OPTIMIZING DRONE DEPLOYMENT FOR RELIABLE COMMUNICATION IN DISASTER-STRICKEN REGIONS

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Melike Çap

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Approved by:

Asst. Prof. İhsan Yanıkoğlu, Advisor
Dept. of Industrial Eng.
Özyeğin University

Asst. Prof. Elvin Çoban Göktürk
Dept. of Industrial Eng.
Özyeğin University

Asst. Prof. Tonguç Yavuz
Dept. of Industrial Eng.
İsbanbul Bilgi University

Date Approved: 24 July 2023

To my family...

ABSTRACT

Natural disasters, such as earthquakes, often lead to the collapse of communication systems, hindering effective response efforts. This research focuses on leveraging drones as innovative communication tools to address this challenge. The study explores the utilization of drones as data collection and transmission platforms in disaster-stricken areas. By collecting information from individuals, including text messages and location data from social media platforms, drones can be crucial conduits for transmitting vital data to the communication backbone. The research aims to enhance the overall effectiveness of disaster response by ensuring timely and reliable communication in post-disaster scenarios. An optimization model is formulated to decide on the 3D location of drones while maximizing the coverage and service quality. In addition, a hub-drone is also required to supply the power for located drones and data transfer. The model also decides on the routing of the hub-drone. To solve the problem efficiently, a clustering-based heuristic is developed to determine the drone locations. The solution performance of the model and the effectiveness of the heuristic algorithm are demonstrated in a case study that utilizes data from Sultanbeyli province in Turkey. The findings offer insights into the potential of using drones in post-disaster scenarios, empowering disaster management agencies with enhanced communication capabilities for improved coordination and response in the face of adversity.

ÖZETÇE

Depremler gibi doğal afetler, genellikle iletişim sistemlerinin çökmesine yol açarak etkin müdahale çabalarını engeller. Bu araştırma, bu zorluğun üstesinden gelmek için insansız hava araçlarını yenilikçi iletişim araçları olarak kullanmaya odaklanmaktadır. Çalışma, afet bölgelerinde veri toplama ve aktarma platformları olarak drone'ların kullanımını araştırıyor. Drone'lar, metin mesajları ve sosyal medya platformlarından konum verileri de dahil olmak üzere bireylerden bilgi toplayarak, hayati verilerin iletişim altyapısına güvenilir bir şekilde iletilmesi için önemli bir araç olabilirler. Araştırma, felaket sonrası senaryolarda zamanında ve güvenilir iletişimi sağlayarak, afet müdahalesinin genel etkinliğini artırmayı amaçlamaktadır. Kapsam ve hizmet kalitesini en üst düzeye çıkarırken drone'ların 3D konumuna karar vermek için bir optimizasyon modeli formüle edilmiştir. Ek olarak, konumlanan drone'lara güç sağlamak ve veri aktarımı için bir merkez-drone da gereklidir. Model ayrıca merkez-drone'un rota planlamasını da belirler. Problemi verimli bir şekilde çözmek için, drone konumlarını belirlemek için kümeleme tabanlı bir sezgisel algoritma geliştirilmiştir. Modelin çözüm performansı ve sezgisel algoritmanın etkinliği, Türkiye'deki Sultanbeyli ilinden elde edilen verileri kullanan bir vaka çalışmasında gösterilmektedir. Bulgular, afet sonrası senaryolarda drone'ları kullanma potansiyeline dair içgörüler sunarak, afet yönetim kurumlarını, sıkıntı karşısında gelişmiş koordinasyon ve müdahale için iletişim yetenekleriyle güçlendiriyor.

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TABLE OF CONTENTS

DEDICATION . . . . . **iii**

ABSTRACT . . . . . **iv**

ÖZETÇE . . . . . **v**

ACKNOWLEDGEMENTS . . . . . **vi**

LIST OF TABLES . . . . . **viii**

LIST OF FIGURES . . . . . **ix**

I INTRODUCTION **1**

II LITERATURE REVIEW **6**

III PROBLEM DEFINITION AND FORMULATIONS **11**

3.1 Nonlinear mathematical model 13

3.2 Linear optimization model 15

IV SOLUTION APPROACH **21**

V NUMERICAL EXPERIMENTS **28**

5.1 Data structure 28

5.2 Evaluating the performance of proposed algorithm 31

5.3 Case study 33

VI CONCLUSION **39**

REFERENCES **41**

VITA **44**

LIST OF TABLES

1 Nomenclature of the nonlinear mathematical optimization model . . . 14

2 Nomenclature of the mathematical optimization model 17

3 Instances. 29

4 General parameters 31

5 Heuristic vs solver (GUROBI) 32

6 Numerical results of the case study 35

7 Numerical results of Extension I 36

8 Numerical results of Extension II 37

LIST OF FIGURES

1 Visual representation of an example node set 17

2 Visual representation of Sultanbeyli 30

3 Visual representation of Sultanbeyli dataset 34

4 Results of case study with 90 drones 35

5 Results of Extension I: Case study with 90 drones 37

6 Results of Extension II: Case study with 90 drones 38

CHAPTER I

INTRODUCTION

In the immediate aftermath of a disaster, it is commonplace to encounter network congestion or overload. This situation arises due to the instinctive response of citizens to rely on cellular phones as their primary communication tool. Faced with the panic and urgency of the situation, individuals immediately seek to make calls to gather information about the well-being of friends and relatives and the latest updates on the severity of the potential danger from news sites. As a result, the increased demand for network resources overwhelms the infrastructure, leading to network congestion and hindering effective communication during those initial critical hours following the disaster. Meanwhile, the physical destruction of base stations and disruption in supporting them after the disaster worsen the situation and cause the disturbance and collapse of the communications system. Establishing efficient communications for disaster management is no less critical than other rescue operations since communication is the primary channel for aid coordination among rescue teams. Any failure in the system may cause a delay in the mobilization of rescue operation teams and paralyze them, which may lead to life loss and damage to properties [1].

The devastating 6 February earthquake that struck Turkey served as a poignant reminder of the critical challenges faced in post-earthquake scenarios, particularly regarding disrupted communication and coordination during search and rescue operations. The earthquake exposed the dire consequences of communication breakdowns, hindering the timely deployment of emergency response teams and exacerbating the loss of lives and damage to infrastructure. As a response to such calamities, technological advancements have paved the way for innovative solutions. In December 2004,

Indian Ocean coastline areas suffered from a devastating earthquake and tsunami. Studying the event and the consequences underlines the catastrophic effects of a breakdown in communications after the disaster. The worldwide seismic monitoring stations detected the massive earthquake that led to the tsunami; however, the dissemination of warnings was delayed due to the need for more procedures for delivering warnings to governments. Although groups of people managed to evacuate after receiving warnings through unofficial channels, there is no need to say that better communications could have more lives saved [1]. It is common for communications to be affected by catastrophic events and disasters, even in developed countries. In March 2011, an earthquake and tsunami damaged cellular and landline phone service in Tokyo. After the earthquake, cellular communication jammed immediately, in most parts of the country, due to a sudden increase in network activity. In 2005, Hurricane Katrina affected an extensive geographic area in the United States and caused more than 1900 deaths, disconnected more than 3 million landline phones, and 2,000 cell sites. The Hurricane threatened the life of 1.5 million people in the Gulf Coast region, and communication was a fundamental requirement for coordinating responsible organizations. Natural disasters such as hurricanes can severely impact communications systems, and this was the case in New Orleans during Hurricane Katrina in 2005. Extreme winds and flooding caused significant damage to infrastructure, making it difficult for organizations to communicate with one another and coordinate rescue operations. Moreover, communication failures were a problem for updates and reports of the rescue operations, and most of the people could not contact the personnel on duty [2, 3]. The incidents show the necessity of urgently deploying an efficient communication network after a disaster. In this context, this thesis explores the potential of utilizing drones for communication in disaster areas, addressing the urgent need for reliable and efficient communication networks in the aftermath of earthquakes and other natural disasters.

The 6th February earthquake in Turkey vividly demonstrated the pivotal role of Twitter and other social media platforms in disaster response. These platforms enabled individuals to quickly share real-time information about their location, well-being, and further details. The widespread adoption of Twitter as a means of communication showcased its power in facilitating real-time updates, organizing relief efforts, and connecting affected individuals with their loved ones and the broader community. This event underscored the significance of social media in harnessing collective intelligence and enhancing disaster response strategies. Also, in Turkey, software called "Afad Acil Çağrı" is developed by the Ministry of Interior to use in case of natural disasters. Affected people can initiate an emergency call to report their situation over the data line, view the assembly areas, and access training videos to increase disaster awareness. While communication tools such as social media platforms and dedicated software applications have become widespread and demonstrated their effectiveness in facilitating communication after earthquakes, it is essential to acknowledge the need for accessibility of a communication network after the disaster, as cell phones or other Wi-Fi communications depend on a system and stations connected by wires [3].

Considering the mentioned cases and studying similar events show the necessity of establishing a quick backup communication network after a disaster to facilitate communication among affected people and rescue teams. This study aims to determine the 3D locations for drones after disasters, where the communications infrastructure has been rendered inoperable due to damages caused by the disasters or high demand. By employing drones as data collection and transmission platforms, the research aims to overcome the limitations of traditional communication channels that often collapse or become overwhelmed during and after earthquakes. These drones can gather essential data from individuals within their range, including text messages and location

information from platforms like Twitter and other relevant sources. The collected information is then transmitted to the communication backbone, ensuring that critical data reaches the appropriate authorities and aid organizations promptly. This innovative approach of leveraging drones as information gatherers and transmitters presents a promising solution to the problem of disrupted communication systems in post-earthquake scenarios, thereby enhancing the overall effectiveness of disaster response efforts. After the disaster, there may be insufficient drones to cover all the affected areas; hence, it is necessary to utilize the available drones efficiently. By increasing the height of a drone, a larger area will be covered, but on the other hand, links with users may weaken. In this study, decisions are made regarding the longitude, latitude, and height of the drones to achieve maximum coverage while maintaining the quality of service above a desirable level. Another challenging issue that should be addressed is the battery capacity of drones. The flight time of the drones is restricted due to the limited power supply. In our proposed network, a hub-drone will be used as an information hub to gather the information from the located drones and deliver them to the central station and the other way around while supplying the necessary power to the located drones simultaneously.

Accordingly, an optimization problem is formulated to maximize the coverage of drones and minimize the total pathloss. The associated problem is referred to as the *drone placement problem* (DPP) and determines the 3D location of the drones and decides on the routing of the hub-drone. Solving this model using exact methods for realistically-sized instances presents computational challenges; hence, a constructive heuristic algorithm is proposed to efficiently solve such instances with improved CPU time compared to the exact method. The proposed algorithm decomposes the problem into two steps: finding drone locations in (Step 1) and obtaining the routes for the hub-drone in (Step 2). For realistically-sized instances, the heuristic algorithms yield efficient solutions where the commercial solver cannot solve the problem within the

given time limit or even create the instance for a given dimension since it needs a large amount of memory to process the data. Moreover, the heuristic algorithm yields close to optimal solutions with (on average) less than 1% optimality gaps for small-sized instances. The objective function and CPU time performances of the proposed heuristic algorithm are also tested using a data set obtained from the Sultanbeyli province of Istanbul, Türkiye.

CHAPTER II

LITERATURE REVIEW

The devastating effects of disasters may impact numerous human beings by causing loss of lives and damaging their properties and the natural environment. Therefore, rescue operations and the decisions made by rescue teams are critical in reducing their impacts. As anticipated, an efficient decision support system is required to manage the operations. To make appropriate decisions, different system components should be able to communicate to exchange the gathered information and receive the orders. [1] describes how communication infrastructure may fail after a disaster and the consequences. As a result of this study, an efficient warning system is essential, and the lack of such a system during a disaster results in severe damage and even the loss of life. In the literature, several works have studied the problem and provided solutions. [4] examines the reasons for the collapse of all communication systems after the Jiji earthquake and offers a MANET-based emergency communication and information system solution for this type of communication failure. It is noted that the collapse of communication systems after such disasters makes rescue operation very difficult and cost many people's lives. A MANET-based network proposes using Wi-Fi-ready notebook PCs possessed by rescue volunteers to develop a network to bolster such a need. The primary benefit of the proposed solution lies in its ability to provide temporary communication support in affected areas that lack servers, infrastructure, and internet connectivity. [5] states that a power outage after a disaster causes a severe network failure that delays rescue efforts in isolated regions and examines the strategies that can be applied before and after the disaster to solve a communication failure. To cite a few examples of possible strategies for establishing emergency

communication networks, it is stated that using a Walkie-Talkie is the most suitable and reliable communication system for emergencies. However, it is not widely used in most countries, and there is also a need for a data network that can support information services such as resource allocation. Another suggested post-disaster emergency strategy is to expand the range by updating the remaining base stations if all base stations do not collapse. [6] proposes a disaster communication network method based on the leaked wave from the resident wireless LANs system. The waves leaking out from each resident can be used as an emergency information infrastructure that not only residents but also public officials can use to transmit disaster information, residents' security information, and evacuation information over the internet.

Unmanned aerial vehicles (UAV), also called drones, offer new opportunities for practitioners in logistical operations as an emerging technology. Employing drones is advantageous in several ways, such as bypassing the physical congestion of transportation systems, faster delivery, lower transportation costs, and requiring no human pilots [7]. Drones can be instrumental in different phases of a natural disaster. E.g., they could be used to study the movement of rivers and floods and identify vulnerable areas to start preventive operations in time. Also, drones could be utilized after the disaster to assess the severity of the disaster or even deliver relief supplies [8]. [9] have discussed utilizing drones in humanitarian response and provided the associated potential uses and challenges. Using drones to establish a wireless communication system has gained increasing interest recently due to mentioned advantages. Moreover, aerial communications can provide better coverage than wireless networks on the ground since aerial links are less prone to fading and more effective when roads are impassable [10].

[11] have suggested using UAVs equipped with base stations, i.e., drone cells, to assist the cellular network in unexpected and temporary situations. A mathematical model is presented for the efficient placement of drone base stations, and the

drones are placed horizontally and vertically. It aimed to find the best 3D placement of the drone by increasing the efficiency of the communication network. Optimal heights of drones for maximum coverage and some calculations related to coverage region for some featured areas are also addressed in [12]. In [3], the loss of landline phone connection after the disaster and the out-of-service of many cell sites were mentioned, and a fully autonomous system using UAV was proposed due to the rapid deployment and creation of an efficient communication network. [13] offers drones to provide cellular coverage in disaster areas where terrestrial infrastructure collapses after disasters such as floods and hurricanes. In this article, the problem caused by the limited battery energy of drones has been addressed, and a solution has been developed. Three different drones are mentioned in the proposed solution; ethered backhaul drone (provides high capacity backhauling), an untethered powering drone (provides on-the-fly battery charging), and an untethered communication drone (provides cellular connectivity). A mathematical model is formulated to decide on the placement of drones by minimizing their energy consumption. In [14], the advantages of wireless communication with drones are considered fast to set up, cost-effective, and more flexible to transport or rearrange. In addition, having high mobility and a battery limit are among the difficulties.

The number of articles published on using drones as base stations to support or create communication systems is increasing. In [15], they build base stations with drones and provide wireless connectivity in various scenarios, such as when a terrestrial base station collapse. They have developed a model to place the drones in a way that will serve the maximum number of users using the minimum required to transmit power. They simplified the problem by separating vertical drone placement from horizontal size, thus developing an algorithm for drone placement. In [16], a heuristic algorithm is developed that finds the 3D locations of drone base stations using the particle swarm optimization algorithm. Their primary purpose is to find

the minimum number of drone base stations to serve the area and the 3D placement of these drones to serve users. In [13], authors have tried to find the trajectory that maximizes the overall transmission rate during the flight time of autonomous flying base stations to serve multiple users. In [17], it has been studied to place multiple drones that act as base stations in a way that maximizes the wireless coverage of users on the ground using circle packing theory. In [18], an efficient solution algorithm is developed to deploy a single drone base station to optimize data rate. Reference [19] focused on supporting ground terminals in communication systems by minimizing the number of mounted mobile base stations, and the authors of [20] aimed to find optimal drone locations that minimize the cost. In [21], the 3D drone placement problem is formulated to deploy drones to possible drone locations. While placing drone base stations that support the existing ground base stations in the given region, the number of users covered is maximized to provide an acceptable *quality of service* (QoS). Reference [22] demonstrated that clustering algorithms could be used to determine the user group to be served by considering the capacities of drone base stations.

In the following, the contribution of this study to the related literature is summarized, considering the provided literature review. In this research, a model was developed to decide on the placement of drones that will serve the population points in the disaster area. To supply the required energy of the stationary drones and transfer the data, a hub-drone is used, and the model decides on the routing of the hub-drone. The objective is to maximize the total number of people covered by the drones and the QoS these people receive. The problem also minimizes the overall distance traveled by the hub-drone. In this study, multiple drones serve a wide area, distinguishing it from other studies in the literature. Another one is using a hub-drone as a solution due to the limited battery capacities of drones and optimizing its route in the model. Finally, considering the QoS while maximizing the total coverage

area of the drones in the objective function contributed to the literature. A constructive heuristic algorithm is developed to solve the problem in two steps. The first step involves determining the deployment locations for drones and assigning them to serve specific population points. Subsequently, improvements are applied to refine the assignment of drones to nodes and the selection of drone locations based on the initial solution. In the second step, the routing plan for the hub-drone is developed to minimize the total distance traveled, considering the limited battery capacity of the drones.

CHAPTER III

PROBLEM DEFINITION AND FORMULATIONS

Given a set of nodes, $\mathcal{N}$ in the affected region, and a set of available drones $\mathcal{I}$ [DPP] is developed to determine the optimal 3D placement of drones in a post-disaster setting. In this context, the term 'nodes' refers to the locations where people are situated, and these locations may also serve as potential sites for deploying drones. The are two types of drones in this problem, i.e., the first type of drones, named stationary drones in this research, depart from a depot and get located at the selected nodes and altitudes. People in the covered nodes contact the associated drone in their region to send information. The second type of drone, hub-drone, departs from the depot to gather information from drones and supplies their required power to stay in the position. The primary purpose of the objective function is to increase the number of people receiving service, with secondary objectives of ensuring high-quality service and minimizing the distance traveled by the hub-drone.

To evaluate the QoS of the drone network, a pathloss model is used to calculate the signal strength at nodes covered by a drone. The model formulated in [11] is used. This model is used to predict the strength of the signal that a drone can transmit to a ground user based on the distance between the drone and the user, as well as other factors, such as the environment and any obstacles that may affect the quality of the communication. Using this model, the QoS at each covered node is determined, and the overall performance of the drone network is assessed. It is assumed that for people to receive adequate service, the signal quality, measured by its *signal to noise ratio* (SNR), must be higher than a certain level. This indicates that the signal strength should be stronger than any surrounding noise to establish a reliable connection. If

the SNR falls below this threshold, the service of the drone to that area is deemed unsatisfactory. The threshold is implemented to ensure that people in that area can receive a certain quality of service. Drone 3D location affects both drone coverage region and the quality of air-to-ground links. The position of the drone in three-dimensional space can affect the area that the drone can cover and the quality of the signal that it can transmit to people in each node. As a result, it is essential to consider the placement of drones to optimize their performance in collecting data from people in each node. Drone positioning may be complicated by the conflict between the drone coverage region and the quality of the air-to-ground links when deciding on their altitude. Increasing the altitude of a drone increases its coverage area. In exchange, this can result in a decline in the quality of the air-to-ground links, which can affect the signal strength and reliability of the ground connection. This trade-off between coverage area and service quality must be carefully considered when determining the optimal 3D positioning of drones. Therefore, the altitudes of the drones are also aimed to be determined to maximize the service quality of air-to-ground links and drone coverage.

Given the locations of drones and users on the ground, there is a LoS link with a certain probability. The probability of LoS connectivity for the user located at node $n \in \mathcal{N}$ relies on factors such as the altitude of the drone, denoted as height $h \in \mathcal{H}$, as well as the horizontal distance separating the drone and the user. The probability of establishing a LoS connection for the ith user, located at coordinates (x_i, y_i), and the drone at node n located at coordinates (x_n, y_n) can be calculated as follows:

$$r_{in} = \sqrt{(x_n - x_i)^2 + (y_i - y_n)^2} \tag{1}$$

$$P(h, r_{in}) = \frac{1}{1 + a\exp\left(-b\left(\arctan\left(\frac{h}{r_{in}}\right) - a\right)\right)} \tag{2}$$

where r_{in} is the horizontal distance between the user and the drone, a and b are constant values that depend on the environment. According to the [12], the likelihood

of a LoS between a drone and a user can be affected by the type of environment, including urban and suburban areas, i.e., the characteristics of the surrounding area may have an impact on the ability of the drone and user to establish a LoS connection.

$$L(h, r_{in}) = 20\log\left(\sqrt{h^2 + r_{in}^2}\right) + (\eta_{LoS} - \eta_{NLoS})\, P(h, r_{in}) + 20\log\left(\frac{4\pi f_c}{c}\right) + \eta_{NLoS} \tag{3}$$

The pathloss model used in this context is a function that considers the strength of the signal transmitted between a drone and a user, and it depends on the height of the drone h and the horizontal distance between the drone and users r_{in}. In other words, both the altitude of the drone in the vertical dimension and the distance between the drone and the user in the horizontal dimension influence the strength of the signal.

3.1 Nonlinear mathematical model

This section introduces a mathematical model designed to optimize the positioning of drones in three-dimensional space, aiming to maximize the number of people that can be effectively served while ensuring high-quality service delivery. Its nonlinearity characterizes the model. For the drone to provide satisfactory service to an individual, the connection between the drone and the individual, which involves receiving data, must meet certain QoS standards. The pathloss, represented by the variable λ, reflects the transmission power needed for the drone to meet these standards. So, mathematically it can be written as $L(h,r_i) < \lambda$.

Table 1: Nomenclature of the nonlinear mathematical optimization model

Sets	
$\mathcal{I}$	Set of drones ($i = 1, \ldots, I$)
$\mathcal{N}$	Set of node ($n = 1, \ldots, N$)
Parameters	
λ	the pathloss corresponding to the QoS requirement
x_{min}	minimum x coordinate of drones
x_{max}	maximum x coordinate of drones
y_{min}	minimum y coordinate of drones
y_{max}	maximum y coordinate of drones
h_{min}	minimum altitude for drones
h_{max}	maximum altitude for drones
Decision variables	
x_i	x coordinate of drone i
y_i	y coordinate of drone i
u_{in}	1, if node n is is served by drone i o.w. 0
h_i	altitude of drone i

$$\max_{\boldsymbol{X},\boldsymbol{U},\boldsymbol{H},\boldsymbol{Y}} \quad \sum_{n\in\mathcal{N}}\sum_{i\in\mathcal{I}} u_{in} - \sum_{n\in\mathcal{N}}\sum_{i\in\mathcal{I}} L(h_i, r_{in})u_{in} \tag{4}$$

$$\text{s.t.} \quad L(h_i, r_{in}) \leq \lambda + M(1 - u_{in}) \qquad \forall i \in I, n \in N \tag{5}$$

$$x_{min} \leq x_i \leq x_{max} \qquad \forall i \in I \tag{6}$$

$$y_{min} \leq y_i \leq y_{max} \qquad \forall i \in I \tag{7}$$

$$h_{min} \leq h_i \leq h_{max} \qquad \forall i \in I \tag{8}$$

$$\boldsymbol{U} \in \{0, 1\} \tag{9}$$

The objective function (4) maximizes the total number of people served and their service quality. In other words, it maximizes drone coverage while minimizing the pathloss of the air-to-ground links of the people served. Constraint (5) ensures that if node n is served by drone i, the air-to-ground link between drone i and node n must meet the QoS requirements. Constraints (6)-(8) denote that the x_i, y_i and h_i values of the drone i are between the determined maximum and minimum values. Constraint (9) is domain constraint.

The problem being considered involves finding the 3D locations of drones given the known (x, y) coordinates of nodes. However, finding a solution to this problem is difficult due to the continuous and nonlinear nature of the drone coordinates and the complex formulation of the model. To simplify the problem, the disaster area is divided into a grid of cells, and the nodes are transformed into population points, representing groups rather than individuals. This makes the problem more realistic and tractable, particularly for larger areas. The model can be linearized and solved easier by creating a set of potential drone locations based on the population points. The specifics of this process will be discussed in the following section.

3.2 Linear optimization model

In this problem, drones collect data from the people at the nodes, which refers to the digital information that must be transmitted between the drones and the individuals. This can include various types of electronic data such as text messages, images, and other similar data. The amount of data is typically measured in bits or bytes, the fundamental units of digital information. The data capacity of a drone refers to the maximum amount of data it can store or transmit during a given period. However, drones have limited data capacity compared to larger communication systems like satellites or ground-based communication systems due to their smaller size and reduced storage space and processing power. To provide more flexibility for the model and increase the number of candidate locations for drone placement, the region is divided into grids, and the centers of these grids are considered additional candidates for drone placement. The population of the generated extra nodes for drone placement is zero. While dividing the region into grids may yield more candidate locations for drone placement, it may also create unnecessary nodes. Any grids that fall outside the convex hull of the population points are removed to eliminate these unnecessary nodes. The convex hull is a geometric shape that encloses all the points in a given set,

and only the points within this shape are considered relevant for determining potential drone locations. By eliminating grids outside the convex hull, the set of possible drone locations is narrowed down to those that are likely useful. For example, Figure 1 shows a sample region with 100 population points and 100 grid nodes. The red dots represent population points. The green cross signs represent grid points, or possible drone locations, while the rhombus-shaped dots are grid points removed due to being outside the convex hull.

As drones have a limited power supply, they require charging to continue providing their services in the air. To address this, a hub-drone charges stationary drones while they remain at their respective positions without requiring movement. The problem formulated involves deciding on the locations of the stationary drones and the route of the hub-drone while minimizing the total distance traveled by the hub-drone. By providing energy to stationary drones through the hub-drone, they can continue to provide service without returning to a charging station or depot. In this model, it is assumed that the coverage region of each drone is circular in shape and that the coverage regions of the drones do not intersect to maximize the quality of the service provided and avoid decreased capacity due to the use of the same frequencies. The parameters and decision variables of the problem are presented in Table 2, and the resulting optimization problem is formulated as follows:

$$[\text{DPP}] : \max_{\boldsymbol{x},\boldsymbol{v},\boldsymbol{u},\boldsymbol{h},\boldsymbol{z},\boldsymbol{b},\boldsymbol{l},\boldsymbol{m}} \quad \alpha \sum_{i\in\mathcal{I}} \sum_{n\in\mathcal{N}} w_n u_{in} - \mu \sum_{i\in\mathcal{I}} \sum_{n\in\mathcal{N}} l_{in} w_n - \beta \sum_{r\in\mathcal{N}} \sum_{k\in\mathcal{N}} d_{rk} z_{rk}$$

The objective function of the model consists of three terms aiming to optimize the total number of people served, provided QoS to nodes, and the total distance traveled by the hub-drone. By optimizing these factors, the model can identify the most effective configuration of drones and routes for collecting data from people. Pathloss values are a measure of the strength of the signal between an individual and the drone, and minimizing these values can improve the QoS provided to the people.

Figure 1: Visual representation of an example node set

Table 2: Nomenclature of the mathematical optimization model

Sets	
$\mathcal{N}$	set of nodes $(n, n' = 0, 1, \ldots, N)$(0 index denotes the depot)
$\mathcal{I}$	set of drones $(i = 1, \ldots, I)$
$\mathcal{H}$	set of possible heights $(h = 1, \ldots, H)$
Parameters	
$L^n_{h,n'}$	pathloss for air-to-ground link of node n, if receives service from a drone located in node n' and height h
λ	the pathloss corresponding to the QoS requirement
s_n	battery consumption at node n
B_{max}	maximum battery of hub-drone
t_{rk}	battery consumption between node r to node k
K	data capacity the drone can collect
w_n	population of node n
$d_{nn'}$	distance between node n and n'
σ	assumed data transfer size of an individual
Decision variables	
x_{in}	1, if drone i is located in node n; o.w. 0
v_{in}	1, if node n is is served by drone i; o.w. 0
u_{in}	service portion of drone i to node n
h_{ih}	1, if drone i is located in height h; o.w. 0
z_{rk}	1, if the hub-drone travels from node r to k; o.w. 0
b_n	battery consumption when drone arrives to node n
l_{in}	pathloss for air-to-ground link of node n and drone i
m_i	service range of drone i

$$\text{s.t.} \quad \sum_{h \in \mathcal{H}} L^n_{h,n'} h_{ih} \leq l_{in'} + M(2 - v_{in'} - x_{in}) \qquad \forall i \in \mathcal{I}, n, n' \in \mathcal{N} \tag{10}$$

$$l_{in} \leq \lambda \qquad \forall i \in \mathcal{I}, n \in \mathcal{N} \tag{11}$$

$$\sum_{n \in \mathcal{N}} x_{in} = 1 \qquad \forall i \in \mathcal{I} \tag{12}$$

$$\sum_{h \in \mathcal{H}} h_{ih} = 1 \qquad \forall i \in \mathcal{I} \tag{13}$$

$$\sum_{i \in \mathcal{I}} u_{in} \leq 1 \qquad \forall n \in \mathcal{N} \tag{14}$$

$$u_{in} \leq v_{in} \qquad \forall i \in \mathcal{I}, \forall n \in \mathcal{N} \tag{15}$$

$$\sum_{n \in \mathcal{N}} u_{in} w_n \sigma \leq K \qquad \forall i \in \mathcal{I} \tag{16}$$

$$M(1 - x_{in}) + m_i \geq d_{nn'} v_{in'} \qquad \forall i \in \mathcal{I}, n, n' \in \mathcal{N} \tag{17}$$

$$d_{nn'} \geq m_i + m_{i'} - M(2 - x_{in} - x_{i'n'}) \qquad \forall i, i' \in \mathcal{I}, n, n' \in \mathcal{N}, n \neq n' \tag{18}$$

$$\sum_{n \in \mathcal{N}} z_{n0} \geq 1 \tag{19}$$

$$\sum_{n \in \mathcal{N}} z_{0n} \geq 1 \tag{20}$$

$$\sum_{n \in \mathcal{N}} z_{nn'} = \sum_{i \in \mathcal{I}} x_{in'} \qquad \forall n' \in \mathcal{N} \backslash \{0\} \tag{21}$$

$$\sum_{n' \in \mathcal{N}} z_{nn'} = \sum_{i \in \mathcal{I}} x_{in} \qquad \forall n \in \mathcal{N} \backslash \{0\} \tag{22}$$

$$b_n + s_n + t_{nn'} - M(1 - z_{nn'}) \leq b_{n'} \qquad \forall n \in \mathcal{N}, n' \in \mathcal{N} \backslash \{0\} \tag{23}$$

$$b_n + s_n + t_{n0} \leq B_{max} \qquad \forall n \in \mathcal{N} \tag{24}$$

$$\boldsymbol{b}, \boldsymbol{l}, \boldsymbol{m} \geq \boldsymbol{0} \tag{25}$$

$$\boldsymbol{u} \in [\boldsymbol{0}, \boldsymbol{1}] \tag{26}$$

$$\boldsymbol{x}, \boldsymbol{v}, \boldsymbol{h}, \boldsymbol{z} \in \{\boldsymbol{0}, \boldsymbol{1}\} \tag{27}$$

Constraint (10) specifies the level of attenuation in signal strength, also known as pathloss value, that occurs when the drone is located at a particular node and is

serving a specific population point, and (11) guarantees that the pathloss value can not be greater than the predetermined threshold. Constraints (12)–(13) ensure that each drone can only be located in one node and at one height. In some situations, drones may only be able to provide service to a particular section of the population. The decision variable denoted by u_{in} determines the percentage of the population in node n that will receive services from drone i. Constraint (14) guarantees that the total sum of the proportions served by drones at each population point is no greater than one. On the other hand, (15) is responsible for storing information regarding whether any portion of the population points receives service from drones or not, and this is indicated by a value of 1 or 0, respectively. The drones have a certain capacity, representing the amount of information they can receive, (16) ensures that the total transferred data is less than or equal to the drone capacity. Constraint (17) specifies the maximum distance each drone can cover. By this definition, the range of drones is measured by the population point it serves at the furthest. Constraint (18) ensures that the coverage areas of two drones do not overlap by ensuring that the distance between the two drones must be greater or equal to the sum of their ranges. Constraints (19)–(22) ensure the hub-drone will visit all nodes where the drones are deployed. In detail, constraints (19)–(20) specify that the hub-drone must start and end its route at the depot, and constraints (21)–(22) ensure that if there is a drone deployed at a specific node, the hub-drone will enter and exit that node once as part of its route, while also preventing from visiting nodes where drones are not deployed. Constraints (23) and (24) are used to manage the battery level of the hub-drone. Constraint (23) specifies the amount of battery that the hub-drone uses until it reaches a particular node. i.e., the battery usage of the drone at the current node will be greater than the sum of its battery usage at the previous node, its current node usage, and the energy needed to travel from the previous node to the current one. Constraint (24) ensures that the total energy required to visit a node (including

the energy needed to return to the storage node after visiting) does not exceed the maximum energy capacity of the hub-drone. These constraints ensure the hub-drone has sufficient battery level to complete its route. Finally, (25)–(27) are restrictions on the decision variables.

CHAPTER IV

SOLUTION APPROACH

DPP is a computationally expensive MILP that cannot be efficiently solved in a post-disaster setting where a quick solution is crucial. A heuristic algorithm is developed to address the problem when a commercial solver fails to achieve an efficient solution in real-world scenarios. The algorithms address the problem in two steps; Step 1 involves solving the placement problem of drones and node assignment, and Step 2 focuses on solving the routing problem for the hub drone. A clustering-based heuristic algorithm is proposed for Step 1, and in Step 2, a *traveling salesman problem* (TSP) is solved for the hub-drone to visit the placed drones. The heuristic algorithms are described in the following, and the routing problem is presented. The inputs of the algorithm are the total number of nodes (N), the total number of drones (I), the distance matrix of the nodes, and the capacity of drones. The algorithm outputs are the 3D locations of the drones and the population points they serve. The steps of the algorithm are as follows:

Step 1: Clustering-based heuristic algorithm. In Step 1.1, an algorithm is proposed to generate clusters. In Step 1.2, the utility of each cluster is calculated, and the selection of the best solution among the candidates is performed in Step 1.3. Subsequently, the node-to-drone assignments are refined in Step 1.4, and in Step 1.5, the drone locations are improved.

Step 1.1: Iterative cluster generation. This step involves generating clusters, where a drone serves each cluster. These clusters are comprised of chosen nodes, and the drone location while the population points it serves within the cluster are determined.

Since each drone has a finite capacity for data transfer with users, the coverage area for the drone is established for each cluster accordingly. A node from the set $\mathcal{N}$ is chosen as the base node, assuming that a drone is located there. The pathloss for all nodes is then calculated based on the altitude of the drone and location, and the nodes are listed in ascending order according to the computed pathloss. Subsequently, nodes are selected from this list to form a cluster, starting from the top and continuing until the total capacity of the drone is exceeded by a certain percentage denoted as ρ. As the pathloss expression depends on the altitude h, this process is repeated for all possible altitudes $h_0, \ldots, h_H$. In other words, the drone is placed at each possible altitude, and a cluster is generated individually for each altitude. Additionally, multiple clusters are generated for the base node, considering ω different values of ρ. Additional clusters can be generated by repeating the aforementioned procedure and randomly selecting nodes from the lists. A probability p is defined for including each node in the cluster, and a random number is generated to determine whether the node will be assigned to the cluster. If the random number exceeds the defined probability, the node is included; otherwise, it is excluded. This process can be repeated e times, and nodes can be randomly assigned to the cluster to generate multiple clusters for each list. These steps are repeated for all nodes in $\mathcal{N}$. At the end of this step, $N \times H \times \omega \times (1 + e)$ clusters will be generated.

Step 1.2: Assignment and cluster utility calculation. Each drone in a cluster aims to serve as many people as possible to maximize the objective function. The service rate assignment process starts by selecting the closest node to the drone and assigning it a service rate 1. Subsequently, each additional node is assigned a service rate of 1 until the drone capacity is exceeded. When the capacity is exceeded, the node that caused the exceed will receive partial service. A service rate of 1 indicates that everyone in that node receives service. Next, the utility of each cluster is calculated

as a factor in determining the optimal solution for the overall problem. The utility of each cluster is computed based on two terms as formulated in equation (28). The first term calculates the total served population, which is obtained by summing the product of the service rate and population of each node in the cluster. The second term calculates the total pathloss between the node and the drone location of the cluster. The formulation is given as follows:

$$B_c = \alpha \sum_{m \in \mathcal{G}_c} u_m w_m - \mu \sum_{m \in \mathcal{G}_c} W_m w_m \qquad \forall c \in \mathcal{C}, \tag{28}$$

where $\mathcal{C}$ is the set of clusters and $\mathcal{G}_c$ denotes the set of nodes in cluster c. The service rate of node $m \in \mathcal{G}_c$ is represented as u_m, W_m is the pathloss expression between node m and the drone location of the cluster, and w_m denotes the population of node m. The parameters α and μ are the coefficent of the [DPP] objective function as defined in Chapter 3.

Step 1.3: Selecting clusters. In this step, a *set partitioning problem* (SPP) is solved to select clusters with high utility among the ones generated in Step 1.1. By solving [SPP], the objective is to choose the clusters that yield the highest returns while ensuring that the number of available drones limits the number of clusters selected and that the coverage regions of the drones do not overlap. A decision variable, λ_c, is introduced, which takes the value one if cluster c is selected; 0, o.w. The distance between the drone locations of two clusters, c and c', is represented by the parameter $d_{cc'}$, and the radius of each cluster is represented by the parameter r_c. The radius of a cluster is determined based on the distance between the farthest assigned node in

the cluster and the drone location. The [SPP] is formulated as follows:

$$
\begin{aligned}
&[\text{SPP}]: \\
&\max_{\boldsymbol{\lambda}} \quad \sum_{c \in \mathcal{C}} B_c \lambda_c \\
&\text{s.t.} \quad \sum_{c \in \mathcal{C}} \lambda_c \leq V && (29) \\
&\qquad d_{cc'} \geq r_c + r_{c'} - M(2 - \lambda_c - \lambda_{c'}) \qquad \forall c, c' \in \mathcal{C}, c \neq c' && (30) \\
&\qquad \boldsymbol{\lambda} \in \{\mathbf{0}, \mathbf{1}\} && (31)
\end{aligned}
$$

where constraint (29) ensures that the number of selected clusters is smaller than the number of drones. (30) imposes a condition that guarantees that the sum of the radius of any two selected clusters is less than or equal to the distance between their respective drone locations. Constraints (31) are 0-1 restrictions. The radius of a cluster is determined based on the distance between the farthest assigned node in the cluster and the drone location.

Step 1.4: Assignments improvements. In this step, the aim is to improve the location of the drones and the assignments of nodes to each drone using the obtained information from the previous steps. A modified version of [DPP] is solved to improve the solution for the given values of the drone placement decision variables obtained in Step 3. Therefore, in the modified version, constraints and decision variables related to the route of the hub-drone are excluded, and the [MIP Model] is formulated to assign nodes to drones based on the location and altitude information of the drones. New parameters are introduced for this purpose. To formulate the model, two distance matrices are defined as d_{in} and $d_{ii'}$ based on the pre-determined drone locations. d_{in} represents the distance between drones and all other nodes, while $d_{ii'}$represents the distance between drones. Additionally, binary parameters are introduced as a_{in}, which take a value of 1 if a drone i can serve a particular node n based on QoS requirements,

0 o.w. The L^*_{in} parameter denotes the pathloss between drone i and node n.

[MIP Model] :

$$\max_{\boldsymbol{u},\boldsymbol{v},\boldsymbol{m}} \quad \alpha \sum_{i\in\mathcal{I}} \sum_{n\in\mathcal{N}} a_{in} w_n u_{in} - \beta \sum_{i\in\mathcal{I}} \sum_{n\in\mathcal{N}} L^*_{in} v_{in} w_n$$

$$\text{s.t.}(14) - (16) \tag{32}$$

$$u_{in} \leq a_{in} \qquad \forall i \in \mathcal{I}, n \in \mathcal{N} \tag{33}$$

$$m_i \geq v_{in} d_{in} \qquad \forall i \in \mathcal{I}, n \in \mathcal{N} \tag{34}$$

$$d_{ii'} \geq m_i + m_{i'} \qquad \forall i, i' \in \mathcal{I}, i \neq i' \tag{35}$$

$$\boldsymbol{m} \geq \mathbf{0} \tag{36}$$

$$\boldsymbol{u} \in [\mathbf{0}, \mathbf{1}] \tag{37}$$

$$\boldsymbol{v} \in \{\mathbf{0}, \mathbf{1}\} \tag{38}$$

The objective function is optimizing the total served population and the total pathloss. Constraint (33) ensures that a drone cannot serve a node if a_{in} is zero. (34) specifies the radius of the drone, which is the maximum distance the drone can serve. Constraint (35) ensures that the sum of the radius of any two drones is less than or equal to the distance between them, which guarantees that the ranges of the drones do not overlap. Constraints (36)-(38) are domain constraints.

Step 1.5: Location improvements. Placing drones only at pre-identified nodes may not necessarily yield the optimal locations for them. This step introduces improvements by allowing drones to be placed in locations other than the pre-defined nodes, thereby providing more flexible placement options. To achieve this, a nonlinear problem is formulated to determine the optimal location for each drone based on the nodes it serves. If the relocation of a drone causes its coverage area to overlap with another drone coverage area, the relocation will be discarded to avoid interference. Once the

relocation process is complete, the overall objective is recalculated as the location of the drones has been altered, resulting in a change in the pathloss expression in node-drone links. Finally, the developed algorithm yields the final drone locations and assignments, and the objective function is calculated accordingly to obtain the optimal solution.

Step 2: Routing problem for hub-drone. After determining the locations of the drones and the population points they will serve in Step 1, the effective route for the hub-drone is obtained in Step 2. The [TSP model] is formulated to get the most effective route, while the route can be a single tour or multiple tours, depending on the battery of the hub-drone. The battery of the hub drone should be maintained before completing its tour in case multiple routes are created. In this problem, $\mathcal{K}^*$ is defined as the set of nodes where drones are located.

[TSP Model] :

$$\min_{\boldsymbol{z},\boldsymbol{b}} \quad \sum_{r\in\mathcal{K}^*}\sum_{k\in\mathcal{K}^*} TC_{rk} z_{rk}$$

$$\text{s.t.} \quad \sum_{k\in\mathcal{K}^*} z_{k0} \geq 1 \tag{39}$$

$$\sum_{k\in\mathcal{K}^*} z_{0k} \geq 1 \tag{40}$$

$$\sum_{k\in\mathcal{K}^*} z_{kk'} = 1 \qquad \forall k' \in \mathcal{K}^*\backslash\{0\} \tag{41}$$

$$\sum_{k'\in\mathcal{K}^*} z_{kk'} = 1 \qquad \forall k \in \mathcal{K}^*\backslash\{0\} \tag{42}$$

$$b_k + s_k + t_{kk'} - M(1 - z_{kk'}) \leq b_{k'} \qquad \forall k \in \mathcal{K}^*, k' \in \mathcal{K}^*\backslash\{0\} \tag{43}$$

$$b_k + s_k + t_{k0} \leq B_{max} \qquad \forall k \in \mathcal{K}^* \tag{44}$$

$$\boldsymbol{b} \geq \boldsymbol{0} \tag{45}$$

$$\boldsymbol{z} \in \{\boldsymbol{0}, \boldsymbol{1}\} \tag{46}$$

The objective of the [TSP model] is to minimize the distance traveled by the hub-drone in visiting all the drone locations in the set $\mathcal{K}^*$. The constraints (39)-(46) have been previously defined and discussed in [DPP]. The only dissimilarity is that the sets of decision variables are separate. Therefore, it is unnecessary to redefine these constraints in the current context.

CHAPTER V

NUMERICAL EXPERIMENTS

In this section, the data structure of the case study and synthetic instances is described in Section 5.1. Subsequently, the performance of the proposed heuristic algorithm is tested and discussed using synthetic instances in Section 5.2. Finally, [DPP] is solved in Section 5.3, and the solution and results for the case study instance are discussed. The computations in this research were run on a 64-bit Windows server with an AMD EPYC 2.00 GHz CPU and 32 GB RAM. The mathematical models and algorithms were coded in Python, and GUROBI 9.5.2 was used as the optimization solver for linear problems, while the GEKKO library was used for solving nonlinear problems.

5.1 Data structure

This section presents the specifications of the case study datasets employed in our study and introduces the synthetic datasets utilized to evaluate the effectiveness of the proposed approach. To compare the performance of the algorithm and the commercial solver GUROBI, multiple instances of small and medium size, varying the number of population points from 30 to 200, are generated. Specifically, the focus is on small and medium-sized instances for this comparison because the commercial solver encounters a memory error beyond a specific instance size. The data creation process involves the generation of random (x, y) coordinates within a specified range, coupled with a population size ranging from 25 to 80 individuals for each population point. Additionally, the impact of incorporating grid points as potential drone locations within the datasets is examined, comparing solutions with and without them. The specifications of the generated instances, along with the corresponding number of

available drones, are presented in Table 3.

Table 3: Instances.

instance ID	# population points	# grid points	# available drones	maximum drone coverage
1	30	0	3	67.22 %
2	50	0	6	78.50 %
3	50	50	6	78.50%
4	100	0	11	70.09%
5	100	100	11	70.09%
6	200	0	23	72.12%
7	200	100	23	72.12%

Case study dataset. Figure 2 illustrates the Sultanbeyli dataset, where the black dots represent living spaces, predominantly apartments. Each point is associated with population information, indicating the number of people residing in that particular location. While the complete dataset consists of approximately 31 thousand data points, the analysis focuses explicitly on the northern section of Sultanbeyli, which is represented by the dark blue points. These dark blue points, totaling 7,000 points, can be treated as nodes within the proposed algorithm. By applying K-means clustering, the 7,000 dark blue nodes are grouped into a total of 700 nodes, and each cluster consists of ten dark blue nodes. These clusters are indicated by red dots in the figure. The populations of the dark blue nodes within each group are aggregated to form the population of the corresponding new red nodes. The performance evaluation of the proposed algorithm is conducted using the generated red nodes. These red nodes, created by combining and clustering the original data points, are the basis for assessing the effectiveness and efficiency of the algorithm.

Pathloss calculation. The pathloss formulation, as described by Equations (1)–(3), is computed using the methodology presented in the study by [12]. These calculations incorporate various parameters specific to different environmental settings. Among these parameters, the values of a, b, η_{LoS}, and η_{NLoS} vary depending on the environment. Here, a and b represent constant values, while η_{LoS} and η_{NLoS} (in

Figure 2: Visual representation of Sultanbeyli

dB) denote the losses associated with LoS and non-line-of-sight (NLoS) connections, respectively. The considered environments encompass suburban, urban, dense urban, and high-rise urban areas. This research assumes that all environments fall within the urban category, and the calculations are conducted accordingly. Specifically, in the urban environment, the parameter values of a, b, η_{LoS}, and η_{NLoS} are set to (9.61, 0.16, 1, 20), respectively.

Hub-drone battery. The parameters utilized for the hub-drone battery calculations are derived from the study by [23]. Moreover, they employ the following formulation to estimate the battery consumption of the hub-drone during travel between node n and node n', denoted as $t_{nn'}$:

$$t_{nn'} = \frac{m_d}{\theta_s \nu} d_{nn'} \tag{47}$$

Table 4 summarizes other parameters used in this research.

Table 4: General parameters

parameter (unit)	indicator	value
altitude (m)	(h_1, h_2, h_3)	(100,300,500)
pathloss threshold (dB)	λ	110
data transfer(MB)	σ	50
drone capacity (GB)	K	15
carrier frequency (GHz)	f_c	2.5
maximum battery (Wh)	B_{max}	777
power transfer efficiency	ν	0.66
lift to drag ratio	θ_s	3.5
drone mass (kg)	m_d	10.77

5.2 Evaluating the performance of proposed algorithm

In this section, the performance between exact and heuristic approaches is evaluated and compared using synthetic instances generated for the study. The instances are solved using both exact and heuristic algorithms. The exact solution is obtained by applying the mathematical optimization problem [DPP] developed in Section 3, utilizing the GUROBI solver. It is important to note that the proposed cluster-based heuristic algorithm consists of two distinct steps. In Step 1, the locations for drone deployment are determined and assigned to serve specific population points. This process involves generating clusters and solving a set partitioning problem to select the best clusters from the generated ones. Once an initial solution is obtained, two improvements are applied to assigning drones to nodes and selecting drone locations. After these improvements, Step 2 is established, where the route for the hub-drone is derived by solving a TSP formulated as [TSP Model].

The numerical results are presented in Table 5, which compares the outcomes obtained from the commercial solver and the proposed heuristic algorithm. The first

column of the table represents the instance ID, which is explained in the previous subsection, and further details regarding each instance can be found in Table 3. Subsequently, the average performances of the objective function value (OFV) and CPU time are computed and documented. To ensure consistency, ten random instances with identical specifications are generated, and their average values are reported in each row. The second and third columns of the table present the OFV performances achieved by GUROBI and the proposed heuristic algorithm, respectively, within the prescribed time limit of 4 hours. In the table, the symbol "$*$" denotes the best solution, while the percentages indicate the relative optimality gap of the other. Moreover, the fourth and fifth columns illustrate the CPU times in seconds for the solver and the proposed heuristic algorithm. Lastly, the last column of the table indicates the optimality gap of the solver for instances that could not be solved within the given time limit. Notably, instances marked with "m" encounter memory errors with the solver and are thus unsolvable within the given time limit.

Table 5: Heuristic vs solver (GUROBI)

instance ID	OFV		CPU		solver optimality
	solver	heuristic	solver	heuristic	gap
1	$*$	$*$	237	28	0%
2	$*$	1%	14400	61	3%
3	1%	$*$	14400	102	4%
4	13%	$*$	14400	174	16%
5	22%	$*$	14400	297	24%
6	m	$*$	m	499	m
7	m	$*$	m	570	m

($*$) denotes the best OFV; (m) denotes the memory error

The numerical results indicate that the proposed heuristic algorithm generates

nearly optimal solutions for instances with IDs 1, 2, and 3. The solver and the algorithm can find the optimal solution for the smallest instance (ID 1). These solutions achieve an optimality gap of less than or nearly 1%, highlighting their proximity to the optimal solution. Furthermore, the algorithm outperforms the commercial solver regarding CPU time for the corresponding instances, demonstrating a significant improvement in efficiency. Specifically, for instance, in ID 2, the algorithm exhibits CPU times of one minute, while the commercial solver only manages to enhance the algorithm's OFV by a maximum of 1% within the given 4-hour time limit. As the number of nodes increased, the optimality gap of the solver became more pronounced. The disparity in OFV performance between the solver and the algorithm became increasingly evident. The solver encounters memory errors and fails to provide results beyond a specific problem size. This emphasizes the growing advantage of the algorithm in handling larger problem instances, where it continues to deliver near-optimal solutions while the solver becomes less viable.

Overall, the numerical outcomes strongly support the effectiveness of the proposed heuristic algorithm in providing near-optimal solutions with improved computational efficiency, which is of paramount importance for the specific context of post-disaster scenarios. Given that the problem needs to be solved promptly with a given number of drones obtaining solutions quickly becomes crucial. This highlights the significance of the heuristic algorithm, demonstrating its capability to deliver efficient solutions within a short time frame and showcasing its practical relevance in time-sensitive disaster response scenarios.

5.3 Case study

In this section, the effectiveness of the proposed algorithms is assessed using a dataset acquired from Sultanbeyli province in Istanbul, as depicted in Figure 3.

Implementing proposed heuristic algorithm. In this case study, 700 nodes

Figure 3: Visual representation of Sultanbeyli dataset

from a specific dataset are selected, as mentioned earlier. Each node in this dataset contains population information. Every person in these nodes transfers approximately 25 MB of data is assumed. Additionally, the drones used in this scenario have a capacity of 60 GB to store and transport data. The proposed heuristic algorithm is implemented using the provided nodes and assumptions, and the numerical results are shown in Table 6. The first column of the table indicates the varying number of drones available for the given dataset. The proposed algorithm is executed multiple times, considering a different number of drones. The last column of the table displays the maximum coverage rate achieved by these drones, indicating the percentage of people in the dataset covered by the drone network. As observed, increasing the number of available drones leads to enhanced coverage of the people. As the number of drones increases, it is observed that the rate at which drones approach the maximum coverage percentage decreases. This can be attributed to the restriction imposed on drone coverage areas, which prevents their overlapping. Consequently, drones cannot cover all nodes, even if their maximum coverage capacity is 100%. In other words,

Figure 4: Results of case study with 90 drones

due to the constraint of non-overlapping coverage areas, the drones may be unable to achieve complete dataset coverage.

Table 6: Numerical results of the case study

# drones	CP	PL	CPU	maximum coverage
75	70%	91	1238	71%
90	78%	91	1440	85%
105	82%	90	1913	100%

(CP) denotes covered population; (PL) denotes pathloss

Extensions. The preceding subsection discussed the outcomes of the case study with the proposed heuristic algorithm. It is acknowledged that certain nodes remained uncovered due to the constraint preventing overlapping drone coverage areas. In light of this result, two extensions are introduced exclusively for the case study to address this issue within the proposed algorithm.

Extension I: relaxing the constraint. In the proposed algorithm, there is a constraint preventing any overlap between the coverage areas of the drones. A slight overlap of 20% of the distance between drone locations is permitted. The purpose behind this

relaxation is to prevent the centers of the coverage areas of drones from intersecting entirely. Allowing an intersection of 20% of the distance between the drone points creates a balance between maintaining separation and optimizing coverage efficiency. The modified algorithm is applied to the same case study, and the results are compared with the previous implementation. Table 7 presents the findings with significant improvement in node coverage compared to the original version. It is important to note that while this extension improves node coverage, it does have limitations. As mentioned in [24], inter-cell interference among multiple drones significantly affects the signal-to-interference-plus-noise ratio (SINR) of on-ground users and degrades overall performance. Therefore, while this extension addresses the coverage issue, careful consideration must be given to the potential impact on system performance. Hence, Extension II will be introduced to reduce the extent to which the coverage areas of drones overlap.

Table 7: Numerical results of Extension I

# drones	CP	PL	CPU	maximum coverage
75	71%	89	1674	71%
90	84%	91	1742	85%
105	93%	93	1853	100%

(CP) denotes covered population; (PL) denotes pathloss

Extension II: iterative heuristic algorithm. This extension involves implementing the original algorithm twice as a brief application. In the first iteration, the original algorithm utilizes 90% of the available drones. However, certain nodes may remain uncovered. The proposed algorithm is reapplied specifically for the uncovered nodes to address this challenge, utilizing the remaining 10% of available drones. During this process, the clustering phase is modified to generate smaller clusters by using only one-fourth of the capacity of drones among the remaining uncovered nodes. The reason for generating smaller clusters is to minimize the overlap between the coverage areas of the 90% of drones initially deployed and the 10% of newly deployed drones.

Figure 5: Results of Extension I: Case study with 90 drones

By deploying available drones with two iterations and generating smaller clusters, the aim is to provide coverage to the remaining previously uncovered nodes. This two-step approach allows for the effective addressing of coverage gaps and the improvement of the overall performance of the algorithm. Table 8 presents the results. By comparing the last row of Tables 5 and 7, it is evident that there is a 3% increase in the coverage of the population, which corresponds to an additional approximately eight thousand people being covered.

Table 8: Numerical results of Extension II

# drones	CP	PL	CPU	maximum coverage
75	71%	89	1053	71%
90	79%	91	1136	85%
105	85%	92	1968	100%

(CP) denotes covered population; (PL) denotes pathloss

Figure 6 displays the results of Extension II when applied to the case study using 90 drones. In the first step, the original algorithm is executed with 81 drones, and the corresponding results are depicted in blue in Figure 6. Subsequently, in the second

Figure 6: Results of Extension II: Case study with 90 drones

step, the algorithm is re-run using the remaining nine drones, and the outcomes of this iteration are shown in green.

CHAPTER VI

CONCLUSION

This study has addressed communication challenges in disaster response by proposing a novel approach that leverages drones as data collection and transmission platforms. The research aimed to overcome the limitations of traditional communication channels that often collapse or become overwhelmed during and after earthquakes. With communication channels, the response teams may be able to effectively mobilize resources, disseminate critical information, and ensure the safety of affected individuals. The significance of communication systems is acknowledged, and by exploring innovative approaches such as drone-based solutions, the speed, accuracy, and reach of information exchange can be enhanced. This, in turn, can contribute to more efficient and coordinated disaster response efforts. By utilizing drones to gather essential data from individuals within their range and transmit it to the communication backbone, the proposed approach demonstrated promising results in enhancing the overall effectiveness of disaster response efforts.

Through the formulation of the [DPP], the study developed an optimization model to maximize drone coverage and minimize total pathloss. Recognizing the computational challenges in solving realistically-sized instances using exact methods, a constructive heuristic algorithm was proposed, which efficiently determined the 3D locations of drones and optimized the routing of the hub-drone. The performance evaluation of the proposed algorithm indicated its effectiveness in providing near-optimal solutions and reducing CPU time compared to the exact methods. One of the key advantages of the algorithm is its ability to solve realistically-sized instances with improved CPU time compared to exact methods. While solving the problem

using exact methods can be computationally challenging and time-consuming, the algorithm provided efficient solutions within reasonable time limits. It outperformed commercial solvers, which either failed to solve the problem or required significant memory to process the data. The utilization of the proposed algorithm has significantly contributed to improving the efficiency and speed of decision-making in disaster response scenarios. The findings of this research highlight the practical implications and significance of drones in disaster response. Using drones as information gatherers and transmitters can significantly improve data collection and transmission in post-disaster scenarios, ensuring critical information reaches the appropriate authorities and aid organizations promptly. The proposed approach offers a promising solution to address the communication limitations that often arise in the aftermath of earthquakes, ultimately enhancing response coordination and efficiency.

In the case study, the reaching of covering 85% of the population in Sultanbeyli, a municipality with a total population of 259.615, using the proposed algorithm, highlights the immense importance of this solution. The ability to reach such a high coverage rate demonstrates the effectiveness and efficiency of the algorithm in disaster response scenarios. This adaptability ensures that the solution can be tailored to different disaster scenarios and population densities, allowing for efficient resource utilization and cost-effectiveness. In conclusion, the proposed approach of utilizing drones as data collection and transmission platforms presents a viable and effective solution to the communication challenges faced in disaster response. The timeliness and effectiveness of communication systems in post-earthquake scenarios can be improved by leveraging advancements in drone technology and positioning techniques, ultimately contributing to more efficient and coordinated disaster response efforts.

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VITA

Melike Çap received the degree of Bachelor of Science in Industrial Engineering in August 2020. Her research focuses on optimizing 3D drone deployment.