USE OF UNMANNED AERIAL VEHICLES FOR POST-DISASTER RESPONSE

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ETHICAL DECLARATION

I hereby declare that I am the sole author of this thesis and that I have conducted my work in accordance with academic rules and ethical behaviour at every stage from the planning of the thesis to its defence. I confirm that I have cited all ideas, information and findings that are not specific to my study, as required by the code of ethical behaviour, and that all statements not cited are my own.

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ABSTRACT

USE OF UNMANNED AERIAL VEHICLES
FOR POST-DISASTER RESPONSE

KARA, MERT

Master's Program in Industrial Engineering

Advisor: Prof. Dr. Selin ÖZPEYNİRCİ

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Each year, many people lose their lives or properties as a result of natural disasters such as earthquakes, floods, and wildfires occurring around the world. In recent years, particularly in residential areas, the increasing frequency of earthquakes and floods has drawn attention due to the urgency of response operations immediately after such disasters strike. In many cases, geological structures in affected areas lead to the collapse or submersion of bridges and highways, rendering ground transportation impossible. Consequently, operations are often restricted to limited air and sea access. With the advancement of technology, drone systems—whose use and significance in daily life continue to grow—have emerged as one of the most effective tools for delivering first aid in disaster zones with restricted access. These systems offer low operational costs, high payload capacities, and the ability to perform a variety of aerial missions. This study aims to address a package delivery problem in which aid packages containing essential supplies and first aid materials are air-dropped via drones into areas where all transportation routes are blocked, during the time before ground-based teams can access the region. The model is applied to the context of the Istanbul earthquake, which is anticipated to occur in the near future by national and international authorities. A scheduling model involving multiple depots and multiple drones is developed, aiming to minimize the total weighted delivery time. To solve the problem, a mathematical model is formulated, and the Variable Neighborhood Search (VNS) metaheuristic is applied.

Keywords: Drone Package Delivery, Post-Disaster Response, Variable Neighborhood Search, Unmanned Aerial Vehicles.

ÖZET

AFET SONRASI MÜDAHALE İÇİN
İNSANSIZ HAVA ARAÇLARININ KULLANIMI

KARA, MERT

Endüstri Mühendisliği Yüksek Lisans Programı

Tez Danışmanı: Prof. Dr. Selin ÖZPEYNİRCİ

Haziran, 2025

Dünya'da her yıl meydana gelen deprem, sel ve yangın gibi doğal afetlerin sonucunda birçok insan hayatını veya mal varlığını kaybetmektedir. Son yıllarda meydana gelme sıklığı ile dikkat çeken deprem ve sel felaketleri, yerleşim alanlarında gerçekleştiği andan itibaren ilgili alanlarda yardım ve müdahale için zamana karşı yarışın başladığı gözlemlenmektedir. Deprem veya sel yaşanan alanların jeolojik yapılarına bakıldığı zaman, bazı durumlarda köprü ve otoyolların yıkılarak kapanması veya su altında kalması sonucunda karadan ulaşımın imkansızlaştığı, havadan ve denizden ise kısıtlı imkanlar ile operasyon icra edilebildiği dikkatleri çekmiştir. Gelişen teknoloji ile her gün biraz daha gündelik hayatta kullanımı ve önemi artan insansız hava araçları, düşük operasyonel maliyetleri, yüksek yük taşıyabilme kapasiteleri ve çeşitli görevlere yönelik havadan yürütmekte oldukları operasyonlar ile afet sonrası ulaşımın sınırlı olduğu alanlarda ilk yardım müdahaleleri için en etkili araçlardan biri konumundadır. Bu çalışmada, afet sonrası tüm ulaşımın kapandığı alanlarda yardım ekiplerin karadan ulaşım sağlayabileceği zamana kadar geçecek sürede hayatta kalan afetzedelere temel erzak ve ilkyardım malzemelerini içeren yardım paketlerinin insansız hava araçları ile yukarıdan atılarak, afetzedelerin hayatta kalmalarının sağlanması amaçlanan bir paket dağıtımı problemi ele alınmış olup, ulusal/uluslararası resmi kuruluşların önümüzdeki kısa dönem içerisinde olmasını öngördüğü İstanbul depremi için uygulanmıştır. Paket dağıtımı için çoklu depo ve çoklu insansız hava araçları kullanılan çizelgeleme çalışmasında, toplam ağırlık sürenin enazlanması için bir matematiksel model geliştirilmiş ve değişken komşuluk arama yöntemi kullanılmıştır.

Anahtar Kelimeler: Drone ile Paket Teslimatı, Afet Sonrası Müdahale, Değişken Komşuluk Arama, İnsansız Hava Araçları

To my family…

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CHAPTER 1: INTRODUCTION

In this chapter, starting with the motivation of the study, the usage areas of drones, the type of problem addressed, and the purpose of this study are explained. The chapter concludes with the general structure of the thesis.

In the world and in our country, residential areas are seriously damaged by the natural disasters that have occurred from past to present and continue to be experienced today. As a result of this damage, people lose their lives and suffer loss of property. Especially the effects of earthquakes, which are frequently experienced all over the world, pose a serious threat to humanity. The geography where the earthquake occurs, its proximity to the earth and its magnitude determines the size of the destructive effect. As a result of two earthquakes of magnitude 7.8 and 7.5 that occurred on the same day in Kahramanmaraş, Türkiye in 2023, the effects of natural disasters on humanity were once again strikingly demonstrated. Therefore, it is of vital importance for the surviving disaster victims to start search & rescue and first aid operations as soon as possible after the earthquakes occur. Considering the geological conditions of the areas where natural disasters occur, it has been observed that bridges, and roads have collapsed, also buildings have collapsed on the roads, therefore, transportation by land vehicles has become impossible, and operational activities are carried out by air and sea with very limited means. Drones, which are one of the most important vehicles of today's developing technology, come to the forefront at the point of delivering the fastest aid to the disaster victims under such difficult conditions.

It is observed that drones, which continue to develop every day with the developing technology and are one of the most important products of technology, are increasingly being used in daily life with their low operational costs, high load carrying capacity and the tasks they can carry out from the air for various missions, from intelligence in the military field to cargo and ammunition transport, agriculture, archaeology, fisheries, media and many other fields. In particular, the acceleration of the work of states and leading companies in the field for drone activities shows the level of success in the use of drones in various tasks. When the developments on drones in the global and in our country are examined, the news published by TRT, the official television organisation of the Republic of Turkey in 2021 about the General Directorate of Civil Aviation's work on cargo transport with drones between Istanbul - Eskisehir – Ankara (Youtube, 2022a), and the news of the leading media outlets about the cargo drones delivered to the Turkish Armed Forces in 2022 (Youtube, 2022b; Youtube, 2025), revealed that the states have been working on the use of drones on the military and civilian side for many years. On the other hand, when the studies carried out by leading companies in the field are examined, in 2022, the world's online shopping giant Amazon Prime Air started cargo transport (Youtube, 2016; Youtube, 2024), and in the following years, several companies from the leading catering and cargo companies in Turkey have started trial flights for food and cargo distribution by selecting pilot regions (Youtube, 2022c; Youtube 2022d). As of 2025, companies carrying out this operation and trials aim to deliver food orders and cargo to homes with drones. To successfully carry out all these operations with drones of various capabilities and sizes under different constraints and parameters without delay, a good scheduling and optimization is needed.

In this thesis, we model the problem as a parallel resources scheduling problem, where the drones represent the parallel resources and each delivery operation corresponds to a job, aligning with the classical definition in scheduling literature where resources perform tasks. This problem emerged with the development of technology, with the simultaneous distribution of packages from m different warehouses to n different demand points. The need for an effective scheduling approach arises from the requirement to optimally and simultaneously distribute multiple packages from warehouses to demand points. When the emergence and development of scheduling studies over the years are examined, it is observed that scheduling emerged as a scientific discipline in the 1950s, coinciding with the continued growth of industrial development, and has since been systematically studied and advanced. The early studies such as Jackson (1955) on minimizing the maximum delay on a single machine, Smith (1956) on minimizing the weighted completion time, and Johnson (1954) on production scheduling in two-machine flow type, expanded their scope with the growth of the industry. In line with the structure of simultaneous package deliveries by multiple drones to multiple demand points, this study addresses a parallel machine scheduling problem. The parallel machine scheduling problem, which aims to execute the process by assigning multiple jobs to the appropriate machines according to constraints so that they can be done simultaneously, is shown to be NP-hard Lenstra et al. (1977). Due to the difficulty of the problem, meta-heuristics such as Variable Neighborhood Search (VNS), Simulated Annealing (SA), Tabu Search (TS) have been developed over the years.

The aim of this thesis is to develop a solution methodology for the use of drones to deliver packages—assumed to be readily available at depots—containing basic supplies such as health kits, blankets, biscuits and water that can be used in first aid interventions so that disaster victims can survive until the arrival of aid teams. We consider the possible Istanbul earthquake as a real-life example, which is predicted to occur in the near future with a magnitude of 7.5 by national/international official organizations such as Kandilli Observatory, Earthquake Research Institute, and expert earthquake professors in the field. When the literature is examined, it is seen that there are very few studies that are formulated as parallel machine scheduling by using multiple warehouses and multiple drones together, and use Variable Neighborhood Search, which is a meta-heuristic method to get a fast and near-optimal solution by defining sub-neighborhoods and comparing the results. In this thesis, we contribute to the literature by establishing our model with a parallel machine scheduling approach and providing a solution to minimize the total weighted delivery time with the VNS approach we have developed. We also generate problem instances from considering the possible warehouse and demand locations in İstanbul and carry out computational experiments with different parameter levels. The proposed approach represents the most comprehensive academic work focused on drone-based emergency logistics for a potential Istanbul earthquake. The study contributes to disaster logistics literature by combining realistic UAV scheduling, official data, and geographic prioritization, offering a practical solution. In addition, the study, which is the first study to offer a solution to a predicted earthquake with real data produced by official institutions, contributes to the literature by being the first study to address package delivery scheduling with drones for the Istanbul earthquake in such a comprehensive manner.

The following chapters of the thesis include literature review, methodology, the case of Istanbul in post-disaster response, computational experiments and conclusion. In Chapter 2, the use of drones in natural disasters, the hybrid use of drones with other vehicles such as trucks, the use of drones among themselves, and studies in the literature using the VNS method are reviewed. Chapter 3 introduces the general problem definition, followed by a detailed presentation of the proposed scheduling model, VNS framework and related neighborhood structures. Chapter 4 focuses on the case study of Istanbul, illustrating how drone-based post-disaster response—introduced in the previous chapter—is applied to this specific context. It also explains how the input data for the solution methods are obtained, and presents maps and descriptions of the areas and districts expected to be affected by the anticipated earthquake. The computational experiments section in Chapter 5 shows how these methods in the methodology are implemented, the calculations performed, and the corresponding results obtained. The final part of the thesis, the conclusion in Chapter 6, discusses the overall thesis topic and outputs and suggests future research topics based on this thesis.

CHAPTER 2: LITERATURE REVIEW

Looking at the literature, there are various research problems and approaches applying scheduling and heuristic algorithms to civilian side missions. In this chapter, we summarize some papers based on scheduling studies for various missions, especially Unmanned Aerial Vehicles (UAV)/drone mission scheduling.

2.1. Package Delivery with Drones

When examining the scenario in which a single drone delivers a package to a demand point and returns to the depot, it is observed that its formalization is largely similar to single-machine scheduling. As the number of drones, packages, or demand points increases in such studies, the drone-based delivery problem begins to be formalized similarly to parallel machine scheduling, eventually becoming NP-hard. In the literature, various modeling approaches, heuristic, and metaheuristic algorithms have been developed to solve NP-hard problems, with the goal of obtaining near-optimal solutions efficiently and in a short amount of time. Liu et al. (2021) aims to minimize the number of drones used in a warehouse where various packages have their own departure times, distances to the warehouse, and personalized deadlines. They proposed a mixed integer programming model for the NP-hard problem. Torabbeigi et al. (2021) proposed a delivery scheduling method to minimize the Expected Loss of Demand (ELOD) by considering drone failures and developed an optimization Drone and Delivery System Full (DDS-F) model to determine the delivery sequence. In their optimization model, they developed a binary integer programming model for path selection based on the Petal algorithm to reduce computation times and a Simulated Annealing (SA) heuristic algorithm including a local neighborhood search algorithm to find better solutions, and their proposed approach produced exact solutions for the case studied in the paper. Saleu et al. (2018) proposed and developed an iterative two-step heuristic approach to minimize completion time. For the usage of drones in urban logistics. In their study, Yilmazer et al. (2021) proposed a solution to the problem with the traveling salesman method by considering the operation of a warehouse and a drone. In the study, a drone takes off from the warehouse after being loaded with a maximum of 3 packages and delivers the cargo to each customer by scanning the QR code by visiting three customers in turn. The biggest feature that distinguishes it from other package delivery studies is that instead of returning to the warehouse after making one delivery, a drone returns to the warehouse by making 3 deliveries using the most optimal route. Choi and Scohonfeld (2017) studied the optimization of a drone system developed for multiple deliveries directly by drones rather than truck-drone cooperation with battery capacities considered in comparison to package payloads and flight ranges. The model developed by the authors to optimize the multi-package delivery system with drones examined four variables: operating time, drone operating speed, demand intensity of the service area and battery capacity to show the sensitivity of system outputs to input parameters. Jung and Kim (2022) adopt a robust optimization considering the uncertainties of wind direction and speed with the objective of delivering cargo by drone to small islands far from the city center. By proposing and solving a model with complex integer programming, the authors also performed a cost analysis to support the use of drones for package delivery to remote islands and showed that the longer the drone-based delivery is operated, the more operating costs can be saved compared to the current practice.

2.2. Package Delivery with Drones and Trucks

There are studies in the literature where drones operate in coordination with various vehicles, such as trucks. When examining the different types of these scenarios, several studies can be found that explore various operational models: scenarios in which drones and trucks deliver packages simultaneously, cases where drones take off from one truck and land on another after completing deliveries in systems with multiple trucks, and scenarios where drones return to the same truck from after completing their deliveries. Additionally, there are studies that summarize these types of scenarios in detail along with their classifications İbroşka et al. (2023). When the existing literature is examined, Liu et al. (2018), focus on solving the drone delivery problem under sparse demand constraints and propose a solution approach using a combination of trucks and drones. They aim to minimize the comprehensive transportation cost, and the enumeration method and the two-stage method are used to solve the problem. Amico et al. (2020), in their paper, examined the parallel drone traveling salesman problem, and mixed integer programming with the aim of minimizing the total delivery time by examining the situation where drones, which are expected to deliver cargo and packages in cities in the future, deliver packages to customers in parallel with trucks. They presented heuristic methods and noted that they performed very well in small/common size problem instances. Huang et al. (2020) conducted a study in which drones, which are considered as one of the future package delivery methods, are used to deliver parcels with public transportation vehicles. Considering conditions such as delivery time and energy consumption, the authors used an exact algorithm based on dynamic programming to propose a solution to the problem and discussed computational complexities such as scheduling the earliest returning customer first. Finally, to demonstrate the scheduling performance to the reader, the authors perform computer simulations. Yuan et al. (2021) published a drone scheduling study for UAVs with heterogeneous fleet structure by considering different criteria such as loading capacity and maximum flight time. They formulated the model based on the traditional non-deterministic problem structure and then developed a genetic-based algorithm to solve the problem. Finally, the authors compare all the algorithms they have used and draw conclusions on the results. Peng et al. (2019) conducted a study involving the delivery of packages by drones, which represents the future of the logistics industry, in cooperation with vehicles. The authors utilized hybrid genetic algorithm in scheduling and routing studies, and unlike other studies, they conducted a study involving simultaneous cargo delivery to multiple customers with multiple drones carried by 1 vehicle at the same time, not 1 vehicle and 1 drone. As a result of the study, unlike previous studies, it was observed that efficiency increased significantly with the use of more than one drone. In their study, Murray and Chu (2015) presented heterogeneous fleet cargo delivery scheduling with drone-truck cooperation using a mixed integer linear programming method and 2 heuristic approaches. Compared to other studies, the authors proceed by considering many criteria, obtaining the solution and evaluating the results. In particular, they published a real-world integrated study that considers the limited payload capacity of UAVs, such as the fact that UAVs are limited to visit only one customer at a time, that UAVs are subject to maximum flight endurance, that UAVs can be separated and reconnected with a delivery truck multiple times along a route, and finally that some customer demands may be too heavy for the UAV.

2.3. Disaster Relief

Following their proven effectiveness in various missions over the years, drones are now frequently utilized in natural disasters. In operations such as damage assessment, sub-surface imaging using specialized cameras, and firefighting, drones are taking on critical roles. A review of the existing literature on such applications reveals several notable studies in this field. Chowdhurry et al. (2017) studied the transportation of emergency relief supplies by drones to demand points in an earthquake-affected region. The authors used the Continuous Approximation (CA) model to visualize and validate the modeling results and used 3 counties of Mississippi (Hancock, Harrison, and Jackson) on the disaster coast as a test region. The Disaster Centre (2016) presented that the disaster relief lifecycle can be divided into four main phases: prevention, preparedness, response and recovery. Drones have the potential to play an important role in all four phases, but studies have mainly focused on their use in the response phase. Rabta et al. (2018) proposed a mixed integer linear programming model for the transportation of light relief supplies (vaccines, water, etc.) by drones to the farthest points in the disaster area when transportation is closed and there is no ground transportation. Considering the load quantity and energy constraints while creating their model, the authors aimed to minimize the time/cost and extend the operating distance of the UAV by charging stations. After solving the model, they numerically demonstrated it with different scenarios. Estrada and Ndoma (2019) published a literature review on how effective the use of drones can be in the disaster area after an earthquake, flood, tsunami or any other natural disaster occurs. In their research, they generally focused on three points for the use of UAVs (or drones) in natural disaster response and humanitarian aid, namely (i) the aerial monitoring post-natural disaster damage evaluation, (ii) natural disaster logistics and cargo delivery, and (iii) the post-natural disaster aerial assessment. On the other hand, they propose a broad list of UAV applications such as military, commercial, natural disasters, health, construction, special uses, education, research, entertainment, sports, national security, logistics, firefighting, agriculture, geology, astronomy, meteorology and environment. Finally, it will highlight the existing and easy to distinguish difference between RC Aircraft, Quadcopters, Drones, Smart Platforms (SP) and Large UAVs (LUAVs) respectively.

2.4. The Use of The Variable Neighborhood Search (VNS) Method in Drone Scheduling

When the structure of various scheduling and optimization studies is examined, the development of metaheuristics and other heuristic methods has accelerated over the years since the solution cannot be obtained in acceptable times due to being NP-hard. These methods have been used more commonly by researchers' as they provide near-optimal solutions within an acceptable time. Variable Neighborhood Search method, which was developed by Mladenovic and Hansen (1997) and is one of the metaheuristics in the literature, produces effective results in the scheduling studies of drones emerging with today's developing technology due to its applicability to large solution space, its ability to perform wider searches by leaving local searches and its flexible structure that can be combined with other heuristic methods. In the literature, Lei and Chen (2022) studied a Parallel Drone Scheduling Travelling Salesman Problem (PDSTSP) in which trucks and drones work together in a hybrid manner to deliver cargo. They used an Iterated Variable Neighborhood Search algorithm (IVNS) to minimize the total completion time for all deliveries. First, they used a total of three algorithms, one Longest Processing Time (LPT) and two Reduced Variability Neighborhood Search (RVNS) algorithms to generate the initial solution. In the study, which continued with the application of the Shaking and IVNS algorithm, the authors conducted various experiments on 90 examples and found that 12 examples were the best solution in the literature. Li et al. (2020) examined the use of drones in logistics and developed a Mixed Integer Linear Program (MILP) model to optimize two objectives, customer satisfaction and total completion time, in the problem of multiple package delivery by multiple drones. In addition, they presented a special coding method within the VNS algorithm framework to be used in solving smaller scale problems. In their experimental results, they observed that the proposed algorithms were effective for the problem they addressed. El-Adle et al. (2023) studied the synchronized delivery of parcels to customers by a vehicle and a drone. A VNS heuristic method is proposed for TSP-D by aiming to minimize the return time to the warehouse in a Drone Travelling Salesman Problem (TSP-D) type study, where both vehicles take off and land at the same point. In their proposed algorithm, they developed the best available results in 113 out of 120 instances. On the other hand, they achieved 1% to 8% improvement in delivery times in customer studies with various locations. Nguyen et al. (2022) defined a new optimization problem called the minimum cost Parallel Drone Scheduling Vehicle Routing Problem (PDSVRP), which is a variant of the Parallel Drone Scheduling Travelling Salesman Problem (PDSTSP), which is a sub-method of the Vehicle Routing Problem (VRP) problem on the hybrid use of drones and trucks. In this problem, the authors aim to minimize the total transport cost by using multiple trucks. After modelling with the MILP model, they developed a Ruin and Recreate algorithm. They obtained the best new solution in 26 of the 90 cases they evaluated.

A closer look at the civilian side of drone studies, which can be divided into two main categories as civilian and military, reveals many different studies ranging from package transportation to agriculture, from imaging to fire fighting. When the aforementioned studies are examined in more detail, solutions to single-objective or multi-objective problems considering many criteria such as battery capacity, payload capacity and flight distance have been proposed with complex integer programming, dynamic programming and some heuristic algorithms, as summarized in Table 1 below.

Table 1. Literature Review of Scheduling for Civilian Application of Drone

Authors	**Objectives**	**Solution Approaches**
Liu et al. (2021)	Minimize the number of drones	Mixed integer programming
Torabbeigi et al. (2021)	Minimize the expected loss of demand	Binary integer programming model, Simulated Annealing (SA) heuristic algorithm,
Saleu et al. (2018)	Minimize completion time	An iterative two-step heuristic
Yilmazer et al. (2021)	Maximize package delivery accuracy and route optimization	QR code generation and reading
Choi and Scohonfeld (2017)	Minimize the total cost changes	The total cost function
Jung and Kim (2022)	Minimize delivery amount	Integer programming
Ibroska et al. (2023)	Minimize the total completion time	General Variable Neighborhood Search algorithm Mathematical model
Liu et al. (2018)	Minimize the comprehensive transportation cost	Enumeration method, the two-stage method
Amico et al. (2020)	Minimize the total time	Mixed integer linear programming and Heuristic algorithms
Huang et al. (2020)	Minimize the completion time	Dynamic programming
Yuan et al. (2021)	Minimize the maximum completion time	Genetic-based algorithm
Peng et al. (2019)	Minimize the total distance cost, minimize the completion time	Hybrid genetic algorithm

Table 1 (Continued). Literature Review of Scheduling for Civilian Application of Drone

Murray and Chu (2015)	Minimize the completion time	Mixed integer linear programming, heuristic algorithms
Chowdhurry et al. (2017)	Minimize total cost of distribution	Two-phase Continuous Approximation (CA) model
Rabta et al. (2018)	Minimize the total travelling distance	Mixed integer linear programming
Estrada and Ndoma (2019)	A review of drones for various missions	QDSPLTCE Table
Lei and Chen (2022)	Minimize the total completion time	Iterated Variable Neighborhood Search algorithm (IVNS)
Li et al. (2020)	Maximize customer satisfaction and minimize the total completion time	Mixed integer linear program Variable neighborhood search
El-Adle et al. (2023)	Minimize the return time	Variable neighborhood search
Nguyen et al. (2022)	Minimize the total transport cost	Mixed integer linear program Ruin and recreate algorithm

CHAPTER 3: METHODOLOGY

In this section, we start by defining the parallel drone scheduling problem, which is a new sub-problem type of the parallel resources scheduling problems in the literature with the drones of each warehouse dropping packages from multiple warehouses to multiple demand points simultaneously and returning to the warehouse from which they departed. After defining the problem, we present the mathematical model we developed for the multi-warehouse and multi-demand point problem. After the model, we describe in detail the entire structure of the VNS approach we propose for the parallel drone scheduling problem, along with the neighborhood methods used.

3.1. Problem Definition

Every year, natural disasters such as earthquakes, floods, landslides, and fires cause severe damage to residential areas in various parts of the world. In particular, earthquakes and floods occur more frequently than other types of natural disasters and, due to the extent of destruction they cause, result in significant loss of life and property, especially when they strike residential areas. When earthquakes and floods occur, it has been observed that roads, bridges, and streets are often destroyed or submerged, making ground transportation nearly impossible and limiting manned interventions to the restricted capabilities of sea and air routes. In our country, the earthquakes of magnitude 7.8 and 7.5 that occurred on the same day in 2023 in Kahramanmaraş province once again revealed the devastating impacts of earthquakes on humanity and demonstrated the severe limitations in ground and air access for emergency response operations after a disaster. Rapid delivery of aid to surviving disaster victims in the immediate aftermath of such disasters is crucial to support their survival until rescue teams arrive. Although citizens are periodically informed by authorized institutions about the preparation of emergency earthquake kits and their recommended contents, not every household is equipped with such a kit due to the still-developing level of disaster awareness. Moreover, even in households where kits are available, the materials may not be sufficient to support survival during the long hours before ground-based rescue teams can arrive following a major earthquake. Therefore, there is a need for an additional logistics system to deliver basic supplies and first aid kits to survivors in the aftermath of such disasters. In this study, it is aimed to deliver all life-sustaining packages, such as basic first aid kits, biscuits, and water, from designated warehouses to surviving disaster victims as quickly as possible via drones, until search and rescue teams reach them, in the aftermath of natural disasters such as earthquakes, floods, and fires occurring in residential areas. The study is formulated as a parallel resources scheduling problem involving the simultaneous delivery of packages from *m* different warehouses to *n* different demand points, with the objective of minimizing the total weighted delivery time.

For this parallel resources scheduling study involving package delivery with multiple depots and multiple demand points, a mathematical model was developed by incorporating constraints such as flight distance, calculated based on charge usage related to the maximum load capacity carried by the drone, as well as drone charging times and package weights.

3.2. Mathematical Model

In this section, we develop a mathematical model for the parallel drone scheduling problem, which is a subcategory of parallel resources scheduling with simultaneous package transportation from multiple warehouses to multiple demand points.

In the study, each depot has its own UAV set, and each UAV departs from its respective depot, flies to a reachable demand point based on its range (R), delivers a single package, and then returns to its original depot. This process continues until all demands are met. Packages are defined as the package set *J*, based on the demand points they are associated with, and each package *j* must be served by one UAV from the UAV set *I*. UAVs are identified with unique index ranges assigned to each depot. For instance, UAVs with index *I* from 1 to k_1 belong to the first depot, which has a total of k_1 UAVs. For the second depot, UAVs indexed from k_1+1 to k_2 belong to that depot, and the total number of UAVs there is k_2-k_1. Similarly, demand points (assembly areas) are defined by the indices of the packages, so that each demand point corresponds to a specific index range. For example, packages with index *j* from 1 to n_1 belong to the first demand point, which has a total demand of n_1 packages. For the second demand point, the packages with index *j* from n_1+1 to n_2 belong to that point, and its total demand is n_2-n_1 packages. In this way, the demand of each point is defined based on index intervals of the packages, which are determined by variable factors such as population density, making the model simpler and more understandable. The travel time between the depot to which a UAV belongs and the point where a package is demanded is defined by j. This duration is calculated based on the distance between the depot and the demand point and the UAV's speed. The objective function is to minimize the total weighted delivery time. By assigning weights (w_j) to the packages, the aim is to prioritize the demand points. These weights are based on the severity of the damage at each location. For instance, in a demand point heavily affected by the earthquake, assigning higher weights to the first packages and lower weights to the later ones allows the model to prioritize those deliveries. It is assumed that an average duration of S is required at the depots for charging the UAVs and loading the packages.

Sets:

I: Set of drones, $I = \{1, 2, \ldots, m\}$

J: Set of demand points, $J = \{1, 2, \ldots, n\}$

Indices:

i: Drone index $i \in I$

j: Package (demand point) index $j \in J$

l: Other packages (for priority comparison) $l \in J,\ l \neq j$

Parameters:

w_j: Weight of package j (priority coefficient)

c_{ij}: One-way flight time of drone i to package j (Straight-line distance)

M: A sufficiently large positive constant

R: Maximum range of the drone (Total round-trip flight time limit)

S: Constant preparation time for battery charging and packet loading for each packet flight

Decision variables:

$$X_{ij} = \begin{cases} 1, & if\ drone\ i\ delivers\ the\ packet\ to\ point\ j \\ 0, & otherwise \end{cases}$$

$$Y_{ijl} = \begin{cases} 1, & if\ drone\ i\ delivers\ the\ package\ to\ point\ j\ before\ point\ l \\ 0, & otherwise \end{cases}$$

A_j: Delivery time of the package to point *j* at the end of the process (Arrival time)

D_{ij}: Departure time of Drone *i* from the depot for delivery of the package to point *j* (Departure time)

$$\text{Min} \sum_j w_j A_j \tag{1}$$

Subject to

$$A_j = \sum_i (D_{ij} + c_{ij} \times X_{ij}) \qquad \forall j \tag{2}$$

$$D_{ij} \leq M \times X_{ij} \qquad \forall i, j \tag{3}$$

$$\sum_i X_{ij} = 1 \qquad \forall j \tag{4}$$

$$2 \times c_{ij} \times X_{ij} \leq R \qquad \forall i, j \tag{5}$$

$$D_{il} \geq D_{ij} + 2 \times c_{ij} + S - M \times (1 - Y_{ijl}) \qquad \forall i, j, l \neq j \tag{6}$$

$$X_{ij} + X_{il} \geq 2 \times (Y_{ijl} + Y_{ilj}) \qquad \forall i, j, l \neq j \tag{7}$$

$$X_{ij} + X_{il} \leq Y_{ijl} + Y_{ilj} + 1 \qquad \forall i, j, l \neq j \tag{8}$$

$$D_{ij} \geq 0 \qquad \forall i, j \tag{9}$$

$$A_j \geq 0 \qquad \forall j \tag{10}$$

$$X_{ij} \in \{0,1\} \qquad \forall i, j \tag{11}$$

$$Y_{ijl} \in \{0,1\} \qquad \forall i, j, l \neq j \tag{12}$$

The objective function (1) tries to minimize the weighted sum of the arrival times to all demand points. Constraint (2) calculates the arrival time of each UAV to the demand point to which it is assigned. Constraint (3) allows the departure time to take a positive value if UAV i is delivering package j. Constraint (4) ensures that each package is delivered by a UAV. Constraint (5) limits the total flight time of each UAV during a package delivery. Constraints (6), (7) and (8) are sequencing constraints. If packages *j* and l are delivered by UAV *i*, then the time for the later delivered package to leave the depot should be after the earlier delivered package has returned to the depot, charged and loaded. Constraints (9)-(12) define the values that the decision variables can take.

When considering the necessity of delivering aid in the shortest possible time during a disaster, solution time becomes a critical performance criterion. In this study, an example problem involving the delivery of packages from 2 depots to 12 demand points revealed that the six-hour time constraint was exceeded. When the time limit is strictly observed, it was found that a maximum of 11 different demand points could be served. The results of the example problem indicate that, despite working with a relatively small data set, the solution time remains considerably high. It is evident that, for a more extensive delivery network, the solution time would increase significantly. Therefore, to reduce the solution time to a reasonable level and to systematically explore potential improvements by utilizing and alternating between neighborhood structures with different search mechanisms, the use of metaheuristic methods such as Variable Neighborhood Search (VNS) becomes necessary. Among these methods, VNS is selected due to its flexible structure and good performance on scheduling and routing problems.

3.3. Proposed General Variable Neighborhood Search (GVNS)

Before presenting the VNS structure, we first describe the solution representation used in this study. The solution is represented in the form of a structured assignment list indicating which drone delivers which package to which demand point and in what sequence. Each drone is treated as a parallel resource, and each package delivery is considered a job to be scheduled. A solution vector includes information such as the assignment of packages to drones, the order of deliveries, and the start-return times of each delivery task. This representation allows the application of neighborhood structures such as swap, move, and reverse by making localized changes on the assignment sequences while preserving feasibility with respect to drone range and delivery constraints.

Variable Neighborhood Search (VNS) is a metaheuristic optimization method developed by Hansen & Mladenovic (1997) with the ability to provide fast solutions and easy applicability to problems. The purpose of the VNS structure, which is formed by the combination of neighborhood methods with various assignment logic, is to reduce the risk of getting stuck in local best solution sets. Due to the high preference of the VNS structure, derivatives such as Basic VNS, Reduced VNS, Skewed VNS and Variable Neighborhood Descent (VND) have been developed over the years for various purposes Hansen and Mladenovic (2001).

In this section, we describe the VNS structure we propose for our problem with multiple depots and multiple demand points. As described in 3.3.1., after obtaining the initial solution of our problem, we use the Weighted Shortest Processing Time (WSPT) output as the input of our VNS with various neighborhood structures. A certain number of iterations are performed on the input for each neighborhood, randomly searching for improvements in the local neighborhoods. If there is an improvement in a specified iteration, the search continues locally in the neighborhood by going back to the beginning in the relevant neighborhood method. If no improvement is encountered in the search process, the process moves to the next neighborhood method. This process continues until it is tested in each neighborhood. After completion in each neighborhood, the best result obtained in the searches is recorded. A flowchart of the process flow is presented in Figure 1.

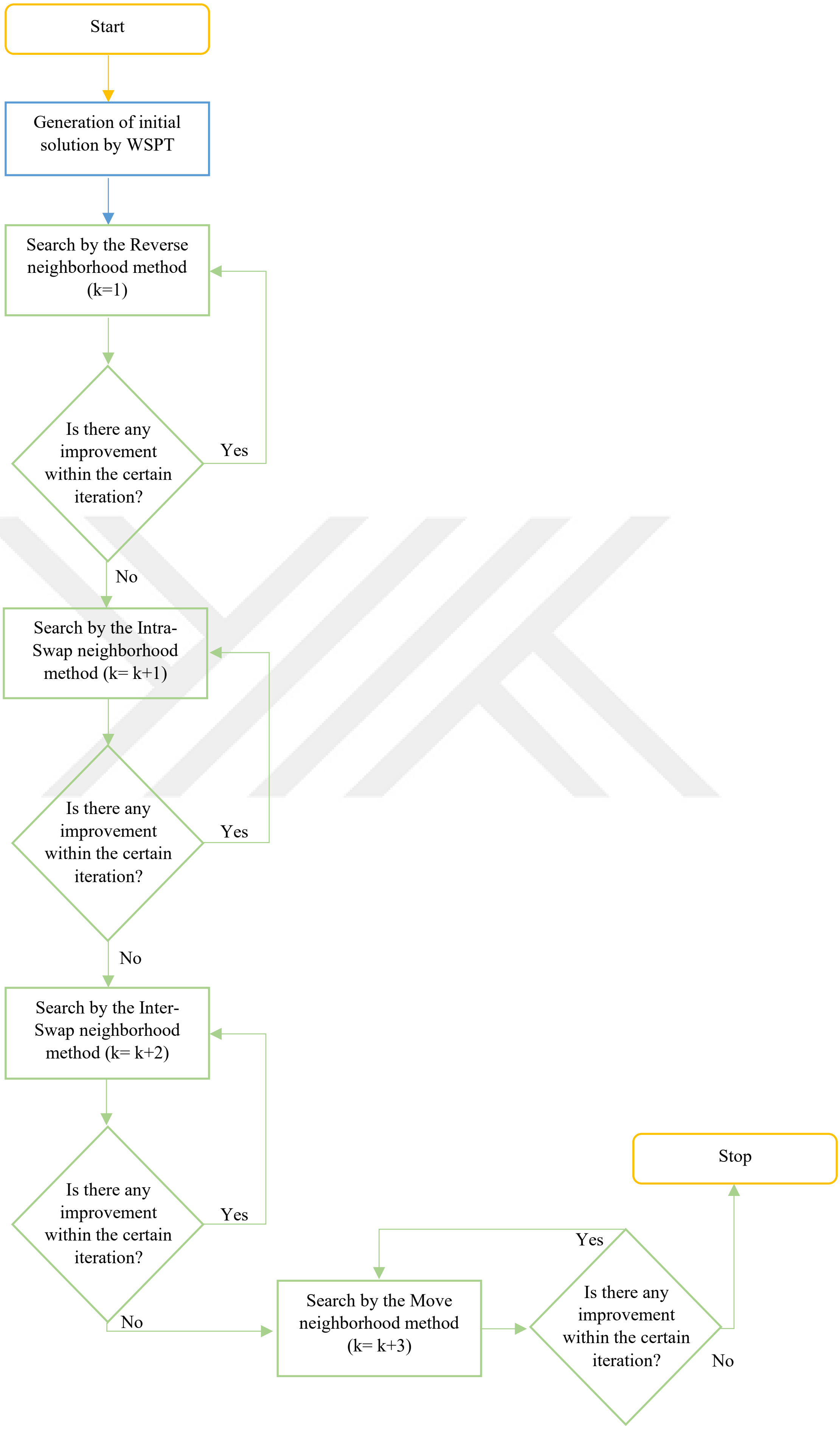

Figure 1. Process Flow of the Proposed Variable Neighborhood Search Structure

3.3.1. Initialization with Weighted Shortest Processing Time Method

In this study, before solving with the neighborhood methods used in the VNS structure, an initial solution is created with the Weighted Shortest Processing Time (WSPT) method for VNS, which is one of the dispatching rules. First used and developed by Smith (1956), the WPST method was introduced for optimal scheduling of jobs with different priorities in some cases single-machine problems. The method, which aims to minimize the sum of the product of p_j (processing time) and w_j (priority weight) of n jobs waiting in the queue, assigns the jobs by following the order from the largest to the smallest by making the $\frac{w_j}{p_j}$ ratio. The method, which has been used in parallel resources scheduling with the developing industry over the years, is also used to obtain the initial solutions of heuristic methods such as VNS. The neighborhood methods that use the initial solution as input to their functions are discussed in detail in the sections between 3.3.2 and 3.3.5.

3.3.2. Reverse Neighborhood Method

Reverse, also known as the inversion neighborhood operator, is used to search for improvements in the large solution space by reversing the ordering between 2 packages randomly selected among the jobs in the assigned machine or drone according to the problem under consideration. In the literature, under the heading of neighborhood search-based heuristic algorithms, the most effective example for the method, which is seen to be used especially in Traveling Salesman Problems (TSP), is the reversal of route points in Lin (1965)'s work. The usage logic of Reverse, which has a strong local optimization capability, is shown in Figure 2 and Figure 3 as before/after cases.

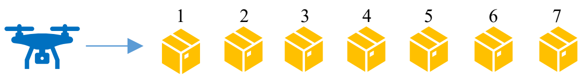

Figure 2. Initial State of Reverse

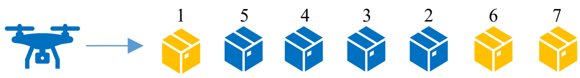

Figure 3. Reverse Implemented Solution

3.3.3. Swap Neighborhood Method

The Swap method, which provides fast and effective results in scheduling and route optimization studies with small neighborhoods, was first used in the literature by Lin (1965) for route optimization. The Swap method can be integrated with all neighborhood structures and thanks to this feature, Inter-Swap, Intra-Swap, Adaptive Swap and Selective Swap variations have been developed over the years. Basically, by swapping two jobs/packages and evaluating all alternatives, this approach aims to improve the targeted objective. In this study, two variations, Inter-Swap and Intra-Swap, are used in a single study to improve (minimizing) the total weighted time in the package distribution operation.

Intra-Swap

It is to randomly select two packages from the packages assigned to the same drone and swap them to improve it. The working algorithm of Intra-Swap is implemented on Figure 2 and the aftermath is shown in Figure 4.

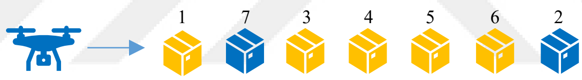

Figure 4. Intra-Swap Implemented Solution

Inter-Swap

In some problems with complex scheduling structure, such as this problem with multiple drones and demand centers, more than one package is assigned to a drone. The Inter-Swap variation, which was developed for these cases, swaps the assigned drones of 2 packets assigned to different drones and is shown in Figure 5 and Figure 6 as before and after states.

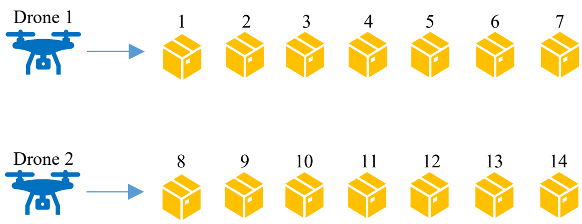

Figure 5. Initial State of Intra-Swap

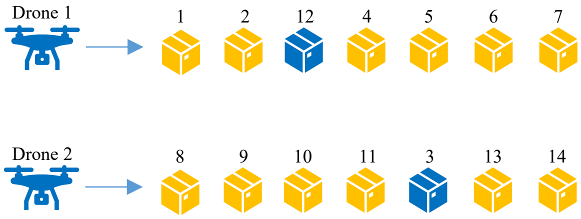

Figure 6. Intra-Swap Implemented Solution

3.3.4. Move Neighborhood Method

When we look at the first use of the Move method, which has the ability to work integrated with all metaheuristics and to generate large neighborhoods, we see that it was applied in Travelling Salesperson Problem (TSP) and Vehicle Routing Problem (VRP) studies. Lin & Kernighan (1973) employed it with their flexible k-opt algorithm, which has the capability of exploring large solution spaces by avoiding local optima. Move, which works with the logic of taking a package from where it is assigned and assigning it to another drone/machine, has developed many variations with different assignment logics such as Deterministic Move, Stochastic Move, Batch Move, Most Time-Consuming Package Move, etc. over many years.

In this study, we aim to minimize the total weighted time with the Move algorithm developed on Max Completion Time-Based Insert. The working logic of the Move algorithm we developed has a similar logic with Greedy Local Balancing, Critical Path Load Transfer and Iterative Balancing Move methods, which have been studied to make the system operational by relieving the congested point called bottleneck in parallel machine scheduling. The algorithm works by taking the last package from the busy drone that carries the most packages from drones that do not have an equal number of packages to be transported, and assigning the package to the drone that has fewer packages to be transported compared to the others. The working algorithm of Max Completion Time-Based Insert Move is shown in Figure 7 and Figure 8 for before and after cases.

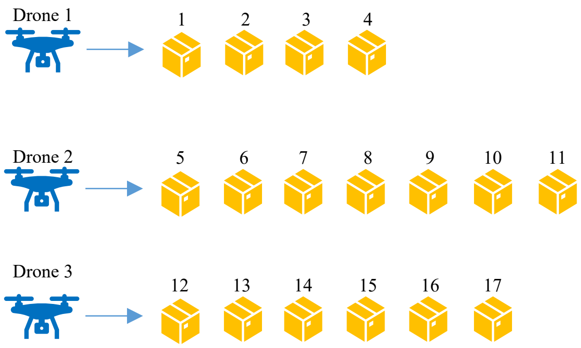

Figure 7. Initial State of Move

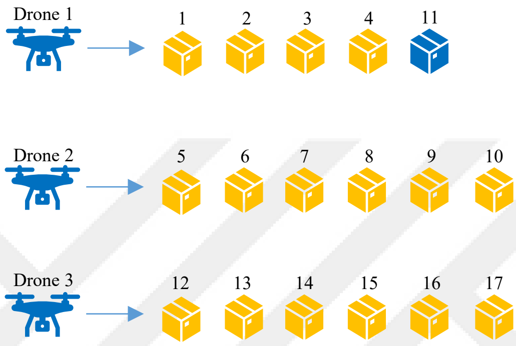

Figure 8. Move Implemented Solution

Following the generation of the initial solution via the Weighted Shortest Processing Time (WSPT) rule, an alternative search may be initiated either by utilizing the newly improved solution set—generated as a result of local enhancements achieved through neighborhood methods—or, in the absence of any local improvement, by employing the original WSPT-based initial solution. In both cases, the process proceeds with a global search by changing the solution through a shaking mechanism.

In this study, the improved solution set obtained through the application of neighborhood methods was first subjected to shaking, and then a series of local searches were performed on newly generated global candidate solutions over a certain number of iterations. During the implementation phase, the steps presented in Figure 1 were followed; subsequently, Sections 3.3.5 and 3.3.6 were incorporated at the final stage to realize the complete VNS structure proposed in Figure 9. Additionally, in this structure, a stopping criterion such as a maximum number of iterations or a time limit can be defined, depending on the computational requirements or the scale of the problem.

3.3.5. Shaking Phase

We apply the shake method, which aims to escape from local optima and explore global improvements, to the solution obtained by following the steps outlined in the flowchart presented in Figure 1. Within the structure of the shake method, one of the Reverse, Swap (Intra and Inter), or Move operators, as detailed in Sections 3.3.2, 3.3.3, and 3.3.4, is randomly selected and applied. After the perturbation introduced by one of these operators, a local search phase is carried out, incorporating various neighborhood structures as described in Section 3.3.6. The Move operator, which was previously used before the shaking phase to explore potential improvements by exchanging packages based on a specific logic, is now used after the shaking phase to seek improvements by randomly exchanging packages according to its working principle.

3.3.6. Local Search

In the local search phase, after perturbing the locally optimal solution to move to a different point globally, the search aims to explore the surroundings of the new point to find solutions that may be better than the previously obtained local optimum, regardless of whether the immediate outcome of the perturbation is better or worse. In the local search phase, the methods Reverse, Intra Swap, Inter Swap, and Move are applied in a predetermined sequence. These methods do not rely on a specific optimization logic; instead, they randomly select and exchange packages based on their own operational principles in search of potential improvements. Although the Move operator was previously applied based on a specific logic during the local optima attainment phase, it is utilized according to a random selection approach during the local search phase.

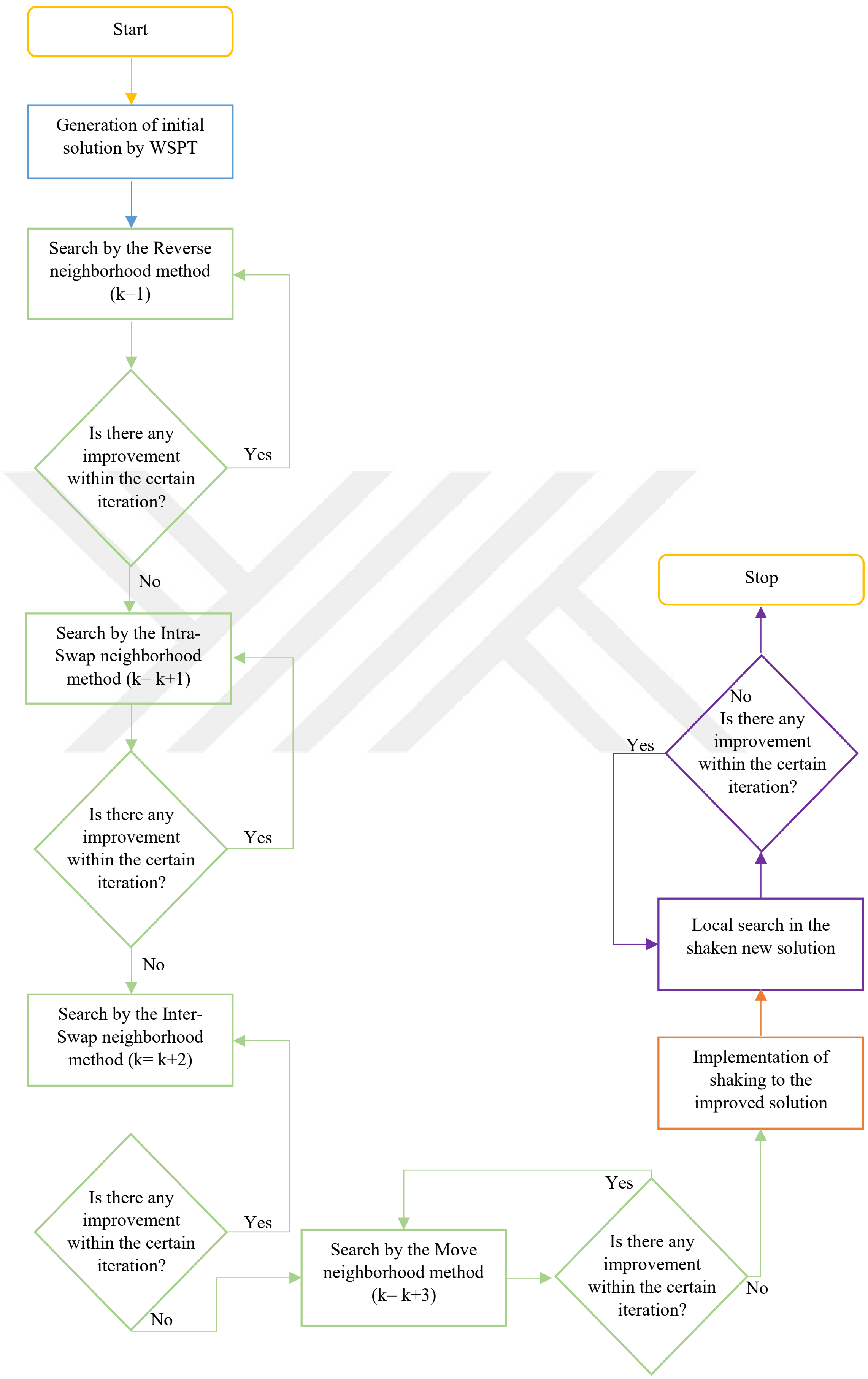

Figure 9. Process Flow of The Proposed Extended Variable Neighborhood Search Structure

CHAPTER 4: POST-DISASTER INTERVENTIONS USING DRONES: THE CASE OF İSTANBUL

In this chapter, the application of the post-disaster drone utilization problem, which is explained in detail in Chapter 3, to the case of the Istanbul earthquake — a disaster projected by official institutions and leading scientists in the field to occur in the near future with a magnitude of Mw=7.5, and which has been the subject of various projects and workshops such as the Istanbul Province Possible Earthquake Loss Estimation Update Project (2019) — is presented. Immediately after the earthquake, during the first 24–48 hours referred to as the critical hours, before search and rescue teams reach the earthquake victims, the aim is to deliver all life-sustaining packages, such as basic first aid kits, biscuits, and water, to the surviving victims from predetermined warehouses via drones as quickly as possible. In the study, the mathematical model presented in Chapter 3 and the VNS structure shown in Figure 9 are employed to solve a parallel machine scheduling problem, in which packages are simultaneously delivered from *m* different warehouses to *n* different demand points. The objective is to minimize the total weighted completion time. All data used in the study were obtained from reports publicly shared by official institutions of the Republic of Turkey.

When the reports published by Kandilli Observatory (2019) are analyzed, it is expected that the earthquake will occur at a location parallel to the southern coast of the European Side, as presented in Figure 10.

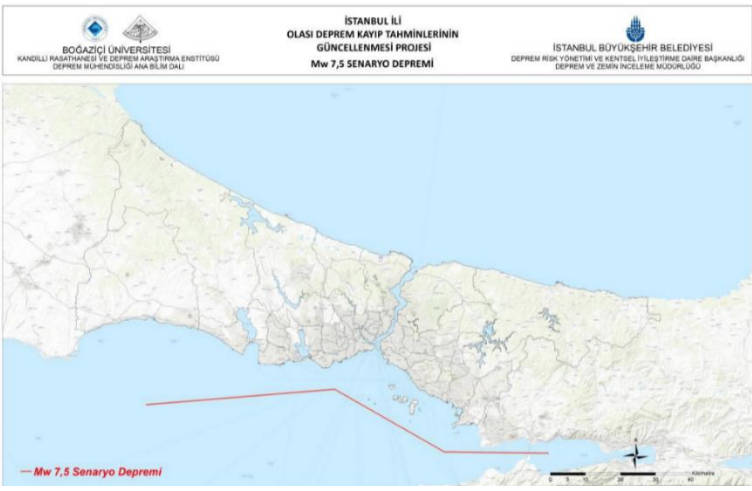

Figure 10. Mw 7.5 Scenario Istanbul Earthquake (Source: Bogazici University Kandilli Observatory and Earthquake Research Institute, 2019)

In case the earthquake occurs in the area shown in Figure 10, according to the report prepared by Kandilli Observatory (2019) presented in Figure 11 and according to the ArcGIS-based live map data shown in Figure 12 prepared by the Istanbul Metropolitan Municipality Earthquake and Soil Investigation Branch Directorate (2023), it is determined that the districts expected to receive the most damage are Avcılar, Bağcılar, Beylikdüzü, Büyükçekmece, Esenyurt, Fatih, Gaziosmanpaşa, Küçükçekmece and Zeytinburnu.

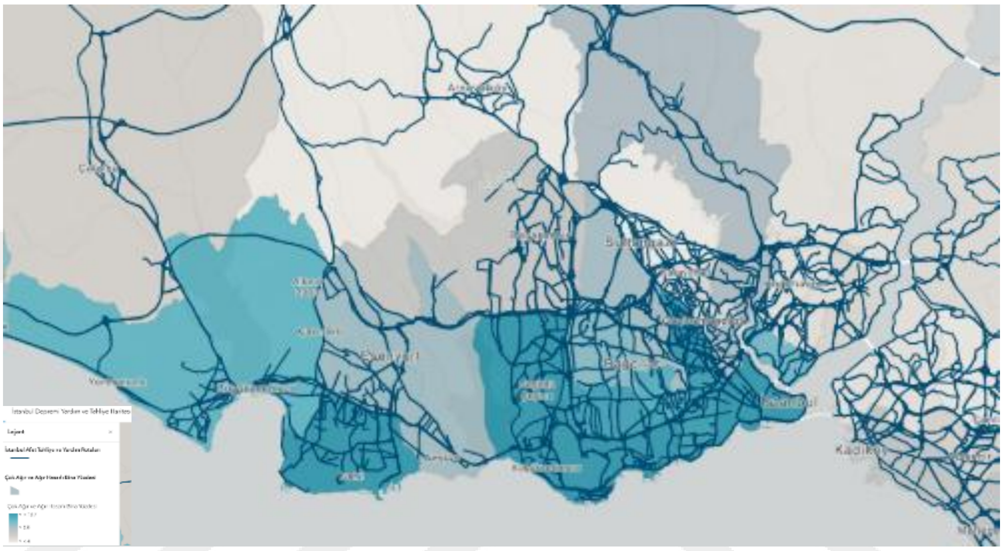

Figure 11. Istanbul Earthquake Relief and Evacuation Map (Source: Istanbul Metropolitan Municipality Earthquake and Soil Investigation Branch Directorate, 2023)

Figure 12. Scenario Earthquake Ground Dependent Maximum Ground Velocity Distribution Map (Source: Bogazici University Kandilli Observatory and Earthquake Research Institute, 2019)

When the reports prepared by the Istanbul Metropolitan Municipality Earthquake and Soil Investigation Branch Directorate (2020) for the districts that are expected to suffer the most damage are examined, it is observed that buildings located in various neighborhoods within the boundaries of Avcılar are anticipated to be severely damaged, as illustrated in Figure 13 for the Avcılar case.

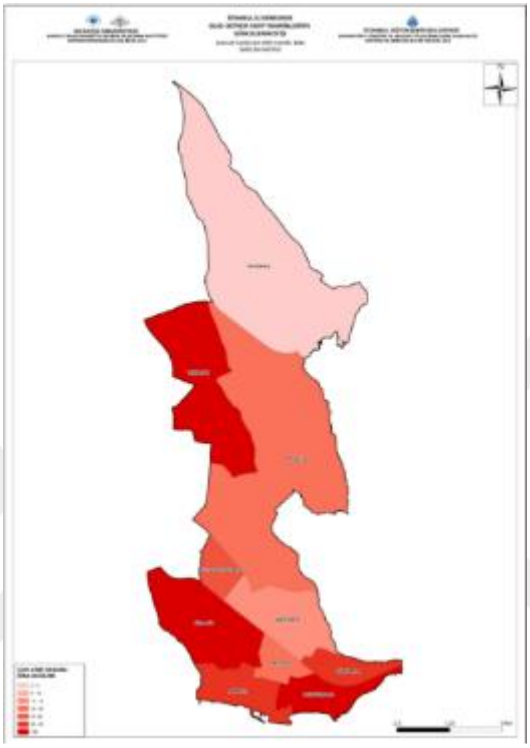

Figure 13. Estimated Number of Severely Damaged Buildings in Avcılar District for Mw=7.5 Scenario Earthquake (Source: Istanbul Metropolitan Municipality Earthquake and Soil Investigation Branch Directorate, 2020)

Very severely damaged building maps for the other districts expected to be most affected by the earthquake, namely Bağcılar, Beylikdüzü, Büyükçekmece, Esenyurt, Fatih, Gaziosmanpaşa, Küçükçekmece and Zeytinburnu, have also been analyzed and are presented in Appendix B.

In the districts where a high number of casualties are expected to occur after the earthquake, the selection of warehouse locations is another important point to deliver aid packages to the disaster victims as soon as possible. In the study, the locations determined and shared by the official institutions of the Republic of Türkiye were used in the process of determining the warehouse locations, and real data were used. When the locations of the warehouses are examined, points such as public warehouses on the sides of highways, airports or ports for maritime transportation were selected to ensure continuous supply from the main logistics points. The warehouses identified at 9 different points in 7 districts, namely Eyüpsultan, Bakırköy, Başakşehir, Esenyurt, Büyükçekmece, Çatalca, Sultangazi and Kağıthane, are marked on Google Earth and are presented in Figure 14 and Figure 15 for the European side base and the overview map of İstanbul.

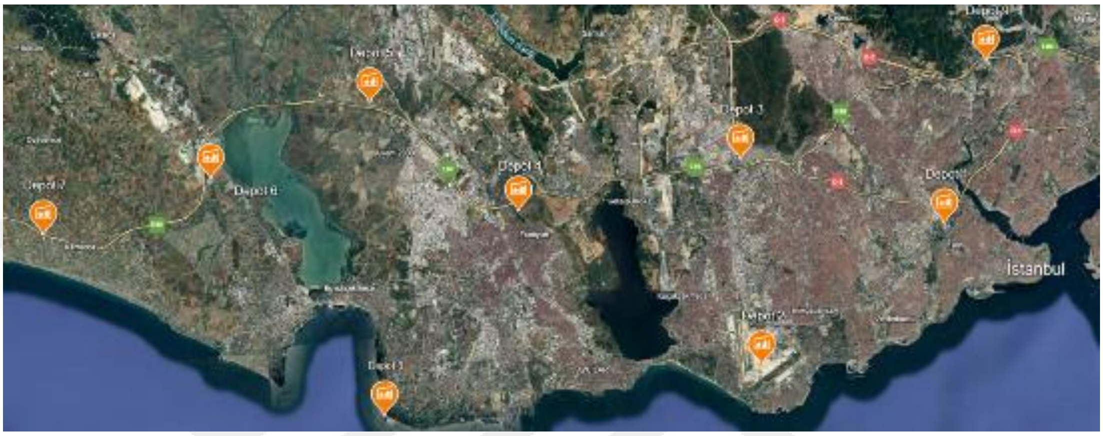

Figure 14. The depots (European Side based)

Figure 15. Overview of The Depots (İstanbul Province Map)

A total of 173 different demand points were selected from the neighborhoods of 9 districts with high risk of destruction in order to quickly deliver the first aid packages carried by drones from the warehouses to the disaster victims. Demand points were selected from the disaster assembly areas determined by AFAD, one of the official institutions of the Republic of Türkiye and shared with the public in open sources. When the details of the selected disaster assembly areas are examined, it is observed that there are various types such as parks, school gardens, sports facilities, squares, market areas and open parking lots. The selected disaster assembly areas determined by AFAD and shared in Appendix A with their details are visualized on Google Earth based map and shown on the European Side based in Figure 16 and on the provincial map of Istanbul in Figure 17.

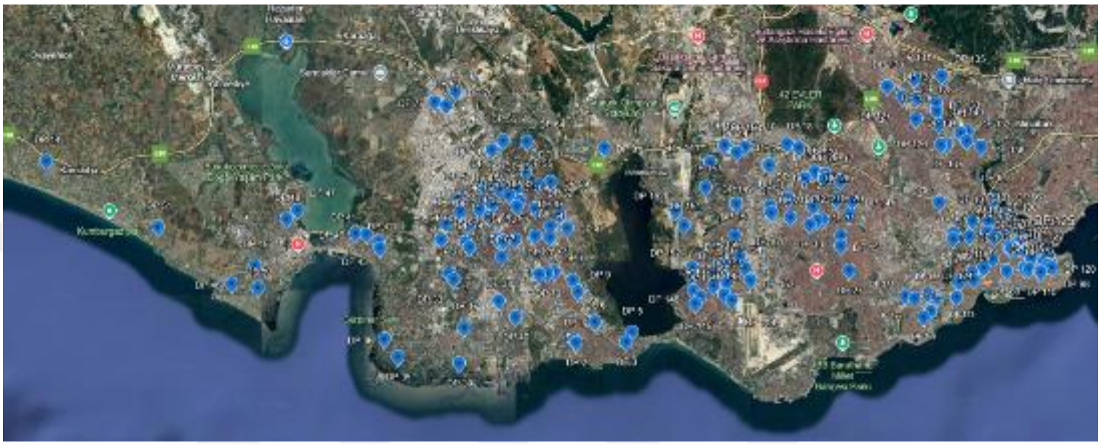

Figure 16. The Demand Points (European Side Based)

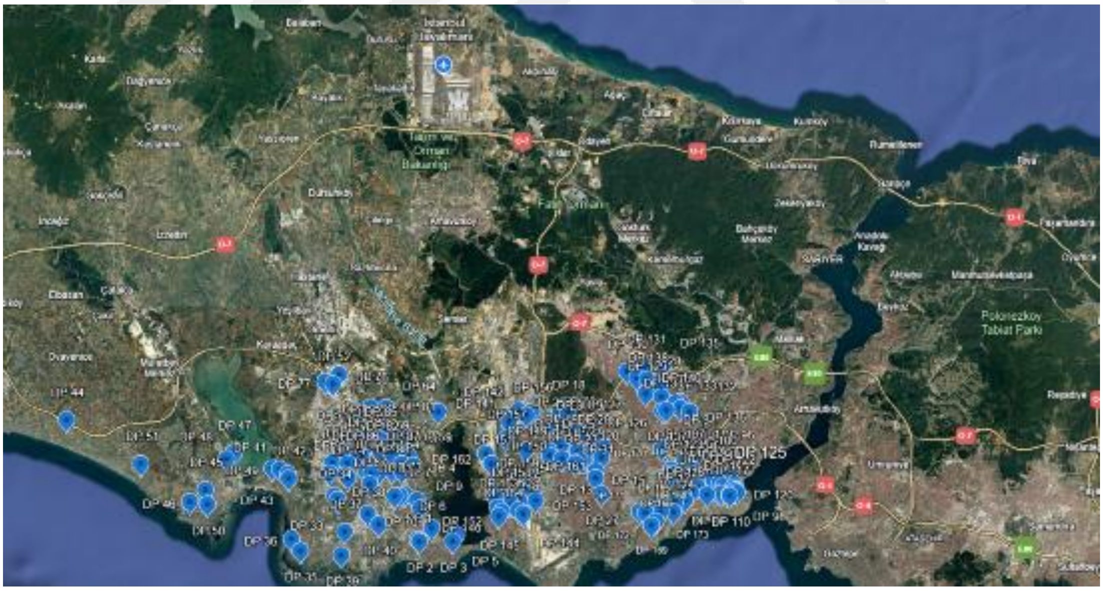

Figure 17. Overview of The Demand Points (İstanbul Province Map)

In this study, which was carried out with the aim of meeting the needs of the surviving disaster victims as soon as possible in the immediate aftermath of the earthquake expected to occur on the southern coast of the European Side of Istanbul province, a general representation of all the storage and demand points together is presented in Figure 18.

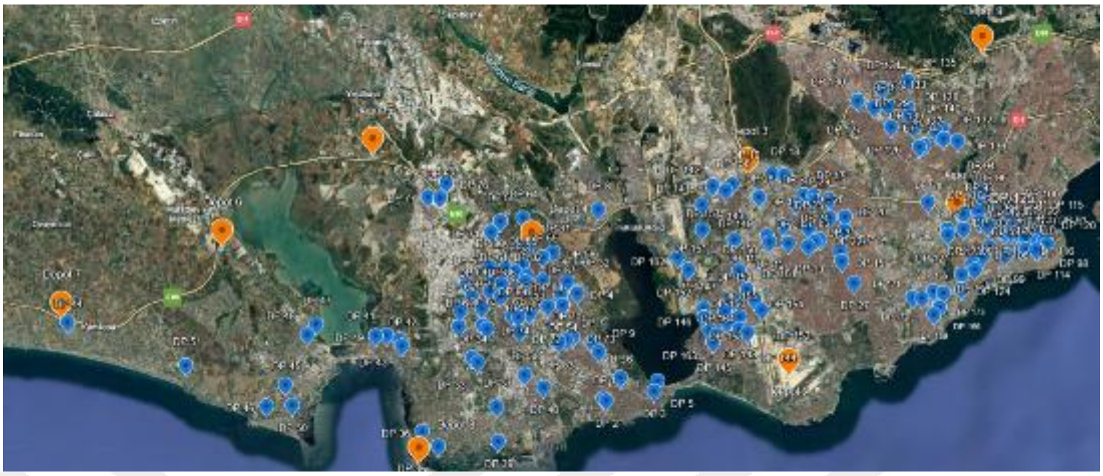

Figure 18. Overview of All Depots and Demand Points (European Side Based)

The range times are calculated based on the distance (in kilometers) that the drone is expected to travel between two points. These distances are computed using the Haversine formula. An analysis of the technical specifications of the FLAYCART 30 drone reveals that it can cover 1 kilometer in 1 minute. Furthermore, as illustrated in Figure 21, the package weights at the demand points decrease by 1 unit for every 2 kilometers of increased distance from the predicted disaster center (earthquake epicenter).

The FLYCART 30 model shown in Figure 19, which has dual batteries and is produced by one of the leading drone manufacturers in the sector, was selected to be used in package transportation operations from 9 warehouses shown in Figure 18 to 173 demand points during first aid interventions after the disaster. Considering the features of the drone selected for the task, it has a carrying capacity of 30 kg, a flight range of 17 km at full capacity, and a cruising speed of 72 km/h. The drone can stay airborne for a maximum of 18 minutes, which would theoretically correspond to a flight distance of 21.6 km under ideal conditions. However, due to factors such as air resistance and wind effects, the practical flight range is assumed to be 17 km. In addition to its high carrying capacity, wide operational range and high cruising speed, it plays an important role in rapid interventions after disasters thanks to its ability to drop packages with the hook system without landing on the ground, as shown in Figure 20 (Dji, 2024).

Figure 19. FLYCART 30 Drone

Figure 20. Package Dropping with Drone's Hook System

The distance measurements between the warehouses, where drones perform package drop operations, and the demand points are calculated using the Haversine distance formula, and the results are presented in Appendix C. The data represents the distance in kilometers (km) between two points.

When the flight ranges of drones are examined, the fact that they have a maximum flight range of 17 km reveals the constraint that the demand center must be within a maximum radius of 8.5 km from the warehouse in order to go from a warehouse to a demand center. On the other hand, there is a priority matrix for the ranking of package transportation to demand centers. For demand centers with a weighting score between 1 and 10, a score of 10 means the most urgent need/critical, while a score of 1 represents the least criticality level. In the weight scoring, as presented in Figure 21, horizontal lines were drawn to the coast on the southern European side, where the earthquake is expected to occur, and a weight score was assigned by decreasing one point every 2 km to the north. For example, the closest demand centers within 2 km as the crow flies to the coast were given 10 points, while the farthest points towards the north were given 1 point.

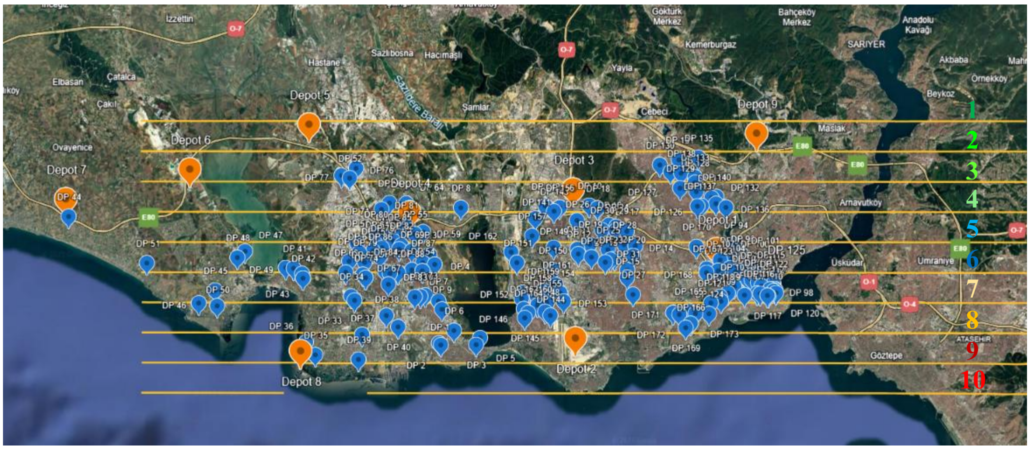

Figure 21. Demand Points Weighting Map

According to the classification in the picture above, Appendix D presents each demand point with its weight

This study, which focuses on drone-based package delivery in post-earthquake response operations anticipated to take place in İstanbul, presents the results and experimental findings obtained from the implemented scenarios in Chapter 5.

CHAPTER 5: COMPUTATIONAL EXPERIMENTS

In this chapter, the experimental results obtained from the application of the mathematical model presented in Chapter 3 and the developed Variable Neighborhood Search (VNS) algorithm to the Istanbul earthquake scenario detailed in Chapter 4 are presented. The problem aims to minimize the total weighted delivery time. The coordinates of the depots and demand points used in the model were retrieved from publicly available reports issued by official institutions of the Republic of Türkiye, and are provided in Chapter 4 and the Appendices. During the solution process based on the mathematical model and the proposed VNS algorithm, it is assumed—due to cost-related constraints—that each depot is equipped with only one drone and that each demand point requires exactly one package. In this study, one package is assumed to be delivered to each demand point. We can also extend this case, and define demand for multiple packages separately at the same point. This will also allow us to give different priorities to different packages. The flight range (R) was set to 17 km, which corresponds to the technical flight limit of the drone. The preparation time (S), representing the time needed to change the battery and load a new package after the drone returns to the depot following a delivery, was determined as 5 minutes. However, the preparation time is excluded from the calculation following the delivery of the final package and the return to the depot. The developed VNS algorithm was implemented in Gurobi Python and executed on a system equipped with a 2.3 GHz 8-core Intel Core i7 processor and 16 GB of 3200 MHz DDR4 RAM.

In the comparative solution process of the mathematical model and the VNS algorithm presented in Table 2, five different datasets were evaluated for 9, 10, and 11 distinct demand points, based on problem data involving 2 and 3 different depots. By entering the distance matrix between the depots and the demand points along with the package weight data, results were observed as the number of depots increased and the number of demand points was gradually raised to 9, 10, and 11, respectively. In the model, which was required to provide an exact solution and was defined as 'MIP Gap = 0', it was observed that solution times significantly increased in datasets where the complexity rose due to packages being accessible from multiple depots. For the datasets in which the solution times increased, the VNS algorithm was observed to produce optimal or near-optimal results in significantly shorter times, depending on the dataset.

Table 2. Solutions of Computational Experiments with Small Instances

Number of drones (*m*)	Number of packages (*n*)	Opt. solution time (seconds)	VNS solution time (seconds)	Opt. solution	VNS solution	Percent deviation (%)
2	9	1.47	0.06	1868.74	1868.74	0
2	9	1.13	0.08	1811.65	1811.65	0
2	9	1.18	0.06	2203.84	2204.45	0.03
2	9	9.35	0.18	1844.25	1844.25	0
2	9	10.10	0.07	953.75	955.19	0.15
3	9	23.90	0.07	668.08	670.38	0.34
3	9	1.22	0.05	1154.70	1154.70	0
3	9	1.06	0.33	2469.43	2469.43	0
3	9	0.47	0.45	1172.10	1172.10	0
3	9	0.25	0.08	1819.86	1819.86	0
2	10	18.34	0.04	2282.87	2286.59	0.16
2	10	4.74	0.06	2248.03	2329.51	3.62
2	10	2.10	0.18	2800.18	2801.23	0.04
2	10	148.13	0.06	2307.37	2351.63	1.92
2	10	124.18	0.06	1149.08	1155.04	0.52
3	10	204.52	0.06	791.07	791.07	0
3	10	11.79	0.07	1550.84	1588.12	2.4
3	10	0.1	0.05	2512.73	2512.73	0
3	10	2.49	0.04	1539.90	1539.90	0
3	10	0.61	0.07	2375.98	2375.98	0
2	11	1943.74	0.43	2798.88	2800.08	0.04
2	11	87.59	0.09	2761.27	2761.27	0
2	11	24.64	0.08	3395.24	3396.65	0.04
2	11	5352.32	0.06	2838.72	2838.75	0.001
2	11	2311.50	0.08	1400.12	1402.66	0.18
3	11	2616.14	0.07	974.75	982.55	0.8
3	11	28.41	0.1	1773.96	1809.14	1.99
3	11	2.24	0.41	2638.85	2638.85	0
3	11	7.79	0.06	1695.29	1625.29	0
3	11	1.22	0.08	2467.19	2467.19	0

As the number of instances in the dataset increased, attempts to obtain the optimal solution using the mathematical model for a case with 2 depots and 12 demand points exceeded the six-hour solution time limit, and no optimal solution could be reached within a reasonable time frame. In light of this limitation—which also highlights the motivation behind the development of heuristic methods—the Variable Neighborhood Search (VNS), a metaheuristic approach, was employed to generate near-optimal solutions within acceptable computational times for large-scale instances. In this study, the solution obtained by the WSPT method was used as the initial solution for VNS. As presented in Table 3, the improvement rates achieved by VNS over the initial WSPT results were comparatively evaluated, and the corresponding percentage improvements were recorded.

Table 3. Solutions of Computational Experiments with Large Instances

Number of drones (*m*)	**Number of packages (*n*)**	**VNS solution time (seconds)**	**WSPT solution**	**VNS solution**	**Percent improvement (%)**
2	20	0.62	9611.17	9537.63	0.77
3	20	0.7	5555.13	5259.39	5.32
5	20	0.91	4256.44	4212.14	1.04
2	30	0.49	19758.74	19746.2	0.06
3	30	1.05	11934.08	10149.21	14.95
5	30	1.33	8813.79	8765.57	0.55
2	50	0.85	47189.87	47155.33	0.07
3	50	1.28	10716.48	10653.69	0.59
5	50	2.12	20026.65	19906.58	0.6

While working on large-scale instances, the problem size was increased by creating various combinations of drones of depot and package numbers within the dataset. Even in scenarios where WSPT produced strong solutions, the VNS algorithm managed to achieve small but measurable improvements within a restricted solution space. In particular, improvement rates such as 5.32% and 14.95% obtained in certain problem sets have provided valuable insights into the algorithm's stability and overall effectiveness. On the other hand, in small-scale problem sets where the mathematical model required long computation times, the algorithm reached either the optimal solution or solutions with less than 1% deviation from the optimum in 90% of the tested instances and did so in significantly shorter time—demonstrating strong performance in terms of both solution quality and computational time. Moreover, in large-scale instances, the improvement rates achieved over WSPT results show that VNS is an effective solution method not only for small problems but also as the problem size increases.

Following the evaluation of the VNS algorithm's performance on different problem sizes, the study proceeded with the real-scale problem involving 9 depots and 173 demand points. Due to the cost of drone systems, it was initially assumed that each depot would be equipped with only one drone. However, in order to provide aid to disaster victims as quickly as possible during the critical hours following a disaster, the impact of increasing the number of drones per depot to two and three, respectively, on the delivery time of the last package was analyzed. The results of this analysis are presented in Table 4.

Table 4. 9 Depots, 173 Demand Points, Different Values for Number of Drones (İstanbul Case)

Number of drones in each depot	**VNS solution time (seconds)**	**VNS solution (seconds)**	**Largest arrival time (minutes)**
1	16.35	179334.79	402.52
2	14.2	88524.99	202.29
3	12.61	58656.07	129.95

The results indicate that when each depot is equipped with only one drone, 6.7 hours are required to deliver the last package to disaster victims. When the number of drones per depot is increased to two, this time decreases to 3.37 hours and further drops to 2.17 hours when three drones are used. These findings suggest that increasing the number of drones per depot has a significant impact on ensuring faster response in the aftermath of a disaster.

CHAPTER 6: CONCLUSION AND FUTURE WORK

In this study, we consider the parallel drone scheduling problem, which is a subcategory of parallel resources scheduling, for distributing packages from multiple warehouses to multiple demand points simultaneously in post-disaster first aid interventions, which is one of the many uses of drones, a product of developing technology. This subcategory, which emerged as a result of developing technology, deals with the optimization of problems for the use of drones in military and civilian sides for various objectives. In this thesis, it is aimed to minimize the total weighted time to deliver packages containing basic health kits and food to disaster victims as soon as possible so that they can survive until the ground teams arrive. We first develop a mathematical model and found the optimal solution to small size problems. Since this parallel drone scheduling with multiple warehouses and multiple demand centers is NP-Hard and the optimal solution could not be found in reasonable time, we have developed a VNS algorithm, which is one of the effective metaheuristics that provides fast results for complex problems.

We used various neighborhood structures to build the structure of the VNS algorithm, which is fast and very close to the optimum with the results it provides. After the VNS structure was created, we used the shaking method to abandon local neighborhood clusters on the current problem set and then used the local search method to search for better results at more distant points.

All data collected for the modeling and algorithms in the study were taken from open-source reports shared by official institutions of the Republic of Türkiye such as Disaster and Emergency Management Presidency (DEMP (AFAD in Turkish)), Istanbul Metropolitan Municipality, Kandilli Observatory, various district municipalities and municipal earthquake research units affiliated to Istanbul Metropolitan Municipality.

In our study, small and large problem sets were addressed by using various combinations of increasing numbers of depots and packages. In small problem sets, the results of the VNS algorithm were analyzed by comparing them with the optimal solutions. The proposed model is primarily intended to evaluate disaster scenarios and support preparedness planning using current data. After a real disaster occurs, the same model can be re-applied using actual field data to enhance operational efficiency. As the problem size increased, optimal solutions could not be obtained within a reasonable time frame, and therefore, the metaheuristic method VNS was applied. Despite strict range constraints and the use of the strong WSPT initial solution, the VNS algorithm demonstrated stable performance—producing either the optimal result or a solution with less than 1% deviation from the optimum in 90% of the small problems. Moreover, as the scope of the problem expanded, it continued to achieve meaningful improvements.

Following the small and large problem sets, a sensitivity analysis was conducted on the real-scale problem instance involving 9 depots and 173 demand points (Istanbul case). The results of our experiments revealed that increasing the number of drones at each depot had a significant impact on the delivery time of the last package. It was concluded that the number of drones assigned to each depot is a critical parameter for ensuring rapid response to disaster victims during the early hours following a disaster, which are often referred to as the critical hours. In this study, the drone model used (DJI Flycart 30) is limited to carrying only one package at a time, with a maximum payload capacity of 30 kg. As a result, it is restricted to visiting a single demand point per trip. Additionally, the drone has a maximum flight range of 17 km and an airtime of up to 17 minutes, which imposes strict operational constraints on feasible delivery routes.

For future studies, by using the mathematical model and VNS algorithm developed in this study-or with the structure that can be developed with different neighborhood methods, studies can be carried out for Erzincan, Bingöl and Izmir North Gediz earthquakes, which are expected to occur larger than magnitude 7 in the near future, such as the Istanbul earthquake. As another further research area, uncertainty in the number of people at the assembly areas can be considered. In addition, as detailed in the previous sections, drones can be used in many different areas on the military and civilian side, and in future studies for various purposes can be carried out by considering fleets in which drones with different characteristics are used heterogeneously together. By doing so, the limitations encountered in this study can be addressed, and the scheduling structure can be extended to allow a single drone to deliver multiple packages of different types to more than one demand point in a single trip. For example, after the earthquakes predicted to occur in the eastern provinces of Turkey during the winter season, in addition to the fight against the disaster, there will also be a fight against the cold in provinces with an average temperature of -30 degrees in winter. In this case, in multi-purpose operations such as maximum customer satisfaction and minimum total completion time, large drones with high carrying capacity and long flight time will be needed to carry heavy heating products such as quilts for warmth, while smaller drones will be needed to carry basic first aid kits, and different drones may be used to meet the demands at the same time.

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APPENDICES

Appendix A - The Disaster Assembly Areas (Demand Points) Respectively – Turkish

Demand Point Code	District	Names of The Demand Points
DP - 1	AVCILAR	İnönü İlkokul Bahçesi
DP - 2	AVCILAR	Avcılar Belediyesi Terminal Arkası
DP - 3	AVCILAR	Denizköşkler Spor Sahası Parkı
DP - 4	AVCILAR	Firüzköy Kadın Yaşam Merkezi ve Firuzköy Çocuk Evi
DP - 5	AVCILAR	Adnan Menderes Parkı
DP - 6	AVCILAR	Merkez Mahellesi İspark Alanı
DP - 7	AVCILAR	Vali Rıdvan Yenişen İlkokulu Bahçesi
DP - 8	AVCILAR	Tahtakale Kent Parkı
DP - 9	AVCILAR	Şehit Kom. Onb. Hakan Kuyucu Parkı
DP - 10	BAĞCILAR	Matbaacılar Parkı
DP - 11	BAĞCILAR	Fatih Sultan Mehmet Parkı
DP - 12	BAĞCILAR	Plevne Cami Parkı
DP - 13	BAĞCILAR	211 Sokak Park Alanı
DP - 14	BAĞCILAR	Ümmü Mihcen Kız Anadolu İmam Hatip Lisesi Bahçesi
DP - 15	BAĞCILAR	Hazım Ersu İlkokul Bahçesi
DP - 16	BAĞCILAR	Ceviz Bahçesi
DP - 17	BAĞCILAR	Mareşal Fevzi Çakmak Parkı
DP - 18	BAĞCILAR	Şeyh Şamil Parkı
DP - 19	BAĞCILAR	Mehmet Niyazi Altuğ Anadolu Lisesi Bahçesi
DP - 20	BAĞCILAR	Güneşlitepe İlkokulu Bahçesi
DP - 21	BAĞCILAR	Gaziosmanpaşa Parkı
DP - 22	BAĞCILAR	Molla Gürani Parkı
DP - 23	BAĞCILAR	264 Sokak Parkı
DP - 24	BAĞCILAR	İ.T.O Özel Eğitim Uygulama Okulu I. Kademe Bahçesi
DP - 25	BAĞCILAR	Kirazlı Metro İstasyonu Alanı
DP - 26	BAĞCILAR	Aliya İzzet Bogoviç Anadolu Lisesi Bahçesi
DP - 27	BAĞCILAR	Aile Parkı
DP - 28	BAĞCILAR	897 Sokak Yeşil Alanı
DP - 29	BAĞCILAR	Bağcılar Çiftlik Meydanı
DP - 30	BAĞCILAR	Bağcılar Cemil Meriç Ortaokulu Bahçesi
DP - 31	BAĞCILAR	Bağcılar Anadolu Lisesi Bahçesi
DP - 32	BEYLİKDÜZÜ	Kıvırcık Ali Parkı
DP - 33	BEYLİKDÜZÜ	Sezen Aksu Parkı
DP - 34	BEYLİKDÜZÜ	Cumhuriyet Parkı

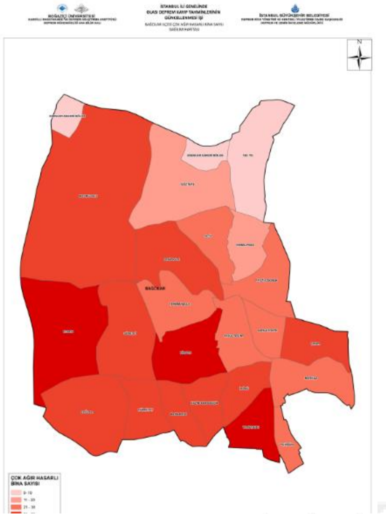
DP - 35	BEYLİKDÜZÜ	Mithat Paşa Ağaçlandırma Alanı
DP - 36	BEYLİKDÜZÜ	Çizgi Sokak Parkı
DP - 37	BEYLİKDÜZÜ	Mustafa Kemal Caddesi Parkı
DP - 38	BEYLİKDÜZÜ	Hürriyet Parkı Karşısı Refüj Alanı
DP - 39	BEYLİKDÜZÜ	Münir Özkul Parkı
DP - 40	BEYLİKDÜZÜ	Şehit Piyade Asb Bilal Özcan Parkı
DP - 41	BÜYÜKÇEKMECE	Çanakkale Şehitleri Anafartalar Parkı
DP - 42	BÜYÜKÇEKMECE	Pembe Panter Parkı
DP - 43	BÜYÜKÇEKMECE	Ahmet Yesevi Cad. Yeşil Alan
DP - 44	BÜYÜKÇEKMECE	Lodos Sokak Parkı
DP - 45	BÜYÜKÇEKMECE	Ali Efendi Sk. Parkı
DP - 46	BÜYÜKÇEKMECE	İfakat Genç Parkı
DP - 47	BÜYÜKÇEKMECE	Büyükçekmece Gölü Doğal Yaşam Parkı
DP - 48	BÜYÜKÇEKMECE	Mehtap Sokak 1 Parkı
DP - 49	BÜYÜKÇEKMECE	Esin 1 Sokak Parkı
DP - 50	BÜYÜKÇEKMECE	Zülfü Livaneli Kültür ve Sanat Merkezi Bahçesi
DP - 51	BÜYÜKÇEKMECE	Rüya Caddesi Parkı
DP - 52	ESENYURT	Alkop Camii Avlusu
DP - 53	ESENYURT	Oba Evleri Parkı
DP - 54	ESENYURT	Şehitler İlköğretim Okulu Bahçesi
DP - 55	ESENYURT	Ardıçlı Mahellesi Otoban Yanı Yeşillik Alan
DP - 56	ESENYURT	Atatürk Yürüyüş Parkı
DP - 57	ESENYURT	Necmettin Erbakan Parkı
DP - 58	ESENYURT	Osmanlı Parkı
DP - 59	ESENYURT	Ahmet Temel Parkı
DP - 60	ESENYURT	Borusam Asım Kocabıyık Anadolu Teknik Lisesi Bahçesi
DP - 61	ESENYURT	Kadir Topbaş Parkı
DP - 62	ESENYURT	Koru Park
DP - 63	ESENYURT	Ihlamur Parkı
DP - 64	ESENYURT	Esenyurt Atatürk Ortaokulu Bahçesi
DP - 65	ESENYURT	Mustafa Yeşil Ortaokulu Bahçesi
DP - 66	ESENYURT	Abdullah Gül Parkı
DP - 67	ESENYURT	Nilüfer Parkı
DP - 68	ESENYURT	Fidan Sokak Kreş Parkı
DP - 69	ESENYURT	Fevzi Danış İlköğretim Okulu Karşısı Otoban Yanı Yeşil Alan
DP - 70	ESENYURT	İSKİ Parkı
DP - 71	ESENYURT	Akbatı Karşısı Otoban Yanı Yeşillik Alanı
DP - 72	ESENYURT	Şehitler Parkı

DP - 73	ESENYURT	Sebahattin Başkan Parkı
DP - 74	ESENYURT	Yunus Balta Parkı
DP - 75	ESENYURT	Toplum Sağlığı Merkez Bahçesi
DP - 76	ESENYURT	Mesire Alanı Parkı
DP - 77	ESENYURT	Esenyurt İlköğretim Okulu Bahçesi
DP - 78	ESENYURT	İmam Hasan Camii Avlusu
DP - 79	ESENYURT	15 Temmuz Şehitler Anadolu Lisesi Bahçesi
DP - 80	ESENYURT	Hacı Kamer Torun Camii Bahçesi ve Yanı Yeşil Alanı
DP - 81	ESENYURT	Ardıç Parkı
DP - 82	ESENYURT	Cumhuriyet Meydanı
DP - 83	ESENYURT	Tevfik Bey Ortaokulu Bahçesi
DP - 84	ESENYURT	Lale Parkı
DP - 85	ESENYURT	Yenikent Kültür Merkezi
DP - 86	ESENYURT	Spor Parkı
DP - 87	ESENYURT	İncirtepe Parkı
DP - 88	ESENYURT	Yeni Belediye Önü Meydanı
DP - 89	FATİH	Marmaray Yenikapı İstasyonu
DP - 90	FATİH	Bali Paşa Camii Avlusu
DP - 91	FATİH	Cağaloğlu Geleneksel Türk Sanatları Mesleki ve Teknik Anadolu Lisesi Bahçesi
DP - 92	FATİH	Fatih Camii Avlusu
DP - 93	FATİH	Yavuz Selim Çocuk Parkı
DP - 94	FATİH	Molla Aşkı Parkı
DP - 95	FATİH	Beyazıt Meydanı
DP - 96	FATİH	Mesnevihane Camii Avlusu
DP - 97	FATİH	Binbirdirek Parkı
DP - 98	FATİH	Mehmet Akif Ersoy Parkı
DP - 99	FATİH	Davutpaşa Anadolu Lisesi Bahçesi
DP - 100	FATİH	Bostan Hamamı Sk. Cevahir Otoparkı
DP - 101	FATİH	Ozel Sultan Fatih Koleji Bahçesi
DP - 102	FATİH	İstanbul Manifacturacılar Çarşısı Parkı
DP - 103	FATİH	Dr. Metin Alatlı Parkı
DP - 104	FATİH	Atikali İlkokulu Bahçesi
DP - 105	FATİH	Arkeoloji Parkı
DP - 106	FATİH	Şehzade Camii Bahçesi
DP - 107	FATİH	İBB Fatih Spor Kompleksi
DP - 108	FATİH	İBB Ana Hizmet Binası Yanı Otopark ve Park
DP - 109	FATİH	Fatih Belediyesi Marmara Semt Konağı Avlusu
DP - 110	FATİH	Kadırga Mesleki ve Teknik Anadolu Lisesi Bahçesi

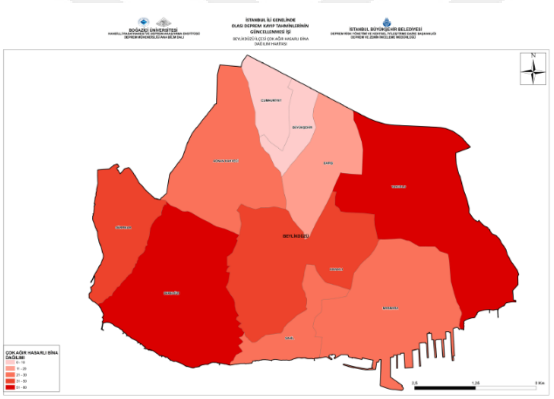
DP - 111	FATİH	Atik İbrahim Paşa Camii Avlusu
DP - 112	FATİH	Çemberlitaş Meydanı
DP - 113	FATİH	Fatih Atatürk İmam Hatip Ortaokulu Bahçesi
DP - 114	FATİH	Eminönü Nişancı Mehmetpaşa Camii Avlusu
DP - 115	FATİH	Yenicamii Meydan Parkı
DP - 116	FATİH	Tevfik Kut Ortaokulu Bahçesi
DP - 117	FATİH	Kadırga Parkı
DP - 118	FATİH	Koca Mustafapaşa Meydanı
DP - 119	FATİH	Fatih Rehberlik ve Araştırma Merkezi
DP - 120	FATİH	Sultanahmet Meydanı
DP - 121	FATİH	Fevziye Küçükefendi Camii Avlusu
DP - 122	FATİH	İstanbul Erkek Lisesi Bahçesi
DP - 123	FATİH	Özel Topkapı Doğa İlkokulu Bahçesi
DP - 124	FATİH	Yedikule Ekipler Parkı
DP - 125	FATİH	Mehmet Emin Tokadi Türbe Çevresi
DP - 126	GAZİOSMANPAŞA	Fahreddin Paşa Parkı
DP - 127	GAZİOSMANPAŞA	Mustafa Yeşil İmam Ortaokulu Bahçesi
DP - 128	GAZİOSMANPAŞA	Şehit Gökhan Topçu Anadolu Lisesi Bahçesi
DP - 129	GAZİOSMANPAŞA	Hürriyet Parkı
DP - 130	GAZİOSMANPAŞA	Evliya Çelebi İmam Hatip Ortaokulu Bahçesi
DP - 131	GAZİOSMANPAŞA	Yıldız Camii Bahçesi
DP - 132	GAZİOSMANPAŞA	Dörtyol Camii Otoparkı
DP - 133	GAZİOSMANPAŞA	805 Sokak Parkı
DP - 134	GAZİOSMANPAŞA	Cumhuriyet Meydanı
DP - 135	GAZİOSMANPAŞA	Muhsin Yazcıoğlu Parkı
DP - 136	GAZİOSMANPAŞA	Şehit Tamer Vardar Parkı
DP - 137	GAZİOSMANPAŞA	Bekir Sami Dedeoğlu İlkokulu Bahçesi
DP - 138	GAZİOSMANPAŞA	Şehit Hüseyin Kültufan Parkı
DP - 139	GAZİOSMANPAŞA	Karlıtepe Ortaokulu Bahçesi
DP - 140	GAZİOSMANPAŞA	Şehit Er Engin Danyıldız Parkı
DP - 141	KÜÇÜKÇEKMECE	5. Cadde No: 4
DP - 142	KÜÇÜKÇEKMECE	İkitelli Spor Kulübü Futbol Sahası
DP - 143	KÜÇÜKÇEKMECE	Dostluk Parkı
DP - 144	KÜÇÜKÇEKMECE	Dr. Oktay Duran Mesleki ve Teknik Anadolu Lisesi Bahçesi
DP - 145	KÜÇÜKÇEKMECE	Yeşilyuva Ortaokulu Bahçesi
DP - 146	KÜÇÜKÇEKMECE	Seyir Parkı
DP - 147	KÜÇÜKÇEKMECE	Mareşal Fevzi Çakmak İlkokulu ve Ortaokulu Bahçesi
DP - 148	KÜÇÜKÇEKMECE	Şehit Mahmut Ergül Parkı
DP - 149	KÜÇÜKÇEKMECE	Sultan Reşat Ortaokulu Bahçesi

DP - 150	KÜÇÜKÇEKMECE	İnönü Parkı
DP - 151	KÜÇÜKÇEKMECE	Küçükçekmece Anadolu İmam Hatip Lisesi Bahçesi
DP - 152	KÜÇÜKÇEKMECE	Mehmet Akif İnan İmam Hatip Ortaokulu Bahçesi
DP - 153	KÜÇÜKÇEKMECE	Nikah Sarayı Altı Parkı
DP - 154	KÜÇÜKÇEKMECE	Kartaltepe Ortaokulu ve Anasıfı Bahçesi
DP - 155	KÜÇÜKÇEKMECE	Mustafa Kemal Paşa İlkokulu Bahçesi
DP - 156	KÜÇÜKÇEKMECE	Tahsin Banguoğlu İlkokulu Bahçesi
DP - 157	KÜÇÜKÇEKMECE	Küçükçekmece Mesleki Eğitim Merkezi Bahçesi
DP - 158	KÜÇÜKÇEKMECE	11173 Parsel Halı Saha
DP - 159	KÜÇÜKÇEKMECE	12939 Parsel Park
DP - 160	KÜÇÜKÇEKMECE	Sultan Murat Ortaokulu Bahçesi
DP - 161	KÜÇÜKÇEKMECE	Şehit Binbaşı Bedir Karabıyık İlkokulu Bahçesi
DP - 162	KÜÇÜKÇEKMECE	Şehit Piyade Er Vedat Kutluca Parkı
DP - 163	KÜÇÜKÇEKMECE	Tepeüstü Meydan
DP - 164	KÜÇÜKÇEKMECE	Behiye Selim Pars Ortaokulu Bahçesi
DP - 165	ZEYTİNBURNU	Zeytinburnu Millet Bahçesi
DP - 166	ZEYTİNBURNU	Zübeyda Hanım Parkı
DP - 167	ZEYTİNBURNU	Topkapı Kültür Parkı
DP - 168	ZEYTİNBURNU	Panorama 1453 parkı
DP - 169	ZEYTİNBURNU	Yenidoğan Meydanı
DP - 170	ZEYTİNBURNU	Atatürk Parkı
DP - 171	ZEYTİNBURNU	Hasan Doğan Spor Tesisleri
DP - 172	ZEYTİNBURNU	Okullar Bölgesi
DP - 173	ZEYTİNBURNU	Zeytinburnu Stadı

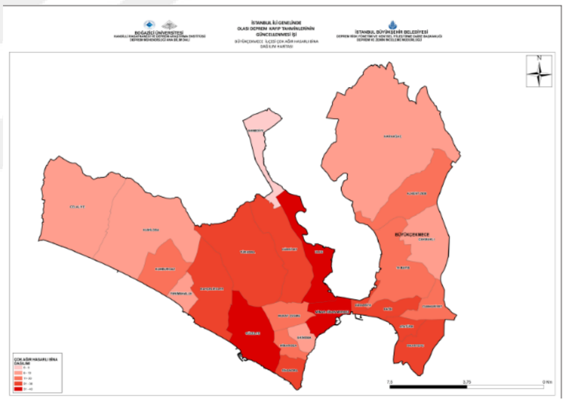
Appendix B - Estimated Number of Severely Damaged Buildings for Mw=7.5 Scenario Earthquake



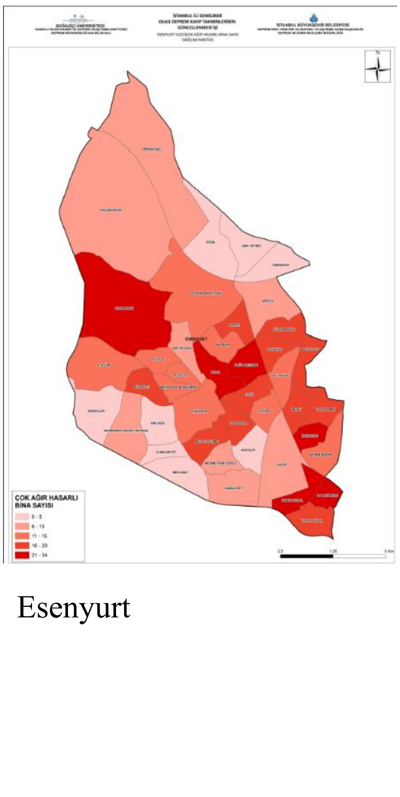
Bağcılar



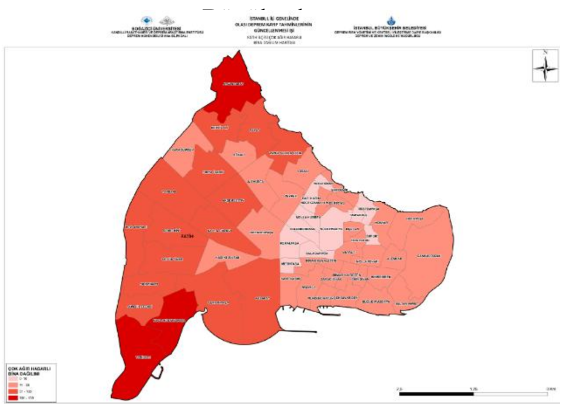
Beylikdüzü



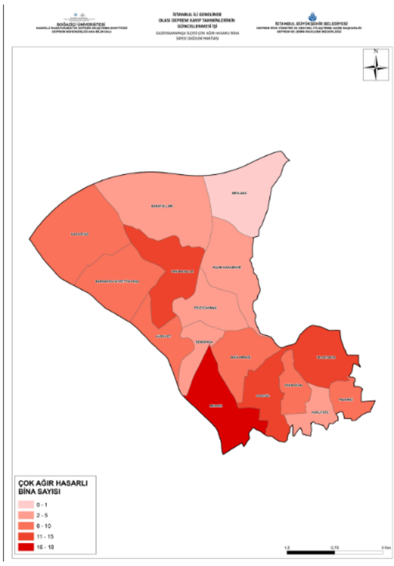
Büyükçekmece



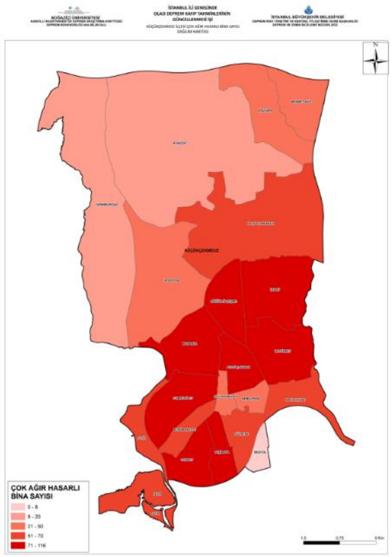
Esenyurt



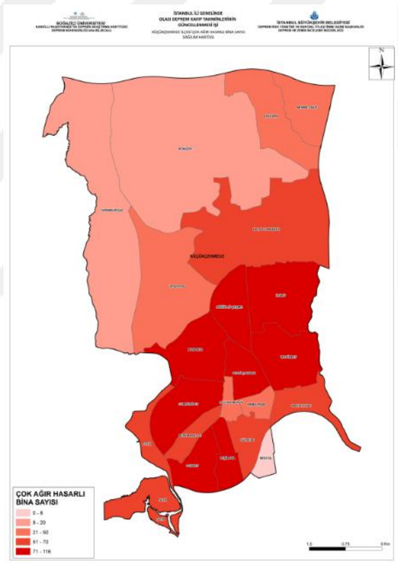
Fatih



Gaziosmanpaşa



Küçükçekmece



Zeytinburnu

Appendix C - Distances Between Depots and Demand Points

DPs/Depots	Depot 1	Depot 2	Depot 3	Depot 4	Depot 5	Depot 6	Depot 7	Depot 8	Depot 9
DP 1	19.31	9.07	13.23	8.44	16.45	19.90	26.39	9.25	24.98
DP 2	19.21	8.93	13.22	8.49	16.63	20.09	26.56	9.37	24.93
DP 3	17.00	6.60	11.78	9.40	17.94	22.05	28.75	11.70	22.99
DP 4	18.70	10.80	10.26	3.42	12.11	17.29	24.80	10.87	22.86
DP 5	18.70	10.80	10.26	3.42	12.11	17.29	24.80	10.87	22.86
DP 6	18.10	8.14	11.91	7.92	16.29	20.30	27.06	10.36	23.67
DP 7	18.65	9.55	11.31	5.74	14.13	18.49	25.56	9.95	23.59
DP 8	17.26	11.93	7.52	3.47	11.23	18.12	26.23	14.60	20.10
DP 9	18.55	9.19	11.50	6.34	14.70	18.93	25.90	9.95	23.66
DP 10	9.07	9.37	1.22	11.94	19.19	26.59	34.75	21.69	11.89
DP 11	9.24	6.43	3.53	11.29	19.40	26.18	34.08	19.75	13.89
DP 12	9.16	6.12	3.84	11.41	19.59	26.31	34.18	19.71	13.99
DP 13	7.40	5.89	4.86	13.26	21.43	28.15	35.99	21.20	12.87
DP 14	5.42	7.73	5.27	15.06	22.90	29.93	37.89	23.44	10.64
DP 15	6.09	5.71	6.45	14.92	23.18	29.80	37.56	22.35	12.47
DP 16	7.42	8.33	3.03	13.21	20.80	28.01	36.08	22.30	11.27
DP 17	6.15	8.33	4.25	14.42	22.06	29.24	37.28	23.24	10.49
DP 18	8.48	9.26	1.80	12.48	19.78	27.16	35.31	22.10	11.44
DP 19	8.42	6.83	3.37	12.06	20.04	26.95	34.89	20.66	13.00
DP 20	5.52	7.11	5.60	15.01	22.99	29.90	37.81	23.11	11.18
DP 21	8.30	5.99	4.22	12.30	20.46	27.19	35.05	20.44	13.40
DP 22	6.76	6.36	4.96	13.83	21.91	28.72	36.59	21.87	12.23
DP 23	7.04	6.19	4.86	13.57	21.68	28.46	36.32	21.59	12.49
DP 24	6.93	8.35	3.48	13.68	21.28	28.49	36.55	22.68	10.93
DP 25	7.21	6.74	4.22	13.29	21.28	28.18	36.10	21.64	12.22
DP 26	9.54	8.34	1.62	11.09	18.69	25.87	33.95	20.51	13.02
DP 27	6.11	5.12	7.61	15.61	24.01	30.44	38.09	22.47	13.08
DP 28	6.17	7.46	4.64	14.31	22.16	29.18	37.14	22.76	11.16
DP 29	6.88	8.15	3.61	13.69	21.35	28.52	36.56	22.60	11.04
DP 30	7.81	7.88	2.93	12.74	20.44	27.57	35.60	21.72	11.86
DP 31	6.00	6.09	6.07	14.81	22.99	29.70	37.51	22.46	12.13
DP 32	19.04	11.43	10.31	2.69	11.40	16.75	24.36	10.98	22.97
DP 33	24.16	14.95	16.06	6.49	11.58	13.71	20.19	5.29	28.66
DP 34	24.34	15.22	16.13	6.38	11.26	13.37	19.91	5.36	28.75
DP 35	27.41	17.27	20.11	10.97	14.83	14.50	19.30	1.03	32.52
DP 36	27.83	17.89	20.23	10.69	13.99	13.46	18.34	1.11	32.74
DP 37	24.08	14.17	16.76	8.28	13.92	15.54	21.46	4.40	29.14
DP 38	22.24	12.71	14.70	6.55	13.21	15.99	22.49	6.39	27.13
DP 39	24.73	14.44	17.92	9.90	15.45	16.52	21.93	3.85	30.13
DP 40	21.64	11.84	14.51	7.18	14.22	17.06	23.48	6.82	26.78
DP 41	28.07	19.41	19.18	8.38	9.14	9.21	15.68	5.98	31.85
DP 42	27.47	18.64	18.75	8.10	9.74	10.12	16.47	5.32	31.43
DP 43	27.53	18.77	18.74	8.03	9.46	9.88	16.32	5.59	31.42
DP 44	43.10	34.76	33.57	22.69	17.01	8.50	0.73	18.05	45.95
DP 45	33.34	24.20	24.59	13.76	12.27	7.76	11.40	7.22	37.26
DP 46	34.53	25.20	25.90	15.11	13.59	8.45	10.92	7.69	38.57
DP 47	31.29	22.83	22.12	11.16	9.05	6.19	12.27	7.99	34.73
DP 48	31.81	23.22	22.69	11.75	9.65	6.24	11.88	7.89	35.31
DP 49	28.60	19.94	19.69	8.86	9.19	8.80	15.16	6.08	32.36
DP 50	33.29	23.93	24.73	14.02	13.09	8.79	12.05	6.52	37.41
DP 51	37.82	29.00	28.68	17.72	13.92	6.44	6.57	12.00	41.27
DP 52	24.83	18.64	14.86	4.80	4.10	10.67	18.98	12.40	27.05
DP 53	21.14	12.74	12.68	3.60	11.03	15.24	22.51	8.64	25.31
DP 54	19.53	11.32	11.18	3.53	11.90	16.68	24.07	9.96	23.78
DP 55	20.04	12.98	10.81	1.05	9.76	15.45	23.27	11.21	23.47
DP 56	21.94	15.55	12.19	1.71	7.13	13.41	21.52	11.89	24.66

DP 57	23.83	15.99	14.67	3.83	8.07	12.00	19.53	8.51	27.32
DP 58	21.43	13.93	12.30	1.80	9.16	14.21	21.90	9.94	24.96
DP 59	19.52	12.63	10.25	1.22	10.05	15.93	23.79	11.70	22.91
DP 60	24.56	15.96	15.88	5.48	9.65	12.21	19.16	6.48	28.55
DP 61	22.59	14.85	13.48	2.79	8.69	13.18	20.76	9.08	26.14
DP 62	21.87	14.43	12.64	1.90	8.69	13.73	21.45	9.91	25.30
DP 63	23.45	14.85	14.88	4.79	10.14	13.25	20.28	6.95	27.54
DP 64	20.86	14.68	11.10	1.08	8.00	14.50	22.62	12.45	23.59
DP 65	21.05	13.35	12.08	2.10	9.80	14.73	22.33	9.78	24.75
DP 66	24.33	16.01	15.46	4.86	9.00	12.02	19.21	7.23	28.13
DP 67	21.85	13.08	13.61	4.55	11.41	15.01	22.04	7.62	26.21
DP 68	23.67	15.61	14.68	4.01	8.69	12.37	19.76	8.03	27.35
DP 69	20.18	12.54	11.30	2.11	10.44	15.59	23.20	10.29	23.97
DP 70	19.81	10.80	12.12	5.15	13.17	17.27	24.31	8.98	24.54
DP 71	22.41	15.73	12.75	1.97	7.04	12.94	20.99	11.26	25.26
DP 72	21.71	13.23	13.23	3.85	10.83	14.77	21.98	8.17	25.87
DP 73	19.48	10.51	11.81	5.14	13.30	17.53	24.61	9.30	24.22
DP 74	23.28	14.62	14.77	4.82	10.38	13.50	20.50	6.92	27.42
DP 75	22.79	14.84	13.80	3.24	8.99	13.15	20.62	8.58	26.47
DP 76	24.56	18.71	14.51	4.89	3.96	11.10	19.47	13.14	26.58
DP 77	25.41	19.18	15.43	5.35	3.63	10.11	18.44	12.41	27.59
DP 78	22.19	14.39	13.16	2.66	9.10	13.63	21.19	9.10	25.83
DP 79	23.33	15.04	14.53	4.14	9.43	12.96	20.21	7.66	27.20
DP 80	22.64	15.19	13.36	2.47	8.10	12.94	20.67	9.64	26.00
DP 81	20.72	13.85	11.30	0.46	8.88	14.70	22.60	11.28	23.93
DP 82	20.91	13.35	11.87	1.82	9.70	14.78	22.44	10.06	24.55
DP 83	20.18	11.14	12.46	5.17	13.02	16.97	23.96	8.63	24.91
DP 84	22.00	13.56	13.46	3.85	10.57	14.45	21.65	8.04	26.11
DP 85	21.08	13.75	11.87	1.37	9.18	14.49	22.24	10.39	24.53
DP 86	22.32	14.27	13.45	3.17	9.51	13.71	21.13	8.57	26.12
DP 87	19.49	11.55	10.93	3.00	11.49	16.50	24.00	10.31	23.56
DP 88	20.20	11.95	11.77	3.37	11.43	16.03	23.39	9.46	24.39
DP 89	3.22	11.71	13.12	22.77	30.83	37.66	45.44	29.77	10.29
DP 90	1.64	11.70	11.85	21.87	29.73	36.76	44.66	29.43	8.79
DP 91	4.43	13.73	14.68	24.62	32.55	39.51	47.35	31.79	9.89
DP 92	2.02	12.16	12.28	22.35	30.19	37.24	45.14	29.92	8.70
DP 93	1.03	11.79	11.30	21.49	29.24	36.36	44.31	29.32	8.11
DP 94	1.45	12.55	11.22	21.66	29.23	36.50	44.52	29.83	7.06
DP 95	3.60	12.96	13.82	23.74	31.67	38.63	46.47	30.97	9.64
DP 96	1.70	12.58	11.85	22.17	29.84	37.03	45.00	30.10	7.66
DP 97	4.45	13.62	14.68	24.58	32.53	39.47	47.30	31.70	10.04
DP 98	4.53	13.77	14.78	24.71	32.64	39.60	47.43	31.85	9.99
DP 99	2.58	10.69	12.08	21.65	29.73	36.53	44.31	28.69	10.28
DP 100	2.57	13.06	12.81	23.04	30.77	37.92	45.86	30.77	8.16
DP 101	1.26	12.15	11.47	21.74	29.44	36.60	44.57	29.64	7.82
DP 102	2.70	12.68	12.97	23.03	30.87	37.92	45.81	30.52	8.87
DP 103	2.39	11.24	12.25	21.99	30.00	36.88	44.70	29.18	9.81
DP 104	1.23	11.52	11.45	21.51	29.34	36.40	44.31	29.16	8.61
DP 105	2.57	12.24	12.78	22.74	30.64	37.63	45.50	30.12	9.19
DP 106	2.81	12.45	13.03	23.00	30.90	37.89	45.76	30.36	9.24
DP 107	0.36	11.16	10.60	20.75	28.52	35.62	43.56	28.60	8.27
DP 108	2.46	12.14	12.66	22.62	30.52	37.51	45.38	30.01	9.17
DP 109	3.04	10.10	12.02	21.35	29.52	36.22	43.95	28.17	10.91
DP 110	4.35	13.23	14.52	24.32	32.33	39.22	47.02	31.34	10.32
DP 111	3.63	13.40	13.90	23.95	31.81	38.84	46.72	31.34	9.20
DP 112	4.20	13.45	14.44	24.35	32.29	39.24	47.08	31.51	9.90
DP 113	2.79	12.72	13.05	23.11	30.96	38.00	45.89	30.58	8.93
DP 114	3.68	12.55	13.79	23.56	31.57	38.45	46.26	30.62	10.13
DP 115	3.80	13.79	14.06	24.20	32.01	39.09	46.99	31.69	8.91
DP 116	3.82	12.73	13.96	23.75	31.75	38.64	46.44	30.80	10.13

DP 117	4.28	13.17	14.45	24.25	32.25	39.14	46.94	31.27	10.28
DP 118	2.70	10.14	11.77	21.20	29.33	36.08	43.83	28.15	10.60
DP 119	3.26	12.79	13.49	23.45	31.36	38.34	46.19	30.75	9.42
DP 120	4.65	13.75	14.88	24.77	32.73	39.66	47.48	31.85	10.18
DP 121	3.14	9.43	11.53	20.72	28.94	35.59	43.29	27.49	11.17
DP 122	4.21	13.76	14.47	24.49	32.37	39.38	47.24	31.77	9.55
DP 123	0.99	10.69	10.78	20.71	28.61	35.60	43.49	28.31	8.99
DP 124	3.86	9.10	11.88	20.79	29.10	35.63	43.27	27.26	11.89
DP 125	2.62	12.84	12.89	23.03	30.83	37.91	45.83	30.63	8.56
DP 126	4.44	12.99	8.16	19.09	25.96	33.64	41.86	28.50	5.23
DP 127	6.34	13.15	6.63	17.57	24.08	31.90	40.19	27.49	6.07
DP 128	5.05	13.43	8.11	19.07	25.78	33.53	41.79	28.66	4.93
DP 129	5.09	12.55	7.08	18.03	24.84	32.54	40.78	27.59	5.97
DP 130	7.10	13.25	6.09	16.97	23.34	31.21	39.52	27.08	6.60
DP 131	6.83	14.13	7.39	18.27	24.56	32.48	40.80	28.35	5.30
DP 132	3.46	13.26	9.45	20.31	27.36	34.95	43.14	29.41	4.97
DP 133	5.42	13.72	8.13	19.10	25.71	33.51	41.78	28.79	4.75
DP 134	3.51	12.30	8.25	19.10	26.20	33.75	41.92	28.21	5.85
DP 135	3.51	12.30	8.25	19.10	26.20	33.75	41.92	28.21	5.85
DP 136	3.27	13.57	10.14	20.98	28.06	35.64	43.81	29.96	4.86
DP 137	3.45	12.49	8.50	19.35	26.44	34.01	42.18	28.46	5.66
DP 138	5.95	13.42	7.28	18.24	24.78	32.60	40.89	28.07	5.45
DP 139	3.84	13.34	9.15	20.06	27.02	34.66	42.86	29.28	4.83
DP 140	3.89	13.59	9.46	20.36	27.31	34.96	43.16	29.58	4.60
DP 141	12.27	8.88	2.94	8.32	16.04	23.10	31.17	18.13	15.55
DP 142	11.81	9.48	1.98	9.03	16.41	23.69	31.84	19.13	14.66
DP 143	11.81	9.48	1.98	9.03	16.41	23.69	31.84	19.13	14.66
DP 144	11.71	2.64	8.06	11.29	20.09	25.65	32.97	16.83	17.92
DP 145	13.37	3.87	8.69	10.03	18.86	24.13	31.35	15.12	19.34
DP 146	13.22	4.76	7.61	9.10	17.91	23.49	30.89	15.22	18.76
DP 147	11.87	4.28	6.69	9.94	18.67	24.55	32.06	16.58	17.44
DP 148	11.96	3.06	7.89	10.86	19.66	25.23	32.57	16.53	18.03
DP 149	10.83	6.71	3.65	9.71	17.91	24.60	32.49	18.34	15.21
DP 150	10.90	5.26	5.10	10.06	18.57	24.89	32.61	17.74	16.01
DP 151	13.24	6.76	5.79	7.67	16.27	22.46	30.18	15.71	17.83
DP 152	13.09	5.00	7.23	8.91	17.70	23.40	30.86	15.37	18.49
DP 153	10.58	3.07	7.01	11.56	20.27	26.17	33.65	17.87	16.65
DP 154	10.66	3.67	6.49	11.10	19.77	25.78	33.32	17.77	16.48
DP 155	11.66	3.44	7.29	10.66	19.42	25.16	32.59	16.78	17.56
DP 156	10.88	9.26	1.17	9.98	17.34	24.65	32.79	19.92	13.77
DP 157	12.30	7.87	3.80	8.18	16.29	23.06	31.02	17.39	16.16
DP 158	12.20	4.12	7.12	9.91	18.68	24.42	31.88	16.24	17.86
DP 159	11.63	4.21	6.56	10.12	18.83	24.75	32.28	16.82	17.21
DP 160	12.31	3.71	7.61	10.21	19.01	24.62	32.00	16.14	18.15
DP 161	10.82	4.28	5.98	10.61	19.24	25.35	32.95	17.65	16.37
DP 162	13.61	7.56	5.54	7.07	15.58	21.93	29.73	15.67	17.85
DP 163	13.25	4.23	8.17	9.62	18.45	23.86	31.17	15.19	19.03
DP 164	13.05	3.85	8.29	9.99	18.82	24.21	31.50	15.42	18.95
DP 165	4.12	7.84	10.78	19.46	27.81	34.28	41.91	25.94	12.18
DP 166	4.80	7.77	11.46	19.85	28.28	34.64	42.19	25.99	12.88
DP 167	1.06	10.11	10.04	19.95	27.85	34.84	42.73	27.61	9.09
DP 168	1.30	9.95	10.16	19.98	27.92	34.87	42.74	27.53	9.35
DP 169	5.18	7.40	11.45	19.65	28.12	34.40	41.92	25.64	13.25
DP 170	1.47	10.35	8.80	19.07	26.75	33.93	41.92	27.28	8.10
DP 171	4.75	6.83	10.15	18.52	26.92	33.32	40.91	24.91	12.67
DP 172	4.61	7.19	10.52	18.95	27.35	33.76	41.35	25.31	12.61
DP 173	4.08	8.24	11.22	19.95	28.29	34.77	42.39	26.38	12.16

Appendix D - Weight Table of Demand Points

Demand Point (DP)	Weight (W)	Demand Point (DP)	Weight (W)	Demand Point (DP)	Weight (W)	Demand Point (DP)	Weight (W)
DP 1	9	DP 56	5	DP 111	7	DP 166	9
DP 2	9	DP 57	6	DP 112	8	DP 167	7
DP 3	9	DP 58	6	DP 113	7	DP 168	7
DP 4	7	DP 59	6	DP 114	8	DP 169	9
DP 5	9	DP 60	7	DP 115	7	DP 170	6
DP 6	9	DP 61	6	DP 116	8	DP 171	8
DP 7	8	DP 62	6	DP 117	8	DP 172	8
DP 8	5	DP 63	7	DP 118	8	DP 173	8
DP 9	8	DP 64	5	DP 119	7		
DP 10	5	DP 65	6	DP 120	8		
DP 11	6	DP 66	7	DP 121	8		
DP 12	6	DP 67	7	DP 122	7		
DP 13	7	DP 68	6	DP 123	7		
DP 14	6	DP 69	6	DP 124	8		
DP 15	7	DP 70	8	DP 125	7		
DP 16	5	DP 71	5	DP 126	4		
DP 17	6	DP 72	7	DP 127	4		
DP 18	5	DP 73	8	DP 128	4		
DP 19	6	DP 74	7	DP 129	4		
DP 20	6	DP 75	6	DP 130	3		
DP 21	6	DP 76	4	DP 131	3		
DP 22	7	DP 77	4	DP 132	5		
DP 23	7	DP 78	6	DP 133	4		
DP 24	5	DP 79	7	DP 134	5		
DP 25	6	DP 80	6	DP 135	3		
DP 26	5	DP 81	5	DP 136	5		
DP 27	8	DP 82	6	DP 137	5		
DP 28	6	DP 83	8	DP 138	4		
DP 29	6	DP 84	7	DP 139	4		
DP 30	6	DP 85	6	DP 140	4		
DP 31	7	DP 86	6	DP 141	5		
DP 32	6	DP 87	7	DP 142	5		
DP 33	8	DP 88	7	DP 143	5		
DP 34	8	DP 89	8	DP 144	8		
DP 35	10	DP 90	7	DP 145	8		
DP 36	9	DP 91	8	DP 146	8		
DP 37	9	DP 92	7	DP 147	8		
DP 38	8	DP 93	7	DP 148	8		
DP 39	10	DP 94	6	DP 149	6		
DP 40	9	DP 95	7	DP 150	7		
DP 41	7	DP 96	6	DP 151	7		
DP 42	7	DP 97	8	DP 152	8		
DP 43	7	DP 98	8	DP 153	8		
DP 44	5	DP 99	8	DP 154	8		
DP 45	8	DP 100	7	DP 155	8		
DP 46	8	DP 101	6	DP 156	5		
DP 47	6	DP 102	7	DP 157	6		
DP 48	6	DP 103	7	DP 158	8		
DP 49	7	DP 104	7	DP 159	8		
DP 50	8	DP 105	7	DP 160	8		
DP 51	7	DP 106	7	DP 161	7		
DP 52	4	DP 107	7	DP 162	6		
DP 53	7	DP 108	7	DP 163	8		
DP 54	7	DP 109	8	DP 164	8		
DP 55	6	DP 110	8	DP 165	8		