, we adjusted the degree of urgency and the degree of inventory risk, respectively, in order to evaluate the objective functions' value for different types of disasters. In order to observe the results of the various scenarios, an indicator and the rate of change (ROC) were applied to measure the percentage change in the objective functions' value resulting from adjustments to the original settings in each scenario.

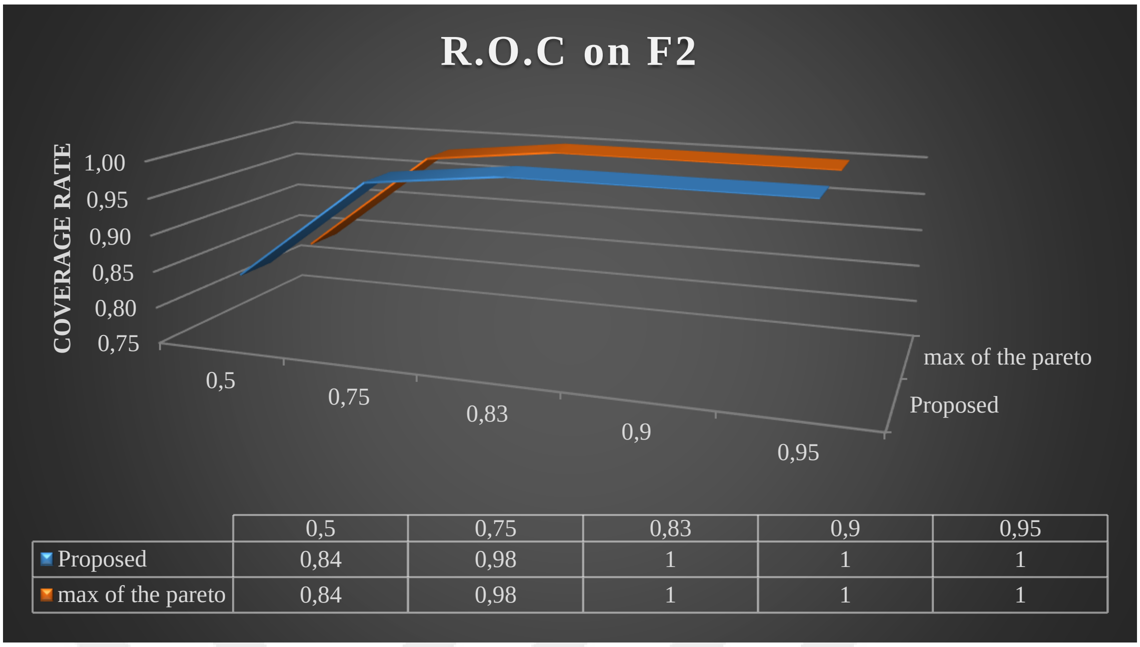
(1) For the first objective function (F1), as the rate of quantity of resources supplied by host government increases, the objective value for the first objective function deceases at the same time. In this scenario, after running algorithm with Visual Studio 13, numerous non-dominated solutions were obtained according to determined configuration. The proposed model, which is configured as a result of the ISM, ANP, and Rating processes, alongside the minimum value of the set of Pareto optimal solutions are all given in Figure 5.5.



	0,5	0,75	0,83	0,9	0,95
Proposed	15.050.580	1.688.459	670.387	389.110	193.127
min of the pareto	15.050.580	1.688.459	670.387	389.110	193.127

Figure 5.5 Rate of change on first objective function

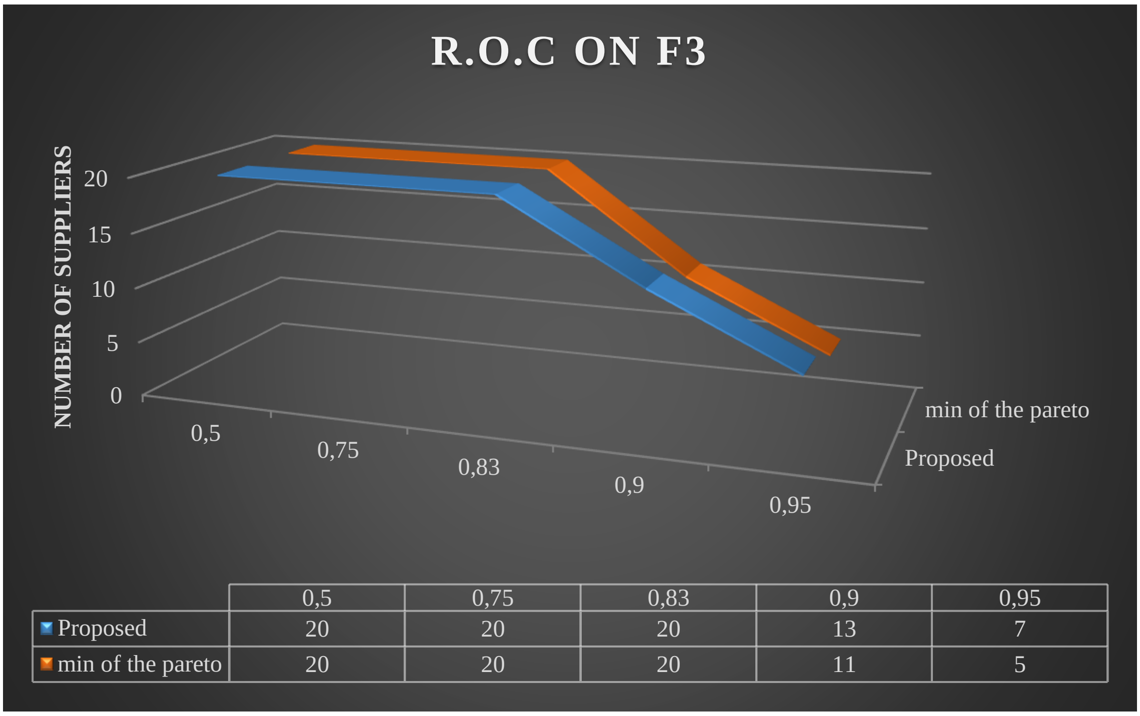
When we analyzed second objective function (F2), in order to provide all resources requested by affected area, the host government had to supply at least 83% of the total demand under the determined circumstances, otherwise demand of affected areas would not be covered. Thus, it may bring about increasing chaos, even may even increase the death toll. Figure 5.6 illustrates the differences between the proposed model and maximum value of set of Pareto optimal solutions.



	0,5	0,75	0,83	0,9	0,95
Proposed	0,84	0,98	1	1	1
max of the pareto	0,84	0,98	1	1	1

Figure 5.6 Rate of change on second objective function

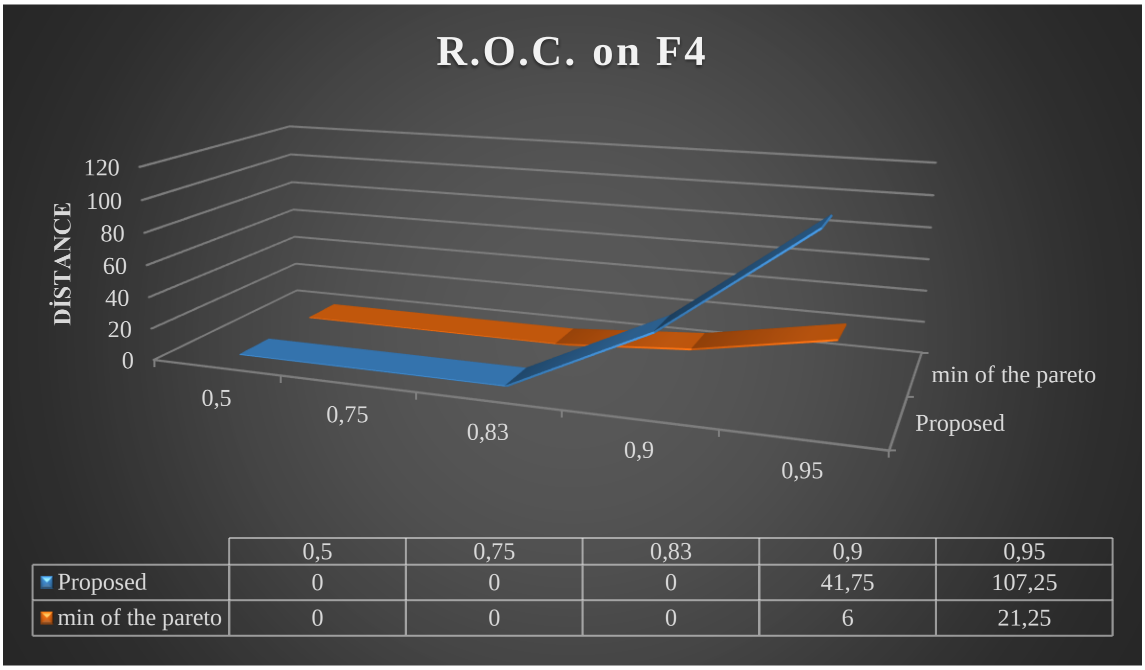
As for third objective function (F3), it is understood that the number of relief supplier and the host government supply rate correlated with one another. Figure 5.7 denotes that if host government supply rate is under or equal to 83%, all of the relief suppliers would be selected as a joint facility location. As the rate increases, the number of suppliers selected as a joint facility location simultaneously decreases.



	0,5	0,75	0,83	0,9	0,95
Proposed	20	20	20	13	7
min of the pareto	20	20	20	11	5

Figure 5.7 Rate of change on third objective function

Finally, when we look into breakdown of distance issue, which is between relief suppliers that is selected as a joint facility location and the other suppliers (F4), one observes that if host government supply is under or equal to 83% of total demand, then all of the candidate suppliers must be selected as a joint facility location, and thus the total distance is equal to zero. If host government provides above 83% of the total demand, the proposed model and minimum value of Pareto will differ as the rate of government assistance changes. Figure 5.8 illustrates the differences between the proposed model and the minimum value of set of Pareto optimal solutions.



	0,5	0,75	0,83	0,9	0,95
Proposed	0	0	0	41,75	107,25
min of the pareto	0	0	0	6	21,25

Figure 5.8 Rate of change on fourth objective function

(2) Within this phase, we designed ten scenarios, and compared their outcomes with the proposed model mentioned in previous sections. The configurations related to government assistance rate alongside the number of relief suppliers are summarized in Table 5.20.

Table 5.20 Summary of configurations for scenarios.

Number of configuration	***Government Assistance Rate*** $\boldsymbol{\Omega_{i,r,k}(t_p)}$	***Number of Relief Suppliers (F)***	***Number of configuration***	***Government Assistance Rate*** $\boldsymbol{\Omega_{i,r,k}(t_p)}$	***Number of Relief Suppliers (F)***
1	% 90	20	6	% 95	15
2	% 95	20	7	% 50	8
3	% 50	15	8	% 75	8
4	% 75	15	9	% 90	8
5	% 90	15	10	% 95	8

According to first configuration, the host government's assistance rate is equal to 90% of all of the relief suppliers, and thus are selected as a joint facility location. When NSGA-II was run in accordance with the first configuration, 28 non-dominated solutions are obtained. The values of the four objective functions and of the order of relief suppliers as a result of NSGA-II were given under determined circumstances in Table 5.21.

Table 5.21 Non-dominated solutions according to the first configuration.

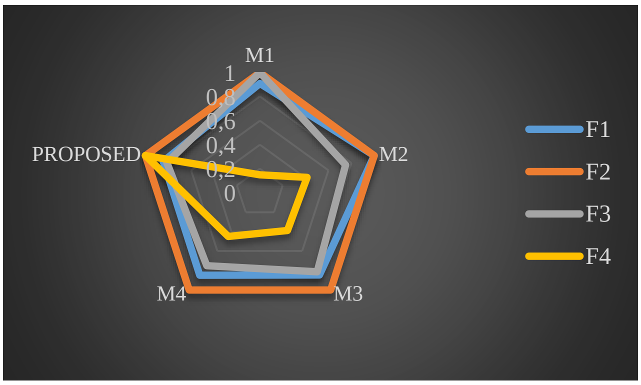
Values of Objective Functions				**Order of Relief Suppliers as a result of NSGA II**
1	**2**	**3**	**4**	
393.281	1	14	10,25	0-1-2-3-4-12-19-7-8-13-9-17-15-11-5-14-18-10-6-16
389.110	1	13	20,75	0-1-2-3-4-5-6-7-8-9-15-10-19-14-11-12-17-13-18-16
389.110	1	12	36,75	0-1-2-3-4-5-6-7-8-19-12-11-9-15-18-10-14-13-17-16
389.110	1	15	11,75	0-1-2-3-4-5-6-7-8-13-12-9-15-18-11-10-14-19-17-16
390.937	1	13	13,25	0-7-3-4-2-9-1-15-17-12-19-8-11-6-13-5-14-18-16-10
390.559	1	12	24,25	0-7-3-4-2-8-1-15-10-12-6-19-11-13-9-5-14-18-16-17
389.110	1	16	9,25	0-1-2-3-4-5-6-7-17-18-8-9-13-10-12-15-19-11-14-16
501.387	1	17	5,6	4-2-3-18-5-9-1-10-13-15-16-12-19-8-14-17-7-0-11-6
389.830	1	15	9,75	0-1-2-3-4-17-6-7-8-13-9-12-18-15-11-5-10-14-19-16
419.114	**1**	**16**	**6,25**	**0-7-11-4-2-9-13-1-10-12-5-14-3-18-17-15-19-8-6-16**
461.098	**1**	**12**	**17,25**	**0-10-2-3-7-12-15-19-8-11-13-9-4-1-5-17-6-14-18-16**
389.830	**1**	**13**	**16,25**	**0-1-2-3-4-14-6-7-11-13-15-9-19-8-12-5-10-17-16-18**
389.839	1	17	9	0-1-2-3-4-5-10-7-8-9-14-6-13-16-17-18-15-11-19-12
390.802	1	12	21,75	0-7-1-4-2-9-3-15-10-19-8-6-5-13-12-11-14-17-16-18

Table 5.21 Non-dominated solutions according to first configuration (continued)

Values of Objective Functions				**Order of Relief Suppliers as a result of NSGA II**
1	**2**	**3**	**4**	
390.217	1	16	6,75	0-1-2-3-4-5-8-7-13-9-17-10-12-14-18-15-19-11-6-16
390.217	1	17	6	0-1-2-3-4-5-16-7-13-9-8-17-10-12-14-18-15-19-11-6
390.937	1	15	7,75	0-7-3-4-2-9-1-15-10-12-8-13-17-14-18-5-11-19-6-16
424.789	1	17	5,75	0-7-4-1-9-6-13-17-2-12-14-15-11-5-8-18-3-10-19-16
390.937	1	14	10,75	0-7-3-4-2-9-1-15-10-12-14-17-13-19-8-18-5-6-11-16
442.599	1	13	12,75	11-1-2-3-4-12-15-7-8-13-9-19-10-6-17-0-5-14-18-16
443.826	1	14	9,75	11-1-2-3-7-12-9-19-8-13-17-15-10-4-5-0-6-14-18-16
390.937	**1**	**12**	**18,75**	**0-7-3-4-2-9-1-15-10-12-19-8-11-6-13-17-14-18-5-16**
390.937	1	11	25,75	0-1-2-3-7-4-15-19-8-11-10-5-6-13-12-9-14-18-16-17
392.189	1	11	24,75	0-1-2-3-7-10-15-19-8-11-12-4-6-9-13-5-14-18-16-17
390.217	1	13	15,75	0-1-2-3-4-5-9-7-8-17-12-15-19-11-18-10-13-16-14-6
389.110	1	14	15,25	0-1-2-3-4-5-6-7-8-13-11-15-9-19-12-10-18-17-14-16
389.830	1	14	12,75	0-1-2-3-4-14-6-7-11-13-9-12-15-19-8-10-5-18-16-17
389.830	1	12	27,75	0-1-2-3-4-14-6-7-11-12-15-19-8-13-10-5-9-17-16-18

The solutions obtained after running NSGA-II were clustered using *k*-means algorithm in order to simplify decision-making mechanism. The results of the *k*-means algorithm denote that the four solutions can represent the other solutions at an average silhouette value of 99%. These final solutions are represented in bold in Table 5.21

The results are represented through two different graphs. Figure 5.9 is a radar plot that includes the normalized values of each solution selected by the *k*-means algorithm. This kind of representation makes it easier to observe all results at once. Another representation is given in Figure 5.10, whereby all fitness values can be compared among given solutions. The results are moreover normalized in Figure 5.10. As can be seen, the solution of proposed model is not in pool of non-dominated solutions.



	F1	F2	F3	F4
M1	419.114	1	16	6,25
M2	461.098	1	12	17,25
M3	389.830	1	13	16,25
M4	390.937	1	12	18,75
PROPOSED	389.110	1	13	41,75

Note:* *'M'* *is representetive of solutions as a result of k-means algorithm

Figure 5.9 A radar diagram of the final solutions with normalized F values. (Host government assistance rate = 90% and number of relief supplier=20)

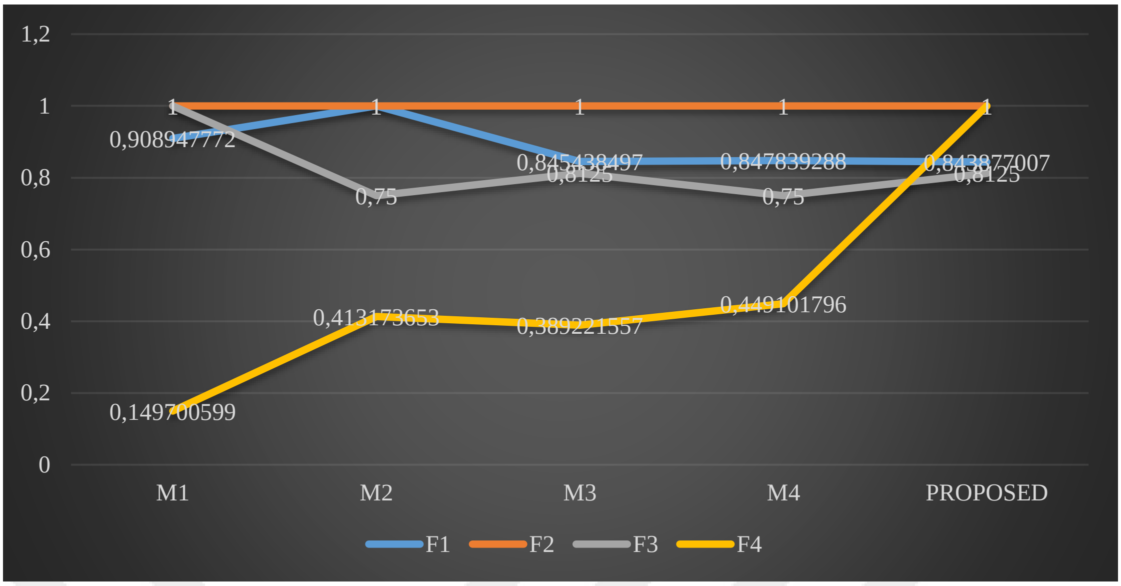


Figure 5.10 The line diagram of the final solutions with normalized F values. (Host government assistance rate = 90% and number of relief supplier=20)

As for second configuration, the host government's assistance rate is equal to 95% and all of the relief suppliers are selected as a joint facility location just as in the former configuration. After running NSGA-II in accordance with second configuration, 38 non-dominated solutions are obtained. The values of the four objective functions and order of relief suppliers as a result of NSGA-II are given under a determined circumstance, as shown in Table 5.22.

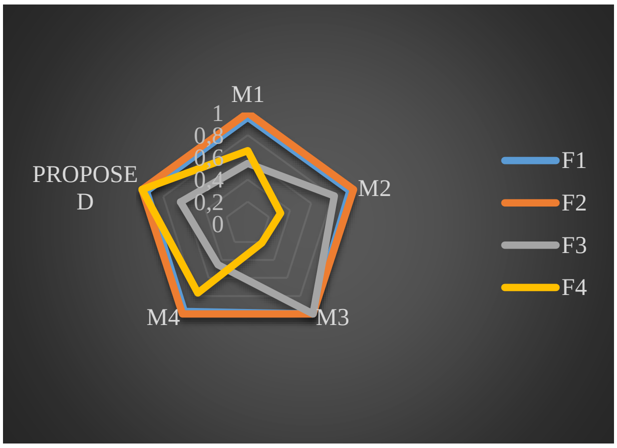
Table 5.22 Non-dominated solutions according to the second configuration.

Values of Objective Functions				**Order of relief suppliers as a result of NSGA II**
1	**2**	**3**	**4**	
193.862	1	6	62,25	1-3-7-2-19-8-10-4-17-13-12-9-0-16-6-18-5-14-15-11
194.394	1	7	46,75	1-4-7-2-19-8-10-3-17-13-12-14-9-0-16-6-18-5-15-11
195.848	1	6	56,25	1-3-8-2-19-12-10-7-17-13-4-9-0-16-6-18-5-14-15-11
194.596	1	6	57,25	1-4-3-2-19-8-10-7-17-13-14-12-9-0-16-6-18-5-15-11
193.127	1	6	99,1	0-6-7-3-4-1-13-2-8-9-17-18-5-15-12-16-10-14-11-19
193.484	**1**	**6**	**70,75**	**7-1-2-3-4-19-8-0-18-5-14-10-6-9-15-12-16-13-11-17**
193.484	1	7	54,75	7-1-2-3-4-17-8-0-18-5-9-6-15-12-16-10-14-13-11-19
193.862	1	7	47,25	7-1-2-3-14-17-19-0-8-5-4-6-15-12-16-10-9-13-11-18
194.243	1	9	34,25	7-1-2-9-4-17-18-0-8-5-14-6-15-12-16-10-3-13-11-19
193.645	1	8	44,75	7-1-2-3-14-17-18-0-8-5-6-9-15-12-16-10-4-13-11-19
193.454	1	8	49,25	7-1-2-3-4-17-18-0-8-5-6-15-12-16-10-14-9-13-11-19
193.412	1	8	60	7-1-6-3-13-5-18-0-8-9-2-15-12-16-10-14-17-4-11-19
193.148	1	7	64,1	7-1-6-3-4-5-18-0-8-9-2-17-12-16-10-14-13-19-11-15

Table 5.22 Non-dominated solutions according to second configuration (continued)

Values of Objective Functions				Order of relief suppliers as a result of NSGA II
1	**2**	**3**	**4**	
193.127	1	7	96,35	7-1-2-3-4-5-6-0-8-9-15-18-12-16-10-14-17-13-11-19
193.454	1	7	61	6-1-7-3-17-18-4-2-8-9-0-10-13-14-5-11-15-12-16-19
193.603	1	8	45,75	6-1-7-3-14-18-13-2-8-9-0-10-4-17-5-11-15-12-16-19
193.162	1	6	75,75	0-1-7-3-2-18-4-14-8-9-6-17-13-5-11-10-15-12-16-19
193.468	1	7	60	6-1-7-3-14-18-4-2-8-9-10-13-0-17-5-11-15-12-16-19
193.442	1	6	72,1	0-1-7-3-14-18-4-2-8-9-6-17-13-5-11-10-15-12-16-19
193.796	1	8	38,75	1-4-2-7-8-18-13-3-14-10-17-11-5-16-15-19-0-12-9-6
194.394	**1**	**9**	**33,25**	**1-4-2-7-17-18-11-9-14-13-5-10-16-15-19-3-0-12-8-6**
193.694	1	9	37,25	1-4-2-7-9-18-13-0-14-10-11-17-16-15-19-3-12-5-8-6
194.394	1	10	29,25	1-4-2-7-9-18-13-12-14-10-11-17-16-15-19-3-0-5-8-6
194.156	1	10	30,85	1-4-2-7-9-18-13-5-14-10-17-6-11-3-0-19-12-16-15-8
198.728	1	11	23,85	1-2-5-17-4-13-18-15-9-14-7-12-3-19-0-8-6-11-10-16
201.463	**1**	**11**	**22,75**	**1-2-8-17-14-13-18-15-9-4-7-10-6-19-11-5-16-3-0-12**
195.370	1	9	28,75	1-2-7-17-14-12-18-15-9-4-3-19-0-5-6-11-10-16-13-8
195.638	**1**	**5**	**82,25**	**2-0-3-11-19-14-7-18-5-9-17-6-4-8-10-1-12-13-15-16**
193.806	1	6	64,25	2-0-3-1-19-14-7-18-5-9-17-6-4-8-10-11-12-13-15-16
193.127	1	5	110,6	0-1-7-4-3-5-6-2-8-9-15-11-13-16-10-12-14-18-17-19
201.862	1	7	39,25	1-2-15-17-12-8-19-7-9-4-0-3-6-5-10-14-13-16-18-11
195.370	1	7	42,75	1-2-7-17-12-8-19-15-9-4-0-3-6-5-10-14-13-16-18-11
193.442	1	5	88,1	0-1-7-3-19-5-4-2-6-9-17-12-18-15-10-14-13-16-8-11
195.370	1	8	34,75	1-2-7-17-12-8-18-15-9-4-11-5-14-10-16-19-3-0-13-6
195.848	1	7	42,25	1-3-8-2-19-13-12-7-17-10-5-4-18-16-14-9-0-6-15-11
198.432	1	12	24,6	1-4-2-5-9-18-16-8-14-13-17-15-6-0-3-19-7-10-11-12
194.062	1	11	29,1	1-4-2-7-9-18-16-5-14-13-3-19-8-12-10-17-0-6-15-11
195.231	1	10	25,75	1-2-7-17-14-13-18-15-9-4-6-0-3-19-5-8-10-11-12-16

The same process is conducted just as was done in former configuration. The results of the *k*-means algorithm denote that four solutions can represent the other solutions at an average silhouette value of 98%. Table 5.22 represents these final solutions in bold. Radar and line diagrams including the normalized values of each solution selected by the *k*-means algorithm are given in Figures 5.11 and 5.12, respectively. As can be seen, the solution of proposed model is not found among non-dominated solutions.



	F1	F2	F3	F4
M1	193.484	1	6	70,75
M2	194.394	1	9	33,25
M3	201.463	1	11	22,75
M4	195.638	1	5	82,25
PROPOSED	193.127	1	7	107,25

***Note:* *'M'* is representetive of solutions as a result of k-means algorithm**

Figure 5.11 The radar diagram of the final solutions with normalized F values. (Host government assistance rate = 95% and number of relief supplier=20)

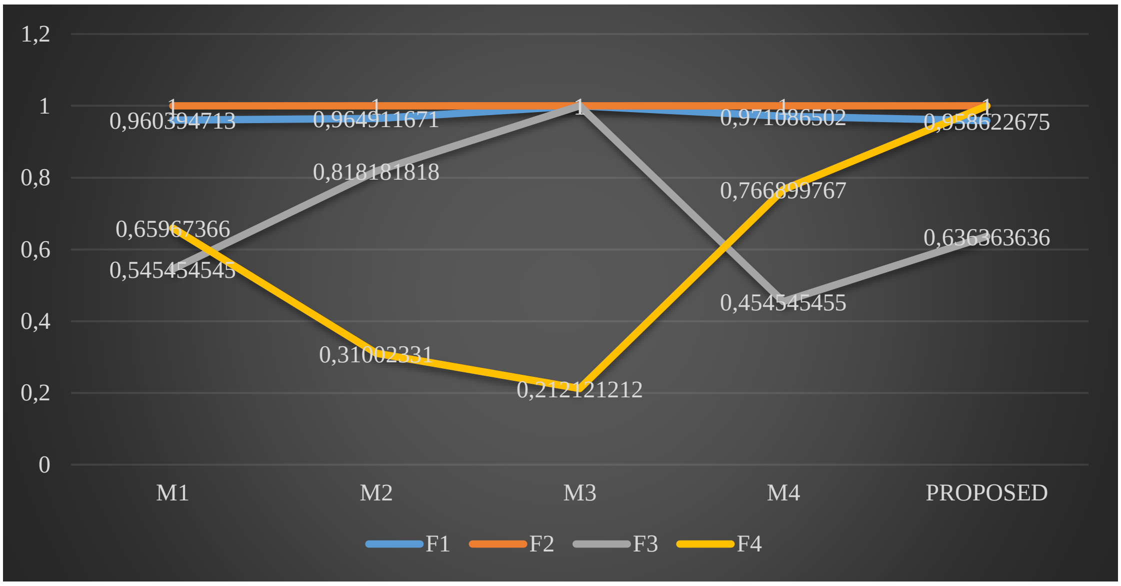


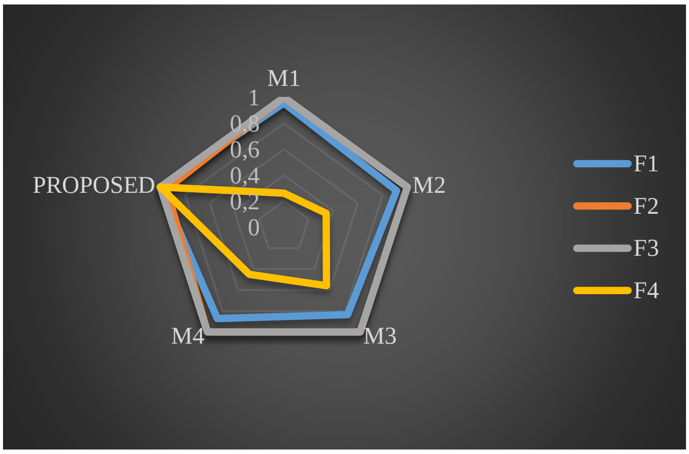
Figure 5.12 Line diagram of the final solutions with normalized F values. (Host government assistance rate = 95% and number of relief supplier=20)

For the third configuration, the host government's assistance rate is equal to 50%, and fifteen relief suppliers are selected as a joint facility location. After running NSGA-II in accordance with the third configuration, 31 non-dominated solutions are obtained. The values of the four objective functions and order of relief suppliers as a result of NSGA-II are given under a determined circumstance, as shown in Table 5.23

Table 5.23 Non-dominated solutions according to third configuration.

Values of Objective Functions				Order of relief suppliers as a result of NSGA II
1	**2**	**3**	**4**	
21.332.883	0,81	15	11	0-11-19-8-12-3-7-2-15-1-18-13-9-16-17-14-4-6-10-5
19.410.936	0,8	15	13,5	3-1-7-0-4-2-8-6-18-15-9-12-19-13-16-17-14-11-5-10
20.082.238	0,81	15	11	18-19-7-0-9-2-1-3-4-15-17-13-16-14-12-6-11-5-8-10
18.578.912	0,81	15	16,5	4-7-6-0-3-2-1-18-8-15-17-16-19-13-12-14-9-11-5-10
18.967.536	0,8	15	15	4-7-6-0-3-2-1-18-8-15-12-13-11-16-17-19-14-9-10-5
19.090.056	0,8	15	12,5	4-7-6-0-3-2-1-18-8-15-17-16-9-13-12-14-19-11-5-10
18.396.727	0,8	15	15,5	4-7-6-0-3-2-1-18-8-15-12-13-14-16-17-19-11-9-10-5
19.749.513	0,81	15	12,5	3-1-7-0-4-2-16-14-8-15-11-13-19-12-17-9-18-6-10-5
21.324.571	**0,8**	**15**	**7,25**	**1-2-7-4-13-3-11-9-15-0-19-12-17-8-14-18-16-6-10-5**
21.502.870	0,81	15	11	3-1-7-0-16-2-18-14-17-15-19-11-13-9-12-8-4-6-10-5
20.614.811	0,8	15	9,5	0-2-7-4-13-3-11-9-15-1-19-12-17-16-14-18-8-6-10-5
20.332.718	**0,8**	**15**	**9,5**	**3-1-7-0-4-2-18-14-17-15-9-11-12-13-16-19-8-6-10-5**
18.589.252	**0,8**	**15**	**15,5**	**3-2-7-0-4-6-1-14-8-15-16-17-19-13-12-11-9-18-10-5**
19.428.344	**0,8**	**15**	**12,5**	**3-1-7-0-4-2-16-6-9-15-17-14-12-19-13-8-11-5-18-10**
19.480.526	0,8	15	13	3-1-7-0-4-2-18-16-8-15-10-17-12-13-14-9-6-11-5-19
20.176.290	0,8	15	9,5	3-1-7-0-4-2-18-16-8-15-12-17-9-13-11-19-14-6-10-5
19.319.928	0,81	15	14	3-1-7-0-4-2-18-16-8-15-19-17-12-13-14-9-6-11-5-10
19.904.993	0,81	15	13,5	3-1-7-0-4-2-19-17-18-15-16-8-11-12-13-14-6-9-10-5
19.787.667	0,8	15	11	3-1-7-0-4-2-19-17-18-15-16-8-12-9-13-11-14-6-10-5
21.204.484	0,8	15	8,25	3-1-7-0-4-2-19-17-18-15-12-8-9-13-11-14-16-6-10-5
19.292.250	0,81	15	16	3-1-7-0-4-2-6-16-18-15-11-19-8-12-13-9-17-14-10-5
19.626.466	0,8	15	10	3-1-7-0-4-2-16-14-8-15-18-12-9-13-17-10-6-5-19-11
19.234.900	0,8	15	12,5	3-1-7-0-4-2-6-16-18-15-9-17-14-12-13-8-11-5-19-10
19.383.073	0,81	15	27	3-1-7-0-4-2-6-16-18-15-11-13-12-19-17-9-14-8-10-5
18.806.428	0,81	15	16,5	3-1-7-0-4-2-6-16-18-15-19-17-14-12-13-8-11-5-9-10
20.633.675	0,8	15	8,75	3-1-7-0-4-2-19-9-18-15-12-8-14-17-13-11-16-6-10-5
19.554.744	0,81	15	12,5	3-1-7-0-4-2-18-14-17-15-16-8-12-11-13-9-10-6-5-19
21.057.300	0,79	15	7,25	3-1-7-0-4-2-18-14-17-15-12-8-13-11-9-19-16-6-10-5
21.360.911	0,8	15	8,25	3-1-7-0-4-2-18-14-17-15-9-13-11-19-12-8-16-6-10-5
20.133.961	0,82	15	13,5	3-1-7-0-4-2-18-14-17-15-11-13-12-19-16-9-8-6-10-5
19.123.963	0,81	15	15	3-1-7-0-4-2-6-16-18-15-14-17-11-12-13-19-8-9-10-5

The same process is conducted just as former configurations. The results of the *k*-means algorithm denote that four solutions can represent the other solutions at an average silhouette value of 99%. These final solutions are represented in bold in Table 5.23. Radar and line diagrams including the normalized values of each solution selected by the *k*-means algorithm are given in Figures 5.13 and 5.14, respectively. As can be seen, solution of proposed model is not in non-dominated solutions.



	F1	F2	F3	F4
PROPOSED	22.290.308	0,76	15	27,75
M1	21.324.571	0,8	15	7,25
M2	20.332.718	0,8	15	9,5
M3	18.589.252	0,8	15	15,5
M4	19.428.344	0,8	15	12,5

Note: *'**M**' is representetive of solutions as a result of k-means algorithm*

Figure 5.13 A radar diagram of the final solutions with normalized F values. (Host government assistance rate = 50% and number of relief supplier=15)

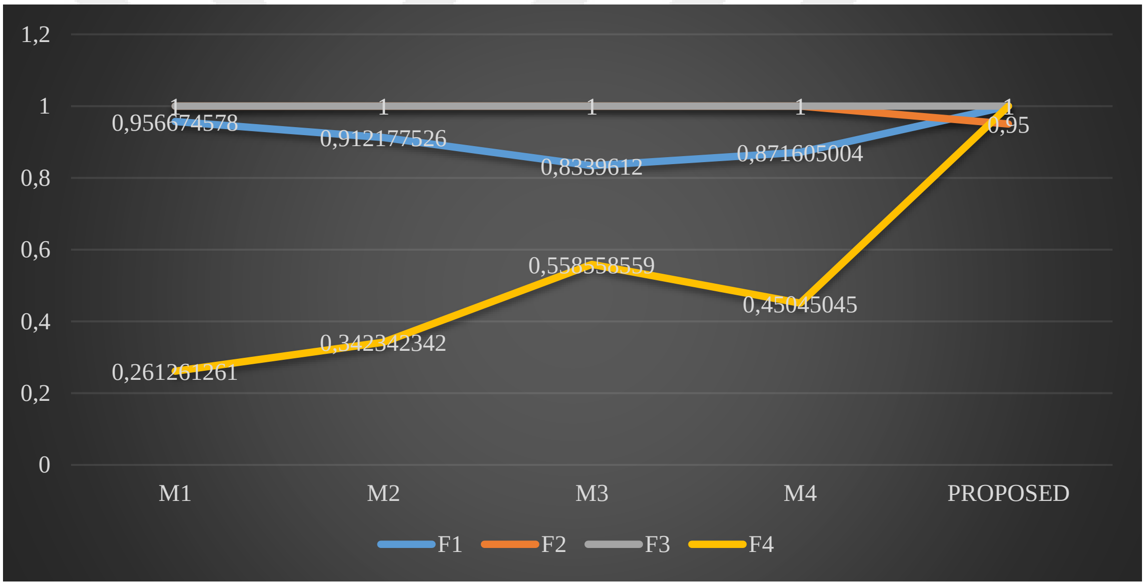


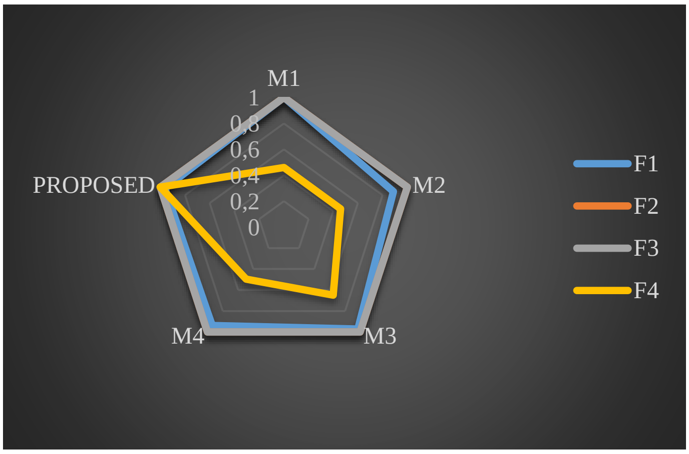
Figure 5.14 Line diagram of the final solutions with normalized F values. (Host government assistance rate = 50% and number of relief supplier=15)

One of the other configurations is whereby the host governments' assistance rate is equal to 75%, and fifteen relief suppliers were selected as a joint facility location. After running NSGA-II in accordance with fourth configuration, 32 non-dominated solutions are obtained. The values of the four objective functions and the order of relief suppliers from the NSGA-II are given under a determined circumstance, as shown in Table 5.24.

Table 5.24 Non-dominated solutions according to one fourth of the configuration.

Values of Objective Functions				Order of relief suppliers as a result of NSGA II
1	**2**	**3**	**4**	
1.718.228	0,96	15	8,75	3-0-2-13-7-4-9-18-1-10-19-17-12-8-15-6-14-11-16-5
1.669.152	0,96	15	9,75	0-1-2-3-4-8-6-7-12-9-11-10-17-15-19-14-13-18-16-5
1.812.721	**0,96**	**15**	**12,75**	**1-11-6-3-7-2-12-0-19-13-4-10-15-14-8-17-9-18-16-5**
1.762.347	0,96	15	9,75	0-1-2-3-7-10-6-4-19-9-13-12-11-15-14-17-8-16-18-5
1.598.812	0,96	15	21,75	0-1-2-3-7-10-6-4-19-9-12-18-17-11-15-14-5-13-8-16
1.608.171	**0,96**	**15**	**12,75**	**0-1-2-3-7-10-6-4-19-9-18-12-11-15-14-17-8-16-13-5**
1.596.051	0,96	15	26,75	0-1-2-3-6-4-7-9-5-12-11-10-17-15-19-14-13-8-16-18
1.760.890	**0,97**	**15**	**18**	**1-2-6-7-4-3-15-0-19-18-8-11-12-10-16-9-13-17-5-14**
1.594.590	0,96	15	13,75	0-1-2-3-6-4-7-9-5-12-11-19-14-10-15-13-8-17-18-16
1.725.779	0,96	15	9,5	0-3-2-1-7-9-12-4-11-10-14-13-15-19-16-8-17-6-5-18
1.749.016	0,96	15	12,25	0-1-2-3-4-5-6-7-8-9-19-12-13-10-15-14-11-17-18-16
1.714.866	0,96	15	12,75	0-1-2-3-4-7-6-19-8-17-12-11-10-14-15-18-16-13-5-9
1.699.622	**0,96**	**15**	**13,75**	**0-1-2-3-4-7-6-19-8-18-11-12-10-13-15-9-14-16-5-17**
1.749.717	0,96	15	11,25	0-1-2-3-4-7-6-19-8-18-12-9-10-17-15-11-14-16-5-13
1.607.884	0,96	15	15,75	0-1-2-3-4-7-6-19-8-18-12-11-10-14-15-17-16-13-5-9
1.802.849	0,96	15	10,25	0-1-2-3-4-7-6-19-8-9-12-10-13-14-15-11-18-16-5-17
1.782.439	0,96	15	11,25	0-1-2-3-4-7-6-19-8-9-12-10-13-18-15-11-14-16-5-17
1.803.905	0,96	15	17	1-6-0-3-4-2-12-11-19-16-15-10-8-7-14-13-5-9-18-17
1.748.509	0,96	15	7,75	0-1-2-3-4-7-14-19-8-9-13-17-10-12-15-18-6-16-5-11
1.801.539	0,96	15	10,25	0-1-2-3-4-7-6-19-8-9-13-17-10-12-15-18-14-16-5-11
1.839.343	0,96	15	12,75	0-13-1-3-7-11-4-8-2-10-12-15-6-17-19-14-5-9-18-16
1.689.466	0,96	15	10,75	0-1-2-3-4-7-6-19-8-9-12-11-15-18-13-10-14-16-5-17
1.677.585	0,96	15	8,75	0-1-2-3-4-7-13-10-8-9-12-18-14-15-19-6-17-11-16-5
1.672.573	0,96	15	9,75	0-1-2-3-4-5-7-19-8-9-12-10-14-13-15-17-11-16-6-18
1.580.875	0,96	15	20,75	0-1-2-3-6-4-7-17-5-12-11-19-14-10-18-8-15-16-13-9
1.620.391	0,96	15	10,75	0-1-2-3-4-15-7-19-8-9-12-6-18-17-11-5-14-10-13-16
1.647.235	0,96	15	9,25	0-3-2-1-7-9-11-4-12-5-14-13-15-19-17-8-16-6-10-18
1.633.771	0,96	15	14,75	0-1-2-3-6-4-7-17-5-12-19-8-10-11-15-18-13-9-14-16
1.738.604	0,96	15	12,25	0-1-2-3-6-4-7-17-5-12-9-8-10-15-19-11-14-18-16-13
1.709.931	0,96	15	7,25	0-3-2-1-7-9-17-4-12-10-14-13-15-19-11-8-16-6-5-18
1.616.841	0,96	15	13,75	0-1-2-3-6-4-7-17-15-12-19-18-8-11-10-16-9-13-5-14
1.679.066	0,96	15	9,75	0-1-2-3-6-4-7-17-15-12-10-19-9-11-14-5-13-8-18-16

The same process is conducted just as former configurations. The results of the *k*-means algorithm show that four solutions can represent the other solutions at an average silhouette value of 99%. These final solutions are represented in bold in Table 5.24. Radar and line diagrams, including the normalized values of each solution selected by the *k*-means algorithm, are given in Figures 5.15 and 5.16, respectively. As can be seen, solution of proposed model is not found in non-dominated solutions.



	F1	F2	F3	F4
M1	1.812.721	0,96	15	12,75
M2	1.608.171	0,96	15	12,75
M3	1.760.890	0,97	15	18
M4	1.699.622	0,96	15	13,75
PROPOSED	1.747.166	0,96	15	27,75

Note: *'M' is representetive of solutions as a result of k-means algorithm*

Figure 5.15 A radar diagram of the final solutions with normalized F values. (Host government assistance rate = %75 and number of relief supplier=15)

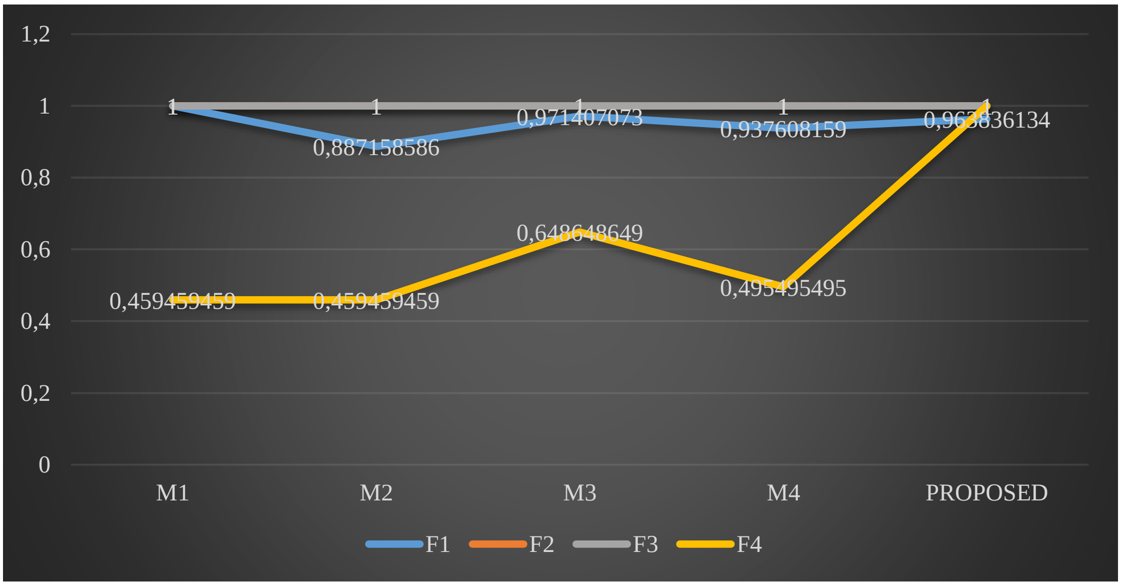


Figure 5.16 A line diagram of the final solutions with normalized F values. (Host government assistance rate = 75% and number of relief supplier=15)

A fifth configuration is the host government's assistance rate is equal to 90%, and fifteen relief suppliers are selected as a joint facility location. After running NSGA-II in accordance with a fifth configuration, 43 non-dominated solutions are obtained. The values of the four objective functions and order of relief suppliers as a result of NSGA-II are given under a determined circumstance, as shown in Table 5.25.

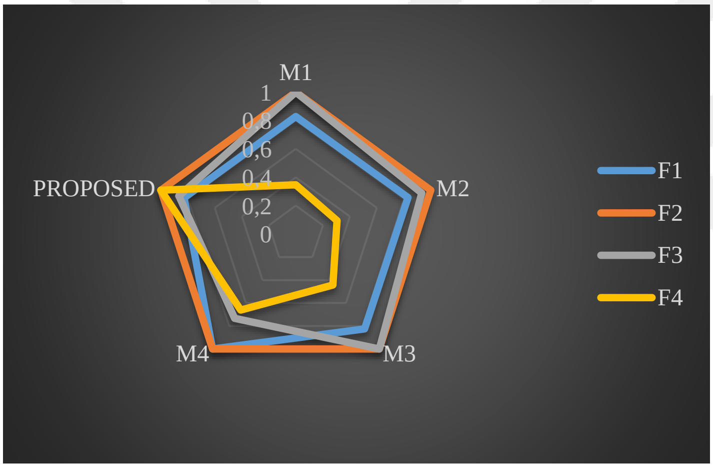
Table 5.25 Non-dominated solutions according to a fifth configuration.

Values of Objective Functions				**Order of relief suppliers as a result of NSGA II**
1	**2**	**3**	**4**	
388.531	1	15	12,25	0-1-2-3-4-5-6-7-17-9-13-18-15-14-12-8-10-11-16-19
387.595	1	15	15	0-1-2-3-4-5-6-7-17-9-13-18-15-14-16-8-10-11-12-19
389.830	1	12	21,75	0-1-2-3-4-7-6-19-8-9-10-15-11-12-5-18-17-14-13-16
387.890	1	15	19,5	0-1-2-3-4-5-6-7-8-9-16-17-18-12-14-15-19-10-11-13
388.876	1	15	28,25	0-1-2-3-4-5-6-7-8-9-12-10-13-14-17-16-19-11-18-15
388.691	1	15	15	0-1-2-3-4-5-6-7-8-9-16-17-18-15-14-12-19-10-11-13
389.048	1	15	33,5	0-1-2-3-4-5-6-7-8-12-10-13-16-17-14-19-11-9-18-15
388.420	1	15	18,5	0-1-2-3-4-5-6-7-8-9-11-16-14-18-13-17-12-19-10-15
389.085	1	15	27	0-1-2-3-4-5-6-7-15-9-10-13-16-17-14-19-11-12-18-8
388.740	1	15	22,5	0-1-2-3-4-5-6-7-11-10-16-17-18-13-14-12-8-19-9-15
387.940	1	15	31	0-1-2-3-4-5-6-7-8-9-10-13-16-17-14-19-11-12-18-15
388.851	**1**	**15**	**14,5**	**0-1-2-3-4-5-6-7-16-9-13-18-15-14-12-8-19-10-11-17**
388.703	1	15	17,5	0-1-2-3-4-5-6-7-16-13-17-18-15-14-12-8-19-10-11-9
387.508	1	15	18,5	0-1-2-3-4-5-6-7-11-9-16-17-18-13-14-12-8-19-10-15
389.036	1	15	14,5	0-1-2-3-4-5-6-7-16-9-17-18-15-14-12-8-19-10-11-13
389.110	1	15	11,75	0-1-2-3-4-5-6-7-11-9-17-18-15-14-12-8-19-10-16-13
388.617	1	15	19	0-1-2-3-4-5-6-7-8-9-13-16-17-14-19-10-12-11-18-15
391.682	1	13	13,25	0-1-2-3-4-17-15-7-8-19-11-9-12-10-13-14-18-6-5-16
390.937	1	12	19,25	0-1-2-3-4-17-11-7-8-19-15-12-10-13-5-18-14-6-9-16
441.805	1	14	10,25	11-1-2-3-4-9-12-7-10-13-0-14-18-15-19-6-8-5-16-17
391.444	1	15	9,25	0-1-2-3-4-17-15-7-8-9-5-18-14-12-11-6-19-10-13-16
388.950	1	15	17,25	0-1-2-3-4-5-6-7-8-9-18-17-14-12-10-15-19-11-13-16
389.830	1	15	9,75	0-1-2-3-4-17-6-7-8-9-18-14-12-11-15-19-5-10-13-16
388.506	1	15	15	0-1-2-3-4-5-6-7-8-9-15-13-18-14-16-17-10-11-12-19
390.217	1	13	15,75	0-1-2-3-4-5-11-7-8-19-17-9-15-10-12-6-18-14-13-16
390.217	**1**	**14**	**12,75**	**0-1-2-3-4-5-13-7-8-19-11-9-17-15-10-12-18-14-6-16**
389.830	1	14	13,25	0-1-2-3-4-17-6-7-8-9-19-13-12-15-14-18-5-11-10-16
389.830	1	13	16,25	0-1-2-3-4-17-6-7-8-9-15-19-12-14-11-10-18-13-16-5
388.100	1	15	16,25	0-1-2-3-4-5-6-7-8-9-17-13-14-18-11-15-10-16-19-12
386.696	1	15	16,25	0-1-2-3-4-5-14-7-8-9-6-13-18-17-12-10-15-19-11-16
388.445	1	15	15	0-1-2-3-4-5-6-7-8-9-13-16-17-18-15-14-12-19-10-11
389.110	1	13	20,75	0-1-2-3-4-5-6-7-9-19-10-15-14-12-17-18-13-8-11-16
389.110	1	12	27,75	0-1-2-3-4-5-6-7-8-19-10-15-14-12-17-18-13-9-11-16
564.011	1	15	6,75	3-10-7-15-1-4-14-12-17-2-18-8-13-9-11-0-19-6-16-5
387.706	**1**	**15**	**18,5**	**0-1-2-3-4-5-6-7-8-9-13-16-12-14-18-11-17-19-10-15**
389.663	1	15	9,75	0-1-2-3-4-5-14-7-8-9-15-12-17-18-13-11-10-19-6-16
388.359	1	15	18,5	0-1-2-3-4-5-6-7-8-9-17-13-16-11-18-14-12-19-10-15
389.110	1	14	15,25	0-1-2-3-4-5-6-7-8-9-12-17-15-19-11-10-13-18-14-16
429.713	1	15	7,25	0-1-2-8-4-17-15-7-3-9-12-14-18-13-11-10-19-6-16-5
469.512	**1**	**11**	**27,6**	**11-6-3-4-0-8-7-15-19-12-10-1-2-5-9-16-17-18-13-14**
438.986	1	11	45,75	11-6-3-4-0-1-7-15-19-12-2-5-8-9-17-13-18-14-16-10
439.230	1	11	31,1	11-6-3-4-0-1-7-15-19-12-8-2-5-9-17-13-18-14-16-10

Table 5.25 Non-dominated solutions according to a fifth configuration (continued)

Values of Objective Functions				**Order of relief suppliers as a result of NSGA II**
1	**2**	**3**	**4**	
388.186	1	15	12,75	0-1-2-3-4-5-6-7-8-9-17-15-13-18-14-16-10-11-12-19

The same process is conducted just as in the former configurations. The results of the *k*-means algorithm show that the four solutions can represent the other solutions at an average silhouette value of 98%. These final solutions are represented in bold in Table 5.25. Radar and line diagrams including the normalized values of each solution selected by the *k*-means algorithm are given in Figures 5.17 and 5.18, respectively. As can be seen, the solution of proposed model is not found in non-dominated solutions.



	F1	F2	F3	F4
M1	388.851	1	15	14,5
M2	390.217	1	14	12,75
M3	387.706	1	15	18,5
M4	469.512	1	11	27,6
PROPOSED	389.110	1	13	41,75

Note: ***'M'*** *is representetive of solutions as a result of k-means algorithm*

Figure 5.17 A radar diagram of the final solutions with normalized F values. (Host government assistance rate = 90% and number of relief supplier=15)

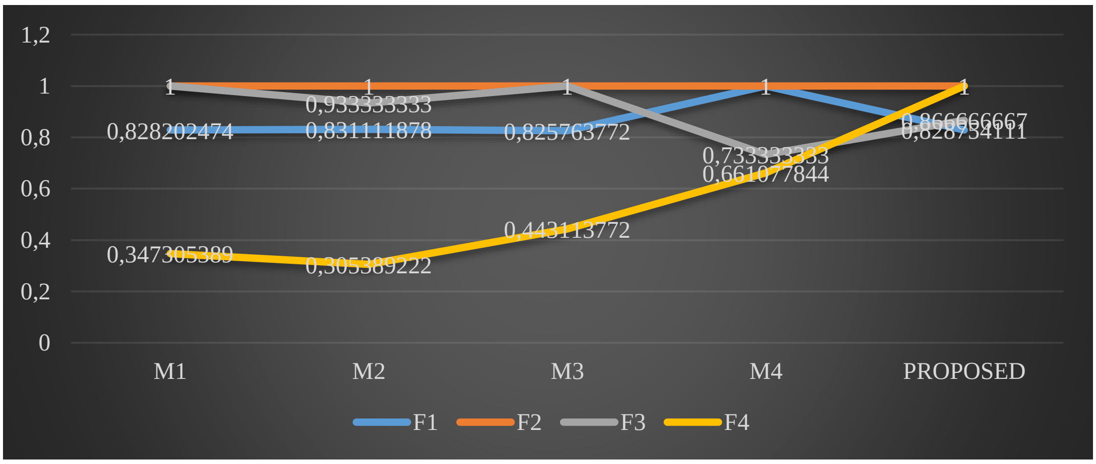


Figure 5.18 Line diagram of the final solutions with normalized F values. (Host government assistance rate = 90% and number of relief supplier=15)

A sixth configuration is the host governments' assistance rate is equal to 95%, and fifteen relief suppliers are selected as a joint facility location. After running NSGA-II in accordance with a sixth configuration, 44 non-dominated solutions were obtained. The values of the four objective functions and order of relief suppliers as a result of NSGA-II are given under a determined circumstance, as shown in Table 5.26.

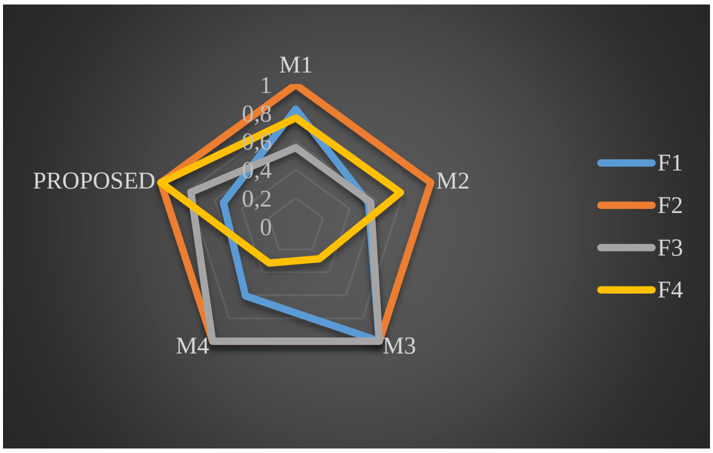
Table 5.26 Non-dominated solutions according to a sixth configuration.

Values of Objective Functions				**Order of relief suppliers as a result of NSGA-II**
1	**2**	**3**	**4**	
193.127	1	5	110,6	0-1-7-3-4-11-6-2-8-9-5-10-14-15-18-17-12-19-16-13
340.771	1	12	22,35	4-5-9-11-10-14-2-18-17-8-13-15-6-1-0-7-16-19-12-3
298.017	1	**5**	**82,1**	**0-11-14-19-3-1-5-7-4-18-2-8-10-6-13-15-17-12-9-16**
193.127	1	6	98,25	3-1-2-6-4-7-0-11-8-9-19-15-17-12-14-5-18-10-16-13
340.585	1	12	23,35	4-5-9-11-10-14-2-18-17-8-13-3-6-1-0-7-16-19-12-15
193.127	1	7	95,75	0-1-2-6-4-7-3-11-8-9-19-15-17-12-14-5-18-10-16-13
414.609	1	6	56,25	12-3-2-19-8-1-5-11-4-18-15-7-9-6-14-13-16-10-0-17
194.086	1	**5**	**83,1**	**0-3-1-19-8-10-5-11-4-18-15-7-2-9-6-14-13-16-12-17**
193.442	1	5	93,1	3-0-1-7-8-17-18-5-16-12-4-2-9-11-6-10-13-14-15-19
360.141	1	**9**	**30,25**	**10-2-9-11-17-4-8-18-15-13-3-1-19-5-7-14-6-16-0-12**
347.544	1	6	56,75	15-3-2-1-8-19-5-11-4-18-7-14-9-6-13-16-10-0-12-17
193.454	1	8	57,75	0-1-2-3-17-5-18-7-8-9-6-4-16-12-10-11-13-14-15-19
254.537	1	9	33,35	4-5-9-11-3-14-2-18-17-8-13-15-6-1-0-7-16-19-12-10
193.190	1	7	69,75	0-1-2-3-4-5-18-7-8-9-6-17-16-12-10-11-13-14-15-19
193.454	1	9	48,25	4-0-1-7-2-17-18-5-3-16-14-8-15-12-6-9-13-19-10-11
193.494	1	8	55,25	4-0-1-7-2-17-14-5-12-16-9-19-8-6-11-18-15-10-3-13
198.770	1	8	38,75	2-4-1-9-19-17-8-0-16-12-6-5-7-11-14-18-15-10-3-13
198.332	1	11	26,85	4-2-5-1-12-14-8-18-17-9-3-7-16-15-0-6-13-19-10-11
193.645	1	8	41,6	4-3-1-7-14-17-18-5-12-16-2-8-15-0-6-9-13-19-10-11
193.778	1	10	34,35	4-2-5-7-1-6-9-18-17-8-0-12-19-16-14-15-10-3-11-13
217.862	1	**9**	**34,25**	**4-2-13-11-10-15-8-18-17-9-14-19-6-1-7-3-12-0-5-16**
217.862	1	10	27,25	4-2-14-11-10-15-8-9-17-18-5-6-16-7-1-19-12-3-0-13
193.386	1	6	76	6-7-3-1-4-19-2-15-17-12-0-14-11-5-18-9-10-8-16-13
195.524	1	6	57,25	4-3-1-19-8-2-5-11-0-18-15-7-9-6-14-13-16-10-12-17
193.278	1	7	64,25	7-1-2-3-4-18-6-11-8-9-5-10-12-13-14-15-16-17-0-19
217.862	1	7	42,25	4-2-19-11-10-15-8-9-17-18-3-0-1-16-12-7-6-13-14-5
193.708	1	7	56,1	3-0-1-4-8-17-18-5-16-12-2-7-15-6-9-13-14-19-10-11
195.497	1	6	64,25	0-3-2-19-8-1-5-11-4-18-7-9-6-14-13-16-10-15-12-17
193.428	1	7	62,75	3-0-1-2-6-17-18-5-16-12-19-7-9-11-10-15-4-13-14-8
196.960	1	7	44,75	2-0-1-12-19-17-8-5-16-7-4-6-9-15-10-3-11-13-18-14
193.806	1	7	49,25	3-0-1-2-8-17-18-5-16-12-7-9-11-10-15-4-13-14-19-6
193.442	1	6	69,1	3-0-1-7-18-17-2-5-16-12-4-15-8-6-9-13-14-19-10-11
193.162	1	6	85,75	3-0-1-7-2-17-18-5-16-12-4-15-8-6-9-13-14-19-10-11
193.596	1	8	44,1	6-0-1-7-18-17-4-8-16-12-5-14-15-11-10-19-9-3-2-13

Table 5.26 Non-dominated solutions according to a sixth configuration (continued)

Values of Objective Functions				**Order of relief suppliers as a result of NSGA-II**
1	**2**	**3**	**4**	
197.757	1	9	35,75	2-1-17-0-18-15-14-5-12-9-4-11-10-8-7-3-19-6-13-16
206.562	1	9	35,35	4-2-5-11-10-15-8-18-17-9-6-16-7-1-14-12-3-0-13-19
193.974	1	9	37,35	4-0-1-7-14-17-18-9-16-12-2-6-8-11-10-15-5-3-13-19
194.016	1	10	28,25	4-2-6-7-1-14-9-18-17-15-0-5-12-16-3-11-10-13-8-19
193.736	1	9	40,5	4-0-1-7-14-17-18-5-12-16-3-6-11-8-9-10-13-2-15-19
193.274	1	6	82,75	0-7-2-3-4-18-9-11-8-6-1-5-10-12-13-14-15-16-17-19
206.562	1	12	24,6	4-2-5-11-16-14-8-18-17-9-10-15-13-3-0-1-7-12-6-19
217.862	1	8	35,25	4-2-9-11-10-15-8-18-17-13-14-19-6-1-7-3-12-0-5-16
198.432	1	11	24,85	4-2-5-1-12-14-8-18-17-9-15-3-19-11-0-16-7-6-13-10
193.989	1	11	29,75	4-2-6-7-1-14-13-18-17-9-0-16-12-5-11-19-3-10-15-8

The same process is conducted just as former configurations. The results of the *k*-means algorithm show that four solutions can represent the other solutions at an average silhouette value of 98%. These final solutions are represented in bold in Table 5.26. Radar and line diagrams including the normalized values of each solution selected by the *k*-means algorithm are given in Figures 5.19 and 5.20, respectively. As can be seen, solution of proposed model is not found in a non-dominated solution.



	F1	F2	F3	F4
M1	298.017	1	5	82,1
M2	194.086	1	5	83,1
M3	360.141	1	9	30,25
M4	217.862	1	9	34,25
PROPOSED	193.127	1	7	107,25

Note:* *'M'* *is representetive of solutions as a result of k-means algorithm

Figure 5.19 A radar diagram of the final solutions with normalized F values. (Host government assistance rate = 95% and number of relief supplier=15)

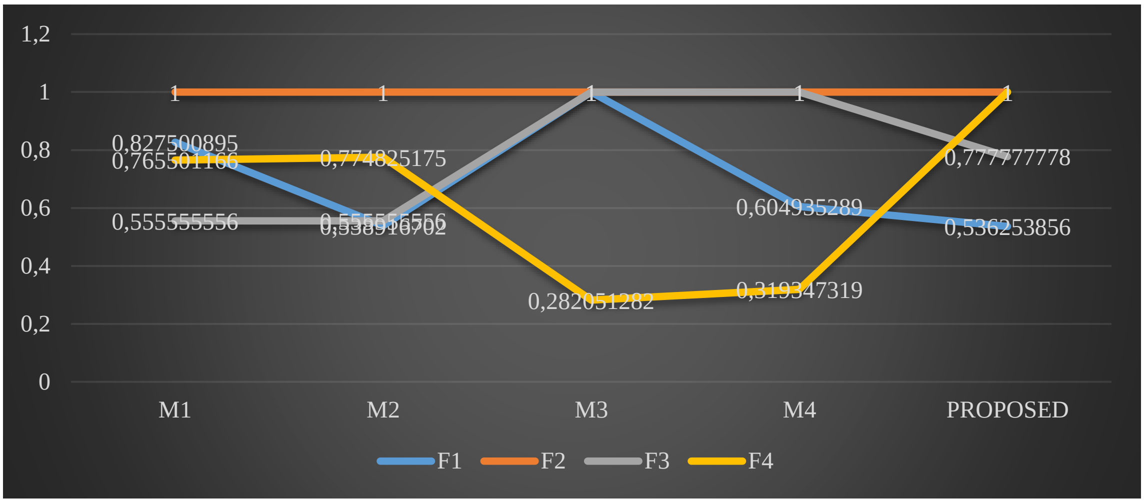


Figure 5.20 A line diagram of the final solutions with normalized F values. (Host government assistance rate = 90% and number of relief supplier=15)

A seventh configuration is the host governments' assistance rate is equal to 50%, and eight relief suppliers are selected as a joint facility location. After running NSGA-II in accordance with seventh configuration, 41 non-dominated solutions are obtained. The values of the four objective functions and order of relief suppliers as a result of NSGA-II are given under the determined circumstance, as shown in Table 5.27.

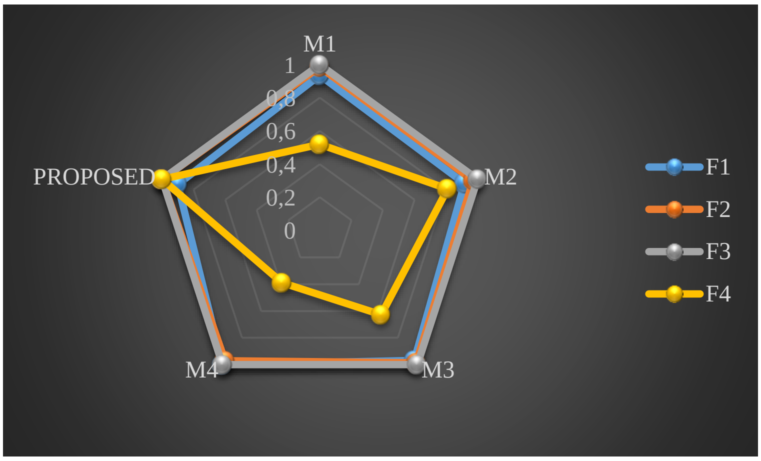
Table 5.27 Non-dominated solutions according to a seventh configuration.

Values of Objective Functions				**Order of relief suppliers as a result of NSGA-II**
1	**2**	**3**	**4**	
33.294.186	0,69	8	43,1	7-1-0-19-3-13-8-12-11-10-16-15-2-18-4-14-5-9-17-6
31.419.773	0,69	8	54,25	7-1-0-2-3-13-8-12-11-10-16-15-6-18-19-4-9-14-17-5
30.856.510	0,7	8	74,5	7-1-0-2-3-17-16-12-11-10-8-15-6-18-19-4-9-14-13-5
30.970.702	0,7	8	71,5	7-1-0-2-3-8-16-12-11-10-15-19-13-18-4-14-5-9-17-6
30.598.106	0,7	8	79,5	7-1-0-2-3-13-16-12-11-10-15-8-6-18-19-4-9-14-17-5
32.313.013	0,7	8	50,75	0-3-15-2-1-13-19-12-11-10-8-18-16-7-4-14-5-9-17-6
33.373.914	0,68	8	37,75	8-1-7-2-3-13-18-12-11-10-19-15-16-0-4-14-5-9-17-6
32.595.456	0,69	8	39,75	8-1-0-2-3-13-18-12-11-10-19-15-16-7-4-14-5-9-17-6
31.598.576	0,7	8	53,25	0-13-7-2-1-3-19-12-11-10-15-16-18-4-8-6-9-14-5-17
32.261.595	0,7	8	60,5	0-13-19-1-2-7-3-16-18-4-15-12-11-10-8-6-9-14-5-17
33.188.188	0,7	8	52,1	17-7-3-1-19-15-0-12-18-11-10-8-16-4-5-6-13-2-9-14
32.393.960	0,69	8	44,75	15-1-0-2-3-17-18-12-11-10-8-7-19-4-16-13-6-9-14-5
32.542.047	0,7	8	48,75	17-2-3-1-19-15-0-12-18-11-8-16-4-5-6-13-10-7-9-14
31.728.025	0,7	8	48,25	2-0-12-1-18-7-3-17-19-4-13-15-8-16-11-14-6-5-10-9
31.223.608	0,7	8	66,5	2-0-12-1-16-7-3-19-17-4-13-15-8-18-11-14-6-5-10-9
33.966.530	0,68	8	35,25	13-2-3-1-19-15-8-12-18-11-0-16-7-4-5-6-17-10-9-14
32.685.202	0,69	8	43,75	0-2-3-1-19-15-8-12-18-11-17-13-7-16-10-4-6-9-5-14
32.726.678	0,69	8	39,75	0-2-3-1-19-8-13-12-18-11-17-15-7-16-10-4-6-9-5-14

Table 5.27 Non-dominated solutions according to a seventh configuration (continued)

Values of Objective Functions				Order of relief suppliers as a result of NSGA-II
1	**2**	**3**	**4**	
32.901.121	0,69	8	38,75	17-2-3-1-19-8-0-12-18-11-15-7-16-13-10-4-6-9-5-14
33.402.998	0,69	8	42,1	7-17-3-1-19-8-0-12-18-11-15-2-16-13-10-4-6-9-5-14
32.581.441	0,68	8	43,75	8-0-3-1-15-12-18-2-6-4-16-17-11-10-19-7-13-9-14-5
30.998.116	0,7	8	64,5	7-1-3-2-18-16-0-12-11-10-13-19-4-8-15-6-9-14-5-17
32.175.806	0,69	8	46,75	2-1-3-15-18-13-0-12-11-10-7-8-6-16-19-4-9-14-17-5
31.434.821	**0,7**	**8**	**49,25**	**7-1-3-2-18-13-0-12-11-10-8-15-16-19-4-6-9-14-5-17**
31.386.180	0,69	8	55,25	8-1-0-15-7-3-2-12-11-10-19-16-18-4-13-6-9-14-5-17
33.521.265	0,69	8	37,75	8-1-19-13-7-3-2-12-11-10-4-16-18-0-6-9-14-17-15-5
30.794.308	**0,69**	**8**	**76,75**	**4-1-0-2-7-3-13-12-11-10-17-19-18-16-8-15-6-9-14-5**
30.345.237	0,7	8	97,5	4-1-0-2-7-3-16-12-11-10-8-18-19-13-6-9-14-17-15-5
32.524.787	**0,7**	**8**	**59,5**	**17-7-19-1-0-16-3-2-18-4-13-12-11-10-8-15-6-9-14-5**
31.903.190	0,7	8	52,25	2-12-0-17-7-19-3-1-8-4-18-11-10-13-6-9-14-16-15-5
31.171.818	0,69	8	61,75	4-1-0-2-7-3-18-12-11-10-8-16-19-13-6-9-14-17-15-5
32.797.731	0,69	8	38,75	8-1-18-3-17-12-0-2-6-4-19-7-11-15-13-10-16-9-14-5
32.256.154	0,7	8	64,5	15-16-19-1-0-7-3-2-18-4-8-17-12-11-14-13-6-5-10-9
33.709.441	0,69	8	36,75	1-2-3-8-19-7-17-12-18-11-0-13-10-16-4-15-6-9-14-5
33.922.510	0,68	8	33,25	17-2-3-1-8-15-18-12-19-11-16-0-7-4-14-13-6-5-10-9
33.865.963	0,67	8	35,25	15-13-8-2-1-3-18-12-11-10-0-19-16-4-6-7-14-5-9-17
32.661.259	0,69	8	43,75	14-1-3-2-15-18-0-12-16-4-8-7-19-13-17-11-6-5-10-9
33.338.606	0,7	8	54,1	1-12-0-18-7-19-3-17-8-4-2-11-16-13-10-6-15-9-5-14
33.578.874	**0,69**	**8**	**36,75**	**1-3-18-17-8-7-2-12-19-11-16-13-0-10-4-6-15-9-5-14**
34.023.263	0,69	8	33,25	1-2-3-19-17-15-8-12-18-11-0-4-7-16-13-10-6-9-5-14
30.252.008	**0,71**	**8**	**94,75**	**0-1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19**

The process is conducted just as former configurations. The results of the *k*-means algorithm show that four solutions can represent other solutions at an average silhouette value of 98%. These final solutions are represented in bold in Table 29. Radar and line diagrams, including the normalized values of each solution selected by the *k*-means algorithm are provided in Figures 5.21 and 5.22, respectively. As can be seen, the solution of proposed model is located within a set of pareto optimal solutions. Proposed model is represented in red in Table 5.27.



	F1	F2	F3	F4
M1	31.434.821	0,7	8	49,25
M2	30.794.308	0,69	8	76,75
M3	32.524.787	0,7	8	59,5
M4	33.578.874	0,69	8	36,75
PROPOSED	30.252.008	0,71	8	94,75

Note: *'**M**' is representetive of solutions as a result of k-means algorithm*

Figure 5.21 Radar diagram of the final solutions with normalized F values. (Host government assistance rate = %50 and number of relief supplier=8)

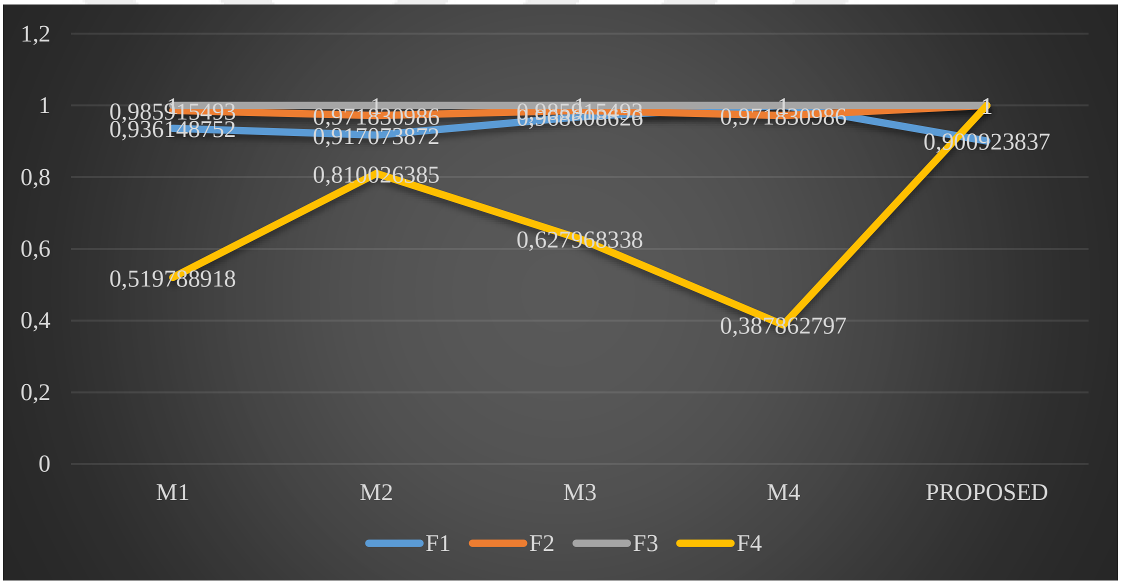


Figure 5.22 A line diagram of the final solutions with normalized F values. (Host government assistance rate = %50 and number of relief supplier=8)

An eighth configuration is the host government assistance rate, which is equal to 75%, and whereby eight relief suppliers are selected as a joint facility location. After running NSGA-II in accordance with eighth configuration, 48 non-dominated solutions are obtained. The values of the four objective functions and order of relief suppliers as a result of NSGA-II are given under determined circumstances, as presented in Table 5.28.

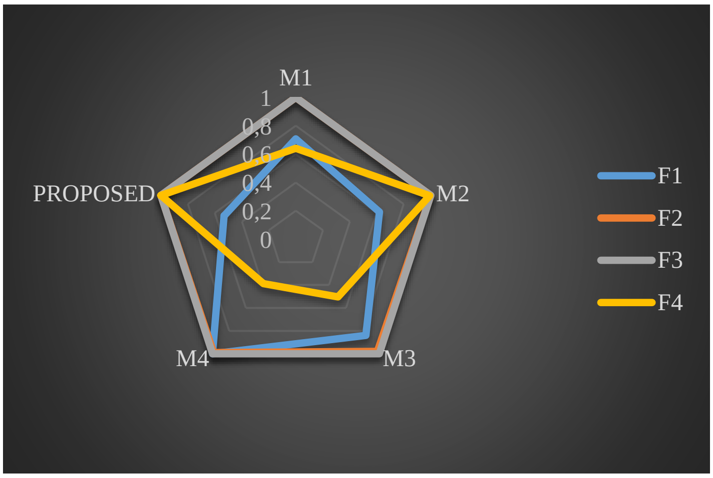
Table 5.28 Non-dominated solutions according to an eighth configuration.

Values of Objective Functions				Order of relief suppliers as a result of NSGA-II
1	**2**	**3**	**4**	
7.391.395	0,92	8	42,1	0-1-14-3-17-7-19-12-8-9-2-4-6-18-5-15-16-13-11-10
4.644.658	0,93	8	71,75	0-1-2-3-7-12-4-17-8-9-6-19-14-18-5-15-16-13-11-10
4.897.785	0,92	8	62,75	0-1-2-3-7-12-14-6-8-9-19-17-18-5-15-16-13-11-4-10
5.314.971	0,93	8	51,25	0-1-2-3-7-12-8-17-14-9-13-19-15-6-18-5-16-11-4-10
5.647.838	0,92	8	49,25	0-1-2-3-7-12-14-17-8-9-19-4-6-18-5-15-16-13-11-10
7.018.109	0,92	8	37,75	13-1-2-3-19-12-14-7-8-9-17-15-6-18-5-16-0-11-4-10
5.717.392	0,93	8	51,25	0-1-2-3-18-12-8-7-15-9-13-4-6-5-14-16-17-19-11-10
4.550.046	0,92	8	68,75	0-1-2-3-4-12-8-7-15-9-13-6-18-5-14-16-17-19-11-10
4.678.776	0,92	8	66,75	0-1-2-3-6-12-8-7-15-9-13-4-18-5-14-16-17-19-11-10
4.295.534	0,93	8	74,75	0-1-2-3-6-12-7-15-8-9-13-4-18-5-14-16-17-19-11-10
5.076.205	**0,93**	**8**	**60,75**	**0-1-2-3-6-12-18-7-8-9-17-15-16-4-5-19-11-14-13-10**
5.147.751	0,93	8	66,25	0-1-2-3-17-12-15-7-8-9-4-13-16-18-5-6-19-11-14-10
4.913.545	0,93	8	61,75	0-1-2-3-4-12-7-18-8-9-13-6-5-15-17-19-11-14-16-10
4.379.244	0,93	8	76,75	0-1-2-3-4-12-7-13-8-9-6-18-5-15-17-19-11-14-16-10
3.989.969	0,92	8	91,25	0-1-2-3-4-12-6-7-8-9-18-5-15-16-17-19-11-14-13-10
7.024.388	0,93	8	50,75	1-0-2-19-12-18-3-17-6-16-7-14-15-10-8-4-11-9-5-13
6.231.200	0,92	8	44,75	1-0-2-15-3-12-18-17-6-16-7-8-19-10-9-11-14-4-5-13
6.646.531	0,92	8	47,1	7-0-3-15-1-8-12-19-10-17-2-18-6-16-14-13-4-9-11-5
6.595.079	0,92	8	39,75	2-0-1-19-3-12-13-14-6-15-4-7-17-8-9-16-10-11-18-5
7.789.032	0,91	8	35,25	13-2-14-1-19-12-15-3-6-0-7-8-9-16-17-18-4-10-11-5
4.849.965	0,93	8	68,25	0-1-2-7-13-12-3-15-8-9-16-19-17-6-14-18-4-10-11-5
4.896.327	0,93	8	78,5	0-1-2-7-16-12-15-3-8-9-19-17-6-14-18-4-10-11-5-13
7.870.273	0,93	8	50,85	15-7-3-19-8-1-0-16-10-11-2-12-6-9-18-4-14-5-17-13
4.445.961	**0,93**	**8**	**94**	**0-1-2-7-6-12-16-3-8-9-13-18-4-17-15-5-11-10-14-19**
6.805.124	0,91	8	37,75	3-1-2-7-8-12-13-18-4-9-17-15-5-0-6-16-11-10-14-19
7.552.504	0,91	8	33,25	8-3-17-18-1-2-15-12-13-5-7-4-9-0-6-16-11-10-14-19
5.981.130	0,91	8	48,25	3-1-2-7-4-12-13-18-8-9-15-17-0-6-16-14-10-11-19-5
5.232.520	0,93	8	54,25	0-1-2-7-8-12-13-3-4-9-15-16-19-10-11-6-17-5-18-14
7.333.518	0,91	8	35,25	1-8-13-18-3-2-15-12-17-5-11-7-0-10-16-14-4-6-9-19
6.030.661	**0,91**	**8**	**47,75**	**0-1-2-15-13-3-14-12-8-9-4-19-10-7-6-11-16-18-17-5**
5.429.273	0,92	8	50,25	0-1-2-7-13-3-14-12-8-9-15-19-10-6-4-18-17-5-16-11
5.198.467	0,93	8	54,25	0-1-2-7-15-3-14-12-8-9-18-17-10-4-19-6-16-11-5-13
4.265.195	0,93	8	97,5	0-1-2-7-4-3-16-12-8-9-18-17-10-15-19-6-14-11-5-13
4.709.471	0,93	8	64,75	0-1-2-7-4-3-14-12-8-9-19-10-15-6-11-16-18-17-5-13
6.693.068	0,92	8	38,75	1-2-3-18-0-14-12-17-10-8-7-4-9-15-19-6-16-11-5-13
6.201.254	0,91	8	45,75	1-2-3-15-0-14-12-17-10-8-7-4-9-18-6-16-11-5-19-13
4.313.556	0,93	8	75,75	0-1-2-7-4-12-15-3-8-9-18-14-19-10-6-16-11-5-17-13
6.347.514	0,92	8	43,75	1-2-3-14-0-15-12-19-10-8-7-17-18-4-6-16-11-9-5-13
6.916.998	0,92	8	47,1	1-7-3-15-0-14-12-19-10-8-17-18-4-6-2-16-11-9-5-13
7.936.866	0,91	8	33,25	3-15-2-1-17-12-14-19-6-13-0-18-8-9-4-7-5-16-11-10
7.172.304	**0,92**	**8**	**36,75**	**3-7-2-1-17-12-14-19-6-13-0-15-18-8-9-4-5-16-11-10**
6.952.578	0,92	8	44,75	3-0-2-1-7-17-14-19-6-13-12-15-18-8-9-4-5-16-11-10

Table 5.28 Non-dominated solutions according to an eighth configuration (continued)

Values of Objective Functions				**Order of relief suppliers as a result of NSGA-II**
1	**2**	**3**	**4**	
5.692.558	0,92	8	49,25	3-0-2-1-7-12-14-19-6-13-15-18-8-9-4-17-5-16-11-10
6.763.866	0,92	8	38,75	3-0-2-1-17-12-14-19-6-13-15-18-8-9-4-7-5-16-11-10
6.275.362	0,92	8	43,75	0-1-2-3-14-12-15-18-8-9-4-7-5-6-16-17-19-11-13-10
6.574.454	0,91	8	39,75	1-14-13-3-2-18-0-12-17-5-7-16-19-10-8-6-4-15-9-11
6.160.196	0,92	8	48,75	1-8-13-3-2-15-0-12-17-5-14-4-6-9-10-18-16-7-11-19
3.813.164	**0,93**	**8**	**94,75**	**0-1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19**

The same process is conducted just as former configurations. The results of the *k*-means algorithm show that four solutions can represent the other solutions at an average silhouette value of 97%. These final solutions are represented in bold in Table 30. Radar and line diagrams, including the normalized values of each solution selected by the *k*-means algorithm, are given in Figures 5.23 and 5.24, respectively. As can be seen, the solution of proposed model is located in a set of Pareto optimal solutions. Proposed model is represented in red in Table 5.28.



	F1	F2	F3	F4
M1	5.076.205	0,93	8	60,75
M2	4.445.961	0,93	8	94
M3	6.030.661	0,91	8	47,75
M4	7.172.304	0,92	8	36,75
PROPOSED	3.813.164	0,93	8	94,75

Note: *'M' is representetive of solutions as a result of k-means algorithm*

Figure 5.23 A radar diagram of the final solutions with normalized F values. (Host government assistance rate = 75% and number of relief supplier=8)

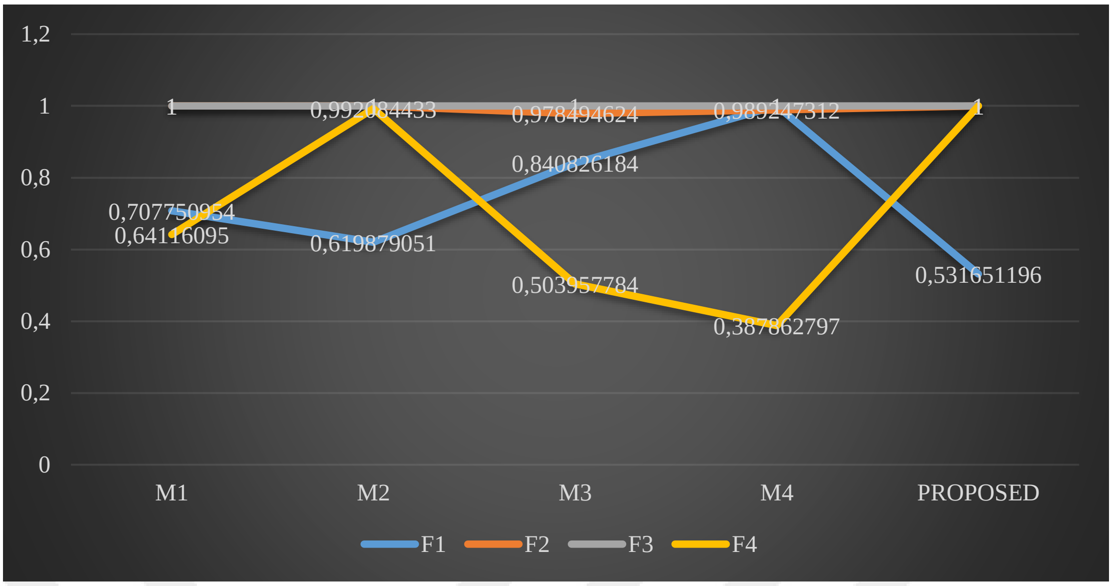


Figure 5.24 A line diagram of the final solutions with normalized F values. (Host government assistance rate = 75% and number of relief supplier=8)

A ninth configuration is the host government assistance rate is equal to 90%, and eight relief suppliers are selected as a joint facility location. After running NSGA-II in accordance with this configuration, 39 non-dominated solutions are obtained. The values of the four objective functions and order of relief suppliers as a result of the NSGA-II are given under a determined circumstance, as is seen in Table 5.29.

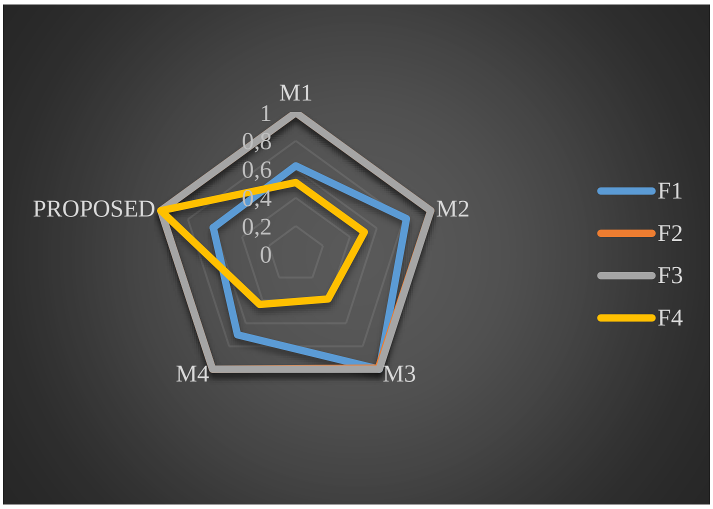
Table 5.29 A non-dominated solutions according to a ninth configuration.

Values of Objective Functions				**Order of relief suppliers as a result of NSGA-II**
1	**2**	**3**	**4**	
397.408	**1**	**8**	**48,1**	**1-4-3-7-0-14-15-19-18-9-8-11-10-2-17-13-5-12-6-16**
394.922	1	8	57,1	1-4-3-7-0-6-15-19-18-9-8-10-2-17-11-12-14-13-5-16
486.813	1	8	54,6	1-8-3-7-0-11-10-19-18-9-2-4-6-15-17-13-5-12-14-16
393.735	1	8	62,6	1-4-3-7-0-11-15-19-18-9-2-8-17-6-12-14-13-5-16-10
453.902	1	8	56,6	1-3-8-7-0-11-15-19-18-9-2-4-17-6-12-14-13-5-16-10
521.278	**1**	**8**	**48,1**	**4-8-3-11-0-7-15-19-18-9-6-1-10-17-13-2-5-12-14-16**
431.555	1	8	46,1	1-0-3-8-7-10-19-4-12-14-2-11-15-9-17-6-16-5-18-13
393.719	1	8	55,25	0-3-7-2-19-10-11-12-1-14-15-4-8-9-17-6-16-5-18-13
391.779	1	8	60,6	1-3-7-0-15-8-4-11-12-14-2-19-6-13-17-18-16-5-10-9
399.433	1	8	39,75	1-3-7-2-19-10-14-12-0-11-15-4-8-9-17-6-16-5-18-13
397.013	1	8	51,1	1-3-7-0-15-10-4-18-12-14-2-8-19-11-13-5-9-17-6-16
393.074	1	8	73,6	1-3-7-0-15-10-4-11-12-14-6-13-17-18-16-5-8-9-2-19
519.449	1	8	39,75	10-2-7-3-8-1-12-19-18-13-4-15-5-9-17-14-6-11-16-0
635.875	**0,99**	**8**	**36,75**	**10-2-7-15-8-1-12-19-18-13-6-3-4-17-14-9-0-11-16-5**
396.774	1	8	42,75	2-1-7-3-8-4-15-19-5-9-13-17-14-18-10-6-11-12-16-0
440.457	0,99	8	36,25	2-1-4-3-8-19-15-13-5-9-17-14-18-7-10-6-11-12-16-0

Table 5.29 Non-dominated solutions according to a ninth configuration (continued)

Values of Objective Functions				**Order of relief suppliers as a result of NSGA-II**
1	**2**	**3**	**4**	
720.522	1	8	39,25	2-15-7-17-19-14-3-1-18-13-10-8-5-9-4-6-11-12-16-0
445.308	**1**	**8**	**41,25**	**2-1-10-3-7-19-15-8-5-9-0-4-11-6-18-17-12-16-13-14**
398.622	1	8	49,75	2-1-0-3-8-19-15-7-5-9-6-11-18-17-12-16-4-13-10-14
552.609	1	8	54,1	3-10-7-0-11-12-19-15-1-14-2-8-9-4-6-17-18-13-5-16
421.745	1	8	55,1	3-4-7-0-11-10-19-15-12-14-8-2-9-1-6-17-18-13-5-16
467.299	1	8	46,1	3-10-7-0-11-4-19-8-12-14-2-15-9-1-6-17-18-13-5-16
404.644	1	8	61,6	1-0-7-11-3-15-19-12-6-14-2-8-9-4-10-17-18-13-5-16
602.049	1	8	41,75	3-11-2-12-7-8-15-19-0-9-10-4-14-1-6-17-18-13-5-16
406.848	1	8	53,6	1-0-7-11-3-8-19-12-6-14-4-10-9-2-15-17-18-13-5-16
405.947	1	8	59,6	1-0-7-11-3-10-19-12-6-14-9-2-15-17-18-13-8-4-5-16
630.742	0,99	8	34,75	1-2-17-15-19-7-12-8-18-13-3-0-10-6-11-14-9-4-16-5
392.566	1	8	80,6	1-3-7-0-15-10-6-11-12-14-8-19-18-9-4-2-17-13-16-5
629.741	0,99	8	35,25	1-19-15-2-3-10-14-12-0-11-18-7-6-9-17-13-8-4-5-16
461.388	0,99	8	37,75	1-2-7-19-3-13-14-12-0-11-6-4-15-17-18-8-9-10-5-16
400.566	1	8	57,1	3-6-7-0-11-4-19-15-12-14-2-17-1-18-13-8-9-10-5-16
592.701	0,99	8	34,75	1-2-19-15-7-14-12-17-18-13-10-0-4-8-9-3-11-6-16-5
550.217	1	8	45,1	3-10-7-0-11-12-8-19-1-14-6-2-15-4-9-17-16-5-18-13
441.798	1	8	63,6	0-3-7-10-11-1-19-15-12-14-2-4-9-17-6-8-18-13-5-16
396.206	1	8	54,25	1-2-3-7-12-11-10-19-18-9-8-4-0-15-17-13-5-6-14-16
493.502	1	8	49,1	3-10-7-0-8-1-19-15-12-14-2-4-5-9-11-6-18-17-16-13
397.314	1	8	53,6	3-0-7-4-1-8-19-12-6-14-10-2-9-15-17-18-13-11-5-16
681.719	0,99	8	33,25	17-2-1-15-19-3-12-14-18-13-0-9-11-4-7-5-10-8-6-16
389.137	**1**	**8**	**94,75**	**0-1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19**

Same process is conducted just as former configurations. The results of the *k*-means algorithm show that four solutions can represent the other solutions sat an average silhouette value of 98%. These final solutions are represented in bold in Table 31. Radar and line diagrams including the normalized values of each solution selected by the *k*-means algorithm are given in Figure 5.25 and 5.26, respectively. As can be seen, the solution of proposed model is located in a set of Pareto optimal solutions. Proposed model is represented in red in Table 5.29.



	F1	F2	F3	F4
M1	397.408	1	8	48,1
M2	521.278	1	8	48,1
M3	635.875	0,99	8	36,75
M4	445.308	1	8	41,25
PROPOSED	389.137	1	8	94,75

Note: *'M' is representetive of solutions as a result of k-means algorithm*

Figure 5.25 A radar diagram of the final solutions with normalized F values. (Host government assistance rate = 90% and number of relief supplier=8)

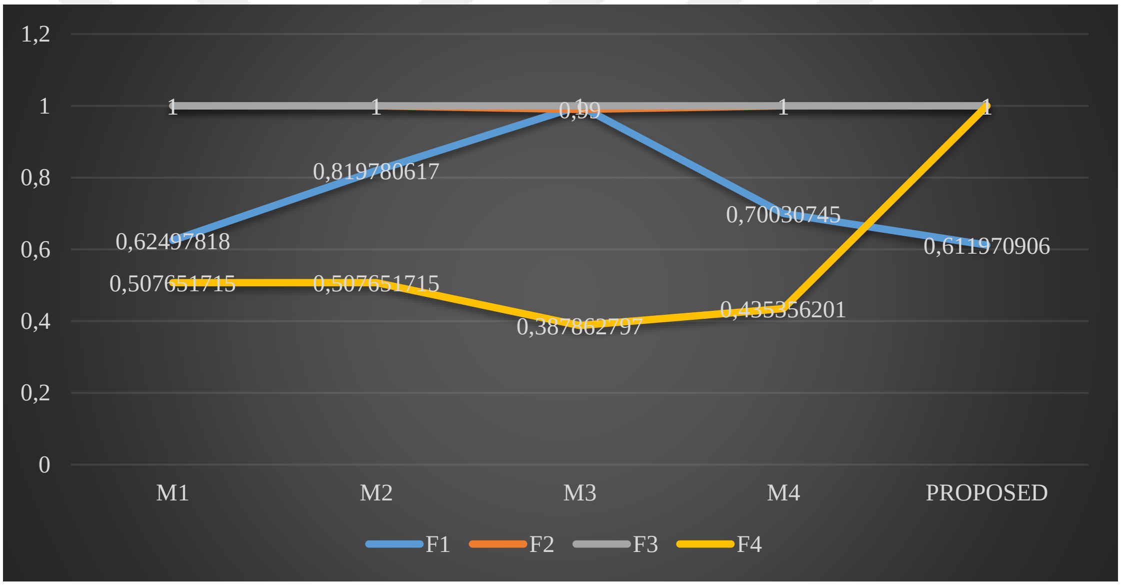


Figure 5.26 A line diagram of the final solutions with normalized F values. (Host government assistance rate = 90% and number of relief supplier=8)

The tenth and final configuration is the host government assistances' rate, which is equal to 95%, and whereby eight relief suppliers are selected as a joint facility location. After running NSGA-II in accordance with this last configuration, 44 non-dominated solutions are obtained. The values of the four objective functions and order of relief suppliers as a result of NSGA-II are given under a determined circumstance, as shown in Table 5.30.

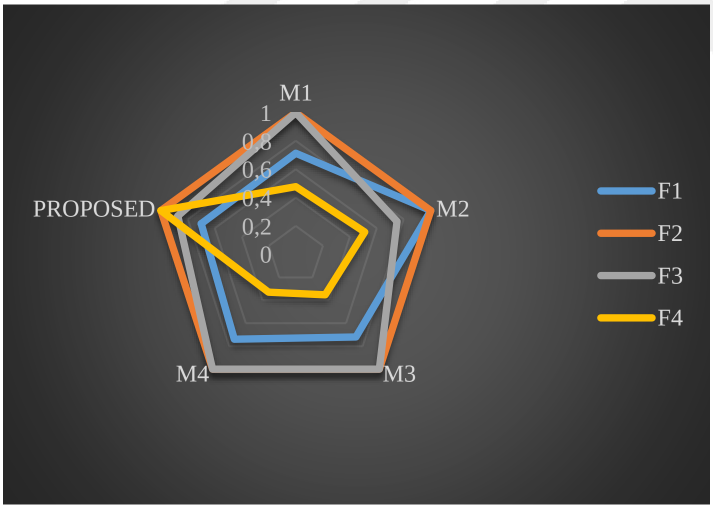
Table 5.30 A non-dominated solutions according to a tenth configuration.

Values of Objective Functions				Order of relief suppliers as a result of NSGA-II
1	**2**	**3**	**4**	
193.806	1	6	64,25	0-1-2-3-14-19-6-4-8-9-7-18-12-10-15-16-11-13-17-5
193.162	1	6	77,75	0-1-2-3-7-19-6-4-8-9-18-12-10-15-16-11-5-14-13-17
193.484	1	8	41,75	7-1-2-3-18-4-14-10-8-9-15-19-5-11-13-0-17-12-6-16
193.484	1	7	52,75	7-1-2-3-17-4-14-10-8-9-6-15-19-5-11-0-13-12-18-16
193.127	1	6	98,25	7-1-2-3-6-4-14-10-8-9-15-19-5-11-13-0-17-12-18-16
193.330	1	7	64,1	0-1-6-3-13-4-14-10-8-9-5-11-17-2-15-7-19-16-18-12
193.428	1	7	55,75	0-1-2-3-13-4-14-10-8-9-5-11-17-6-15-7-19-16-18-12
193.148	1	7	66,1	7-1-4-3-6-5-14-18-8-9-2-10-12-11-19-15-16-0-13-17
193.078	1	8	60,85	7-4-2-3-13-5-9-18-8-14-1-17-10-12-11-19-15-16-0-6
192.964	1	8	53,85	7-4-2-3-13-5-14-18-8-9-10-12-11-19-15-16-1-0-6-17
193.421	1	8	55,35	7-1-2-3-13-5-17-18-8-9-10-12-11-19-15-16-4-0-6-14
193.428	1	6	72,75	2-4-3-0-1-19-18-8-5-14-13-11-10-6-9-16-17-7-12-15
194.071	1	8	38,75	2-4-3-1-13-14-18-7-5-19-8-10-17-11-15-0-9-6-12-16
193.484	1	6	70,75	2-4-3-7-1-19-18-8-5-14-10-17-11-15-13-0-9-6-12-16
192.952	1	8	40,75	2-4-3-13-1-14-18-6-5-19-17-11-15-7-0-10-9-8-12-16
193.974	1	8	40,25	2-4-3-13-1-14-18-8-5-19-10-17-11-0-6-9-16-7-12-15
194.610	1	7	43,25	2-4-3-13-1-8-19-18-5-14-17-11-15-7-0-10-9-6-12-16
195.382	1	6	63,25	2-4-3-10-1-19-18-8-5-14-13-11-0-6-9-16-17-7-12-15
192.525	1	8	67,75	7-1-0-9-2-5-14-18-8-3-13-4-12-10-11-19-15-16-6-17
193.166	1	8	44,25	7-1-0-18-13-4-2-14-8-3-5-10-19-15-16-17-9-11-6-12
192.331	1	8	59,75	7-1-0-5-13-9-2-14-8-3-6-10-18-19-15-16-17-4-11-12
193.280	1	**8**	**51,25**	**7-1-0-4-13-9-2-18-8-3-6-10-14-19-15-16-17-5-11-12**
193.284	1	8	42,1	7-1-0-4-17-9-14-18-8-3-13-2-10-19-15-16-5-11-6-12
192.624	1	8	58,75	7-1-0-5-13-9-2-18-8-3-10-14-19-15-16-17-4-11-6-12
192.679	1	8	47,5	7-1-0-5-17-9-14-18-8-3-10-2-19-15-16-13-4-11-6-12
270.926	1	**6**	**54,75**	**10-2-3-19-1-8-5-15-14-16-7-0-13-9-18-11-17-4-12-6**
349.006	1	8	33,25	15-1-2-18-17-4-8-9-14-5-7-3-6-13-0-19-11-10-12-16
193.127	1	7	96,35	7-1-2-3-6-5-4-18-8-9-14-13-15-19-0-11-10-17-12-16
193.127	1	5	110,6	0-3-7-4-1-17-10-16-8-9-2-18-19-14-5-11-15-6-12-13
195.848	1	6	61,75	2-3-1-19-17-15-14-9-8-5-4-13-18-11-10-0-6-7-12-16
195.818	1	8	35,75	2-3-1-18-17-15-14-9-8-5-0-7-19-10-16-11-4-6-12-13
194.987	1	**8**	**37,75**	**2-3-1-18-17-4-14-7-8-5-11-19-13-15-10-0-6-9-12-16**
194.563	1	8	35,25	2-3-1-18-17-4-14-9-8-5-13-15-19-11-10-0-6-7-12-16
200.867	1	7	42,25	2-3-11-19-17-4-14-9-8-5-13-15-18-1-10-0-6-7-12-16
200.210	1	**8**	**35,25**	**2-3-8-18-17-4-11-9-14-5-0-7-19-1-10-16-13-15-6-12**
193.617	1	5	102,1	0-3-7-10-1-17-19-16-8-9-2-11-18-4-14-5-13-15-6-12
193.771	1	5	88,1	0-3-7-19-1-17-10-16-8-9-2-11-18-4-14-5-15-6-12-13
199.600	1	8	35,25	2-3-11-18-17-4-14-9-8-5-13-15-19-1-10-0-6-7-12-16
251.135	1	8	34,25	1-18-2-17-15-4-3-14-8-5-7-0-19-6-9-13-16-11-10-12
193.452	1	8	51,25	7-1-2-3-13-4-14-6-8-9-18-10-5-11-15-19-17-0-12-16
194.418	1	5	86,6	0-3-14-7-19-17-10-16-15-9-1-2-6-4-11-5-8-12-13-18
334.684	1	8	33,25	1-12-2-18-15-9-14-17-8-5-3-4-10-19-7-0-11-6-16-13

Table 5.30 A non-dominated solutions according to a tenth configuration (continued)

Values of Objective Functions				**Order of relief suppliers as a result of NSGA-II**
1	**2**	**3**	**4**	
199.592	1	8	33,25	1-4-2-18-15-9-14-17-8-5-3-7-0-19-11-12-6-10-16-13
190.040	**1**	**7**	**107,25**	**0-1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19**

Same process is conducted just as former configurations. The results of the *k*-means algorithm show that four solutions can represent the other solutions at an average silhouette value of 97%. These final solutions are represented in bold in Table 32. Radar and line diagrams including the normalized values of each solution selected by the *k*-means algorithm are given in Figures 5.27 and 5.28, respectively. As can be seen, solution of proposed model locates in set of Pareto optimal solutions. Proposed model is represented in red in Table 5.30.



	F1	F2	F3	F4
M1	193.280	1	8	51,25
M2	270.926	1	6	54,75
M3	194.987	1	8	37,75
M4	200.210	1	8	35,25
PROPOSED	**190.040**	**1**	**7**	**107,25**

Note: *'**M**' is representetive of solutions as a result of k-means algorithm*

Figure 5.27 Radar diagram of the final solutions with normalized F values. (Host government assistance rate = 95% and number of relief supplier=8)

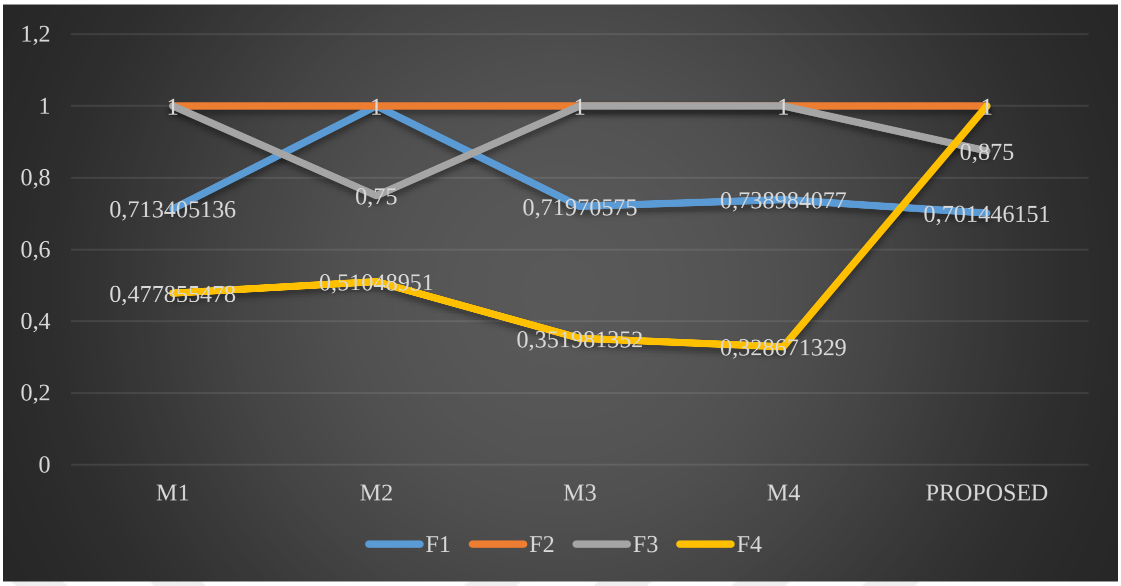


Figure 5.28 Line diagram of the final solutions with normalized F values. (Host government assistance rate = 95% and number of relief supplier=8)

(3) Finally, it is adjusted the degree of urgency and then the degree of inventory risk, respectively, in order to observe its effects over the values of the objective function of proposed model. Both parameter values are changed (-0,2, -0,1, 0,1, 0,2) one by one. First, the degree of urgency value is changed under the determined circumstance, whereas the degree of inventory risk value is constant. Then same configurations are applied to the degree of inventory risk value. Table 5.31 gives us rate of change over the values of objective functions under these scenarios.

Table 5.31 The ROC on degree of urgency value and degree of inventory risk value over the values of objective functions under the scenarios.

		Adjustment			
Proposed model	**Objective function**	**-0,2**	**-0,1**	**0,1**	**0,2**
Degree of urgency value (ROC%)	1	7,4	4,5	5,6	16,2
	2	0	0	0	0
	3	0	0	0	0
	4	0	0	0	0
Degree of inventory risk value (ROC%)	1	8,7	4,7	**23**	**41**
	2	0	0	0	0
	3	0	0	0	0
	4	0	0	0	0

When we analyze the effects of the rate of changes (degree of urgency value and degree of inventory risk value) over values of objective functions after applying NSGA-II, certain non-sorting solutions could not be in the set of Pareto optimal solutions upon adjusting both the value of degree of urgency alongside the degree of inventory risk because of the NSGA-II. The main reason behind this circumstance is that some of the Pareto optimal solutions determined are dominated by other solutions (especially for first objective function).

The value of first objective function with the positive adjustments of degree of urgency are greater than those in proposed model, and this gap is not significant to evaluate because the values of rate of change are less than 20%. In the contrary of this, the value of objective function with the negative adjustment is not much smaller than that in the proposed model.

The value of first objective function with the positive adjustments of degree of inventory risk is much greater than that in proposed model which is larger than **20%**, with regard to the value of objective function with the negative adjustment, and in which is not much smaller than that of proposed model. This gap is not significant to evaluate, because values of rate of change are less than 20%.

5.3.4 Results

For the first scenario, all values of objective functions were observed under determined circumstance all the while a rate of government assistance changed. As government assistance rate increases, the value of first objective function decreased at the same time. It was also observed that value of proposed model and minimum value of set of Pareto optimal solutions were the same. As for second objective function, if it is wanted to cover all of the requirements of demand side for the Anatolian side of Istanbul, the government assistance rate is equal to at least 83% under the determined data, or else it might give rise to increase death toll as well as to secondary damages. When one looks into the values of proposed model and maximum value of set of Pareto optimal solution, one sees that both values are the same just as first objective function. For the third objective function, as the government assistance rate increases, the number of relief suppliers selected decreases at the same time. Unlike former objective function's solutions, there are different values between the proposed model and the minimum value of set of Pareto optimal solution in terms of the number of relief suppliers if government assistance rate is over the 83%. Finally, when the last objective function is evaluated, all of the relief suppliers are selected as a joint facility location in the event that government assistance rate is equal or under 83%. Thus, the distance between suppliers is equal to zero. As the government assistance rate increases, so does the distance between the suppliers as well. There are different values between the proposed model and minimum value of set of Pareto optimal solution in terms of the distances between the relief suppliers selected as a joint facility location and other candidate suppliers provided that the government assistance rate is over 83%.

For the second scenario, 10 configurations are tested using NSGA-II. It is observed that if the F value, that is, the suppliers selected as a joint facility location, is equal to 15 or 20, the solution of our proposed model is not in the Pareto optimal frontier. But, when F value is equal to 8 (only highly collative groups are selected), it is seen that solution of our proposed model is in the Pareto optimal frontier. This result shows that, rating relief suppliers in pre-disaster period ensures that one is able to select the most appropriate supplier both during and following a large scale disaster. That is, solutions of grouped model in accordance with proposed model are more optimal than ungrouped models. The elimination of inappropriate relief suppliers during the pre-disaster period may ensure to mitigate the possibility of an imbalance in supplies distribution as well as a waste of supplies and therefore of coordination cost, which is related to relief suppliers.

As for the final scenario, according to results mentioned in the scenario analysis, in order to mitigate the degree of the inventory risk, one needs to locate sufficient facility places in order to store relief resources adequately, hence meaning that it is an alleviated impact of the imbalance of relief resources distribution.

6. CONCLUSION

Turkey has faced many a large-scale natural disaster due to is terrain structure, climatic characteristics, as well as geological structure, and thus has learned many bitter lessons from those disasters Natural as well as man-made disasters both have an impact over the social and economic structure of countries...

In this sense, encouraging a culture of risk prevention, mitigation, and management in the society, using modern devices for struggling against disasters, and expanding cooperation not only on a local scale but also regional even global scale is incredibly important in order to mitigate the destructive effects of disasters.

When we analyze disasters from the beginning of the 20th Century up to now, we see that most domestic relief suppliers distribute resources to affected area without any cooperation with the host government, which thus leads to the imbalance in the distribution of relief supplies. A sufficient number of relief suppliers should be chosen in order to improve coordination with host government in an effective manner, as well as in order to mitigate the total cost, including both the cost of investment and of transportation. This study proposes a novel approach to relief supply collaboration that mitigates supply-demand imbalance in humanitarian logistical activities, and that fulfills needs of affected area in a timely manner in the aftermath of large-scale disasters.

The main contributions of this study are comprised of four main phases. First, it presents a determination of criteria process in order to identify candidate relief suppliers during the pre-disaster period. For this purpose, the Interpretive Structural Modeling (ISM) was used to identify and rank the criteria as well as find the interactions among them. Among fifteen criteria determined through both a literature review and through face-to-face surveys with experts, seven were found to be more important and more effective than the others. These criteria include geographic positioning, collaboration attributes, the use of information technology tools, data accuracy, evaluation and certification systems, resource and information sharing, and trust development.

Second, we used the Analytic Network Process (ANP) to determine the weights of the criteria selected by the ISM method, whereupon we then evaluated the candidate suppliers and ranked them in terms of these determined criteria using the Rating technique. Rating can enable the host government to form a clustering mechanism including potential relief suppliers. As a result of this mechanism, inappropriate domestic relief suppliers are eliminated according to determined weighted criteria. This process may lead to a reduce in cost for coordination-related management, and moreover, may eliminate the inappropriate distribution of relief resources to casualties.

Finally, in this study, a multi-objective optimization model was used to optimize four objective functions minimizing the impact of an undersupply or oversupply to the affected area, thus maximizing coverage rate of the remaining demand after it has been supplied by government, and thus minimizing the number of Joint facility locations as well as the distances between suppliers who are chosen as a joint facility location and other relief suppliers who are not. We solved the model using the NSGA-II (Deb et al., 2000) and obtained a set of Pareto optimal solutions. We then reduced the number of candidate solutions in the Pareto optimal set are reduced by applying the *k*-means clustering algorithm so as to obtain the representative solutions.

Most of the former studies related to humanitarian logistics activities mainly concentrate on the issue of facility location, resource allocation, and relief distribution. Only one study discusses relief supply collaboration (Sheu & Pan, 2016) in the literature. This is the first study whereby ISM, ANP, and NSGA-II have applied together. Another of the other distinctive feature of this thesis is our comparing the results of multi criteria decision-making algorithm with results of multi-objective optimization algorithm using NSGA-II.

As a result of the numerical results of case study, several important questions have been answered: How many relief suppliers ought to be chosen among the candidate relief suppliers in the mitigation period? What is the optimal sequence of relief suppliers if they are selected as a joint facility location? What should be the coverage rate of government under determined circumstance if any large-scale earthquake occurs on the Anatolian side of Istanbul? Not only do these questions encourage the government to provide resources to relief supplier, but they also question the current capability in terms of relief resources, and thus evoke one to engage in relief supply planning.

In this respect, in this study, we tested various scenarios of the proposed model, as well as addressed some of the important outcomes. For instance, when the host government collaborates with only highly collaborative relief suppliers under determined circumstances, our proposed model’s solution locates the Pareto optimal frontiers as a result of the NSGA-II. Thus, the government should determine and select the most appropriate relief suppliers such as joint facility location during pre-disaster period in order to ensure sufficient inventory levels, thus fulfilling the needs of those affected at a minimum cost.

There is still great potential to develop performance of our proposed model approach. The proposed model should be used for humanitarian logistics activities, and could be used as a decision support tool for emergency logistics operations as well. This study underlines a number of points that may be valuable for further research.

First, future research should take into consideration other key criteria for selecting the most appropriate relief suppliers in order to collaborate for humanitarian logistics activities. In addition, the criteria selected through ISM and weighted using ANP should correlate with objective functions. In this study, for example, the resource size among the pool of criteria is eliminated upon using ISM, however this criterion is directly correlated with objective functions.

Second, this study mainly focuses on a certain number and kind of relief suppliers. Future studies may also expand number and diversity of candidate relief suppliers in order determine who the most suitable suppliers are.

Third, in this study, it is deemed that the relief feed rate of the candidate relief suppliers conforms to normal distribution. In fact, the relief feed rate can vary depending on the magnitude, type as well as time (winter or summer time, night or day time) of disasters or traits of the potential relief suppliers. Thus, further studies may concentrate on the relief feed rate in order to expedite responses to disasters of various types and magnitudes.

Fourth, the proposed study is a pilot study for the Anatolian side of Istanbul. Future studies could extend to include all regions across Turkey.

Finally, the focus of this study was selecting the most appropriate relief suppliers under determined circumstances. This study does not investigate resource allocation inefficiency resulting from a lack of relief supply collaboration. Further research could potentially improve joint and combined allocation, as well as could improve the distribution mechanism considering distances in order to enhance the efficiency level of emergency logistics as part of relief supply collaboration.

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APPENDIX

Appendix 1 Resource capacity of candidate relief suppliers in phase of disasters

	Supplier 1		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
$\mathbf{r_1}$:non-consumable commodities (kg.)	50.000	75.000	65.000
$\mathbf{r_2}$:consumable commodities (kg.)	150.000	250.000	100.000
	Supplier 2		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
$\mathbf{r_1}$:non-consumable commodities (kg.)	45.000	65.000	35.000
$\mathbf{r_2}$:consumable commodities (kg.)	150.000	230.000	125.000
	Supplier 3		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
$\mathbf{r_1}$:non-consumable commodities (kg.)	22.500	34.000	42.000
$\mathbf{r_2}$:consumable commodities (kg.)	175.000	275.000	153.000
	Supplier 4		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
$\mathbf{r_1}$:non-consumable commodities (kg.)	27.500	43.000	18.300
$\mathbf{r_2}$:consumable commodities (kg.)	182.000	225.000	178.000
	Supplier 5		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
$\mathbf{r_1}$:non-consumable commodities (kg.)	18.500	32.000	26.790
$\mathbf{r_2}$:consumable commodities (kg.)	120.000	165.000	98.000

	Supplier 6		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r$_1$:non-consumable commodities (kg.)	8.500	12.500	9.800
r$_2$:consumable commodities (kg.)	55.000	75.000	28.900

	Supplier 7		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r$_1$:non-consumable commodities (kg.)	12.500	14.700	11.890
r$_2$:consumable commodities (kg.)	125.000	138.000	125.000

	Supplier 8		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r$_1$:non-consumable commodities (kg.)	17.000	32.000	14.300
r$_2$:consumable commodities (kg.)	150.000	175.900	123.000

	Supplier 9		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r$_1$:non-consumable commodities (kg.)	22.500	27.600	17.500
r$_2$:consumable commodities (kg.)	45.000	54.000	22.000

	Supplier 10		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r$_1$:non-consumable commodities (kg.)	16.000	13.050	12.000
r$_2$:consumable commodities (kg.)	32.000	54.000	27.500

	Supplier 11		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r$_1$:non-consumable commodities (kg.)	11.500	22.300	16.500
r$_2$:consumable commodities (kg.)	37.000	54.900	38.050

	Supplier 12		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r_1:non-consumable commodities (kg.)	100.000		
r_2:consumable commodities (kg.)	10.000	13.500	8.500

	Supplier 13		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r_1:non-consumable commodities (kg.)	25.000	54.000	38.000
r_2:consumable commodities (kg.)	150.000	230.000	78.000

	Supplier 14		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r_1:non-consumable commodities (kg.)	34.000	54.000	27.000
r_2:consumable commodities (kg.)	68.500	112.000	78.500

	Supplier 15		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r_1:non-consumable commodities (kg.)	18.000	56.000	17.600
r_2:consumable commodities (kg.)	39.000	112.000	56.000

	Supplier 16		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r_1:non-consumable commodities (kg.)	23.000	48.000	23.000
r_2:consumable commodities (kg.)	78.000	132.000	78.500

	Supplier 17		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r_1:non-consumable commodities (kg.)	43.000	75.000	65.000
r_2:consumable commodities (kg.)	83.000	112.300	54.000

	Supplier 18		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r$_1$:non-consumable commodities (kg.)	23.000	54.700	28.900
r$_2$:consumable commodities (kg.)	42.000	117.000	65.000
	Supplier 19		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r$_1$:non-consumable commodities (kg.)	34.000	68.000	23.400
r$_2$:consumable commodities (kg.)	28.000	87.000	43.500
	Highly Supplier 20		
	Phase of disaster (p)		
R:Set of relief resources	p_1	p_2	p_3
r$_1$:non-consumable commodities (kg.)	54.000	23.000	43.000
r$_2$:consumable commodities (kg.)	23.000	58.000	34.000

Appendix 2 Distances between the potential relief suppliers (km.)

Number	Suppliers	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Carrefoursa Shopping Mall		10	2,5	11,5	7,3	1,6	3	21,6	27	8,7	8,2	10	6,5	13	28	18	3	10	19	19
2	Maltepe Park Shopping Mall			10	19	15,5	10,5	11	13	17	17	16	3,5	14,5	21	16	18	14	19	15	13,5
3	Metro Shopping Mall				8	6,5	1		4,5	27	8	7,6	10,5	5,5	12,5	27	20	0,75	10	18	19
4	Buyaka Shopping Mall					14	9	10	30	28	10	6	18	12	8	29	13	11	6	20	20
5	Tepe Nautilus Shopping Mall						8	11	29	40	7	15	17	3,5	21	41	26	7	16	25	25
6	Palladium Shopping Mall							4	23	25	10	6	11	6	13	26	22	2	8,5	17	18
7	Brandium Shopping Mall								26	21	11,5	3	10	10	8	22	12	6,5	5	14	13
8	Neomarin Shopping Mall									13	30	23	15	26	36	12	27	24	25	20	21
9	Via/Port Outlet Shopping Mall										30	20	28	31	28	3	22	31	28	9	12
10	Capitol Shopping Mall											12	21	6	14	31	20	7	15	22	24
11	Real Shopping Mall												13	13	5	21	10	9	3	12	11
12	Cevahir Hotel													16	24	25	21	13	21	17	16
13	Akasya Shopping Mall														18	31	23	4	18	22	23
14	Beşyıldız Shopping Mall															28	7	14	3	13	12
15	World Atlantis Shopping Mall																22	28	27	8	9
16	Kardiyum Shopping Mall																	21	8	11	9
17	Optimum Outlet Shopping Mall																		14	18	17
18	Asyapark Outlet Shopping Mall																			11	10
19	Plato Shopping Mall																				2
20	Rings Shopping Mall																				

Appendix 3 Population of Anatolian side according to last census in 2016.

Population of Anatolian side of Istanbul by district					
Year of Census	**District**	**Total population**	**Men**	**Women**	**Rate**
2016	Ümraniye	694.158	348.788	345.370	4,69%
2016	Pendik	691.681	350.782	340.899	4,67%
2016	Üsküdar	535.537	262.390	273.147	3,62%
2016	Maltepe	490.151	241.411	248.740	3,31%
2016	Kartal	459.298	228.304	230.994	3,10%
2016	Kadıköy	452.302	204.382	247.920	3,06%
2016	Ataşehir	422.513	208.267	214.246	2,85%
2016	Sancaktepe	377.047	192.982	184.065	2,55%
2016	Sultanbeyli	324.709	167.194	157.515	2,19%
2016	Beykoz	250.410	124.209	126.201	1,69%
2016	Tuzla	242.232	123.941	118.291	1,64%
2016	Çekmeköy	239.611	120.826	118.785	1,62%
2016	Şile	34.241	17.595	16.646	0,23%
2016	Adalar	14.478	7.420	7.058	0,10%

Appendix 4 Distribution of building by district in Anatolian side (TUIK, 2000)

Building distribution district by district in Anatolian side					
Year	**District**	**Total population**	**Number of building**	**Building density**	**Total field**
2000	Ümraniye	443.350	43.480	10	4.560
2000	Pendik	372.550	39.880	8	4.730
2000	Üsküdar	496.405	43.023	11	3.780
2000	Maltepe	345.665	25.321	5	5.535
2000	Kartal	332.095	24.305	8	3.135
2000	Kadıköy	660.623	38.615	9	4.129
2000	Ataşehir	-	-	-	-
2000	Sancaktepe	-	-	-	-
2000	Sultanbeyli	-	-	-	-
2000	Beykoz	182.875	28.282	7	4.158
2000	Tuzla	100.611	14.727	3	4.997
2000	Çekmeköy	-	-	-	-
2000	Şile	-	-	-	-
2000	Adalar	17.738	6.518	6	1.100

Appendix 5 Construction's year of building by district in Anatolian side (TUIK, 2000)

District	Year of construction						Ratio of contruction by year					
	Before 1949	1950-1959	1960-1969	1970-1979	1980-1989	1990 and after	Before 1949	1950-1959	1960-1969	1970-1979	1980-1989	1990 and after
Ümraniye	67	185	963	4.897	13.280	23.205	0,20	0,40	2,30	11,50	31,20	54,50
Pendik	198	395	1.796	5.168	14.176	17.750	0,50	1,00	4,50	13,10	35,90	45,00
Üsküdar	2.095	1.275	3.560	9.530	12.336	13.700	4,94	3,00	8,40	22,40	29,00	32,20
Maltepe	160	285	1.650	4.905	9.030	9.070	0,60	1,10	6,60	19,50	36,00	36,20
Kartal	206	406	2.054	5.875	9.387	6.255	0,80	1,70	8,50	24,30	38,80	25,90
Kadıköy	1.143	1.460	4.253	11.738	11.888	7.660	3,00	3,80	11,10	30,80	31,20	20,10
Ataşehir	–	–	–	–	–	–	–	–	–	–	–	–
Sancaktepe	–	–	–	–	–	–	–	–	–	–	–	–
Sultanbeyli	–	–	–	–	–	–	–	–	–	–	–	–
Beykoz	1.171	758	2.729	7.152	11.065	4.985	4,20	2,70	9,80	25,70	39,70	17,90
Tuzla	185	142	390	1.584	4.608	7.590	1,30	1,00	2,70	10,90	31,80	52,40
Çekmeköy	–	–	–	–	–	–	–	–	–	–	–	–
Şile	–	–	–	–	–	–	–	–	–	–	–	–
Adalar	1.912	720	850	970	1.187	815	29,70	11,20	13,10	15,00	18,40	12,60

Appendix 6 Quantity of buildings according to storey's number by district in Anatolian side (TUIK, 2000)

District	Number of storey/Number of building				Ratio of building according to number of storey			
	1-3	**4-7**	**8-15**	**above 16**	**1-3**	**4-7**	**8-15**	**above 16**
Ümraniye	30.526	12.510	306	29	70,40	28,80	0,70	0,10
Pendik	27.615	11.550	560	2	69,50	29,10	1,40	0,00
Üsküdar	24.115	18.294	370	0	56,40	42,80	0,90	0,00
Maltepe	14.318	10.090	780	8	56,80	40,00	3,10	0,00
Kartal	13.981	9.018	1.226	15	57,70	37,20	5,10	0,10
Kadıköy	16.136	17.065	4.965	195	42,10	44,50	12,90	0,50
Ataşehir	_	_	_	_	_	_	_	_
Sancaktepe	_	_	_	_	_	_	_	_
Sultanbeyli	_	_	_	_	_	_	_	_
Beykoz	25.038	2.735	67	0	89,90	9,80	0,20	0,00
Tuzla	10.925	3.710	40	8	74,40	25,30	0,30	0,00
Çekmeköy	_	_	_	_	_	_	_	_
Şile	_	_	_	_	_	_	_	_
Adalar	5.295	1.216	0	0	81,30	18,70	0,00	0,00

BIOGRAPHY

Eren SALLI was born in 1982 in Muğla, Turkey. He graduated from Kuleli Military High School in 2000, whereupon his undergraduate and graduate studies in Engineering and Business Administration at the Turkish Military Academy and Gaziantep University continued in 2004 and 2009. He is currently working on his doctorate studies at Doğuş University.