POST-DISASTER ASSESSMENT ROUTING PROBLEM

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

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ABSTRACT

POST-DISASTER ASSESSMENT ROUTING PROBLEM

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Post-disaster assessment operations constitute the basis for the operations conducted in the response phase of the disaster management. Through the assessment of the road segments, the extent of damage and the amount of debris will be determined, and debris removal operations will benefit from this assessment. Via assessing the damage at the population centers, the needs of the affected area will be determined and the distribution of relief supplies will be made accordingly. Hence, the damage assessment allows disaster management operation coordinators to determine immediate actions necessary to respond to the effects of the disaster with the effective use of resources for alleviating human suffering.

In this study, we propose a post-disaster assessment strategy as part of response operations in which effective and fast relief routing are of utmost importance. In particular, the road segments and the population points to perform assessment activities on are selected based on the value they add to the consecutive response operations. To this end, we develop a bi-objective mathematical model that utilizes a heterogeneous vehicle set. The proposed model for disaster assessment considers motorcycles, which can be utilized under off-road conditions, and/or unmanned-aerial-vehicles, drones. The first objective aims to maximize the total value added by the assessment of the road segments (arcs) whereas the second maximizes the total profit generated by assessing points of interests (nodes). Bi-objectivity of the problem is studied with the ϵ-constraint method. Since obtaining solutions as fast as possible is crucial in the post-disaster condition, heuristic methods are also proposed. To test the mathematical model and the heuristic methods, a data set belonging to Kartal district of Istanbul is used.

Keywords: Disaster Management, Humanitarian Logistics, Bi-Objective, General Routing.

ÖZET

AFET SONRASI DURUM TESPİT ARAÇ ROTALAMA PROBLEMİ

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Afet sonrası durum tespit çalışmaları, afet yönetiminin müdahale safhasında gerçekleştirilen operasyonlara temel oluşturmaktadır. Yollardaki hasarın değerlendirilmesi ile hasarın, enkazın büyüklüğü tespit edilecek, enkaz kaldırma işlemleri bu değerlendirme sonucundan faydalanacaktır. Nüfus merkezlerindeki hasarın tespiti ile afetten etkilenen bölgenin ihtiyaçları belirlenecek ve yardım malzemelerinin dağıtımı buna göre yapılacaktır. İnsan acısının hafifletilmesi ve sınırlı kaynakların ihtiyaç noktalarına etkili bir şekilde dağılımı için hasar tespit çalışmasının hızlılığının önemi göze çarpmaktadır.

Bu çalışmada, afet müdehale operasyonların hızlı ve etkili bir biçimde yürütülmesinin önemi göz önünde bulundurularak afet ile mücadelede yol gösterici olacak bir afet sonrası durum tespit stratejisi önerilmektedir. Öncelikle, durum tespiti yapılacak yollar ve nüfus merkezleri takip eden müdehale operasyonlarına kattıkları faydaya göre seçilmektedir. Bu amaçla, heterojen bir araç seti kullanan iki amaçlı bir matematiksel model geliştirilmiştir. Afet sonrası durum tespiti için önerilen model, engebeli arazi koşullarında hareket edebililen motorsikletlerin ve/veya dronların kullanımını dikkate almaktadır. İlk amaç, yolların (ayrıtların) değerlendirilmesiyle eklenen toplam karın en üst düzeye çıkarılmasıdır; ikincisi ise, nüfus merkezlerinin (düğümlerin) değerlendirilmesiyle oluşan toplam karı maksimize etmektedir. Problemin iki amaçlı yapısı ϵ-kısıt yöntemi ile ele alınmaktadır. Afet sonrası koşullarda mümkün olduğu kadar hızlı çözümler elde edilmesinin çok önemli olmasından dolayı, sezgisel yöntemler de önerilmektedir. Matematiksel modeli ve sezgisel yöntemi test etmek için İstanbul'un Kartal ilçesine ait bir veri seti kullanılmaktadır.

Anahtar sözcükler: Afet Yönetimi, İnsani Yardım Lojistiği, İkili Amaç, Genel Rotalama.

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Chapter 1

Introduction

In case of disasters, availability of shelter, food, and water may be disrupted and even worse, people may be in need of urgent medical attention. Therefore, after disasters, logistics operations need to be conducted mainly for providing relief goods, such as food, and shelter to the disaster-affected regions, evacuating people from the danger zones, alleviating human suffering, and most importantly, saving lives. Having capable resources to handle the situation and reaching and activating them on time to alleviate the disaster impact on population and infrastructure are some of the challenges of the humanitarian disaster relief operations. The Haiti earthquake in 2010 constitutes an example on how these challenges have an impact on disaster management. During 2010 Haiti earthquake, limited airport space, damaged port and lack of fuel restrained the humanitarian aid from arriving in Haiti [4]. Moreover, logistics operations often have to be carried out in an environment with destructed transportation infrastructures [5]. Disrupted roads and debris blocking the roads are main sources of difficulty in terms of both aid distribution to disaster victims and re-establishing normal state in disaster-affected areas. In addition, the unpredictable nature of the disaster and demand uncertainty may complicate handling and distribution operations. In that perspective, assessing damage at early stages of the disaster plays a crucial role in further activation of resources.

Under above-described disaster circumstances, it is clear that effective damage assessment is crucial. The damage assessment operations are carried out to obtain an overview of the extent of damage in the shortest possible time to evaluate the situation in the affected regions. Death toll, damages on the roads and critical facilities, locations of the injured population, etc. can be determined during this process. Damage assessment informations can be collected from various channels which may include motorcycles, drones or even satellite imagery. The information collected may allow disaster management operations' coordinators to determine the immediate actions to be taken in order to prepare an effective response plan.

This thesis introduces and formulates the problem of determining routes for heterogeneous set of vehicles to assess critical population points and road segments in an aftermath of a disaster event. The aim is to obtain an overview of the extent of damage in a shortest possible time in order to manage further disaster operations effectively. To this end, a mathematical model is formulated by considering problem specific requirements. Moreover, fast construction and improvement based heuristic methodologies are developed in order to find a set of good solutions without compromising the solution quality.

In the following chapter; firstly, the human vulnerability in the face of disasters is demonstrated by anticipating disasters will continue to damage human life based on some historical data. Then, the rise and the characteristic features of the humanitarian logistics operations are discussed. Next, the types of disasters are defined and classified. Then, post-disaster damage assessment routing problem is introduced after emphasizing the importance of damage assessment in disaster relief.

In Chapter 3, the most relevant literature to this study is reviewed. Moreover, distinguishing characteristics of this thesis are pointed out while reviewing the main characteristics of the relevant studies in the literature.

In Chapter 4, a bi-objective mixed integer programming model for the problem is developed. First, features of the mathematical model are presented with an emphasis on two objectives of the problem. Next, mathematical formulation of the model which determines assessment routes of the heterogeneous set of vehicles while satisfying the necessary requirements is presented. Technical details of the formulation are discussed in detail. Then, in order to handle bi-objectivity of the problem, the ϵ-constraint method, a scalarization approach in multi-objective optimization with its technical details is presented. During our preliminary computational analysis, it is observed that the proposed model is computationally challenging. Hence, a slightly different optimization problem is proposed in order to find a better initial solution for warm-starting the main model. Then, the feasibility of the initial solution in the main model is proved.

In Chapter 5, the computational studies of the mathematical model are presented and the corresponding results are analysed in detail. The features of the data set utilized in this study are described and the results of the model are discussed. The performance metrics to be used in the evaluation of the mathematical models' performance is presented. Finally, certain sensitivity analyses are performed and the models' performances are investigated under different ϵ settings with the help of these metrics.

Chapter 6 is dedicated to the development of a construction and two improvement based heuristic methodologies. First, we developed a fast constructive heuristic solution method. Then, to find a set of good solutions, we applied two improvement methodologies, random and purposive improvement. Random improvement heuristic is essentially a random search procedure whereas purposive improvement heuristic seeks the best improvement in both objectives among the feasible ones under random moves. In Chapter 7, the computational studies of the heuristic methods are discussed and their performances are compared with each other and the mathematical formulation via some performance metrics.

A possible extension for the proposed model is presented in Chapter 8 that considers incorporating a certain amount of time on the node/arc being assessed. The thesis ends with a concluding chapter that combines an overview of the work done along with some guidelines for future research.

The results of this thesis are submitted to Transportation Research Part B:

Methodological Journal, the paper is currently under revision [6].

Chapter 2

Motivation and Problem Definition

In the course of the last 70 years, disasters have grown exponentially both in number and magnitude [7]. Balcik and Beamon [8] point out that the number of people affected by disasters between 2000-2004 was 33% more than 1995-1999. This trend, unfortunately, still continues today. As put forward by the International Federation of Red Cross and Red Crescent Societies (IFRC) in the 2016 World Disasters Report, "humanitarian needs are growing at an extraordinary pace - a historical pace - and are outstripping the resources that are required to respond." [9].

As the numbers presented in Table 2.1 demonstrate, disasters continue to cause loss of human life, in addition to environmental and infrastructural damage. The need for disaster preparedness and relief will continue to expand as the natural disasters are expected to increase five-fold from 2005 to 2055 [10]. These led to the development of humanitarian logistics and disaster management practices which deal with the development of approaches for at least preventing some portion of these losses. Furthermore, Van Wassenhove [1] states that logistics operations account for %80 of disaster relief operations. Hence, humanitarian logistics which compromise of logistics activities while focusing on alleviating the suffering of

Years	Number of Disasters	Number of People Died	Number of People Affected (in thousands)	Cost of Damage (in millions of US dolars)
2006	35	18,504	102,527	35,563
2007	355	15,651	204,291	80,815
2008	320	233,433	109,215	18,900
2009	297	9,410	114,907	45,871
2010	341	240,205	207,508	132,268
2011	293	30,509	181,740	390,693
2012	273	7,894	97,447	138,107
2013	294	19,777	88,246	116,779
2014	280	6,714	71,143	52,415
2015	308	15,194	85,728	60,062

Table 2.1: Disasters (earthquakes, floods, storms, landslides) since 2006 [3]

vulnerable people is considered as one of the imperfect areas to invest in for both academics and practitioners [11].

IFRC defines disaster as “a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community’s or society’s ability to cope using its own resources” [12]. Disasters can be classified based on cause, timing, and place. Initially, disasters based on their causes can be natural and man-made. Natural disasters include geological (e.g. earthquakes, landslides, volcanic eruptions), hydrological (e.g. tsunamis, floods) and meteorological (e.g. droughts, storms, heat waves) events, and their timing and/or place might be known beforehand. While political and refugee crises, terrorist and chemical attacks fall into the man-made category, they can be further classified according to their onset length. Figure 2.1 summarizes this disaster classification. Although logistics activities are an important aspect to mitigate calamitous effects of each disaster type, it should be noted that logistics planning beforehand and activating plans at post-disaster phase are utmost importance for sudden onset natural disasters.

As part of humanitarian logistics, Disaster Operations Management (DOM),

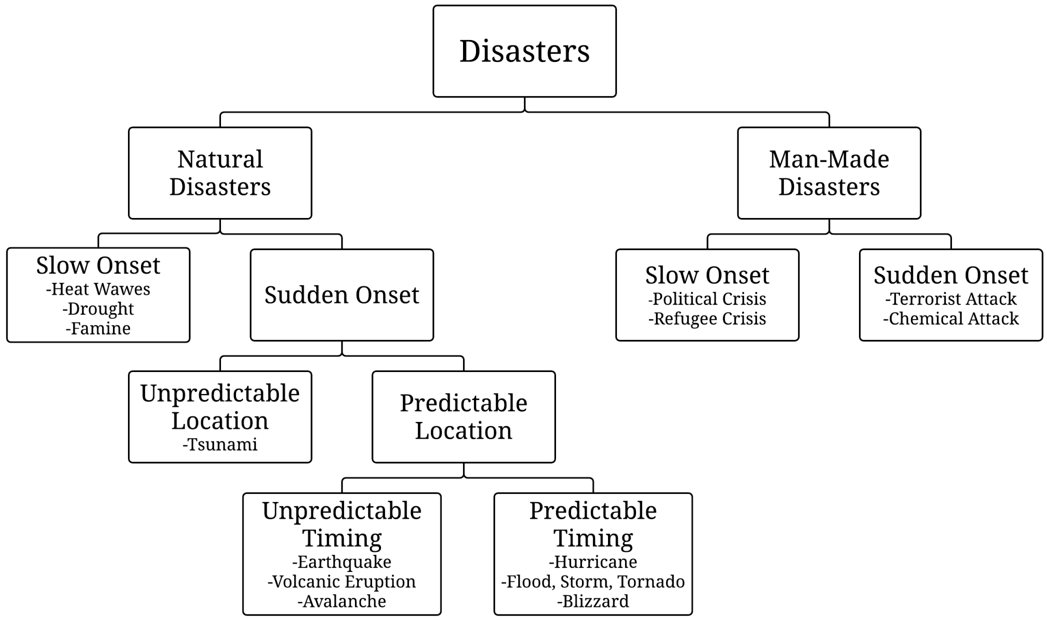


Figure 2.1: Classification of disasters based on cause, timing and place [1]

is defined as activities that are performed before, during, and after a disaster to prevent loss of human life, reduce its impact, and regain the normalcy [13]. The life cycle of disaster operations is divided into three categories as, pre-disaster, response and recovery operations. Pre-disaster operations -mitigation and preparedness- include taking measures to avoid disaster or to reduce the impact and to gain the ability to respond to the disaster. Response is the stage where resources are utilized to reach the disaster area, save lives and prevent further damage. Recovery activities are post-disaster operations that aim to re-establish normal state. Although measures and precautions are taken, disasters are not preventable and predictable. Thus, planning disaster relief operations in advance, and implementing them in disaster and post-disaster phases are significant to mitigate the destructive impact of disasters. The main activities of each stage are listed below:

- **Mitigation:** mapping under-risk areas, disaster insurance, disaster inspections of the buildings.
- **Preparedness:** emergency operations plans, hiring and training personnel,

education on emergency situations, inventory prepositioning, emergency communication system and disaster simulation drills.

- **Response:** activating an emergency plan, impact assessment, relief item distribution, search and rescue operations, medical assistance, and evacuation.
- **Recovery:** debris clearing, contamination control, restoring facilities and infrastructure, and providing temporary housing.

Many of the disaster response operations are actually logistics operations, and in case of a disaster, logistics operations often have to be carried out in an environment with destructed transportation infrastructures [5]. Disrupted roads and debris blocking the roads are main sources of difficulty in terms of aid distribution to disaster victims, evacuation and re-establishing normal state in disaster-affected areas. The unpredictable nature of the disaster and demand uncertainty are other factors that may complicate handling and distribution operations. Hence, to obtain an overview of the extent of damage in the shortest possible time to evaluate the situation in the affected regions and to facilitate effective disaster response operations, the damage assessment operations should be carried out.

2.1 Post-Disaster Damage Assessment Problem

The damage assessment module of any disaster should include the information on the death toll, location of victims and casualties, and the extent of damage to roads, arteries and critical facilities like hospitals and schools. The information for these can be collected from various channels, which may include mobile teams, drones, satellite imagery, and various other reports. The information collected allows disaster management operation coordinators to determine immediate actions necessary to respond to the effects of the damage with the effective use of resources.

Damage assessment can be divided into two categories based on its focus; it could focus on areas with the concentrated population (node module) and the road segments connecting them (arc module). Efficient disaster management operations should consider both elements of damage assessment simultaneously. In that perspective, post-disaster assessment operations should mainly concentrate on assessment of critical population points and critical road segments. Densely populated population points are candidates for critical and should be prioritized. Early assessment of those points results with a better understanding of essential needs such as the number of vehicles for evacuation, the number of ambulances/search and rescue teams to be dispatched or any type of relief items and their quantities. Besides the assessment of critical points, ground network conditions have to be assessed in order to determine the available transportation routes and the roads that have to be unblocked by removing debris. The critical points, such as hospitals and schools, should remain accessible by disaster victims. Furthermore, critical points may be in need of emergency relief item supply. Hence, to be able to maintain access to these points, assessing the disaster impact on the ground transportation network is important. The two components of damage assessment are complementary; therefore, both of them should be taken into account simultaneously during disaster assessment phase.

The main purpose of this thesis is to provide a framework that considers early damage assessment regarding the severity of the disaster impact and the urgency of the need for relief on road network and population areas. The reason for early damage assessment is to find the most effective strategy for further disaster operations. With the help of the early assessment, it is possible to estimate the number of casualties, to detect which hospitals and rallying points are reachable, to determine routes for the relief. Also, to ensure the connectivity of disaster network, by estimating the amount of debris on the roads, immediate debris removal actions can be determined to unblock the disrupted road segments. Since damage assessment operations must be completed quickly, the assessment teams are not required to assess all of the affected regions and the transportation network. Therefore the population points and the roads to be assessed are selected based on their importance in the network.

In this study, we focus on developing a systematic method that can be used by municipalities or local relief agencies to determine disaster impact on their region. We assume that the critical network elements of the area are known. The criticality of population points and road segments are determined by the amount of population and the related distances. Then, given the set of importance carried by each network element, we define the Post-disaster Assessment Routing Problem (PDARP) that determines: (i) the population points to visit, (ii) road segments to traverse, and (iii) the vehicle routes while considering maximum assessment in (i) and (ii) within the assessment period. The proposed system considers the assignment of assessment teams like motorcycles and/or drones to potential starting points, the depots. As there will possibly be debris or destruction on the roads, post-disaster transportation network is considered to be off-road. The vehicles start their tours just after the disaster hits and they assess critical population centers and critical roads in the predetermined time frame and after the vehicles complete their tours, disaster information is reported to the depots (disaster management centers). It is assumed that the motorcycles can only conduct an assessment of the road segments and points that lie in their paths. Whereas, as drones can fly at certain altitudes, flying over certain road segments with drones will enable the assessment of other roads and nodes in their point of view.

The problem proposed has two objectives which are the assessment of critical roads (arcs) and population centers (nodes). As we aim to have information on both arcs and nodes, the problem can be considered as a variant of the general routing problem (GRP) with profits. In our case, the problem has the goals of assessing critical population points and monitoring critical roads. Aiming to assess critical population points may hinder the assessment of the critical roads in a given time period. On the other hand, aiming to assess the critical roads in limited time may result in an assessment of lesser population points but assessing/visiting them multiple times. Due to the nature of the problem, monitoring critical nodes and critical arcs at the same time, the standard requirement of the classical routing problems, that each node is to be visited exactly once, is no longer valid. Allowing multiple node passages, combining two objectives in a bi-objective manner, utilizing a heterogeneous set of vehicles and enabling a wider view, raise a new problem that we refer as Post-Disaster Assessment Routing Problem (PDARP).

The main contribution of this study is as follows:

We are proposing a different modelling perspective for the post-disaster assessment problem by considering assessment of population points and road segments through utilizing heterogeneous set of vehicles, motorcycles and drones which can provide wider point of view, multiple node/arc passages to capture the damage in the disaster aftermath. By considering this new perspective and by using real data from Istanbul, we highlight the importance of considering both network elements in doing an assessment and develop an appropriate assessment strategy. With the developed strategy, assessment teams aim to choose and traverse densely populated regions and critical road segments. We develop a mathematical model that provides damage information in the affected region by considering both the importance of population centers and road segments on the transportation network through using aerial and ground vehicles (drones and motorcycles). To assist post-disaster response phase operations by obtaining information about the extent of damage in the area in a short period; thus, saving lives and defusing the chaotic post-disaster environment, a completion deadline is imposed via route duration constraints. As opposed to standard vehicle routing problems, we allow population points to be visited multiple times to better capture the disaster impact on road segments.

Chapter 3

Literature Review

As our study revolves around relief routing and assessment, the primary focus will be on those studies in the literature review. The relief routing models will be categorized according to the application areas and the problem characteristics. Then, PDARP's connections to GRP and its variants will be reviewed with a focus on the pioneering works. At last, we will consider drone applications in routing/delivery and data acquisition.

3.1 Relief Routing Literature

Especially with the beginning of 21st century, the increase in attention to humanitarian logistics by both academics and practitioners is followed by an increase in the number of studies [11]. Hence, various literature reviews are conducted on humanitarian logistics. Altay and Green [13], Galindo and Batta [14], Kovács and Spens [11] and Celik et al. [15] evaluate disaster management and relief operations literature, respectively, based on disaster timeline, types and application areas together with the solution methodologies. Caunhye et al. [16] categorize optimization problems arise in the emergency logistics in terms of objectives, prominent constraints, and decisions they make. Further, Celik et al. [15] provide case studies to reflect the important aspect of the different humanitarian problems. The survey conducted by Ozdamar and Ertem [7] includes the models of response and recovery planning phases of disaster with the information system applications. Most recently, Kara and Savaser [17] survey operations research (OR) problems encountered in the relief and development logistics within 2007 and 2017, and provide some case studies for various disaster management phases.

Relief routing literature mainly focused on evacuation problems, relief item distribution, and debris removal problems. Evacuation problems focus on the safe and rapid transfer of disaster-affected people to the healthcare centers and shelters. Na and Banerjee [18] aim to maximize survival rate of transferred disaster victims to the hospitals while having a budget constraint. Sheu and Pan [19] handle evacuation problem in a multi-objective manner considering minimization of the evacuation distance and cost of operations. Bayram and Yaman [20] study shelter site location problem for earthquakes while considering evacuation decisions under a stochastic environment. Similar to [20], An et al. [21] consider location and evacuation together while minimizing the total cost.

Relief item distribution problem aims to find an efficient and effective distribution of pre-positioned relief items to people in need. Campbell et al. [22], Houming et al. [23], Ozkapici et al.[24] tackle minimization of total delivery time or latest arrival of a vehicle in a deterministic setting. Camacho-Vallejo et al. [25] minimize the cost of most efficient relief item distribution. Tzeng et al. [26] study the efficient and fair distribution to disaster victims in a multi-objective manner. Yuan and Wang [27] consider path selection problem with the objective of minimization of total travel times and path complexity induced by chaos and congestion. Besides relief item distribution, Yan and Shih [28] incorporate emergency road repair to the problem. They determine fast distribution routes while allowing road repairs on the routes. Ozdamar [29] provides another joint study where the helicopters are utilized in relief item distribution and evacuation at the same time. Similar to Ozdamar [29], Nafaji et al. [30] takes two problems together; however, in the problem-setting, first evacuation, then distribution decisions are made.

Debris removal aspect of relief logistics literature considers reaching critical nodes and restoring network connectivity. Sahin et al. [31] and Berktas et al. [32] route debris removal vehicles to assure accessibility to critical points like hospitals and schools after an earthquake. Akbari and Salman [33] work on the post-earthquake network to sustain the connectivity in a short period of time. Hua and Sheu [34] aim to remove debris with the least cost. Celik et al. [35] study the debris clearance problem in a stochastic setting and the aim is to maximize the total satisfied demand. (Table 3.1)

Application Area	Article	Multi-objective	Deterministic (D)/ Stochastic (S)
Evacuation	Na and Banerjee [18]	No	D
	Sheu and Pan [19]	Yes	D
	Bayram and Yaman [20]	No	S
	An et al. [21]	No	S
Relief Item Distribution	Campbell et al. [22]	No	D
	Houming et al. [23]	No	D
	Ozkapici et al. [24]	No	D
	Camacho-Vallejo [25]	No	D
	Tzeng et al. [26]	Yes	D
	Yuan and Wang [27]	Yes	D
	Yan and Shih [28]	Yes	D
	Ozdamar [29]	No	D
	Nafaji et al. [30]	Yes	S
Debris Removal	Sahin et al. [31]	No	D
	Berktas et al. [32]	No	D
	Akbari and Salman [33]	No	D
	Hua and Sheu [34]	Yes	S
	Celik et al. [35]	No	D

Table 3.1: Relief Routing Problems

From these studies, we observe that although the damage on roads and the needs of disaster victims are considered in some relief routing problems, collecting information about the extent of damage is not received much attention. Although need assessment problem is investigated by Tatham [36], it is not covered in an OR context. In some studies, needs assessment of disaster victims is conducted using sampling techniques. Johnson and Wilfert [37] use cluster sampling technique which divides the disaster-affected region into disjoint clusters. In Daley et al. [38], geography-based sampling scheme is provided, and this scheme is implemented for identifying the needs after the August 1999 Marmara earthquake in Turkey. Huang et al. [39] determine the routes for vehicles to assess needs of all communities in a disaster region such that the total arrival times is minimized via continuous approximation. A recent study of Balcik [40] considers needs assessment of community groups where communities to conduct assessment are selected based on community characteristics using purposive sampling. In that study, routing policies are developed such that each community group and each arc can be traversed at most once by each team. The study of Balcik [40] is the closest relative to PDARP in the humanitarian logistics domain that develops routing strategies and selects communities to assess. The problem discussed in Balcik [40] and PDARP differ in the objectives and assumptions. While Balcik [40] focuses on monitoring disaster impact on population centers, assuming each community/road can be visited at most once, in this paper, we relax that assumption and provide an assessment strategy that focuses both on population points and road segments.The studies that consider assessment of needs are summarized in Table 3.2. Next, we will examine the pioneering studies that mainly focus on GRP and its variants.

Article	Focus
Tatham [36]	Feasibility of assessment
Johnson and Wilfert [37]	Cluster sampling on nodes
Daley et al. [38]	Geography based sampling on nodes
Huang et al. [41]	Node Routing (min total arrival time)
Balcik [40]	Sampling through node routing

Table 3.2: Assessment studies in the relief literature

3.2 General Routing Literature

The GRP aims to find a least-cost route that starts and ends at the same node and visits the required nodes by traversing through the required edges at least once [42]. There is a variant of GRP -Undirected Capacitated GRP with Profits

(UCGRP with profits) [43] and Bus Touring Problem (BTP) [44]- that does not have required nodes or edges to be traversed. In UCGRP with profits, there is a fleet of homogeneous vehicles to serve the customers which are located on nodes and edges of the network. Customers to serve; i.e. nodes and edges to traverse are selected based on maximizing the difference between the profit gained by traversing nodes and edges, and cost of traversal. UCGRP with profits can be considered as a bi-objective; however, its bi-objectivity is defined as the profit minus cost. In BTP, cost of traversal is not considered as an objective and there is a single vehicle available which aims to maximize the total attractiveness (profit) of the tour by selecting nodes to be visited and arcs to be travelled while having side constraints, such as route duration or cost. Profit terms appear on the objective of both problems include node and arc profit; however, their effects on one another is not studied in a bi-objective fashion.

Since, GRP includes both node and arc routing aspects, node routing and arc routing problems can be considered as special cases of GRP. Due to their closeness to the proposed problem, we study both the node (vehicle) routing problems (VRP), and the arc routing problems (ARP).

3.2.1 Node Routing Problems

If there is a subset of nodes required to be visited with an empty required edge set, the GRP reduces to the Travelling Salesman Problem (TSP) or its multi-vehicle version VRP [45, 46]. Travelling Purchaser Problem is defined as a generalization of TSP, in which, in contrast to TSP, nodes to be visited are not pre-specified and different selections are possible [47]. (Table 3.3)

Node routing problems where the vehicle(s) performing a profit-maximizing tour with selecting customers to visit, are classified under the TSP with profits name [48]. TSP with profits are further classified according to how they tackle the bi-objective nature of the problem, namely collected profit and travel costs.

Finding a tour that maximizes the difference between the profit gained by

Problem	Objective	Node Selection	Number of Vehicles	First Proposed By
Travelling Salesman Problem (TSP)	min cost	No	1	Dantzig et al. [45]
Vehicle Routing Problem (VRP)	min cost	No	multiple	Dantzig and Ramser [46]
Travelling Purchaser Problem (TPP)	min cost	Yes	1	Golden et al. [47]

Table 3.3: Node Routing Problems

visiting nodes and the travel cost -by subtracting the cost from the profit- are categorized as Profitable Tour Problems. There are two versions of the problem. An uncapacitated version of the problem, Profitable Tour Problem (PTP) proposed by Dell'Amico et al. [49]. Years later, the capacitated version, Capacitated Profitable Tour Problem (CPTP) is defined by Archetti et al. [50]. Maximum Benefit TSP (MBTSP) can also be considered in this category, as opposed to Profitable Tour problems, its objective is the minimization of the difference between the profit gained by visited nodes and the travel cost -by subtracting the profit from the cost- [51].

Other variants can be characterized based on their profit-maximizing objective while having limited time, capacity or cost constraint. Those problems are usually defined as variants of Orienteering Problem (OP). In an orienteering event, contestants must visit all specified control points and the one who successfully traverses them all in the shortest period of time is the winner. There also exists a score maximizing version of orienteering which is referred with "-score" prefix (SOP). OP discussed in the literature, in general, refers to score orienteering version of the event. Although OP/SOP looks for a benefit maximizing path between the start and end point, in many applications, this difference is eliminated by including a costless arc from the end to the start point.

OP is first proposed by Tsiligirides [52] as finding a profit-maximizing path with distinct start and end points and solved by heuristic algorithms. Selective Travelling Salesman Problem (STSP) [53] is similar to OP. The only difference is that in STSP the start and end nodes are the same. Therefore, it can be said that while STSP pursues a maximum profit circuit, OP aims to find a maximum profit open path. Maximum Collection Problem [54] and Bank Robber Problem [55] are other names given to OP. Also, there exists a version of OP that has generalized cost function as a limiting constraint instead of using Euclidian metric. It is called Generalized Orienteering Problem (GOP) [56]. The multi-vehicle or multi-member team version of OP are Team Orienteering Problem (TOP) [57], Capacitated Team Orienteering Problem (CTOP) [50] and Multiple Tour Maximum Collection Problem (MTMCP) [58]. The capacitated version of TOP has additional capacity constraints together with former time/cost constraints. MTMCP can be seen as a tour version of the TOP.

Another alternative for dealing with bi-objective nature of the TSP with profits is by introducing cost minimization as an objective and profit as a constraint. This category is defined as Prize-Collecting TSP (PCTSP) by Balas [59]. In PCTSP, the aim is to minimize cost while visiting enough points to have pre-defined profit.

As the profit for each vertex can be collected at most once and there is a cost associated with travel, in all node routing with profits problems, a constraint is imposed so that each customer is visited at most once. In Table 3.4, properties of node routing problems with profits are summarized.

3.2.2 Arc Routing Problems

Routing problems where customers are located at arcs on a directed network are categorized under ARPs. In ARPs, the aim is to find minimum cost tour that includes required arc (edge) subset of a graph with some additional constraints. Chinese Postman Problem (CPP) and Rural Postman Problem (RPP) are the two well-known problems of this category. CPP was first proposed by the Chinese mathematician Guan [60]. CPP concerns with finding minimum cost tour that traverses all edges at least once whereas RPP only deals with a subset of edges that have to be traversed [42]. (Table 3.5)

Problem Family	Problem	Objective	Multiple Vehicles	Application Dynamics	First Proposed By
Profitable Tour	Profitable Tour Problem (PTP)	max profit-cost	No	At most one visit to node	Dell'Amico et al. [49]
	Capacitated Profitable Tour Problem (CPTP)	max profit-cost	No	Route based modelling	Archetti et al. [50]
	Maximum Benefit Travelling Salesman Problem (MTSP)	min cost-profit	No	Multiple Traversal of Arcs	Malandraki and Daskin [51]
Orienteering	Orienteering Problem (OP)	max profit	No	At most one visit to node	Tsiligirides [52]
	Selective Travelling Salesman Problem (STSP)	max profit	No	At most one visit to node	Laporte and Martello [53]
	Maximum Collection Problem (MCP)	max profit	No	At most one visit to node	Kataoka and Morito [54]
	Bank Robber Problem (BRP)	max profit	No	No specific starting point	Awerbuch et al. [55]
	Generalized Orienteering Problem (GOP)	max profit	No	Generalized cost function	Ramesh and Brown [56]
	Team Orienteering Problem (TOP)	max profit	Yes	Different Start and End	Chao et al. [57]
	Capacitated Team Orienteering (CTOP)	max profit	Yes	Route based modelling	Archetti et al. [50]
	Multiple Tour Maximum Collection Problem (MTMCP)	max profit	Yes	Time Spent on Nodes	Butt and Cavalier [58]
Prize-Collecting	Prize-Collecting TSP (PCTSP)	min cost	No	Penalties for not visiting	Balas [59]

Table 3.4: Node Routing Problems with profit

Problem	Objective	Required Set	Multiple Vehicles	Multi-Traversal of Nodes	First Proposed By
Chinese Postman Problem (CPP)	min cost	E	No	Yes	Guan [60]
Rural Postman Problem (RPP)	min cost	$E^R \subset E$	No	Yes	Orloff[42]

Table 3.5: Arc Routing Problems

In parallel to Feillet et al. [48], ARPs that concern with finding a profit-maximizing tour while selecting arcs to traverse can be gathered under the ARP with profits. Finding a tour that maximizes the difference between the profit gained by traversing arcs and the travel cost -by subtracting the cost from the profit- can be categorized as Profitable Arc Tour Problems [48, 51, 61]. Profitable Arc Tour Problem (PATP) introduced by Feillet et al. [48], aims to find a set of routes maximizing the difference between the total collected profit and the traveling cost within the traveling time limit. Contrary to PATP, Maximum Benefit Chinese Postman Problem (MBCPP) pursue a route that minimizes the total cost of travelling, where the collected profit is subtracted from the total cost, within the traveling time limit [51]. Prize-Collecting Rural Postman Problem (PCRPP), or Privatized Rural Postman Problem can be considered as a special case of the MBCPP where the profit of an edge can be collected at most once [61].

Where the goal is to find a maximum profit arc tour under limited time, capacity or cost consideration provides other versions of ARP with profits. Those problems are usually variants of Arc OP [62]. Multi-vehicle extension of AOP, The Team Orienteering Arc Routing Problem (TOARP) is studied by Archetti et al. [63]. Undirected Capacitated Arc Routing with Profits (UCARPP) is another version of AOP which have both time and capacity constraints [64]. In the Table 3.6, properties of arc routing problems with profits are summarized.

Problem Family	Problem	Objective	Required Set	Selection	Multiple Vehicles	First Proposed By
Profitable Arc Tour	Profitable Arc Tour Problem (PATP)	max profit-cost	No	A	Yes	Feillet et al. [48]
	Maximum Benefit Chinese Postman Problem (MBCPP)	min cost-profit	No	A	No	Malandraki and Daskin [51]
	Privatized Rural Postman Problem (PCRPP)	min cost-profit	No	E	No	Aráoz et al. [61]
Arc Orienteering	Arc Orienteering Problem (AOP)	max profit	No	A	No	Archetti et al. [63]
	Team Orienteering Arc Routing Problem (TOARP)	max profit	Yes	A	Yes	Aráoz et al. [61]
	Undirected Capacitated Arc Routing Problem (UCARPP)	max profit	No	A	Yes	Archetti et al. [64]

Table 3.6: Arc Routing Problems with profits

3.2.3 Multi-objectivity in GRP

The minimization of the total cost, the total distance, the number of vehicles used, and maximizing the profit or quality/customer satisfaction, and balancing the workload are the prevalent objectives in multi-objective routing problems [65]. In this context, problems discussed above are implicitly multi-objective, in which objectives of profit maximization and cost minimization are present. The closest relatives of PDARP are BTP and UCGRP with profits. BTP maximizes the profit collected from visited nodes and arcs and treats cost objective as constraint [44]. The later one considers the maximization of the difference between the profit collected from visited nodes and arcs, and the cost of traversal via utilizing homogeneous vehicle set [43].

Use of heterogeneous vehicle set which consists of motorcycles and drones, having an angular point of view for servicing/assessing the disaster region and handling bi-objective nature of the problem with the ϵ-constraint method are the distinguishing features of the PDARP. Hence, these features differentiate PDARP from the mentioned closest relatives. When we put differences in the objectives and usage of drones aside, PDARP and UCGRP with profits and BTP have similar feasible regions. However, PDARP has a tighter feasible region because it considers a ground transportation network, not a complete graph. As PDARP operates in ground transportation network, two-phase branch-and-cut based method proposed by Archetti et al. is not suitable for the problem at hand [43].

The proposed problem in this study, PDARP does not have required nodes or edges to be traversed, and the problem has the goals of assessing nodes and monitoring arcs. Two goals may have conflicting interests and the value of assessing an arc or node is not comparable with a single metric. Hence, the problem can be taken as a variant of bi-criteria GRP with profits. Allowing multiple node passages with the heterogeneous set of vehicles (drones and motorcyles) and considering two objectives in a bi-objective manner raise a new problem to the literature we refer as PDARP. As bi-objectivity of the problem is handled with ϵ-constraint method, PDARP can be considered as a variant of both TSP with profits and ARP with profits; but, contrary to both, PDARP does not have cost concerns.

3.3 Drone Applications

As the use of motorcycles and/or drones are considered in the proposed problem, the application areas of the drone systems and the studies in the OR literature, in which drones are used, will be investigated.

Drone systems are primarily developed for military applications. Unmanned surveillance, inspection, and mapping areas are the leading aims for the usage of drones for the military. Recently, drones have become popular for delivery and civilian data acquisition. Large organizations like Amazon, Deutsche Post DHL, Google, the United Arab Emirates have shown interest in drone delivery [66, 67, 68, 69]. To date, there have been numbers of studies on this issue [70, 71, 72]. In Scott and Scott [73], use of drone delivery for healthcare is discussed and mathematical models are developed to facilitate timely and efficient delivery in the non-commercial setting.

Some civilian data acquisition applications are for agriculture, forestry, archaeology, environment, emergency management and traffic monitoring [74]. In emergency management, drones are used for obtaining images for the impact assessment and the rescue planning. For example, in 2015 Nepal earthquake, drones assisted search and rescue teams to locate survivors [75]. Chou et al. [76] propose an emergency drone application after a typhoon, while Haarbrink and Koers [77] focuse on rapid response operations such as traffic incidents. Molina et al. [78] investigate the utilization of drones for searching the lost people. Although drone applications in the emergency management are started to be studied, they are not covered with OR perspective, rather they focus on technicalities of such applications. Hence, as the usefulness of the drones in the disaster management is put forward, this necessitates a further study that develops effective routing policies and models to support assessment efforts.

To the best of our knowledge, there is no study that develops bi-objective routing policies and models for joint use of motorcycles and drones to support assessment efforts that focuses on both transportation network and disaster victims' needs in relief operations.

Chapter 4

Model Development

Consider a disaster-affected region as a directed, incomplete graph. Districts constitute nodes and roads constitute edges. Districts can be classified into two categories, the ones that require assessment and the ones who provide necessary forces for assessment operations, namely depots or disaster management centers. Further classification of districts can be made according to population and type of facilities they have. The ones which have facilities like hospitals, schools or have relatively high populations constitute critical nodes. In a similar fashion, roads connecting critical nodes or the ones with blockage on it cause a significant increase in the distance travelled by disaster victims constitute critical edges. The aim is to reach and assess critical nodes together with critical edges as soon as possible by traversing along paths that may even include debris-blocked edges. To do so, the vehicles, which are suitable for off-road conditions such as drones, motorcycles are dispatched from a depot node. Vehicles travel to reach and assess the critical nodes and the arcs in a limited time frame.

Let $G = (N, E)$ be a network where N represents the nodes and E represents the edges. $A = \{(i, j) \cup (j, i) : i, j \in E\}$ constitutes the arc set of the network. The node set contains the supply node s, and critical nodes. Also, it is worth noting that even if the arcs are directed, the parameter settings of arcs (i, j) and (j, i) are symmetric. If either of (i, j) or (j, i) is traversed, it is assumed that the condition of edge (i, j) is assessed. Let d_{ij} represent the distance between node $i \in N$ and node $j \in N$. We also define a parameter, E, for existence of arcs. If arc (i, j) is in the transportation network, then E_{ij}=1. E_{ij}=0 means arc (i, j) does not exist.

Weights are introduced in order to present the criticality of nodes and arcs. Weight for each node in N denotes importance and we assume populations will provide a good estimate for the weights. Potential population levels for the critical points like hospitals, and schools are estimated by nearest assignment of neighbouring points' population. Node weights, p_i, are calculated with respect to the modified populations of the nodes.

The weight of arc (i, j), which is denoted as q_{ij}, characterizes the importance of road connecting node i to node j. It is calculated with respect to criticality of the road segment and population points it connects. We define criticality of a road segment by the total percentage change in the distance travelled when road segment is unavailable by populations when the road is blocked.

Let M, and D represent the sets of motorcycles and drones, respectively, available at the disaster management center (depot). Vehicles in respective sets M and D, are considered to be identical and cardinality of these sets are $|M|$ and $|D|$. Let V represent the set of all vehicles available at the disaster management center (depot). Note that set V consists of vehicles in M and D in an ordered fashion where first nm vehicles are motorcycles. As previously discussed, candidate vehicles are taken as off-road motorcycles and/or drones. Average velocity v is given accordingly. The output of the model will be $nm + nd$ tours each of which starts their tour and returns to depot within a predetermined time bound T.

If the vehicle is in the set of motorcycles, M, assessment of arcs and nodes is only possible by traversing them. If the vehicle is in the set of drones, D, as drones have angular point of view; flying from node i to node j may result with also assessment of nodes m,n and arcs (i, m), (i, n), (j, m), (j, n), (m, n). Parameters a^l_{ij} and b^{lm}_{ij} are introduced to denote node and arc monitoring capabilities of drones over each arc. If drone flying over arc (i, j) can monitor node l, then a_{ij}^l=1. a_{ij}^l=0 means drone cannot assess node l through flying over arc (i, j). Similarly, if drone flying over arc (i, j) can make assessment on arc (l, m), then b_{ij}^{lm}=1. b_{ij}^{lm}=0 means drone cannot assess node l through flying over arc (i, j). Assessment capabilities of drones, a_{ij}^l and b_{ij}^{lm}, are calculated with respect to the distances from nodes l and m to arc (i, j). If the distances from nodes l and m to arc (i, j) are below some threshold, it it assumed that a_{ij}^l and b_{ij}^{lm} take value 1. For example, as in Figure 4.1, consider a drone flying over arc $(1, 2)$, the shaded area around the traversed arc marks the assessment region of the drone. The nodes and the arcs that lie entirely in the shaded region are considered to be assessed by flying over arc $(1, 2)$.

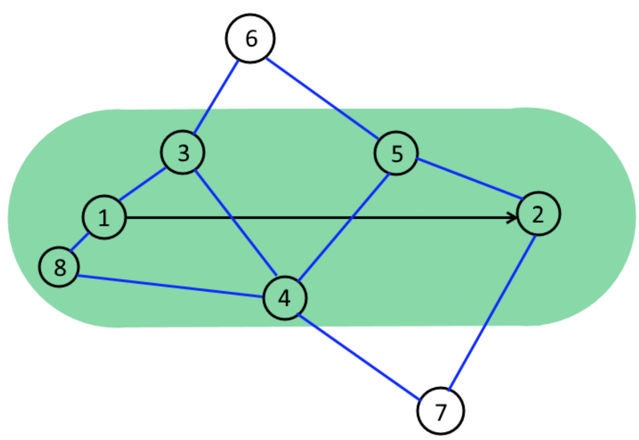
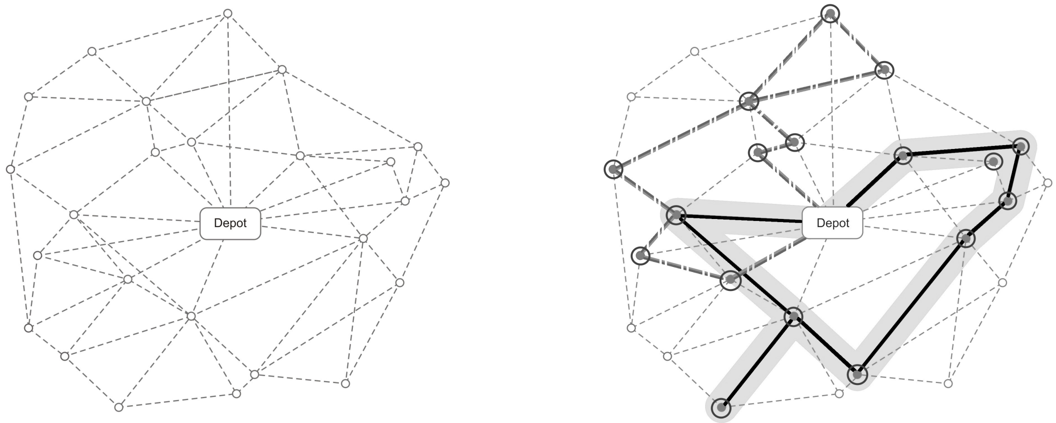


Figure 4.1: Illustrative example of angular point of view of a drone

In the context of general routing with profit, [43], prove that every directed arc in the graph can be traversed at most twice by a vehicle. We will also make use of this result in our model.

Similar to the Figure 4.1, a basic node-arc diagram of for a potential solution of the proposed model can be provided (See Figure 4.2.). Consider a disaster network as depicted in the Figure 4.2a. When we have 1 drone and 1 motorcycle, depending on the distance and the weight values, it is possible to observe routes as given in the Figure 4.2b. Since there is a time-bound for vehicles, some nodes cannot be visited as depicted in the figure. In Figure 4.2b, grey-coloured arcs define motorcycle route while black-coloured arcs make up the route of a drone.



(a) An example disaster network diagram

(b) An example routes of a proposed model for 1 drone and 1 motorcycle on a given network

Figure 4.2: An example node-arc diagram and possible routes of proposed model

As in Figure 4.1, the shaded region around the black coloured arc marks the assessment region of the drone. The nodes and the arcs that lie entirely in the shaded region are being assessed by flying over a given route. However, only the nodes and arcs that lie in the motorcycle route, coloured grey, are considered to be assessed. There are two non-depot nodes in the figure which are visited multiple times. Also, one of the nodes that lie in the shaded region around the drone route is visited along the motorcycle route. Although its assessment can be conducted with the visit of the motorcycle, assessment arcs emerging from it that lie in the shaded region is only possible with the drone. In the figure, circled nodes filled grey represent the nodes being assessed by either of the vehicles. It is important to note that the twice traversal of an arc is not depicted in the figure to avoid complications arising from the superposition of routes.

In the following sections, we first present a bi-objective mixed-integer linear programming model which determines the paths of the vehicles, then introduce a well-known approach in multi-objective optimization. Finally, formulation of the model with ϵ-constraint method is presented.

4.1 PDARP Formulation

In this section we introduce a bi-objective mixed-integer linear programming model which determines the paths of the vehicles. Before presenting the optimization model for the post-disaster assessment routing problem, we provide the nomenclature.

Sets:

N	Set of all nodes.
A	Set of all arcs.
M	Set of motorcycles.
D	Set of drones.
V	Set of vehicles. $V = M \cup D$.

Note that V is an ordered set of M and D.
Depot node is denoted by $s \in N$.

Parameters:

$$E_{ij} \quad : \begin{cases} 1 & \text{if arc } (i,j) \in A \text{ exists in transportation network,} \\ 0 & \text{otherwise.} \end{cases}$$

d_{ij} : distance from node $i \in N$ to node $j \in N$.

p_i : gain from assessing node $i \in N$.

q_{ij} : gain from assessing arc $(i,j) \in A$.

T : time bound for each vehicle.

v : driving speed of motorcycle and flight speed of drone

$$a_{ij}^{l} \quad : \begin{cases} 1 & \text{if node } l \in N \text{ can be monitored by passing through arc } (i,j) \in A \text{ ,} \\ 0 & \text{otherwise.} \end{cases}$$

$$b_{ij}^{lm} \quad : \begin{cases} 1 & \text{if arc } (l,m) \in A \text{ can be monitored by passing through arc } (i,j) \in A, \\ 0 & \text{otherwise.} \end{cases}$$

The decisions to be made can be represented by the following sets of variables:

Decision Variables:

$$X_{ijk} \quad : \begin{cases} 2, & \text{if vehicle } k \in V \text{ traverses through arc } (i,j) \in A \text{ twice,} \\ 1, & \text{if vehicle } k \in V \text{ traverses through arc } (i,j) \in A \text{ once,} \\ 0, & \text{otherwise.} \end{cases}$$

$$Y_j \quad : \begin{cases} 1, & \text{if node } j \in N \text{ is monitored,} \\ 0, & \text{otherwise.} \end{cases}$$

$$Z_{ij} \quad : \begin{cases} 1, & \text{if arc } (i,j) \in A \text{ is monitored,} \\ 0, & \text{otherwise.} \end{cases}$$

u_{ijk} : connectivity variable for vehicle $k \in V$ over arc $(i,j) \in A$

The following mixed integer linear program for PDARP can now be proposed:

$$\text{maximize} \quad f1, f2 \tag{4.0}$$

subject to

$$f1 = \sum_{\substack{i<j \\ (i,j)\in A}} q_{ij} \cdot Z_{ij} \tag{4.1}$$

$$f2 = \sum_{j\in N} p_j \cdot Y_j \tag{4.2}$$

$$X_{ijk} \leq 2 \cdot E_{ij} \qquad \forall (i,j) \in A, \forall k \in V \tag{4.3}$$

$$Z_{ij} \leq 1 \cdot E_{ij} \qquad \forall (i,j) \in A \tag{4.4}$$

$$\sum_{i\in N} X_{ijk} - \sum_{i\in N} X_{jik} = 0 \qquad \forall j \in N, \forall k \in V \tag{4.5}$$

$$Y_j \leq \sum_{i\in N} (\sum_{k\in M} X_{ijk} + \sum_{l\in N} \sum_{k\in D} a_{il}^j \cdot X_{ilk}) \qquad \forall j \in N \tag{4.6}$$

$$Y_j \geq \frac{1}{2} \cdot X_{ijk} \qquad \forall (i,j) \in A, \forall k \in M \tag{4.7}$$

$$Y_j \geq a_{il}^j \cdot \frac{1}{2} \cdot X_{ilk} \qquad \forall (i,l) \in A, \forall j \in N, \forall k \in D \tag{4.8}$$

$$Z_{ij} \leq \sum_{k\in M} (X_{ijk} + X_{jik}) + \sum_{k\in D} \sum_{(l,m)\in A} (b_{lm}^{ij} \cdot X_{lmk}) \qquad \forall (i,j), (j,i) \in A \tag{4.9}$$

$$Z_{ij} \geq \frac{1}{2 \cdot 2} \cdot (X_{ijk} + X_{jik}) \qquad \forall (i,j), (j,i) \in A \forall k \in M \tag{4.10}$$

$$Z_{ij} \geq \frac{1}{2} \cdot (b_{lm}^{ij} \cdot X_{lmk}) \qquad \forall (i,j),(l,m) \in A, \forall k \in D \tag{4.11}$$

$$\sum_{i \in N} X_{isk} = 1 \qquad \forall k \in V \tag{4.12}$$

$$\sum_{j \in N} X_{sjk} = 1 \qquad \forall k \in V \tag{4.13}$$

$$\sum_{(i,j) \in A} d_{ij} \cdot X_{ijk} \leq v \cdot T \qquad \forall k \in V \tag{4.14}$$

$$\sum_{j \in N} (u_{ijk} - u_{jik}) - \sum_{j \in N} d_{ij} \cdot X_{ijk} = 0 \qquad \forall i \in N \backslash \{s\}, \forall k \in V \tag{4.15}$$

$$u_{sjk} = d_{sj} \cdot X_{sjk} \qquad \forall j \in N \backslash \{s\}, \forall k \in V \tag{4.16}$$

$$u_{isk} \leq v \cdot T \cdot X_{isk} \qquad \forall i \in N \backslash \{s\}, \forall k \in V \tag{4.17}$$

$$u_{ijk} \leq (v \cdot T - d_{js}) \cdot X_{ijk} \qquad \forall (i,j) \in A, j \neq s, \forall k \in V \tag{4.18}$$

$$u_{ijk} \leq \max\{v \cdot T - d_{js}, 0\} \qquad \forall (i,j) \in A, j \neq s, \forall k \in V \tag{4.19}$$

$$u_{ijk} \geq (d_{si} + d_{ij}) \cdot \frac{1}{2} \cdot X_{ijk} \qquad \forall (i,j) \in A, i \neq s, \forall k \in V \tag{4.20}$$

$$X_{ijk} \in \{0,1,2\}, \qquad \forall (i,j) \in A, \forall k \in V \tag{4.21}$$

$$Z_{ij} \in \{0,1\}, \qquad \forall (i,j) \in A; \tag{4.22}$$

$$Y_j \in \{0,1\}, \qquad \forall j \in N \tag{4.23}$$

The objective function (4.0) maximizes the total importance of arcs and nodes assessed. We remind here that although we are working on a directed graph, assessment is made through monitoring either direction.

As X_{ijk}, Z_{ij} are defined for each node pair, constraints (4.3) and (4.4) are imposed to guarantee that each arc traversed/assessed exists in the ground transportation network. Constraint (4.5) specifies the flow balance conditions for vehicle k. Constraints (4.6)-(4.8) monitor the assessment of node j by any of the vehicles. Constraints (4.9)-(4.11) check if arc (i,j) is monitored by any vehicles in either direction. Constraints (4.12) and (4.13) ensure all vehicles leave the depot once and return once. Total distance bound is given by the constraint (4.14). Constraint (4.15) ensures the connectivity of the tour for each vehicle k. Constraint (4.16) calculates the distance travelled by vehicle k, leaving the depot. By constraints (4.17) - (4.19), an upper bound on non-depot entering connectivity variable is imposed. To explain further, constraint (4.17) bounds the ones entering the depot by the total travel distance limit. Constraint (4.18) bounds the non-depot entering ones by considering the travel distance limit and the distance which has to be travelled to return the depot. Constraint (4.19) imposes a positive distance bound on the non-depot entering connectivity variables. By constraint (4.20), we ensure that connectivity variable takes a positive value when a vehicle traverses that particular network element. Therefore, disconnected tours are eliminated via constraints (4.15)-(4.20). Note that when $X_{ijk} = 0$, they force u_{ijk} to be 0; while they force u_{ijk} to be between $(d_{si} + d_{ij}) \cdot \frac{1}{2} \cdot X_{ijk}$ and $(v \cdot T - d_{js})$ when $X_{ijk} > 0$ for $j \neq s$. In this way, multiple visits to nodes are allowed while avoiding disconnected sub-tours. Constraints (4.21) - (4.23) are the domain constraints.

In the objective function (4.0), we have two terms to maximize which are defined by (4.1) and (4.2). To tackle the bi-objectivity, we use ϵ-constraint method. It is critical to note that as the problem is a mixed integer program, resulting Pareto frontier may have Pareto efficient solutions which cannot be found using weighted-sum scalarization technique. Additionally, weighted-sum scalarization with fixed weights would return only one of the Pareto-efficient points. Since assessment of the node or arc have distinct implications on the disaster management operations, and their importance is calculated using different metrics, we prefer to utilize a bi-objective methodology.

4.1.1 The ϵ-Constraint Method

Suppose a multi-objective optimization problem with 2 objective functions, $Z_k(x)$, $k = \{1, 2\}$ where x denotes a solution vector. Then this generic problem can be formulated as follows in vectorial notation:

$$\begin{aligned} \text{maximize} \quad & f(x) = [f_1(x), f_2(x)] \\ \text{subject to} \quad & x \in S \end{aligned}$$

where S denotes the feasibility space; i.e., the set of solution vector (x) satisfying all of the specified constraints.

In general, there is no single solution that maximizes all the objectives of multi-objective problems simultaneously. Lack of single optimality leads to pursuit of Pareto-optimality or efficiency by means of finding efficient solutions [79]. In order to find efficient solutions, an appropriate scalarization method should be adopted. Those scalarization methods are categorically weighting methods, constraint methods, reference point methods and direction based methods.

In this thesis, the ϵ-constraint method among the constraint methods is adopted. A generic optimization model to be used in this method is:

$$\begin{aligned} &\text{maximize} \quad f_r(x) \\ &\quad \text{subject to} \\ &f_k(x) \geq \epsilon_k \qquad\qquad \forall k \in \{1, 2\}, k \neq r \\ &x \in S \end{aligned} \tag{4.24}$$

In this method, by changing the ϵ values systematically and solving the given model iteratively, one can obtain non-dominated (efficient) solutions. Those efficient solutions can be later presented to decision maker for evaluation and posterior preference articulation procedure.

For a bi-objective setting, one can make use of a lexicographic approach to find efficient solutions through solving ϵ-constrained optimization models iteratively. Let $P_1(x, \epsilon_2)$ and $P_2(x, \epsilon_1)$ be respective optimization models for each objective. Then $P_1(x, \epsilon_2)$ and $P_2(x, \epsilon_1)$ can be defined as follows:

$$
\begin{array}{ll}
P_1(x,\epsilon_2): & P_2(x,\epsilon_1): \\
\text{maximize} \quad Z_1(x) & \text{maximize} \quad Z_2(x) \\
\quad \text{subject to} & \quad \text{subject to} \\
Z_2(x) \geq \epsilon_2 & Z_1(x) = \epsilon_1 \\
x \in S & x \in S
\end{array}
$$

Initially, P_1 is solved without the ϵ-constraint and ϵ_1 is set to its optimal objective function value f_1^*. Then, P_2 is solved in order to find best objective function value having the same f_1^* value. Lets say f_2^* is the objective function value. The resulting objective values for $Z_1 = f_1^*$ and $Z_2 = f_2^*$ is recorded as one of the Pareto efficient solutions. After this, ϵ_2 is equated to $f_2^* + stepsize$ in order to find the next Pareto efficient solution by solving P_1 again and following the similar procedure as initial step. These algorithmic steps are repeated until the infeasibility in solving P_1 occurs.

4.1.2 PDARP Formulation with the ϵ-Constraint Method

The following additional parameters are defined for ϵ-constraint method.

- ν : lower bound on the total assessed node profit.
- ρ : lower bound on the total assessed arc profit.
- ϵ : increment

For the arc profit PDARP, $f1$ is taken as the objective and $f2$ is considered as a constraint. For the node profit PDARP, objective function $f1$ is replaced by objective $f2$ and ϵ-constraint (4.25) is replaced with the constraint (4.26). The mathematical models are given in the Table 4.1.

In order to justify the utilization of ϵ-constraint method, we show that optimal solutions of Table 4.1 problems are at least weakly efficient. We first need to provide some definitions.

Arc Profit PDARP			Node Profit PDARP		
maximize $f1$			maximize $f2$		
subject to			subject to		
(4.1) − (4.23)			(4.1) − (4.23)		
$f2 \geq \epsilon_2$	$(\epsilon_2 = \nu + \epsilon)$	(4.25)	$f1 \geq \epsilon_1$	$(\epsilon_1 = \rho)$	(4.26)

Table 4.1: ϵ-constrained mathematical models

A feasible solution $\bar{x} \in S$ is called *efficient* or *Pareto optimal*, if there is no $x \in S$ such that $f(x) \geq f(\bar{x})$. If $\bar{x}$ is efficient, $f(\bar{x})$ is a *non-dominated* point.

A feasible solution $\bar{x} \in S$ is called *weakly efficient* (*weakly Pareto optimal*) if there is no $x \in S$such that $f(x) > f(\bar{x})$, i.e. $f_j(x) > f_j(\bar{x})$ for all $j = 1, 2$. The point $f(\bar{x})$ is then called *weakly non-dominated*.

Proposition 1. *Let $\bar{x}$ be an optimal solution of one of the problems in Table 4.1 for some $j \in \{1, 2\}$, then $\bar{x}$ is weakly efficient.*

Proof. Assume $\bar{x}$ is not weakly efficient. Then $\exists k \in \{1, 2\}$ and $x \in S$ such that $f_k(x) > f_k(\bar{x})$. Let us say $f_j(x) > f_j(\bar{x})$ for $k \neq j$, the solution x is feasible for one of the problems in Table 4.1 for some $j \in \{1, 2\}$. This contradicts to $\bar{x}$ being an optimal solution of one of the problems in Table 4.1 for some $j \in \{1, 2\}$. $\square$

Corollary 1. *Let $X \in S$ be a solution of one of the problems in Table 4.1 with an optimality gap, then Pareto optimality of the solution X cannot be asserted. Thus, $f(x)$ is called Pareto approximate.*

4.2 Finding Initial Solution for PDARP

During our preliminary computational analysis, we observe that PDARP is a computationally challenging problem. Warm-starting arc profit PDARP is considered as a method to reduce the computation time. A slightly different optimization problem can be utilized to obtain an initial point for the current problem for the warm-start procedure. Therefore, we propose a version of the arc profit PDARP to find a feasible starting point. To do so, we redefine X_{ijk} so that second pass is not allowed.

Updated Decision Variable:

$$X'_{ijk} : \begin{cases} 1, & \text{if vehicle } k \text{ traverses through arc } (i,j) \in A, \\ 0, & \text{otherwise.} \end{cases}$$

The following mixed integer linear program for arc profit 1-PDARP can now be proposed:

$$\text{maximize} \quad f1, f2$$
$$\text{subject to}$$
$$(4.1) - (4.2),$$
$$(4.4) - (4.6),$$
$$(4.9),$$
$$(4.12) - (4.19),$$
$$(4.22) - (4.25),$$
$$X'_{ijk} \leq E_{ij} \qquad \forall (i,j) \in A, \forall k \in V \tag{4.3a}$$
$$Y_j \geq X'_{ijk} \qquad \forall (i,j) \in A, \forall k \in M \tag{4.7a}$$
$$Y_j \geq a^j_{il} \cdot X'_{ilk} \qquad \forall (i,l) \in A, \forall j \in N, \forall k \in D \tag{4.8a}$$
$$Z_{ij} \geq \frac{1}{2} \cdot (X'_{ijk} + X'_{jik}) \qquad \forall (i,j),(j,i) \in A, \forall k \in M \tag{4.10a}$$
$$Z_{ij} \geq b^{ij}_{lm} \cdot X'_{lmk} \qquad \forall (i,j),(l,m) \in A, \forall k \in D \tag{4.11a}$$
$$u_{ijk} \geq (d_{si} + d_{ij}) \cdot X'_{ijk} \qquad \forall (i,j) \in A, i \neq s, \forall k \in V \tag{4.20a}$$
$$X'_{ijk} \in \{0,1\} \qquad \forall (i,j) \in A, \ \forall k \in V \tag{4.21a}$$

Proposition 2. *A feasible solution to arc profit 1-PDARP is also feasible to the arc profit PDARP.*

Proof. Take a feasible solution $\bar{X}$ of arc profit 1-PDARP. The constraints (4.1), (4.2), (4.4)-(4.6), (4.9), (4.12) -(4.19),(4.22), (4.23), (4.25) are automatically satisfied as they are the same for both problems. The feasible solution $\bar{X}$ to restricted problem satisfies $\bar{X} \subset X$ where $\bar{X} = \{\bar{X}_{ijk} : \bar{X}_{ijk} \in \{0,1\}\ \forall (i,j) \in A,\ \forall k \in V\}$ and $X = \{X_{ijk} : X_{ijk} \in \{0,1,2\}\ \forall (i,j) \in A,\ \forall k \in V\}$. To prove $\bar{X}$'s feasibility for the original problem, we need to check whether $\bar{X}$ satisfies remaining constraints of the arc profit PDARP.

- As E is a non-negative matrix, $E_{ij} \leq 2 \cdot E_{ij} \quad \forall (i,j) \in A$. For feasible $\bar{X}$, $\bar{X}_{ijk} \leq E_{ij} \quad \forall (i,j) \in A$ is satisfied by the constraint (4.3a). So, the following is satisfied $\bar{X}_{ijk} \leq 2 \cdot E_{ij} \quad \forall (i,j) \in A$. Hence, $\bar{X}$ does not violate the constraint (4.3).

- The constraint (4.7a), $Y_j \geq \bar{X}_{ijk} \quad \forall (i,j) \in A, \forall k \in M$, is satisfied by feasible $\bar{X}$ and $\bar{X}_{ijk} \geq \frac{1}{2} \cdot (\bar{X}_{ijk}) \quad \forall (i,j) \in A, \forall k \in M$ for $\bar{X}$. Hence, the constraint (4.7), $Y_j \geq \frac{1}{2} \cdot X_{ijk} \quad \forall (i,j) \in A, \forall k \in M$ holds.

- For any $\bar{X}$, $\bar{X}_{ilk} \geq \frac{1}{2} \cdot \bar{X}_{ilk} \quad \forall (i,l) \in A, \forall k \in D$ is satisfied. $Y_j \geq a^j_{il} \cdot \bar{X}_{ilk}$ $\forall (i,l) \in A, \forall k \in D$ for feasible $\bar{X}$ by the constraint (4.8a). Considering two inequalities together, $Y_j \geq a^j_{il} \cdot \bar{X}_{ilk} \geq a^j_{il} \cdot \frac{1}{2} \cdot \bar{X}_{ilk} \quad \forall (i,l) \in A, \forall k \in D$. So, the constraint (4.8) is not violated by feasible solution $\bar{X}$.

- Take constraint (4.10a), $Z_{ij} \geq \frac{1}{2} \cdot (\bar{X}_{ijk} + \bar{X}_{jik}) \quad \forall (i,j),(j,i) \in A, \forall k \in M$. This constraint is satisfied with feasible solution $\bar{X}$. And for any $\bar{X}$, $\frac{1}{2} \cdot (\bar{X}_{ijk} + \bar{X}_{jik}) \geq \frac{1}{2 \cdot 2} \cdot (\bar{X}_{ijk} + \bar{X}_{jik}) \quad \forall (i,j),(j,i) \in A, \forall k \in M$. Hence, feasible solution $\bar{X}$ will also satisfy the constraint (4.10) which is $Z_{ij} \geq \frac{1}{2 \cdot 2} \cdot (X_{ijk} + X_{jik})$ $\forall (i,j),(j,i) \in A, \forall k \in M$.

- For feasible solution $\bar{X}$, constraint (4.11a) holds. That is, $Z_{ij} \geq b^{ij}_{lm} \cdot \bar{X}_{lmk}$ $\forall (i,j),(l,m) \in A, \forall k \in D$. For feasible solution $\bar{X}$ and non-negative matrix b, the following inequality holds: $b^{ij}_{lm} \cdot \bar{X}_{lmk} \geq \frac{1}{2} \cdot b^{ij}_{lm} \cdot \bar{X}_{lmk} \quad \forall (i,j),(l,m) \in A, \forall k \in D$. So, the following is satisfied $Z_{ij} \geq \frac{1}{2} \cdot b^{ij}_{lm} \cdot \bar{X}_{lmk} \quad \forall (i,j),(l,m) \in A, \forall k \in D$. Thus, $\bar{X}$ does not violate the constraint (4.11).

- The constraint (4.20a), $u_{ijk} \geq (d_{si} + d_{ij}) \cdot \bar{X}_{ijk} \quad \forall (i,j) \in A, \forall k \in V$, is satisfied by feasible $\bar{X}$ and $(d_{si}+d_{ij}) \cdot \bar{X}_{ijk} \geq (d_{si}+d_{ij}) \cdot \frac{1}{2} \cdot \bar{X}_{ijk} \quad \forall (i,j) \in A, \forall k \in V$

for $\bar{X}$. So, the constraint (4.20), $u_{ijk} \geq (d_{si} + d_{ij}) \cdot \frac{1}{2} \cdot X_{ijk} \quad \forall (i,j) \in A, \forall k \in V$ holds for $\bar{X}$. $\square$

Hence, the feasible solution $\bar{X}$ found for the model that restricts traversal of arcs by at most once provide a feasible solution to arc profit PDARP. Thus, we first formulated the single pass version of the problem and warm-started the PDARP with the paths we generated with the single-pass version. In this way, the solution time is speeded up.

Chapter 5

Computational Analysis of the Mathematical Model

In this chapter, computational studies of the mathematical model are conducted and corresponding results are analysed in detail. First, the characteristics of the data set utilized in this study are explained. The results of the model are discussed. Finally, certain sensitivity analyses are performed and the model performances are investigated under different ϵ settings with the help of some performance metrics.

5.1 Data

To measure the effectiveness of the developed mathematical model, and the heuristic solution methodology, we used a data set from Turkey based on Istanbul's Kartal district [80]. Kartal is specified as the 11th most crowded district among the 39 districts of Istanbul and has nearly $425,000$ inhabitants.

There are 20 sub-districts in Kartal and the population of each is assumed to be concentrated in its center. Moreover, there are 25 points of interests (POI) which are determined as emergency rallying points. These POIs include school yards, mall parking lots and some other appropriate points. The locations of 45 nodes are presented in Figure 5.1. Sub-districts together with POIs are taken as population points as POIs have the possibility of being densely populated during the disaster. There are 7 POIs containing schools and hospitals. Those are illustrated with yellow squares and green stars, respectively, while red dots are used for other nodes. The Marmara Region Disaster Center of the Turkish Red Crescent, which is located in Kartal, is considered as a candidate depot for disaster relief operations and represented by a red triangle in Figure 5.1. Features of the data set are summarized in Table 5.1

	Kartal municipality
Number of Nodes	45
Depot node (node number)	16
Number of schools (node numbers)	3 (14, 21, 22)
Number of hospitals (node numbers)	4 (26, 33, 41, 43)

Table 5.1: Features of the data set

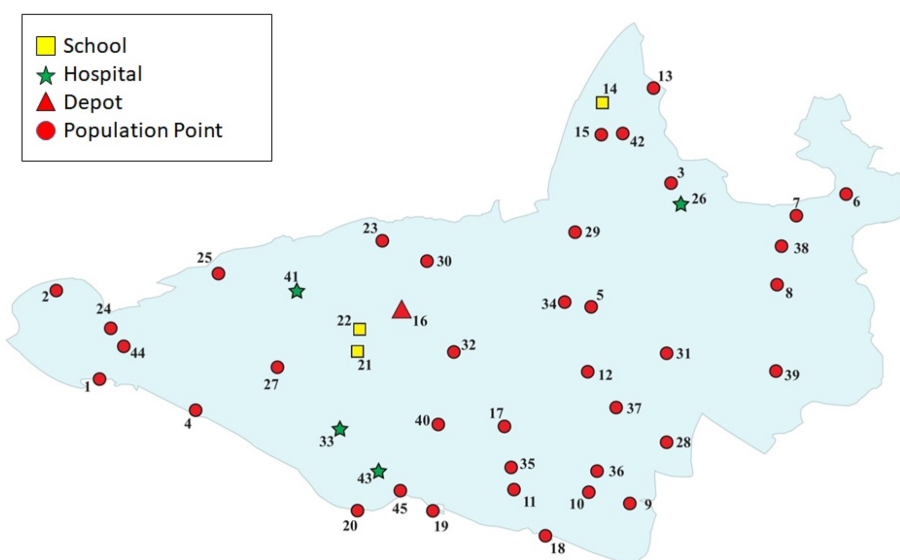


Figure 5.1: The location of depot and critical nodes in Kartal municipality [2]

In order to determine the critical elements of a network, certain weights need to be assigned to the nodes and arcs. For nodes, the weights are determined based on the number of people living in a district. To give a relatively higher importance to the points like hospitals and schools, potential population levels are determined. To do so, the populations of the districts are aggregated and assigned to each nearest hospital and school. Node weights ($nodew_i$) are calculated with respect to the resulted aggregated populations and reduced to the $[0,1]$ interval.

The importance of roads is determined based on the population of the points that it connects and criticality of the road. If blockage on the road causes a significant increase in the distance travelled by disaster victims and the weights of the nodes connected by that road are high, then the importance of the arc increases along with the weight value assigned to it. Hence, the weight assigned to the arc (i, j) is directly proportional to the shortest path distance change from node i to j when (i, j) is blocked and the sum of population at i and j and inversely proportional to the complete network distance.

The number of vehicles available for assessment operations considered to be at most 2 drones and 3 motorcycles. The reason is that after a disaster, resources are scarce and available vehicles may be allocated to other response operations. Due to its endurance and camera specifications, Aeromapper Talon model of Aeromao Inc. is considered as a candidate vehicle [81]. It has a cruise speed of 50 km/h, considering take-off and landing, average drone speed assumed is about 40 km/h. Additionally, for the motorcycles, the vehicle speed is considered to be again about 40 km/h, which is suitable for off-road motorcycles. As the first hours after a disaster is critical for response operations, time-window for vehicles is set to 2 hours in order to make the assessment in short period of time. This 2 hours time limit is also in line with the endurance of the Aeromapper Talon drone. The range is another property to be considered in utilizing drones; Aeromapper Talon has a range of 30 + which underlines its usefulness in assessment. Under this parameter setting, it is not required to include a constraint regarding range properties.

Maximum flight altitude for a drone is restricted in most countries by 120 meters. Chosen drone, Aeromapper Talon, has Sony A6000 model camera mounted on it [81]. Sony A6000 camera can have a focal length ranging from 16 mm to 50 mm. As focal length gets smaller, the field of view increases, so the focal length setting is taken as 16 mm. With the focal length of 16 mm and flight altitude of 120 meters, it is possible to monitor all the points within a circle of 75-80 meters radius. In this study, we take this radius as 75 meters. Considering densely populated city such as Istanbul, using drones for assessment purposes promises evaluation of nearby points and roads while passing through a particular path. To that end, we introduced parameters for node and arc monitoring capabilities of drones over each arc. If a point m is within 75 meters distance to any point on arc (i, j), its assessment can be done while flying over arc (i, j). Similarly, each arc connecting the points, which lie within 75 meters of distance to any point on arc (i, j), can be assessed by traversing through arc (i, j) by drone.

Since mathematical model requires ϵ-value, it is determined by the smallest weight difference between population points and it is taken as 0.001. Larger ϵ-values, 0.1 and 0.01, are also used in order to compare the resulting frontiers in terms of quality, how well they approximate the Pareto front, and the computational requirement of the overall procedure. In the Table 5.2, parameters of the model is summarized.

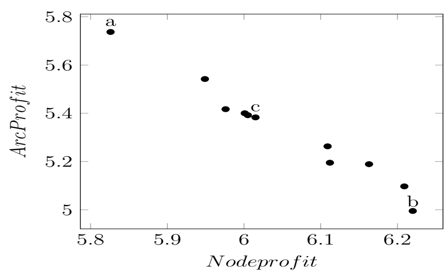
Driving/Flight Speed	40 km/hr
Epsilon (ϵ)	0.001, 0.01, 0.1
Number of Drones	1, 2
Number of Motorcycles	1, 2, 3
Time bound	2 hr

Table 5.2: Test parameters of the model

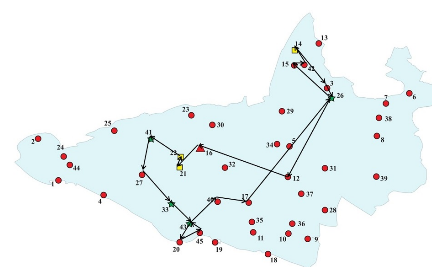
5.2 Computation Analysis

All computations are performed on a 4xAMD Opteron Interlagos 2.6GHz processor and 96 GB RAM computer with Linux operating system. The MIP model is solved using CPLEX 12.6.

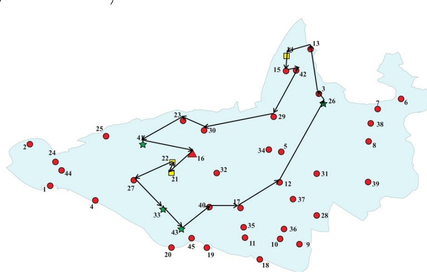
To illustrate computational results of the PDARP, routes of a sample instance are given in Figure 5.2 which consists 1 motorcycle and no drones, under $\epsilon = 0.001$. In the Figure 5.2a, Pareto efficient solutions obtained by solving the bi-objective model iteratively are illustrated. Solution a corresponds to the arc profit PDARP where ν and ϵ value are set to 0. Solution b corresponds to the node profit PDARP in which ϵ_2 takes highest possible value, so that the model acts as if the node profit is maximized without any violation or it can be obtained by solving node profit PDARP model directly. Solution c is one of the non-dominated solutions in the Pareto frontier. The routes of motorcycle in these three solution can be found in Figure 5.2b, 5.2c and 5.2d respectively.



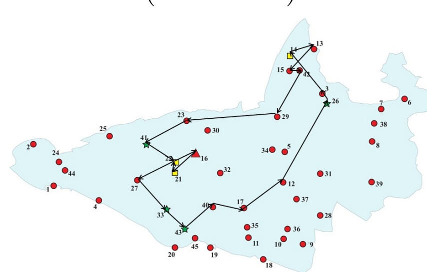
(a) Pareto Chart when the number of motorcycles is 1, the number of drones is 0



(b) Arc Profit PDARP (Solution a)



(c) Node profit PDARP (Solution b)



(d) An Example Non-dominated Pareto Solution (Solution c)

Figure 5.2: Comparison of solutions with 1 motorcycle

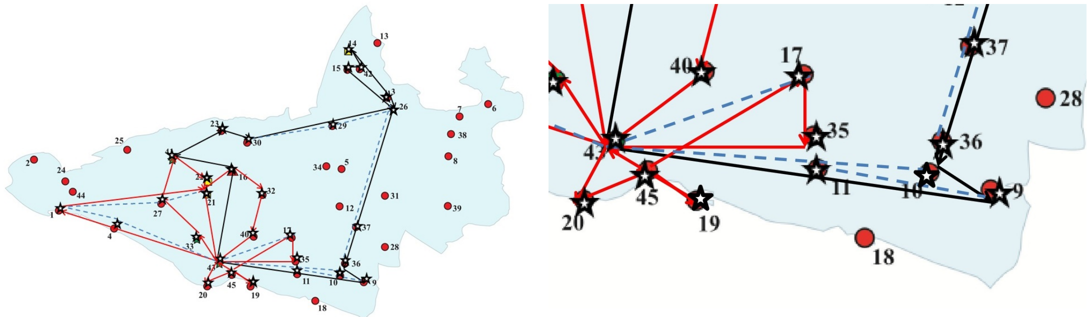
In solution a, it is observed that certain nodes like node 43 are visited multiple times to traverse critical arcs as much as possible in 2 hours. Node 43 is a hospital; therefore, it is logical to traverse that node multiple times and route on the arcs connected to it as they have higher weights. On the other hand, in solution b, it is recognized that each node is visited at most once to be able to increase the overall node profits. Therefore, even if multiple passages are allowed, the model performs as if it is a classical routing problem. Finally, in solution c, the number of nodes visited and overall node profit collected are higher than solution a while multiple passages through some nodes are observed contrary to solution b. This indicates that bi-objective solution clearly demonstrates the characteristics of both single-objective solution approaches. The total weights of the visited nodes and traversed arcs can be found in Table 5.3. As it is seen, best overall arc weight and node weight are obtained in solution a and b, respectively. Solution c seems to compensate the drawbacks of both solutions and provides a somewhat balanced solution in terms of both objective values. It is important to observe that even in the 1 motorcycle instance with no lower bound on total node profit, all the critical nodes are visited. Underlying reason can be attributed to the weights of arcs connecting critical nodes to other nodes being high.

	Solution a	Solution b	Solution c
Total weights of Assessed Nodes	5.826	6.220	6.015
Total weights of Assessed Arcs	5.737	4.995	5.383

Table 5.3: Weights of nodes and arcs for solutions with 1 motorcycle, 0 drone

Using drones for assessment purposes ensure assessment of the nearby points and roads. This characteristic can be observed in the Figure 5.3 where the routes of 2 drones and no motorcycles instance are given. In the figure, the solid lines (red, black) indicate the arcs lie in flight paths of drones, while the dashed lines reflect the assessed arcs that do not lie in the flight paths. For example taking the figure into consideration, arcs $(43, 17)$, $(10, 11)$ are not in any of the drones' paths, but they are monitored through flying over arcs $(9, 43)$, $(17, 45)$. Similarly, roads $(9, 11)$, $(11, 43)$, and $(37, 36)$ are assessed by flying over the roads parallel to them.

It is important to recall Corollary 1 at this point. Thus; when a solution is obtained with a gap during ϵ-constraint procedure, resulting Pareto front is called as approximate. In Table 5.4, model performances are summarized for $\epsilon = 0.001$. It can be seen that in 8 instances out of 11, we could not find exact Pareto fronts for PDARP while allocating 2 hours to arc profit 1-PDARP and 4 hours to arc profit PDARP as a solution time for finding each Pareto solution. In 6 of the instances, the mathematical model was able to find some of the exact



(a) Arc profit PDARP with 2 drones

(b) Zoomed view of arc profit PDARP with 2 drones

Figure 5.3: Assessing nearby nodes and arcs by using drones for assessment purposes

Pareto optimal solutions but not all of them. Average solution time required for an exact/approximate Pareto solution is over 3 hours in 7 of the instances and is more than 4.5 hours in 6 of them. When the number of drones is 1 or 0, the total number of Pareto solutions tends to be much higher compared to the 2 drone cases. Additionally, having 3 or more vehicles at hand result with approximate Pareto solutions where allowed solution time is mostly consumed.

Instance (|D|,|M|)	Number of Pareto Solutions	Number of Exact Pareto Solutions	Number of Approximate Pareto Solutions	Total Solution Time per Pareto solution (hours)	Average GAP (%)
(0,1)	11	11	-	0.05	0.00
(0,2)	70	47	23	3.07	1.33
(0,3)	25	-	25	5.84	3.97
(1,0)	19	18	1	1.66	0.06
(1,1)	22	22	-	0.94	0.00
(1,2)	10	-	10	5.98	1.76
(1,3)	4	-	4	6.00	1.50
(2,0)	8	8	-	0.08	0.00
(2,1)	6	2	4	4.83	0.70
(2,2)	4	-	4	6.00	1.49
(2,3)	1	-	1	6.00	1.10

Table 5.4: Model performances of Kartal instances

As in the most of the cases, having exact Pareto solutions is computationally difficult, for this reason, we utilized larger ϵ-values. Table 5.5 depicts the performance results of the model under different ϵ values. In each instance, the

Instance ($\|D\|$,$\|M\|$)	ϵ values	Number of Pareto Solutions	Number of Exact Pareto Solutions	Total CPU (hours)	Total CPU per Pareto solution (hours)	Average GAP (%)
(0,1)	0.001	11	11	0.46	0.06	0.00
	0.01	9	9	0.43	0.05	0.00
	0.1	4	4	0.29	0.07	0.00
(0,2)	0.001	70	47	214.91	3.07	1.33
	0.01	55	47	115.99	2.11	0.40
	0.1	13	11	27.73	2.13	0.20
(0,3)	0.001	25	-	146.03	5.84	3.97
	0.01	21	-	125.29	5.97	3.12
	0.1	10	-	59.29	5.93	2.51
(1,0)	0.001	19	18	31.51	1.66	0.06
	0.01	16	16	23.66	1.48	0.00
	0.1	8	8	12.09	1.51	0.00
(1,1)	0.001	22	22	20.67	0.94	0.00
	0.01	16	16	7.40	0.46	0.00
	0.1	6	6	3.06	0.51	0.00
(1,2)	0.001	10	-	60.00	6.00	1.76
	0.01	10	-	40.00	6.00	1.18
	0.1	4	-	24.00	6.00	1.08
(1,3)	0.001	4	-	24.00	6.00	1.50
	0.01	3	-	18.00	6.00	1.59
	0.1	2	-	12.00	6.00	1.54
(2,0)	0.001	8	8	4.69	0.58	0.00
	0.01	6	6	3.13	0.52	0.00
	0.1	3	3	0.86	0.29	0.00
(2,1)	0.001	6	2	28.98	4.83	0.70
	0.01	5	2	22.67	4.53	0.66
	0.1	3	2	8.72	2.90	0.37
(2,2)	0.001	4	-	24.00	6.00	1.49
	0.01	4	-	24.00	6.00	1.16
	0.1	2	-	12.00	6.00	1.13
(2,3)	0.001	1	-	6.00	6.00	1.10
	0.01	1	-	6.00	6.00	1.10
	0.1	1	-	6.00	6.00	1.10

Table 5.5: Model performances under ϵ values: 0.001, 0.01, 0.1

number of Pareto solutions, CPU requirements, and solution gap is reported. As expected, with larger ϵ values, the Pareto front is approximated in a shorter period of time at the expense of obtaining less Pareto points. By using $\epsilon = 0.01$, 19% of the previously detected Pareto points are lost while the computational time is decreased by 31%. Taking ϵ as 0.1 enables us to spend 70% less time on computation; however, in turn, we lose 69% of the Pareto points. Beside total computational time benefits, larger ϵ values turn out to be effective in decreasing average solution gap and total CPU time per each Pareto solution. As it can be observed in the Table 5.6, utilizing larger epsilon values provides a great benefit in decreasing computational time requirements at the expense of finding a worse off Pareto front approximation.

	Instance (|D|,|M|)										
	(0,1)	(0,2)	(0,3)	(1,0)	(1,1)	(1,2)	(1,3)	(2,0)	(2,1)	(2,2)	(2,3)
ϵ=0.01	4.4	46.0	14.2	24.9	64.2	33.3	25.0	33.3	21.8	0.0	0.0
ϵ=0.1	36.9	87.1	59.4	61.6	85.4	60.0	50.0	81.7	69.9	50.0	0.0

Table 5.6: Decrease (%) in CPU time requirements with the mathematical models under $\epsilon = 0.01$, $\epsilon = 0.1$ compared to the model under $\epsilon = 0.001$

The performance of the model under different ϵ-values should be evaluated and it is essential to use quantitative performance metrics to evaluate the quality of the approximate Pareto front. To this end, three popular performance measures are used, which are spacing metric (S)[82], maximum spread metric (MS)[83], and set coverage (SC) [84]. These three metrics can be used with approximate Pareto solutions set.

Spacing (S): To measure the spread uniformity of the solutions set this measure can be used. The definition of this metric is as follows:

$$S = \sqrt{\frac{1}{n-1} \cdot \sum_{i=1}^{n} (d_i - \bar{d})^2} \tag{5.1}$$

$$d_i = \min_j \sum_{k=1}^{m} |O_k^i - O_k^j| \qquad i, j = 1, 2, ..., n \tag{5.2}$$

where n is the number of non-dominated solutions in the solution pool, m is the number of objectives, O_k^i is the k^{th} objective value of a solution i and $\bar{d}$ is the mean value of all d_i [82]. When S is close to zero, it means all the points spread uniformly. That is, the smaller S value is better in terms of diversity.

Maximum Spread (MS): This metric measures the maximum extension covered by the non-dominated solution set, i.e., the maximum euclidean distance between a solution and other non-dominated solutions in that set [83]. Mathematically, it is defined by the following equation:

$$MS = \sqrt{\sum_{i=1}^{n} \max_{\substack{j=\{1,\dots,n\} \\ j \neq i}} (\|O^i - O^j\|)} \tag{5.3}$$

where $\|O^i - O^j\|$ is the Euclidian distance between objective values of O^i and O^j in the solution set of heuristic or mathematical model. In this equation, n indicates the number of non-dominated solutions in the set.

Set Coverage (SC): This metric is used to compare two sets of non-dominated solutions found by two different methods [84]. Let $method1$ and $method2$ be sets of solutions found by two different methods. $SC(method1,$ $method2)$ is the ratio of points that are dominated by or equal to at least one point in method1. It is expressed by the following equation:

$$SC(method1, method2) = \frac{|\{O^i \in method2|\ \exists O^j \in method1 : O^i \leq O^j\}|}{|method2|} \tag{5.4}$$

If $SC(method1, method2) = 1$, all points in $method2$ are dominated by or equal to some points in $method1$, while the $SC(method1, method2) = 0$ implies the opposite. As there are intersections between these sets, both $SC(method1,$ $method2)$ and $SC(method2, method1)$ should be considered. We can say that second method is better than the first in terms of accuracy if and only if $SC(method1, method2) = 0$ and $SC(method2, method1) = 1$ [84].

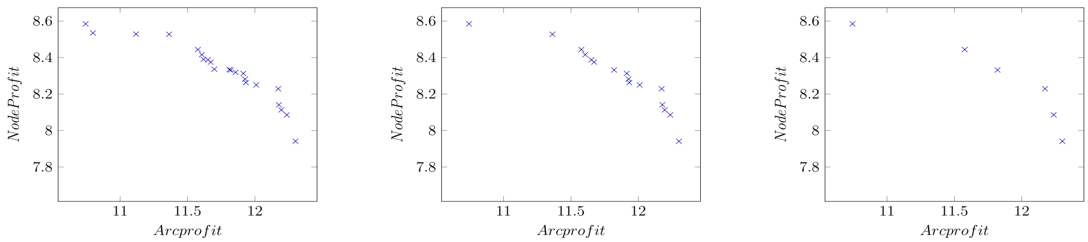
Average Maximum Spread (AMS): As MS is heavily affected by the number of non-dominated solutions found by the method, Average Maximum Spread measure is proposed which is equal to Maximum Spread per non-dominated solutions found. Larger the AMS value is, the better the solution set is because higher AMS value indicates the solutions are more spread and the set is able to cover further edges of the Pareto front.

Instance		Spacing			Maximum Spread			Average Maximum Spread		
$\|D\|$	$\|M\|$	Model (ϵ=0.001)	Model (ϵ=0.01)	Model (ϵ=0.1)	Model (ϵ=0.001)	Model (ϵ=0.01)	Model (ϵ=0.1)	Model (ϵ=0.001)	Model (ϵ=0.01)	Model (ϵ=0.1)
0	1	0.008	0.008	0.001	2.585	2.370	1.600	0.235	0.263	0.400
0	2	0.008	0.006	0.025	14.362	12.780	5.613	0.205	0.232	0.432
0	3	0.003	0.002	0.005	6.205	5.702	3.999	0.248	0.272	0.400
1	0	0.007	0.007	0.237	7.264	6.625	4.708	0.382	0.414	0.588
1	1	0.005	0.027	0.089	5.227	4.501	2.899	0.238	0.281	0.483
1	2	0.005	0.005	0.012	2.394	2.391	1.327	0.239	0.239	0.332
1	3	0.003	0.000	0.000	0.766	0.685	0.482	0.192	0.228	0.241
2	0	0.001	0.022	0.020	2.645	2.243	1.348	0.331	0.374	0.449
2	1	0.004	0.001	0.005	1.700	1.592	1.062	0.283	0.318	0.354
2	2	0.002	0.001	0.000	0.755	0.737	0.583	0.189	0.184	0.291
2	3	NAN	NAN	NAN	0.000	0.000	0.000	0.000	0.000	0.000

Table 5.7: Performance analysis of mathematical models with $\epsilon = 0.001$, $\epsilon = 0.01$ and $\epsilon = 0.1$ using performance metrics

In the Table 5.7, the performances of the mathematical models under different epsilon values are compared in terms of spacing, maximum spread, and average maximum spread. Spacing metric measures the deviation distance from the average solution, which is higher in the model with $\epsilon = 0.1$ than the models with other epsilon values. The reason for this can be the following: the number of points returned by the model with $\epsilon = 0.001$ is larger and those points are located close to each other, thus the deviation (S) is lower. Hence, the model with $\epsilon = 0.001$ is performing better by having lower deviation. For example, Pareto fronts obtained in 1 motorcycle 1 drone instance of the model under different ϵ values are depicted in Figure 5.4. In Figure 5.4, sub-figures are for the Pareto fronts of the ϵ values 0.001, 0.01 and 0.1, respectively. When ϵ value is smaller, Pareto points are located close to each other. In the largest ϵ case, Pareto points are diversely located in the Pareto front. As it is illustrated by the figures, having $\epsilon = 0.001$ results with having a better performance in terms of Spacing measure.

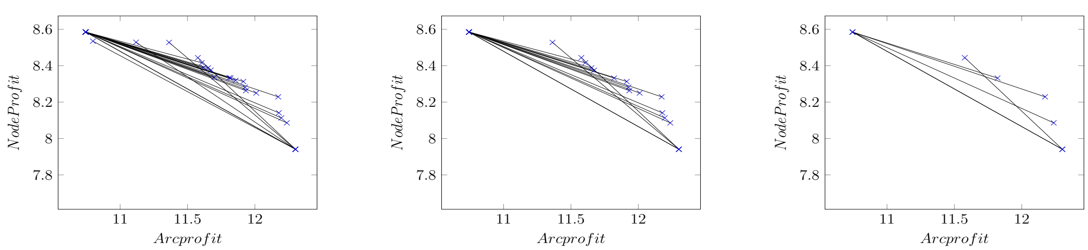
Another diversity metric Maximum Spread is also higher in the model with



(a) Under ϵ=0.001 (b) Under ϵ=0.01 (c) Under ϵ=0.1

Figure 5.4: Spacing performances of Pareto Fronts of the instance ($|D|$,$|M|$)=(1,1) under ϵ values 0.001, 0.01, 0.1

$\epsilon = 0.001$, which can be explained by the larger number of Pareto points. For example, Pareto fronts obtained in 1 motorcycle 1 drone instance of the model under different ϵ values and maximum Euclidean distances of each Pareto point are depicted in Figure 5.5. In Figure 5.5, sub-figures are for the Pareto fronts of the ϵ values 0.001, 0.01 and 0.1, respectively. When we compare maximum Euclidean distances of Pareto points, it can be observed that in $\epsilon = 0.001$ case having a larger number of Pareto points have a huge impact on the MS measure. Additionally, Average Maximum Spread metric attains its' highest values with the $\epsilon = 0.1$. This result can be attributed to the approximation of Pareto front with a fewer number of points and not having many Pareto points located in the center of the Pareto front (See Figure 5.5c).



(a) Under ϵ=0.001 (b) Under ϵ=0.01 (c) Under ϵ=0.1

Figure 5.5: Maximum Spread performances of Pareto Fronts of the instance ($|D|$,$|M|$)=(1,1) under ϵ values 0.001, 0.01, 0.1

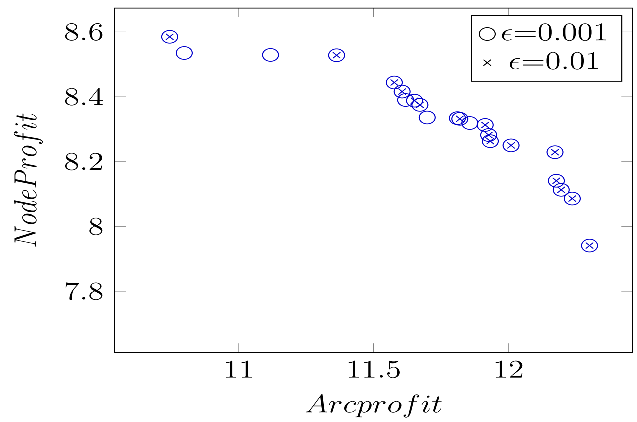
Set Coverage (SC) provides a comparative analysis and it measures the ratio of (weakly) domination by the other set. SC metrics show how better a method is than one another. The closer the SC value to 1, the better the solution is. If points of the method A dominate all points of the method B, then by the definition SC(A,B) equals to 1. However, this information alone is not enough to compare A and B. Both SC(A,B) and SC(B,A) values should be considered to determine which method is better, due to intersections between the two sets.

	Instance ($\|D\|$,$\|M\|$)										
	(0,1)	(0,2)	(0,3)	(1,0)	(1,1)	(1,2)	(1,3)	(2,0)	(2,1)	(2,2)	(2,3)
ϵ=0.1	0.444	0.218	0.429	0.500	0.375	0.400	0.667	0.500	0.600	0.500	1.000
ϵ=0.01	1.000	0.923	0.700	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ϵ=0.1	0.364	0.186	0.480	0.421	0.273	0.364	0.500	0.375	0.500	0.500	1.000
ϵ=0.001	1.000	1.000	0.900	1.000	1.000	1.000	1.000	1.000	1.000	0.500	1.000
ϵ=0.01	0.818	0.757	0.680	0.842	0.727	1.000	0.750	0.750	0.833	1.000	1.000
ϵ=0.001	1.000	0.964	0.762	1.000	1.000	0.800	1.000	1.000	1.000	0.500	1.000

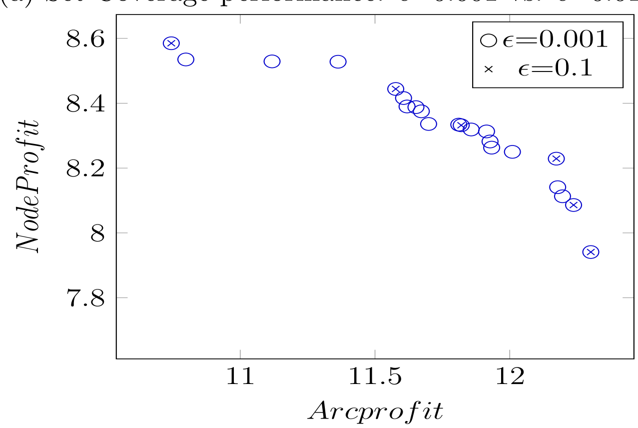
Table 5.8: Performance analysis of mathematical models using set coverage metric

Now, the performance of the model under different ϵ values, and the heuristic methodologies, provided in Table 5.8, will be discussed and compared using SC metric. If the performance of the mathematical models with different ϵ values is compared, on average 51% of the points obtained with $\epsilon = 0.1$ dominates the points obtained with $\epsilon = 0.01$ whereas 97% of the points obtained with $\epsilon = 0.1$ are dominated by $\epsilon = 0.01$. Similarly, the points obtained with $\epsilon = 0.001$ dominate 95% of $\epsilon = 0.1$ and 91% of $\epsilon = 0.01$. In turn, 45% and 83% of the points obtained with $\epsilon = 0.1$ and $\epsilon = 0.01$ are dominated by $\epsilon = 0.001$. These results can be observed in Figure 5.6 where Pareto points of each ϵ pairs depicted in a single graph for 1 motorcycle and 1 drone instance. As in this instance, the model under $\epsilon = 0.001$ gives the exact Pareto, larger ϵ values is dominated by the smallest ϵ. Furthermore, 72.7% and 27.3% of the points obtained by the model with smallest ϵ can be found by the model with ϵ values 0.01 and 0.1, respectively (See Figure 5.6a, 5.6b). In parallel, 37.5% of points obtained by the model with $\epsilon = 0.01$ can be found by the model with $\epsilon = 0.1$ (See Figure 5.6c).

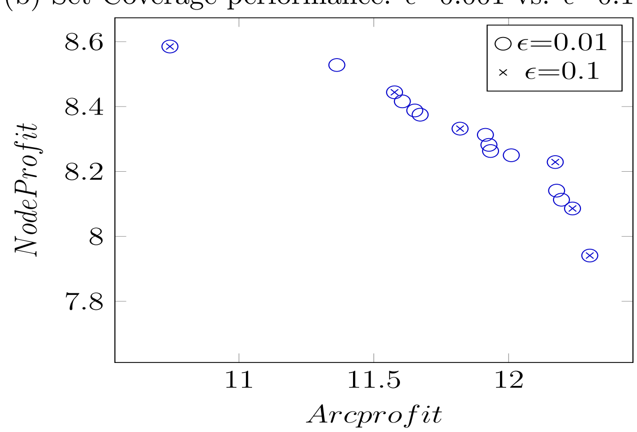
SC measure underlines the performance of the model with $\epsilon = 0.001$ in approximating/finding Pareto frontier. Additionally, in 2 instances, the model with $\epsilon = 0.1$ was able to find a dominating solution to Pareto approximate solutions of the model with $\epsilon = 0.001$. The model with $\epsilon = 0.01$ was able to find a dominating solution to Pareto approximate solutions of the model with $\epsilon = 0.001$ in 4 instances. These results emerge from some of the solutions found with $\epsilon = 0.001$



(a) Set Coverage performance: ϵ=0.001 vs. ϵ=0.01



(b) Set Coverage performance: ϵ=0.001 vs. ϵ=0.1



(c) Set Coverage performance: ϵ=0.01 vs. ϵ=0.1

Figure 5.6: Set Coverage performances of Pareto Fronts of the instance $(|D|,|M|)$=(1,1) under ϵ values 0.001, 0.01, 0.1

not being optimal (See Corollary 1.). As having $\epsilon = 0.001$ provides better Pareto front approximation, heuristics' performances will be examined with respect to the model with $\epsilon = 0.001$ in the sequel.

Chapter 6

Heuristic Solution Methodologies for PDARP

Experiments we conducted with the mathematical model has shown that as the bound on node criticality increases, it is harder to reach the optimal solution in the course of a reasonable time frame. It may take hours to find the Pareto optimal solution for some instances. However, due to the problem characteristics, immediate decisions are required. Therefore, we decided to develop a heuristic solution methodology, which can find a set of good Pareto solutions within the scope of solution quality and time trade-off.

For that purpose, we developed a fast constructive heuristic solution method which we refer to as Base Route Heuristic (BRH), based on some maximum profit definitions. To find a set of good Pareto solutions, we also applied improvement methodologies.

6.1 Construction

BRH constructs paths that start from the depot node and return in an allowed time frame. The algorithm uses the shortest path network between each critical node calculated over the existing network via Dijkstra's algorithm. For each vehicle, the first node is selected as the one with the most profit among the feasible ones. At each step, one additional node is inserted into each path among the most profitable ones without violating time bound. Then, until the time limit violation, the same steps applied. When no shortest path satisfying time condition is found, the last inserted path segment is removed and a path to the depot is added.

It is assumed that vehicles assess the nodes and edges of this constructed path (motorcycle, drone) or assesses the nodes and edges nearby (drone). After a node or edge is assessed, it cannot be assessed again. While calculating profits to be collected, this assumption is taken into consideration and only the new assessments are considered in profit calculations.

A node to be inserted in the path is determined based on one of the 4 profit definitions. The profit can be a value added by traversing arc/node, or a ratio of value added by traversing arc/node per distance. The value added by traversing a network element corresponds to a change in either objective function value. Heuristic solution methods relies on those 4 construction methods and applies the consecutive improvement operations on the corresponding constructed paths. The integral part of the algorithm lies in the construction of the initial paths. Algorithm 1 performs this task. An illustrative example of the construction algorithm can be found at Appendix A.

6.2 Random Improvement

In a broad sense, random improvement heuristic searches for a new solution by generating random solutions from the current solution. During the search, it

Algorithm 1 Base Route Heuristic

procedure CONSTRUCT($\#ofvehicles$, $\#ofdrones$, $dist$, E, a, b, p, q)
    for $nv = 1 \rightarrow \#ofvehicles$ **do**
        $constructedpath_{nv} = [s]$
        $totaldist_{nv} = 0$
        while $totaldist_{nv} < T \cdot v$ **do**
            for $i = 1 \rightarrow |N|$ and $i \neq s$ **do**
                $shortestpath_i \leftarrow$ shortest path from $constructedpath_{nv}(lastindex)$ to i using Dijkstra(E)
                $shortestdist_i \leftarrow$ shortest distance from $constructedpath_{nv}(lastindex)$ to i using Dijkstra(E)
                $returnpath_i \leftarrow$ shortest path from i to s using Dijkstra(E)
                $returndist_i \leftarrow$ shortest distance from i to s using Dijkstra(E)
                if $totaldist_{nv} + shortestdist_i + returndist_i < T \cdot v$ **then**
                    $profit_i$ = increase in arc objective per distance travelled by traversing from nv to i (or increase in arc/node objective or increase in node objective per distance travelled by traversing from nv to i)
            if $\min_{i \in N \setminus s}\{totaldist_{nv} + shortestdist_i + returndist_i\} > T \cdot v$ **then**
                exit while loop
            if $\mathrm{I} = \arg\max_{i \in N \setminus s} profit_i$ **then**
                $previousconstructedpath_{nv} \leftarrow constructedpath_{nv}$
                $constructedpath_{nv} \leftarrow [constructedpath_{nv}, shortestpath_I]$
                $previoustotaldist_{nv} \leftarrow totaldist_{nv}$
                $totaldist_{nv} \leftarrow totaldist_{nv} + shortestdist_I$
        if $totaldist_{nv} > T \cdot v$ **then**
            $constructedpath_{nv} \leftarrow previousconstructedpath_{nv}$
            $totaldist_{nv} \leftarrow previoustotaldist_{nv}$
            $constructedpath_{nv} \leftarrow [constructedpath_{nv}, returnpath_I]$
            $totaldist_{nv} \leftarrow totaldist_{nv} + returndist_I$

records each result found that does not violate the time constraint. After some number of iterations, dominated solutions are eliminated from the pool of records. Then the algorithm returns all the non-dominated tours in the solution pool.

Our improvement heuristic consists of five random improvement algorithms: swap, insertion, reversion, add and remove-add. At each iteration, a new random solution is generated by randomly calling one of the five improvement algorithms. As we have multiple vehicles, there are multiple routes to consider in each improvement heuristics.

In each improvement algorithm application, a route to apply the algorithm is determined randomly in multi-vehicle problem instances. For each algorithm, Let $depot \to i1 \to i2 \to i3 \to .... \to j1 \to j2 \to j3 \to depot$ be the given route. If the operation specific conditions are not met, the operation is re-run till success or till reaching the maximum number of trials.

6.2.1 Swap

The swap algorithm randomly choose two non-depot nodes on the route and exchanges their positions. Let us say algorithm chooses $i2$ and $j2$ nodes from the route. If arcs $(i1, j2)$, $(j2, i3)$, $(j1, i2)$, and $(i2, j3)$ exist in the transportation network, swap operation is successfully done. Then, the new route is $depot \to i1 \to j2 \to i3 \to .... \to j1 \to i2 \to j3 \to depot$.

6.2.2 Insertion

Two locations on a given route are randomly chosen, then, a node in the left location is moved to another location in the right by shifting subsequent elements of the paths to left. Let us say algorithm chooses locations of $i2$ and $j2$ on the route and $i2$ is subjected to move. If $i1 \neq i3$, $j2 \neq i2$, $i2 \neq j3$ and arcs $(i1, i3)$, $(j2, i2)$, $(i2, j3)$ exist in the transportation network, insertion can be successfully performed. Then, the new route is $depot \to i1 \to i3 \to .... \to j1 \to j2 \to i2 \to$

$j3 \rightarrow depot$.

6.2.3 Reversion

The algorithm randomly chooses two non-depot nodes on the route and reverses the path segment in between. Let us say algorithm chooses $i2$ and $j2$ nodes from the route. If arcs $(i1, j2)$, and $(i2, j3)$ exist in the transportation network, reversion operation is successfully done. Then algorithm returns the new route, $depot \rightarrow i1 \rightarrow j2 \rightarrow j1 \rightarrow .... \rightarrow i3 \rightarrow i2 \rightarrow j3 \rightarrow depot$.

6.2.4 Add

In the algorithm, a non-depot node from N and a location to add new node on a given route are randomly chosen. Let us say algorithm chooses a non-depot node $k1$ and a location of $i2$ on the route. There are two conditions that lead to success. First, if $k1 \neq i1$, $k1 \neq i2$, and arcs $(i1, k1)$, $(k1, i2)$ exist in the transportation network, add operation can be successfully performed. Then, the new route is $depot \rightarrow i1 \rightarrow k1 \rightarrow i2 \rightarrow i3 \rightarrow .... \rightarrow j1 \rightarrow j2 \rightarrow j3 \rightarrow depot$. The other condition for successful operation is having $j1 \neq i2$, and arc $(j1, i2)$'s existence in the transportation network. Then, the resulting route is $depot \rightarrow i1 \rightarrow i2 \rightarrow k1 \rightarrow i2 \rightarrow i3 \rightarrow .... \rightarrow j1 \rightarrow j2 \rightarrow j3 \rightarrow depot$.

6.2.5 Remove-Add

In the remove-add algorithm, a non-depot node from N and a location to remove and add new node on a given route are randomly chosen. Let us say algorithm chooses a non-depot node $k1$ and a location of $i2$ on the route. If $k1 \neq i1$, $k1 \neq i3$, and arcs $(i1, k1)$, $(k1, i3)$ exist in the transportation network, remove-add operation can be successfully performed. Then, the resulting route is $depot \rightarrow i1 \rightarrow j1 \rightarrow i3 \rightarrow .... \rightarrow j1 \rightarrow j2 \rightarrow j3 \rightarrow depot$.

A detailed pseudo-code combining the construction, BRH, and random improvement heuristic is given in Algorithm 2. The integral part of the algorithm lies in the construction of the initial paths. Algorithm 1 performs this task. Improvement heuristics are visualized in the Figure 6.1.

Algorithm 2 Outline of the random improvement heuristic solution methodology

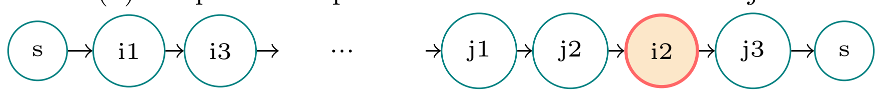
$paths \leftarrow$ Construct $(\#ofvehicles, \#ofdrones, dist, E, a, b, p, q)$
$storedpaths \leftarrow paths$
$counter \leftarrow 1$
while $time < Timelimit$ **do**
    $i \leftarrow randomintegerfrom\{1, .., 5\}$
    if $i = 1$ **then** $paths \leftarrow Swap$(paths,E)
    else if $i = 2$ **then** $paths \leftarrow$ Insertion (paths,E)
    else if $i = 3$ **then** $paths \leftarrow$ Reversion (paths,E)
    else if $i = 4$ **then** $paths \leftarrow$ Add (paths,E)
    else if $i = 5$ **then** $paths \leftarrow$ Remove-Add (paths,E)
    if $totaldistanceofpath \leq T * \cdot v$ **then**
        $counter \leftarrow counter + 1$
        $storedpaths_{counter} \leftarrow paths$
for $i = 1 \rightarrow counter$ **do** calculate two objective values (arc and node)
remove dominated paths from the $storedpaths$

6.3 Purposive Improvement

Similar to the random improvement heuristic, the purposive improvement heuristic searches for new solutions by generating random solutions from the current solution. Instead of randomly moving between solutions, purposive improvement seeks the best improvement on both objectives under a random number of iterations using all of the improvement algorithms. During the search, procedure records the two best results in terms of arc, and node assessment objectives found that does not violate the time constraint. After a predetermined number of iterations, dominated solutions are eliminated from the pool of solutions. Then the algorithm returns all the non-dominated routes in the solution pool.

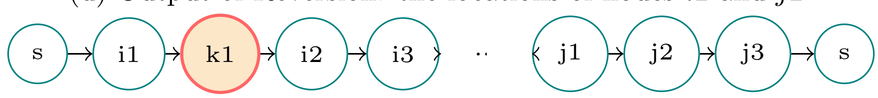
(a) Input of improvement algorithms

(b) Output of Swap: the locations of nodes $i2$ and $j2$

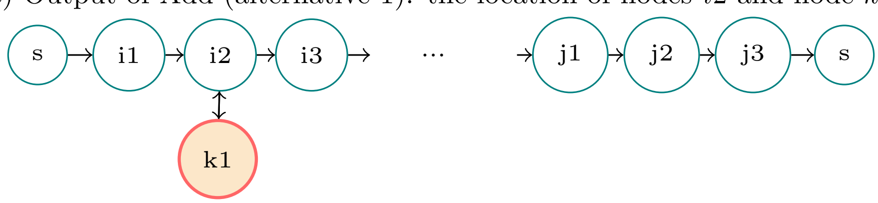


(c) Output of Insertion: the locations of nodes $i2$ and $j2$

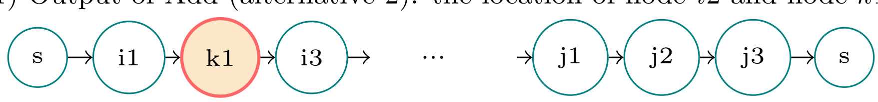
(d) Output of Reversion: the locations of nodes $i2$ and $j2$



(e) Output of Add (alternative 1): the location of nodes $i2$ and node $k1$



(f) Output of Add (alternative 2): the location of node $i2$ and node $k1$



(g) Output of Remove-Add: the location of node $i2$ and node $k1$

Figure 6.1: Illustrative example of the improvement algorithms.

The proposed purposive improvement heuristic consists of the same five improvement algorithms: swap, insertion, reversion, add and remove-add as in the improvement heuristic (See 6.2.1-6.2.5). At each iteration, five new solutions are generated by calling the five improvement algorithms.

Recall the five improvement algorithms, this time the randomness in the improvement algorithms is eliminated, meaning, the improvement algorithms are called with the same parameters. Note here that there are multiple routes to consider in each improvement heuristics due to the multiple number of vehicles.

First parameter is, a route to apply the algorithm in multi-vehicle problem instances. The others are the two locations $i2$, $j2$ from the route, and a node, $k1 \in N$. If the operation specific conditions are not met for all of the algorithms, the same operation is repeated with new parameters till success.

A detailed pseudo-code combining the construction, and purposive improvement heuristics is given in Algorithm 3. Algorithm 1 performs an integral part of the algorithm 3, which is the initial path's construction.

Algorithm 3 Outline of the purposive improvement heuristic solution methodology

$paths \leftarrow$ Construct ($\#ofvehicles, \#ofdrones, dist, E, a, b, p, q$)
$storedpaths \leftarrow paths$
$counter \leftarrow 1$
$state \leftarrow 1$
while $time < Timelimit$ **do**
  for i={1,...,5} **do**
    $checker_i \leftarrow 0$
  while $\sum_{i=0}^{5} checker_i = 0$ **do**
    $vehicle \leftarrow randomintegerfrom\{1, ..., \#ofvehicles\}$
    $i2 \leftarrow randomintegerfrom\{1, ..., lengthofstoredpaths_{state}\}$
    $j2 \leftarrow randomintegerfrom\{1, ..., lengthofstoredpaths_{state}\}$
    $k1 \leftarrow randomintegerfrom\{1, ..., N\}$
    $path_1 \leftarrow$ Swap ($storedpaths_{state}$, E, $vehicle, i2, j2$)
    $path_2 \leftarrow$ Insertion ($storedpaths_{state}$, E, $vehicle, i2, j2$)
    $path_3 \leftarrow$ Reversion ($storedpaths_{state}$, E, $vehicle, i2, j2$)
    $path_4 \leftarrow$ Add ($storedpaths_{state}$, E, $vehicle, i2, k1$)
    $path_5 \leftarrow$ Remove-Add ($storedpaths_{state}$, E, $vehicle, i2, k1$)
    for i={1,...,5} **do**
      if $totaldistanceofpath_i \leq T * \cdot v$ **then**
        $checker_i \leftarrow 1$
        calculate two objective values (arc and node)
    Select the best improvements on both objectives
    $counter \leftarrow counter + 1$
    add best node objective to $storedpaths_{counter}$
    $counter \leftarrow counter + 1$
    add best arc objective to $storedpaths_{counter}$
    $state \leftarrow state + 1$
for $i = 1 \rightarrow counter$ **do** calculate two objective values (arc and node)
remove dominated paths from the $storedpaths$

Chapter 7

Computational Analysis of the Proposed Heuristic Methodologies

As in the most of the cases, having exact Pareto solutions is computationally difficult, for this reason, we developed our heuristic methodology that quickly reaches good, feasible Pareto solutions for this problem. The heuristic algorithms were coded in Matlab R2015b on the Intel Core i7-4702MQ, 2.2 GHz processor with 8 GB RAM computer with Windows 10 operating system.

Both heuristics and mathematical models' results and performances are summarized in Table 7.1, 7.2, and 7.3. The solution times of the random and purposive heuristics are bounded by 1 hour for each instance.

As discussed in the Table 5.6, utilizing larger epsilon values provides a great benefit in decreasing computational time requirements at the expense of finding a worse off Pareto front approximation. In the Table 7.1, computational performances of the models under different ϵ values and the heuristics are presented in comparison to the model under $\epsilon = 0.001$. Heuristic approaches' performance in reducing the computational effort requirement stands out, as the heuristics provide a CPU time reduction up to 99.5%. Although heuristic approaches show a significant performance in terms of solution time, their performances' should be further investigated.

	(%) Decrease in CPU Time Requirement in Instance ($\|D\|$,$\|M\|$)										
	(0,1)	(0,2)	(0,3)	(1,0)	(1,1)	(1,2)	(1,3)	(2,0)	(2,1)	(2,2)	(2,3)
ϵ=0.01	4.4	46.0	14.2	24.9	64.2	33.3	25.0	33.3	21.8	0.0	-
ϵ=0.1	36.9	87.1	59.4	61.6	85.4	60.0	50.0	81.7	69.9	50.0	-
Random	-	99.5	99.3	96.8	95.2	98.3	95.8	78.7	96.5	95.8	83.3
Purposive	-	99.5	99.3	96.8	95.2	98.3	95.8	78.7	96.5	95.8	83.3

Table 7.1: Decrease (%) in CPU time requirements with the mathematical models under $\epsilon = 0.01$, $\epsilon = 0.1$ and heuristics with random and purposive improvement in CPU time requirement compared to the model under $\epsilon = 0.001$

It is essential to use quantitative performance metrics to evaluate the quality of the approximate Pareto front. To this end, three performance metrics presented in Chapter 5 can be used with approximate Pareto solutions set.

	Instance ($\|D\|$,$\|M\|$)										
	(0,1)	(0,2)	(0,3)	(1,0)	(1,1)	(1,2)	(1,3)	(2,0)	(2,1)	(2,2)	(2,3)
random	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ϵ=0.001	1.000	1.000	1.000	0.800	1.000	1.000	1.000	0.875	1.000	1.000	1.000
purposive	0.000	0.000	0.000	0.526	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ϵ=0.001	1.000	1.000	1.000	0.583	1.000	1.000	1.000	0.722	1.000	1.000	1.000
random	1.000	1.000	1.000	0.167	0.235	0.875	0.250	0.333	1.000	0.700	1.000
purposive	0.000	0.000	0.000	0.600	0.714	0.000	0.125	0.375	0.000	0.000	0.000

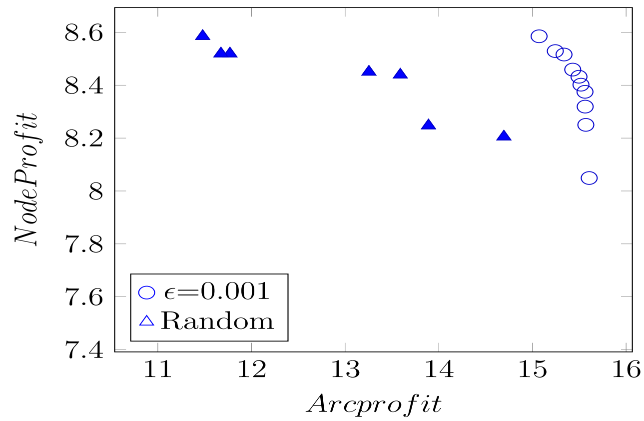
Table 7.2: Comparative performance analysis of mathematical model under $\epsilon = 0.001$ and heuristics with random and purposive improvement using set coverage metric

Now, the performance of the model under $\epsilon = 0.001$, and the heuristic methodologies, provided in Table 7.2, will be discussed and compared using SC metric. In 9 out of 11 instances, model performance is better than both heuristic methodologies when we consider set coverage measure. Additionally, in 2 instances, the random and purposive heuristic methodologies were able to find a dominating solution to Pareto approximate solutions of the model. When heuristic methodologies is compared with respect to each other, on average 16% of the points obtained with the purposive heuristic can dominate the points obtained with the random heuristic whereas 67% of the points obtained with the purposive heuristic can be dominated by the random heuristic. Moreover, in 4 out of 11 instances, the purposive heuristic methodology was able to find a dominating solution to Pareto approximate solutions of the random heuristic. The instance with 2 motorcycles and 1 drone can be used to exemplify the methods' performances with respect to performance metrics because this instance reflects the overall performances of the solution methodologies. These results can be observed in Figure 7.1 where Pareto points of each method pairs depicted in a single graph for 2 motorcycles and 1 drone instance. In the figures, filled shapes indicates the dominated points of a corresponding method. When the model under $\epsilon = 0.001$ with random and purposive improvement heuristics are compared, the model dominates all of the solutions found by the heuristic solution methodologies (See Figure 7.1a and 7.1b). When two solution methodologies are compared, none of the points of random improvement heuristic is dominated by the purposive improvement heuristic whereas many of the points of purposive improvement heuristic is dominated. With respect to set coverage metric, random improvement heuristic has an obvious advantage over the purposive improvement heuristic. However, as randomness is inherited in both heuristics, it is possible for purposive improvement heuristic to find a dominating point to the random improvement heuristic.

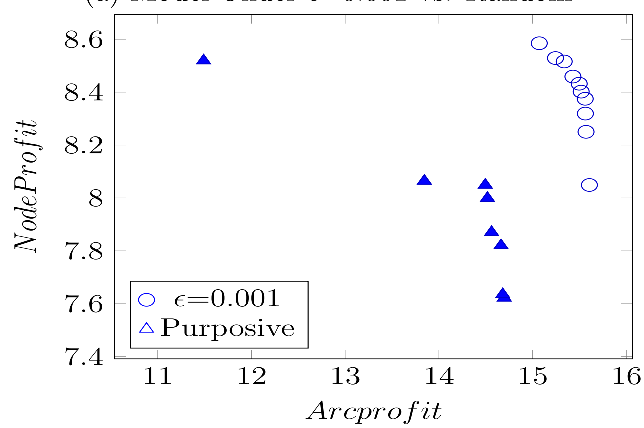
Instance		Spacing			Maximum Spread			Average Maximum Spread		
$\|D\|$	$\|M\|$	Model	Random Heuristic	Purposive Heuristic	Model	Random Heuristic	Purposive Heuristic	Model	Random Heuristic	Purposive Heuristic
0	1	0.008	0.579	0.413	2.585	2.802	2.435	0.235	0.700	0.812
0	2	0.008	0.021	1.038	14.362	3.749	3.461	0.205	0.536	0.865
0	3	0.003	0.015	0.000	6.205	8.622	3.015	0.248	0.375	1.507
1	0	0.007	0.009	0.029	7.264	1.803	5.150	0.382	0.361	0.429
1	1	0.005	0.011	0.006	5.227	3.509	8.543	0.238	0.501	0.503
1	2	0.005	0.067	0.051	2.394	4.334	6.284	0.239	0.619	0.785
1	3	0.003	0.006	0.003	0.766	3.035	5.932	0.192	0.379	1.483
2	0	0.001	0.241	0.113	2.645	4.530	8.788	0.331	0.566	0.488
2	1	0.004	0.012	0.031	1.700	2.160	7.090	0.283	0.432	0.788
2	2	0.002	0.032	0.077	0.755	1.991	6.031	0.189	0.498	0.603
2	3	-	0.012	0.006	0.000	2.100	1.300	0.000	0.525	0.325

Table 7.3: Performance analysis of mathematical model with $\epsilon = 0.001$ and heuristics with random and purposive improvement using performance metrics

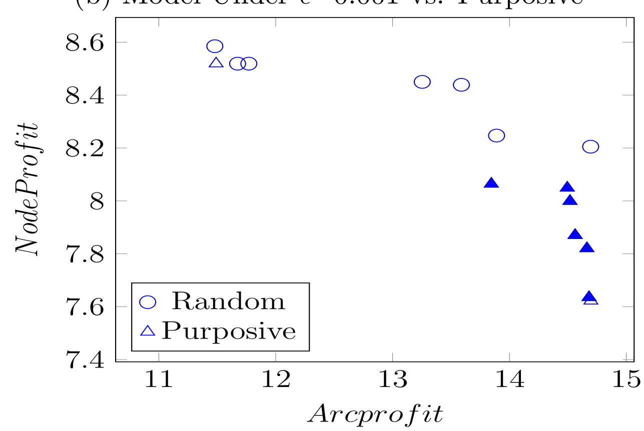
Table 7.3 provides a more detailed analysis on the performance of the heuristic solution methodologies compared to the mathematical model with $\epsilon = 0.001$.



(a) Model Under ϵ=0.001 vs. Random



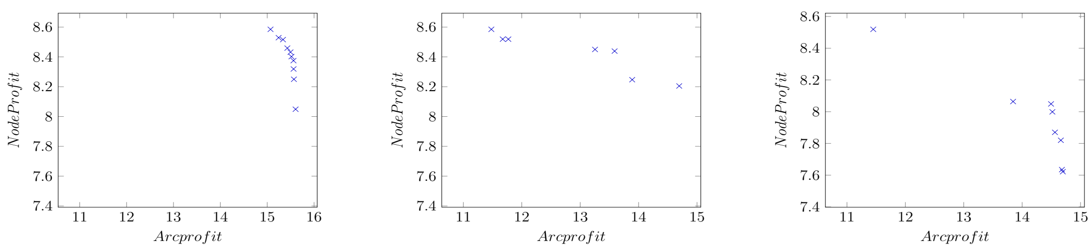
(b) Model Under ϵ=0.001 vs. Purposive



(c) Random vs. Purposive

Figure 7.1: Set Coverage performances of Pareto Fronts of the instance ($|D|$,$|M|$)=(1,2) model under ϵ value 0.001 and random and purposive improvement heuristics

With respect to the spacing measure, model performance is better in all instances, meaning that solution set of the model is more uniform. For instance, in 2 motorcycles and 1 drone case, Pareto fronts obtained by each solution methods are depicted in Figure 7.2. The solutions obtained with the model are located very close to each other, whereas the solutions of the heuristics are diversely located. These figures explain why the model performs better in terms of Spacing metric.

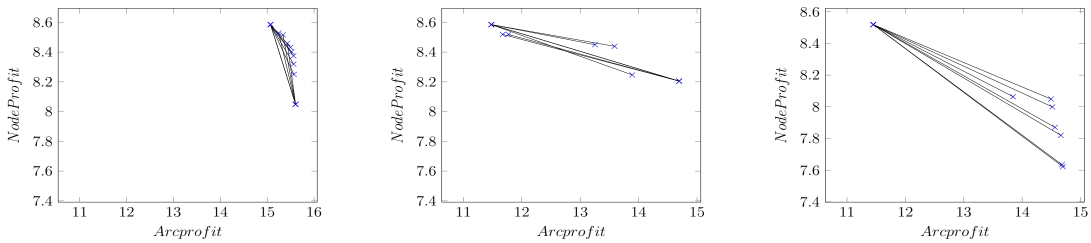


(a) Model Under ϵ=0.001 (b) Random (c) Purposive

Figure 7.2: Spacing performances of Pareto Fronts of the instance $(|D|,|M|)=(1,2)$ model under ϵ value 0.001 and random and purposive improvement heuristics

If we consider maximum spread measure, in 9 of the instances, the heuristic methods yield a larger value, that is, heuristics were able to capture a larger spectrum of the Pareto front. Additionally, in 6 of those instances, purposive heuristic has better performance than both the model and the random heuristic. Only in 3 of the instances, the random heuristic was better in terms of covering a larger spectrum of the Pareto front. In 2 motorcycles and 1 drone instance, for example, although there are many points found by the mathematical model, since those points are closely located, mathematical model's performance with respect to maximum spread and average maximum spread is low compared to heuristics (See Figure 7.3). Purposive improvement heuristic's performance in covering a larger Pareto front spectrum can be attributed to the out-lier solution which can be found in top left of the Pareto front in Figure 7.3c.

Furthermore, Pareto front spectrum covered per non-dominated solution is larger in all heuristic instances and in 9 out of 11 instances, the purposive heuristic captures a larger spectrum with a non-dominated solution. The reason for such outcome can be attributed to both its performance with respect to maximum spread metric and having a fewer number of points generated by the method.



(a) Model Under ϵ=0.001 (b) Random (c) Purposive

Figure 7.3: Maximum Spread performances of Pareto Fronts of the instance ($|D|$,$|M|$)=(1,2) model under ϵ value 0.001 and random and purposive improvement heuristics

Hence, it can be asserted that purposive improvement heuristic captures the Pareto front with less number of points to approximate the Pareto front.

Overall, the performance of the heuristic solution methodologies are better than the model under $\epsilon = 0.001$ in terms of maximum spread, average maximum spread and computation time in comparison to mathematical model under $\epsilon = 0.001$; however, in terms of spacing and set coverage heuristics are not performing well. The purposive improvement heuristic methodology performs better compared the random improvement heuristic when maximum spread and average maximum spread measures are considered; however, when set coverage performances of two heuristics are compared, random improvement heuristic outperforms the purposive improvement heuristic. This result can be attributed to the purposive heuristic being stuck in local optima and generating a fewer number of points.

Another analysis can be made based on how much the improvement methods improve the solution obtained in the construction phase in terms of both arc and node objectives. Table 7.4 depicts the improvement percentages of both of the heuristics in both objectives. The highest percentages are highlighted in the Table 7.4. It can be observed that random improvement heuristic improves arc and node objectives up to 59 % and 25%, respectively. Purposive improvement heuristic, on the other hand, contributes to improvement at most 55% in arc objective and 24% in node objective. The random improvement heuristic is more successful than the purposive improvement heuristic in finding corners of the Pareto front most of the time. Moreover, average improvement percentages underpin the success of random improvement heuristic; however, the difference in percentages is not that significant. On average, the random improvement heuristic can improve arc objective 43.9%, node objective 12.9%; on the other hand, these improvement percentages become 42.6% and 12.5%, respectively, with the purposive improvement heuristic.

Instance ($\|D\|$,$\|M\|$)	Heuristics	Improvement % in Arc Objective	Improvement % in Node Objective
(0,1)	Random	**20**	**22**
	Purposive	18	19
(0,2)	Random	**41**	**25**
	Purposive	28	24
(0,3)	Random	**49**	**19**
	Purposive	45	17
(1,0)	Random	45	15
	Purposive	**54**	**17**
(1,1)	Random	46	14
	Purposive	**50**	**16**
(1,2)	Random	**54**	**12**
	Purposive	54	11
(1,3)	Random	50	7
	Purposive	**55**	**7**
(2,0)	Random	45	12
	Purposive	**53**	**13**
(2,1)	Random	**59**	**7**
	Purposive	53	7
(2,2)	Random	31	**7**
	Purposive	**33**	6
(2,3)	Random	**43**	**3**
	Purposive	26	3

Table 7.4: Improvement heuristics comparison with respect to their contribution to arc and node objectives

As discussed via Tables 5.4 - 5.8 and Tables 7.1 - 7.4, the random and purposive improvement heuristics have really good performance in terms of the computational time, maximum spread and average maximum spread. Moreover, random improvement heuristic has an advantage over the purposive improvement heuristic by providing larger improvements in both objectives and performing better than purposive improvement heuristic with respect to the set coverage metric. Hence, considering the computational requirements, improvement in both objectives and the performance with respect to set coverage, maximum and average maximum spread metrics, random improvement heuristic is more suitable than the other methodologies. With respect to spacing and set coverage metric, the mathematical model under $\epsilon = 0.001$ dominates the other methodologies; however, the model's computational time requirement remains as a challenge.

Chapter 8

Extensions

In the scope of this thesis, the PDARP and its heuristic methodologies are considered to facilitate early assessment of the disaster-affected region. There can be several extensions of the proposed model such as incorporating assessment times. These types of extensions can be considered as a detailed assessment of the disaster-affected region where these assessments may require spending a certain amount of time on the node/arc being assessed. The model proposed in this thesis can be modified to capture the need to spend a certain amount of time in the node/arc being assessed. We refer new formulation as Post-disaster Assessment Routing with Assessment Time Problem (PDARATP).

8.1 Post-disaster Assessment Routing with Assessment Time Problem

The new model, PDARATP, has similar structure to PDARP; however, in order to incorporate spending certain amount of time for assessment we need to detect which vehicle is responsible from the assessment of which nodes/arcs. Therefore, we need additional decision variables to keep track of which vehicle is conducting assessment of which nodes/arcs as well as node/arc assessment time parameters. In addition to nomenclature provided in Chapter 2, the following additional parameters and decision variables need to be defined for the PDARATP.

Additional Parameters:

κ_i : time spent for assessing node $i \in N$.
λ_{ij} : time spent for assessing arc $(i,j) \in A$.

Additional Decision Variables:

$$Y'_{ik} : \begin{cases} 1, & \text{if vehicle } k \text{ monitors node } i \in N, \\ 0, & \text{otherwise.} \end{cases}$$

$$Z'_{ijk} : \begin{cases} 1, & \text{if vehicle } k \text{ monitors arc } (i,j) \in A, \\ 0, & \text{otherwise.} \end{cases}$$

The following mixed integer non-linear program for PDARATP can now be proposed:

$$\text{maximize} \quad f1, f2$$

$$\text{subject to}$$

$$(4.1) - (4.13),$$

$$(4.21) - (4.23),$$

$$Y'_{jk} \leq \sum_{i \in N} X_{ijk} \qquad \forall j \in N, \forall k \in M \tag{8.1}$$

$$Y'_{jk} \leq \sum_{i \in N} \sum_{l \in N} a^j_{il} \cdot X_{ilk} \qquad \forall j \in N, \forall k \in D \tag{8.2}$$

$$Y'_{jk} \geq \frac{1}{2} \cdot X_{ijk} \qquad \forall (i,j) \in A, \forall k \in M \tag{8.3}$$

$$Y'_{jk} \geq a^j_{il} \cdot \frac{1}{2} \cdot X_{ilk} \qquad \forall (i,l) \in A, \forall j \in N, \forall k \in D \tag{8.4}$$

$$Z'_{ijk} \leq (X_{ijk} + X_{jik}) \qquad \forall (i,j),(j,i) \in A, \forall k \in M \tag{8.5}$$

$$Z'_{ijk} \leq \sum_{(l,m) \in A} (b^{ij}_{lm} \cdot X_{lmk}) \qquad \forall (i,j) \in A, \forall k \in D \tag{8.6}$$

$$Z'_{ijk} \geq \frac{(X_{ijk} + X_{jik})}{2 \cdot 2} \qquad \forall (i,j),(j,i) \in A \forall k \in M \tag{8.7}$$

$$Z'_{ijk} \geq \frac{b^{ij}_{lm} \cdot X_{lmk}}{2} \qquad \forall (i,j),(l,m) \in A, \forall k \in D \tag{8.8}$$

$$\sum_{(i,j)\in A} (\frac{d_{ij}}{v} \cdot X_{ijk} + \lambda_{ij} \cdot Z'_{ijk}) +$$

$$\sum_{i \in N} \kappa_i \cdot Y'_{ik} \leq T \qquad \forall k \in V \tag{8.9}$$

$$\sum_{j \in N} (u_{ijk} - u_{jik}) - (\sum_{j \in N} \frac{d_{ij}}{v} \cdot X_{ijk} +$$

$$\lambda_{ij} \cdot Z'_{ijk} + \kappa_j \cdot Y'_{jk}) = 0 \qquad \forall i \in N \backslash \{s\}, \forall k \in V \tag{8.10}$$

$$u_{sjk} = \frac{d_{sj}}{v} \cdot X_{sjk} + \lambda_{sj} \cdot Z'_{sjk} + \kappa_j \cdot Y'_{jk} \qquad \forall j \in N \backslash \{s\}, \forall k \in V \tag{8.11}$$

$$u_{isk} \leq T \cdot X_{isk} \qquad \forall i \in N \backslash \{s\}, \forall k \in V \tag{8.12}$$

$$u_{ijk} \leq (T - \frac{d_{js}}{v}) \cdot X_{ijk} \qquad \forall (i,j) \in A, j \neq s, \forall k \in V \tag{8.13}$$

$$u_{ijk} \leq \max\{T - \frac{d_{js}}{v}, 0\} \qquad \forall (i,j) \in A, j \neq s, \forall k \in V \tag{8.14}$$

$$u_{ijk} \geq \frac{(d_{si} + d_{ij})}{2 \cdot v} \cdot X_{ijk} + \kappa_s \cdot Y'_{sk} +$$

$$\kappa_j \cdot Y'_{jk} + \lambda_{ij} \cdot Z'_{ijk} \qquad \forall (i,j) \in A, i \neq s, \forall k \in V \tag{8.15}$$

$$Z^k_{ij} \in \{0,1\}, \qquad \forall (i,j) \in A, \forall k \in V \tag{8.16}$$

$$Y^k_j \in \{0,1\}, \qquad \forall j \in N \, \forall k \in V \tag{8.17}$$

Constraints (4.1) - (4.13) and (4.21)- (4.23) of PDARP is preserved in the new model for the following reasons. Two problems have the same objectives and consider routing on a ground transportation network; thus, the constraints (4.1)-(4.4) remain. As PDARATP have the objectives of maximum weighted arc and node assessment, the constraints (4.6)-(4.11) keeping track of assessed nodes/arcs remained as they are, with their domain specifications (4.23)-(4.22). (4.5), (4.12), (4.13), (4.21) constraints are imposed in order to ensure flow balance on the route with leaving the depot once and returning.

Constraints (8.1) - (8.4) monitor the assessment of node j by the vehicle k. Constraints (8.1) and (8.2) are similar to constraint (4.6). As the new decision variable, Y'_{ik} takes vehicle index into account, constraints (8.1) and (8.2) are the separated version of the constraint (4.6) to capture which vehicle conducts assessment of node i. Constraints (8.3) and (8.4) are similar to constraints (4.7) and (4.8). Constraints (8.5)-(8.8) check if arc (i, j) is monitored by the vehicle k in either direction. Constraints (8.5) and (8.6) are a version of the constraint (4.9) without summation over vehicle sets. Constraints (8.7) and (8.8) are similar to constraints (4.10) and (4.11), only difference is that the left hand side of the constraints bear a vehicle index for arc assessment. Total time bound is given by the constraint (8.9) which is a version of the constraint (4.14). Constraint (8.10) ensures the connectivity of the tour for each vehicle k considering assessment time requirements. In paralel to constraint (4.16), constraint (8.11) assigns the time spent by leaving the depot but adds the assessment time of nodes/arcs on the way to the connectivity variable. By constraints (8.12) - (8.14), an upper bound on connectivity variable is imposed. Those three constraints are indeed a version of (4.17) - (4.19) where connectivity variable is time-based. By constraint (8.15), we ensure that connectivity variable takes a positive value when a vehicle traverses that particular network element. Therefore, disconnected tours are eliminated via constraints (8.10)-(8.15).

To test the developed mathematical model, we used the data set Kartal as discussed in the section 5.1 [80]. Test parameter specifications of the PDARP are still valid for this problem. However, for this problem setting, we only consider 1 drone and 1 motorcycle. Additional parameters, κ, and λ that represent the time required for assessment, are defined based on node weights and distance values, respectively. κ values assigned to the nodes in a way that node with the highest node weight gets 10 minutes for assessment and the rest are assigned proportionally to their weight values. λ is defined as 10% of the travel time of the particular arc.

The performances of the models are presented in Table 8.1. As the new model allocates an extra time for the assessment efforts, it is expected that the number of population points and the road segments assessed will decline. It is observed that when certain assessment times are introduced for the network elements, in first two hours in the disaster aftermath approximately 36% of time, 43 minutes, spent solely on assessing network elements, while the rest is spent on traversal and the assessment. As two new binary variables are introduced to the problem and they appear in connectivity constraints, PDARATP is computationally more challenging. Total solution time per Pareto solution and the average gap values are reported in the Table 8.1.

Since first hours in the disaster aftermath bear a great importance on the alleviation of the human suffering, one might consider PDARP as an immediate assessment strategy and PDARATP as a more detailed assessment operation following the PDARP. The reasons for proposing PDARP as an immediate assessment strategy are PDARP's ability to evaluate disaster impact on more network elements (population points and road segments) and PDARP enables a disaster overview of a wider area.

$\|D\|$	$\|M\|$	Criteria	PDARP	PDARATP
		Average Node objective	6.053	2.806
		Average Arc Objective	5.328	3.675
0	1	Number of Pareto Solutions	11	1
		Total Solution Time per Pareto Solution	0.05	0.08
		Average Gap	0.00	0.00
		Required Assessment Time over Route Duration	-	36
		Average Node Objective	7.536	2.893
		Average Arc Objective	7.050	4.299
1	0	Number of Pareto Solutions	19	1
		Total Solution Time per Pareto Solution	1.66	1.74
		Average Gap	0.06	0.00
		Required Assessment Time over Route Duration	-	36
		Average Node Objective	8.324	5.279
		Average Arc Objective	11.736	6.389
1	1	Number of Pareto Solutions	22	4
		Total Solution Time per Pareto Solution	0.94	6.00
		Average Gap	0.00	9.14
		Required Assessment Time over Route Duration	-	35

Table 8.1: Comparison of the models PDARP and PDARATP

Chapter 9

Conclusions

Having capable resources to handle the disaster aftermath and reaching and activating them on time to alleviate the disaster impact on population and infrastructure are some of the challenges of humanitarian disaster relief operations. Disrupted roads and debris blocking the roads are main sources of difficulty in terms of aid distribution to disaster victims. In addition, the unpredictable nature of the disaster and demand uncertainty may complicate handling and distribution operations. In that perspective, assessing damage at early stages of the disaster plays a crucial role in further activation of resources. In this study, the post-disaster assessment strategy is developed as a tool to assist disaster relief operations by assessing the severity and the urgency for relief. Several managerial insights provided by this research can be presented.

An assessment strategy is a valuable tool which provides a variety of advantages. This study develops a model for the damage assessment in an aftermath of any disaster which focuses on population points and road segments. Damage information obtained from both elements translate into resolved uncertainties in three immediate logistics operations: evacuation, relief item distribution, and debris removal. The consecutive operations may perform poorly with the unresolved uncertainties in the demand. Thus, post-disaster assessments can facilitate more timely and to the point response operations with resolving uncertainty by conducting early assessments to determine the severity of the disaster impact and urgency of the need for relief.

Assessment problems studied in the literature largely focus on needs assessment in population points. In this study, with having capable resources at hand, we observe that it is possible to conduct an assessment in not only population points but also on the road segments. Considering the aftermath of a disaster, solely determining needs in population points will not be enough. To reach disaster victims, evacuate them from the affected region or supply them with relief items in a short period, disaster impact on the transportation network should also be known. With preparing the post-disaster assessment strategy, the disaster management authorities could produce more efficient responses; thus, mitigates the pain and suffering of disaster victims.

Due to the importance of information in the post-disaster response phase, this study focuses on the damage assessment process in an aftermath of a disaster and introduces a new problem that facilitates effective information gathering on population centers (nodes) and road segments (arcs) through deciding on assessment team routes. In the literature, there is a limited number of studies that focus on assessment operations in the aftermath of a disaster. Existing studies solely focus on the assessment of population points. To the best of our knowledge, there is no study that considers assessment in both elements; although transportation network condition directly influences evacuation and relief item distribution operations. With this study, we highlight the importance of considering both network elements in doing an assessment and develop an appropriate assessment strategy. With the developed strategy, assessment teams aim to choose and traverse densely populated regions and critical road segments. We develop a mathematical model that provides damage information in the affected region by considering both the importance of population centers and road segments on the transportation network through using aerial and ground vehicles (drones and motorcycles). We define a new problem to the literature and name it as PDARP. To assist post-disaster response phase operations by obtaining information about the extent of damage in the area in a short period, a completion deadline is imposed via route duration constraints. Additionally, as opposed to standard vehicle routing problems, we let population points to be visited multiple times to better capture the disaster impact on road segments.

The problem characteristics imply a general routing aspect which combines assessment of critical population centers (nodes), and road segments (arcs). However, as assessment operation is focused on two distinct network elements, a bi-objective approach to the problem is required. For this reason, we studied relief routing, multi-objective routing and general routing problems in the literature with its variants. Then, we mathematically modeled bi-objective general routing with profits problem considering arc and node profits as separate objectives. Bi-objectivity of the problem is handled with $\epsilon-$constraint method. The model returns routes for vehicles where arcs and nodes to assess are selected. Additionally, the use of aerial vehicles contributes to the assessment of a possibly large number of arcs and nodes due to its angular point of view. We present a heuristic solution methodology to solve the PDARP. Our computational results show that the proposed algorithm can find a high-quality approximation of Pareto front for the PDARP that mitigates the solution time difficulties.

Damage assessment operations have not received much attention in humanitarian logistics or in OR literature. Hence, there can be several research directions that focus on damage assessments in disaster aftermath. First, although this study presents some results suggesting that the proposed heuristic methodologies may attain good solutions as it provides an approximation of Pareto front in a short processing time, developing solution methodologies that can provide exact Pareto fronts or better Pareto front approximation would be valuable to obtain better benchmark solutions to evaluate the performance of the heuristics.

Future research direction can be related to characterizing the post-disaster uncertainties in developing an assessment plan. Our study considers disaster network as an off-road network where off-road motorcycles are utilized with a certain average speed; however, in the aftermath of a disaster, there can be some road segments which are severely disrupted and some with little to no damage. Hence, it would be valuable to incorporate travel time uncertainties and terrain conditions in routing decisions, making the model more robust. Also, uncertainties may arise during the assessment process; for instance, making an assessment in some population centers may require spending some time on the node being assessed. Although the proposed model in this study can be modified to spend a certain amount of time in the node being assessed, the node assessment uncertainties cannot be captured with the current model. Additionally, the current study considers data collected about disaster impact is made available once the assessment vehicles return to the depot (disaster management center). This can be counted as a valid assumption considering the disruptions can occur in the information transmission infrastructure as a result of a disaster. However, one can consider relaxing this assumption and incorporate spatial-temporal uncertainties that arise when the drones and motorcycles are conducting assessments in collaboration given that the drone's angular field of view can assist the motorcycle in assessment. We hope that the model and algorithms proposed in this study will constitute a new angle for future research that considers further complexities in decision making for post-disaster damage assessments.

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Appendix A

Illustration of the Constructive Heuristic Algorithm

For example, suppose we have a disaster network as demonstrated in the Figure A.1 and 1 drone to be utilized in assessment. On a given network, it is important to note that fourth node can be assessed by flying over arc (3,9) and (9,3).

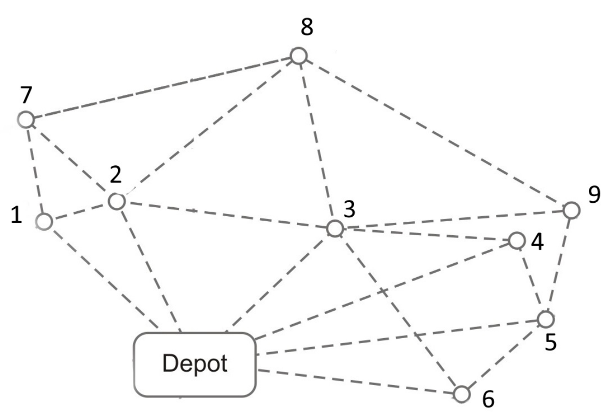

Figure A.1: An example disaster network diagram

Assume that the profit is defined by the value added by traversing node per distance travelled and there is a distance limit for the drone, and it is 20. We first start by evaluating the shortest paths of each node pairs. Then, among the feasible paths (a vehicle can complete its tour within the distance limit), the one which yields the highest node profit per distance is added to the path. Let shortest path distances of the network be:

$$\begin{bmatrix} 0.0 & 3.7 & 3.2 & 3.4 & 6.2 & 6.3 & 4.8 & 5.4 & 6.5 & 7.6 \\ 3.7 & 0.0 & 1.4 & 5.3 & 8.5 & 9.9 & 8.5 & 1.9 & 5.5 & 9.5 \\ 3.2 & 1.4 & 0.0 & 3.9 & 7.1 & 8.5 & 7.6 & 2.2 & 4.1 & 8.1 \\ 3.4 & 5.3 & 3.9 & 0.0 & 3.2 & 4.6 & 3.7 & 6.1 & 3.1 & 4.2 \\ 6.2 & 8.5 & 7.1 & 3.2 & 0.0 & 1.4 & 3.4 & 9.3 & 6.3 & 3.5 \\ 6.3 & 9.9 & 8.5 & 4.6 & 1.4 & 0.0 & 2.0 & 10.7 & 7.7 & 2.1 \\ 4.8 & 8.5 & 7.6 & 3.7 & 3.4 & 2.0 & 0.0 & 9.8 & 6.8 & 4.1 \\ 5.4 & 1.9 & 2.2 & 6.1 & 9.3 & 10.7 & 9.8 & 0.0 & 5.1 & 10.3 \\ 6.5 & 5.5 & 4.1 & 3.1 & 6.3 & 7.7 & 6.8 & 5.1 & 0.0 & 5.7 \\ 7.6 & 9.5 & 8.1 & 4.2 & 3.5 & 2.1 & 4.1 & 10.3 & 5.7 & 0.0 \end{bmatrix}$$

In the Table A.1, the shortest paths emerging from the depot node to other nodes are indicated.

From	To	Shortest Path
0	1	[0 1]
0	2	[0 2]
0	3	[0 3]
0	4	[0 4]
0	5	[0 5]
0	6	[0 6]
0	7	[0 2 7]
0	8	[0 3 8]
0	9	[0 3 9]

Table A.1: Shortest paths from the depot node to other nodes

Moreover, let the following vector to be node weights of the corresponding nodes.

$$\begin{bmatrix} 0.5 & 0.2 & 0.7 & 0.3 & 0.5 & 1.0 & 0.1 & 0.1 & 0.5 & 0.5 \end{bmatrix}$$

It is observed that there is at least one node where a drone can go and come back to the depot. For each path emerging from the depot node to other nodes, profits that can be collected are calculated. That is, values of nodes on the path divided by the shortest path distance.

$$\begin{bmatrix} - & 0.189 & 0.281 & 0.294 & 0.129 & 0.238 & 0.229 & 0.241 & 0.200 & 0.237 \end{bmatrix}$$

Since the path from the depot node, 0, to the node 3 yields the highest profit, we add [0,3] to the path. Total distance traveled becomes 3.4. Then, from the node 3, we evaluate the profits of the feasible paths. In the Table A.2, the shortest paths from the node 3 to other nodes are indicated.

From	To	Shortest Path
3	0	[3 0]
3	1	[3 2 1]
3	2	[3 2]
3	4	[3 4]
3	5	[3 4 5]
3	6	[3 6]
3	7	[3 2 7]
3	8	[3 8]
3	9	[3 9]

Table A.2: Shortest paths from the node 3 to other nodes

For each path emerging from the node 3 to the other nodes, profits that can be collected are calculated based on the profit definition. That is, values of not assessed nodes on the path divided by the shortest path distance.

$$\begin{bmatrix} 0.000 & 0.038 & 0.179 & - & 0.156 & 0.326 & 0.027 & 0.131 & 0.161 & 0.238 \end{bmatrix}$$

As the path from the node 3 to the node 5 yields the highest profit and it does not violate the total distance constraint, it is considered as a candidate. Total tour distance of [0,3,4,5,0] is 14.3. Hence we add [3,4,5] to the path. Total distance travelled becomes 8.0. Then, from node 5 we evaluate the profits of the feasible paths. In the Table A.3, the shortest paths from the node 5 to other nodes are indicated.

From	To	Shortest Path
5	0	[5 0]
5	1	[5 4 3 2 1]
5	2	[5 4 3 2]
5	3	[5 4 3]
5	4	[5 4]
5	6	[5 6]
5	7	[5 4 3 2 7]
5	8	[5 4 3 8]
5	9	[5 9]

Table A.3: Shortest paths from the node 5 to other nodes

For each path emerging from the node 5 to the other nodes, profits that can be collected are calculated based on the profit definition. That is, values of not assessed nodes on the path divided by the shortest path distance.

$$\begin{bmatrix} 0.000 & 0.091 & 0.082 & 0.000 & 0.000 & - & 0.050 & 0.075 & 0.065 & 0.238 \end{bmatrix}$$

Some of the paths are now infeasible. Those are the paths going to the nodes 2, 7, and 8. Among the feasible paths, the path, from the node 5 to the node 9 yields the highest profit, and total tour distance of [0,3,4,5,9,0] is 17.7. Hence, we append path [5,9] to the path. Total distance travelled becomes 10.1. Then, from the node 9, we evaluate the profits of the feasible paths. The constructive algorithm procedure continues in this fashion, at each step, we aim to guarantee a vehicle can return to the depot. In this example, we used the node weight collected over distance traveled as the profit definition; however, the other definitions discussed in the Section 6.1 can also be used.