Mehmet Akcan

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A PLANNING MODEL FOR TASK ASSIGNMENT AND ENERGY OPTIMIZATION IN UAV-BASED MOBILE BASE STATIONS FOR POST-DISASTER COMMUNICATION

M.Sc. THESIS
SUBMITTED TO THE DEPARTMENT OF INDUSTRIAL ENGINEERING
AND THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE
OF ABDULLAH GUL UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
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SCIENTIFIC ETHICS COMPLIANCE

I hereby declare that all information in this document has been obtained in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

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M.Sc. thesis titled "A Planning Model for Task Assignment and Energy Optimization in UAV-Based Mobile Base Stations for Post-Disaster Communication" has been prepared in accordance with the Thesis Writing Guidelines of the Abdullah Gül University, Graduate School of Engineering & Science.

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ACCEPTANCE AND APPROVAL

M.Sc. thesis titled “A Planning Model for Task Assignment and Energy Optimization in UAV-Based Mobile Base Stations for Post-Disaster Communication” and prepared by Mehmet Akcan has been accepted by the jury in the Industrial Engineering Graduate Program at Abdullah Gül University, Graduate School of Engineering & Science.

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JURY:

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Graduate School Dean
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ABSTRACT

A PLANNING MODEL FOR TASK ASSIGNMENT AND ENERGY OPTIMIZATION IN UAV-BASED MOBILE BASE STATIONS FOR POST-DISASTER COMMUNICATION

Mehmet Akcan
MSc. in Industrial Engineering Program
Advisor: Asst. Prof. Betül Çoban
July 2025

Ensuring the sustainability of communications infrastructure following natural disasters is of vital importance. Unmanned Aerial Vehicles (UAVs), equipped with base station technologies, provide that enables connectivity in disaster zones. While UAVs offer key advantages such as mobility, coverage, and prolonged airtime, their effective use in real-world scenarios is often constrained by operational factors such as battery capacity, adverse weather conditions, and dynamic disaster environments. This study introduces a Mixed-Integer Linear Programming (MILP) model designed to optimize the positioning and energy replenishment of UAV-based bases. The model incorporates dynamic user demand based on population density and disaster impact severity, battery limitations, and charging logistics. A hexagonal grid-based spatial framework is employed to maximize coverage in complex urban landscapes. The model is implemented using GAMS and its performance is evaluated through a case study, using district-level demographic and risk data. Scenarios are used to test the proposed solution method by varying the number of UAVs, deployment sites, and available charging stations. The results demonstrate the model's capability to produce effective and energy-efficient UAV assignment plans that significantly improve post-disaster communication coverage. Furthermore, the findings reveal that although the model performs well under moderate-scale conditions, execution times increase considerably in large-scale scenarios. This limitation suggests the necessity of integrating heuristic and metaheuristic approaches in future work to enhance real-time responsiveness and scalability. Overall, this study contributes a novel optimization framework that bridges theoretical modeling and practical deployment strategies, reinforcing the critical role of UAVs as not only a technological solution but also a humanitarian asset in disaster response systems.

Keywords: Post-Disaster Communication, Facility Location Problem, UAV-Based Base Stations, Energy Management and Deployment Optimization

ÖZET

AFET SONRASI İLETİŞİM İÇİN UAV TABANLI MOBİL BAZ İSTASYONLARINDA GÖREV ATAMA VE ENERJİ OPTİMİZASYONUNA YÖNELİK BİR PLANLAMA MODELİ

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Endüstri Mühendisliği Anabilim Dalı Yüksek Lisans
Tez Danışmanı: Asst. Prof. Betül Çoban
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Doğal afetlerin ardından haberleşme altyapısının sürdürülebilirliğini sağlamak hayati öneme sahiptir. Üzerlerinde baz istasyonu teknolojisi bulunan İnsansız Hava Araçları (İHA'lar), afet bölgelerinde bağlantıların kurulmasını mümkün kılmaktadır. İHA'ların hareket kabiliyetleri, kapsama yetenekleri ve havada uzun süre kalabilmeleri gibi avantajları bulunsa da; batarya ömrü, olumsuz hava koşulları ve değişken afet ortamları gibi faktörler bu sistemlerin sahadaki etkinliğini kısıtlamaktadır. Bu tez çalışması İHA tabanlı mobil baz istasyonlarının konumlandırılması ve enerji ikmali süreçlerinin optimizasyonunu hedefleyen bir Karma Tamsayılı Doğrusal Programlama (MILP) modeli önermektedir. Modelde nüfus yoğunluğu ve afet etki şiddeti dikkate alınarak talep değerleri dinamik biçimde belirlenmekte; batarya sınırlamaları ve şarj altyapısı gibi kısıtlar entegre edilmektedir. Altıgen grid temelli bir mekânsal yapı kullanılarak kentsel alanlarda kapsama performansı en üst düzeye çıkarılmaktadır. Model, GAMS ile uygulamaya alınmış ve vaka çalışması ile test edilmiştir. İHA sayıları, konuşlanma noktaları ve şarj istasyonu senaryoları kullanılarak simülasyonlar gerçekleştirilmiştir. Elde edilen sonuçlar, modelin enerji verimliliğini koruyarak yüksek kapsama sağlayan etkin konuşlanma planları oluşturabildiğini göstermektedir. Ayrıca, büyük ölçekli uygulamalarda modelin çözüm sürelerinin önemli ölçüde arttığı gözlemlenmiştir. Bu durum, gerçek zamanlı kullanım için sezgisel ve meta-sezgisel algoritmaların entegrasyonunun gerekliliğini ortaya koymaktadır. Bu çalışma, İHA'ların afet sonrası iletişimde etkin kullanılabilmesi için özgün bir optimizasyon yaklaşımı sunmakta ve teorik modelleme ile pratik konuşlanma stratejileri arasında köprü kurarak hem akademik literatüre hem de afet yönetimi uygulamalarına anlamlı bir katkı sağlamaktadır.

Anahtar kelimeler: Afet Sonrası İletişim, Tesis Yerleşimi Problemi, İnsansız Hava Araçları (İHA), Enerji Yönetimi ve Konumlandırma Optimizasyonu

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LIST OF ABBREVIATIONS

GAMS	General Algebraic Modeling System
MILP	Mixed-Integer Linear Programming
QoS	Quality Of Life Requirements
UAV	Unmanned Aerial Vehicles
UAV-BS	Unmanned Aerial Vehicles Base Stations

To My Family

Chapter 1

Introduction

Unmanned Aerial Vehicles (UAVs) have been widely used in civil, commercial, military and aviation fields. Applications of UAVs can be generally categorized as military and civilian uses [1]. In recent years, developments in wireless communication technologies and advances in UAV's technology have offered new opportunities in mobile communication infrastructure. UAV Base Stations (UAV-BS) have emerged as an alternative or complementary solution to traditional fixed base stations. These systems are of great importance in terms of sustainability of communication services, especially in disaster situations, temporary intensive use scenarios and rural areas. UAV-BS systems are defined as mobile base stations that can be positioned in the air.

Compact structures that can be mounted on UAVs are often referred to as "payloads". Payload refers to equipment such as cameras, sensors, and radars that UAVs carry to perform their main missions. This term covers all equipment carried by the UAV and used to perform a specific mission. For example, sensor systems mounted on UAVs used in agricultural fields for vegetation detection are generally passive systems and use rays reflected from the sun. These sensors help UAVs collect data to increase agricultural productivity [2]. In addition, air data relay systems integrated into UAVs are used to increase the operational range between the target and the ground control station. These systems allow UAVs to operate effectively in wider areas [3]. Such compact structures enable UAVs to be used flexibly in different missions, finding a wide range of applications from agriculture to military operations. The most important advantages of these systems include rapid deployment, flexible positioning, wide coverage and dynamic repositioning features. UAV-BS systems are especially critical after natural disasters. In large-scale disasters such as earthquakes, not only when the established communication infrastructure is damaged, but also when the demand in the affected area is much higher than expected, terrestrial base stations cannot meet this density. At this point, UAV-BSs with a mobile structure can provide communication services by changing location depending on the intensity of demand. Especially in earthquake-affected areas, these systems have the potential to provide critical communication support for people trying to reach their relatives under the rubble. Such a scenario was witnessed in the 2011 Japan Tōhoku earthquake and tsunami. During the disaster, the established infrastructure was severely damaged and mobile communication systems were inadequate to meet urgent communication needs [4]. Similarly, in the 2023 Kahramanmaraş earthquake, serious interruptions in communication occurred due to damage to traditional base stations and increased demand [5]. In the devastating earthquake that occurred in Haiti in 2010, established telecommunications infrastructure was severely damaged, and mobile communication solutions became vital [6]. In the 7.1 magnitude earthquake in Mexico in 2017, serious interruptions in communication occurred due to infrastructure damage, and mobile base stations and satellite-supported devices were used to provide temporary communication solutions in disaster areas [7]. Although it was not a disaster-type earthquake in 2020, communication outages spread over wide areas during the forest fires in Australia, and mobile communication became a necessity for both rescue teams and those affected by the disaster. solutions have played a critical role [8]. These examples further reinforce the necessity of UAV-BSs to be activated in cases where the communication infrastructure is damaged in different disaster scenarios.

UAVs are increasingly favoured in disaster management due to their flexibility and adaptability. UAVs, which play important roles in the preparation, intervention, and recovery stages of various natural disasters such as earthquakes, fires, and floods, accelerate the aid processes for disaster victims with their fast mobility, aerial imaging, data collection, instant information transmission, sound detection, uninterrupted communication and ability to integrate into crisis management easily. They play a vital role in observing disasters and delivering humanitarian aid, especially in regions with difficult access. In cases where manpower is insufficient or rapid intervention is essential, UAVs stand out as an effective alternative. Post-disaster operations include tasks such as logistics support, establishing communication networks, data collection, rescue efforts, and ensuring the functionality of mobile base stations [9, 10, 11].

Aftermath of a disaster, protecting the communication infrastructure and ensuring continuity is of critical importance. However, natural disasters can cause serious damage to fixed communication lines, causing regions to become isolated. Traditional base stations may be insufficient in terms of communication networks during this process and repair times may be prolonged [12]. UAVs, especially those operating at low altitudes and equipped with small cellular base stations, provide an important option to overcome this problem by providing temporary coverage and emergency communication connections in disaster areas [13].

Commercial low-cost UAV can serve as flying base stations thanks to the base station hardware on them. This function provides critical support in disaster areas by filling the communication gap created by terrestrial base stations damaged in natural disasters or by meeting the increasing need for mobile data and communication [14]. UAVs allow disaster victims to communicate with each other and emergency services via mobile devices, thus supporting more effective humanitarian aid and rescue operations. In addition, their autonomous mobility and ability to stay in the air for relatively long periods make this technology a vital tool in the rapid reconstruction of damaged communication infrastructure. These features enable both the smooth transmission of emergency calls and effective coordination between rescue teams and disaster management authorities. For example, during rescue operations, flying base stations can help rescue teams communicate in real-time and provide rapid transfer of situation assessment reports [13].

In addition, such UAVs support data transfer by acting as “flying hubs” in mobile network transitions or in areas with insufficient coverage. UAV-based base stations, especially those that can adapt to 4G/5G infrastructure, increase connection continuity in times of crisis with high bandwidth and low latency [11]. With these aspects, UAVs not only provide temporary solutions but also provide long-term infrastructure support in post-disaster recovery processes, becoming a critical component of disaster management. In using UAV-BSs, site selection is of critical importance in terms of effectiveness and efficiency. When the communication infrastructure needs to be re-established quickly in emergencies such as earthquakes, the correct positioning of UAV-BSs ensures that the coverage area is maximized, and communication interruptions are minimized [15]. In addition, since the battery life and flight duration of UAV-BSs are limited, strategic location selection is required to optimize energy consumption [16]. Wrong placement may lead to problems such as signal weakening, network congestion, and decreased service quality [17].Therefore, the placement of UAV-BSs should be carefully planned, considering parameters such as geographical conditions, user density, the status of existing infrastructure, and flight safety [18].This approach ensures the establishment of a life-saving communication network in crises and the effective use of resources.

In light of the challenges described, this thesis focuses on the development of a mathematical decision-making framework for optimizing the deployment and energy management of UAV-based mobile base stations in post-earthquake communication scenarios. The central problem addressed in this study is how to position UAVs in disaster-affected urban areas—considering battery limitations, population dynamics, and infrastructure damage—in a way that maximizes coverage and operational efficiency. To achieve this, a Mixed-Integer Linear Programming (MILP) model is formulated and tested on a case study based in Istanbul.

The remainder of the thesis is organized as follows: Chapter 2 provides a comprehensive literature review on UAV-BS placement strategies, energy management, and real-time optimization approaches in disaster communication. Chapter 3 introduces the problem assumptions, the MILP model formulation, and the data preparation techniques. In addition, it presents the implementation of the model using the GAMS platform, including scenario analysis and discussion of results. Finally, Chapter 4 offers conclusions and recommendations for future research directions, especially regarding real-time optimization and the integration of heuristic methods.

Chapter 2

LITERATURE REVIEW

Recent studies on UAV-based base station (UAV-BS) placement in the literature address a wide spectrum of research problems, which can be categorized under several thematic areas. One major stream of research focuses on energy-efficient coverage strategies in UAV networks, where methods are developed to optimize the coverage area while minimizing power consumption, often incorporating wireless charging technologies. In the context of post-disaster scenarios, particularly earthquakes, scholars have explored the site selection of UAV bases for earthquake response, focusing on rapid and effective UAV deployment to restore communication services and support rescue operations. Meanwhile, researchers have also investigated mathematical programming approaches for UAV-BS positioning, leveraging models such as mixed-integer linear programming and heuristic algorithms to identify optimal UAV locations under various constraints.

2.1 Energy Efficiency and Wireless Charging Technologies

The optimization model used in the study by Choi et al. [19] and his colleagues plays a fundamental role in the design of wireless charging stations and in ensuring operational continuity. This model was developed to improve the energy management of UAVs and optimize the charging cycle. It focuses on the development of automatic wireless charging stations to ensure the uninterrupted operational capacity of UAVs. Charging stations are designed as a critical infrastructure to meet the energy needs of UAVs during operation. The study addresses the feasibility of wireless charging technology and the creation of an environment that will enable long-term operations by providing continuous energy support for UAVs [19].

Cui, J, et al. [20]. present an energy-efficient UAV deployment strategy to provide wireless coverage in indoor areas during emergency situations. The study develops optimization methods to effectively meet the communication services required by users by minimizing energy consumption. The proposed model improves the coverage performance by optimizing the position and communication power of the UAV. Simulation results show that the method is advantageous in terms of both energy efficiency and coverage quality [20].

Deniz, F et al. [13] discusses energy-efficient and fault-tolerant UAV-based base station placement in heterogeneous wireless sensor networks. In the study, a new placement algorithm is developed that optimizes the energy consumption of the network and provides resilience to fault conditions. Simulations show that the proposed method minimizes energy consumption and link loss while improving the coverage quality. This method provides an effective solution for communication continuity, especially in energy-constrained environments [13].

2.2 Optimization of Coverage Area and Placement of UAV-BSs

Adam et al. [21] discusses optimization strategies for the placement of multiple UAV-BSs in the study. The study aims to solve the placement problem in line with the goals of expanding the coverage area of UAVs and improving the communication quality. Simulation results show that the proposed methods improve network performance and increase resource efficiency. This study offers effective solutions, especially in disaster scenarios and high-density user demands.

Akram, T. et al. [22] addresses the problem of multi-criteria UAV-BSs placement in disaster management scenarios. The study develops a new optimization approach to ensure effective coverage, increase energy efficiency, and improve the connection quality of UAVs. The proposed method provides a balance of different criteria and enables rapid reconstruction of the communication infrastructure after a disaster. Simulation results show that the model offers a practical solution for disaster management applications [22].

Çicek, C. et al. [14] addresses the location optimization of UAV-BSs in next-generation wireless networks. The study aims to increase the network performance by dynamic and energy-efficient deployment of UAVs. In addition, the existing literature in this field is reviewed and suggestions for future research directions are presented. The flexible positioning features of UAVs are considered a critical solution, especially in disaster scenarios and intensive user demands [14].

I.A. Elnabty [22] presents a comprehensive review of three-dimensional layout optimization in unmanned aerial vehicle (UAV)-supported communication systems in his study. This study analyses the role of UAVs in communication networks and the impact of layout strategies on performance. Elnabty's study emphasizes the importance of 3D layout optimization in UAV-supported communication systems and provides a comprehensive resource for research in this field. The study provides a comprehensive perspective for researchers and practitioners by classifying different optimization techniques, performance metrics, and application scenarios.

In Kahriman's [23] study, the placement of UAV base stations for both aerial and underwater to provide maximum coverage in land and underwater networks was examined. This study addresses the efficient placement of UAV base stations, which have gained importance, especially in 5G and beyond communication technologies. In the study, optimal placement strategies were investigated so that UAV and UAV base stations can provide fast and effective service in emergencies such as disaster areas or support fixed communication infrastructure in situations requiring intense communication traffic such as concerts and matches. For this purpose, factors such as aerodynamic models, air-ground channel modelling, antenna models, service quality, and UAV power were taken into consideration.

2.3 User Demand and Quality Oriented Models

Feng et al. [24] and his colleagues discuss a model predictive control (MPC) based method used for autonomous landing of a UAV on a moving platform. In the study, a control system is designed that ensures the landing of the UAV while maintaining its stability. The model was developed by considering the dynamics of the moving platform and the flight characteristics of the UAV; the experimental results show the accuracy and effectiveness of the approach. This method increases the safety of UAV operations, especially in dynamic environments [24].

Alzenad, M. et al. [25] proposes a method for 3D placement of an UAV-BS to provide maximum coverage for users with different quality of life requirements (QoS). The study develops a model that optimizes the coverage area by meeting the QoS demands of users. The proposed algorithm takes into account both the height and horizontal positioning of the UAV, thus increasing the coverage area while minimizing energy consumption. Simulation results verify the performance of the approach according to the user density [25].

2.4 UAV-BS Deployment Optimization in Content Delivery Networks

Recent research explores the integration of metaheuristic optimization algorithms for enhancing UAV-BS deployment. Li et al. [30] develop an Artificial Bee Colony (ABC) algorithm-based model that aims to optimize the placement of UAV base stations within device-to-device (D2D) content delivery networks. The proposed model addresses multiple objectives, including maximizing network coverage and improving D2D transmission performance. Their simulation results indicate that the ABC-based approach significantly outperforms conventional methods, providing better coverage ratios and lower latency in complex 3D environments. This study highlights the importance of global search capabilities in deployment optimization and offers a scalable method for dense wireless networks.

2.5 Site Selection of UAV Bases for Earthquake Response

In disaster preparedness and emergency communication planning, selecting the most strategic UAV base station location is critical. Yazırdağ and Altan [31] propose a multi-criteria decision-making approach using the TOPSIS method to identify optimal UAV base station locations in the event of a potential Marmara earthquake in Turkey. The evaluation process considers six expert-defined criteria across seven alternative sites. The study concludes that the Sivrihisar Aviation Center is the most suitable option due to its logistical accessibility and distance from major fault lines. This work emphasizes the value of structured decision-support systems in enhancing UAV deployment strategies for disaster response.

2.6 Energy-Efficient Coverage Strategies in UAV Networks

Optimizing energy consumption while ensuring reliable coverage remains a major challenge in UAV-BS planning. A 2023 study published in Applied Sciences [32] introduces a circular coverage model based on binomial power functions to address this issue. The model is designed to enable convex optimization, allowing for precise control over UAV deployment while reducing power usage. Compared to traditional hexagonal coverage schemes and energy-focused deployments, the circular approach achieves approximately 14.75% energy savings. This research demonstrates that coverage geometry plays a crucial role in the operational efficiency of UAV-assisted wireless networks.

2.7 Mathematical Programming for UAV-BS Positioning

Mathematical models continue to be instrumental in solving complex UAV-BS placement problems. Premkumar and Van Scoy [33] propose a Mixed-Integer Linear Programming (MILP) formulation to determine the optimal three-dimensional positioning of UAV base stations. Their model incorporates user clustering to reduce complexity and jointly optimizes user association and UAV location in a single step. Simulation results suggest that the proposed MILP model not only scales efficiently with user numbers but also outperforms traditional greedy algorithms in both coverage and computational efficiency. This work contributes a rigorous mathematical framework for real-world UAV network deployment.

2.8 Integrated Communication and Localization with UAVs

Modern UAV systems increasingly support multifunctional roles, including communication and positioning. Bi et al. [34] address this dual functionality by developing a joint optimization framework for three-dimensional UAV deployment and resource allocation. Their model maximizes total system throughput while maintaining localization accuracy, making it highly relevant for emergency and mission-critical scenarios. To solve the complex optimization problem, the authors apply a hybrid method combining Block Coordinate Descent (BCD) and Gibbs Sampling. The results demonstrate that this approach offers near-optimal solutions with significantly reduced computational cost compared to traditional heuristics. The integration of communication and localization into a unified deployment model represents a notable advancement in UAV network design.

Although recent studies have made notable progress in optimizing UAV base station (UAV-BS) deployment, several critical limitations persist in the literature. Many works focus on either maximizing coverage or minimizing energy consumption, yet few attempt to integrate both objectives within a unified decision-making framework. Moreover, these models often rely on static or quasi-static assumptions regarding user distributions, which limits their applicability in highly dynamic environments such as post-disaster scenarios, where user densities and communication demands can change rapidly over time.

In addition, while approaches based on multi-criteria decision-making [31] and mathematical programming [33] provide robust theoretical models, they frequently fail to address real-time operational constraints—such as UAV battery endurance, charging infrastructure limitations, and mobility-related energy costs. Furthermore, most existing studies do not consider the integration of task allocation with deployment strategies, despite the increasing need for UAVs to perform simultaneous functions including communication, localization, and sensing [34].

2.9 Conclusion

Few studies propose comprehensive models that simultaneously handle energy optimization, dynamic coverage, charging logistics, and task scheduling under real-world constraints. Deterministic approaches fall short in capturing the uncertainties of post-disaster environments, making their practical implementation limited.

To address these challenges, this study proposes an integrated planning model for energy-efficient deployment and task assignment of UAV-BSs in post-disaster communication networks. The model is designed to operate under multi-period conditions, enabling UAVs to recharge and redeploy dynamically over time. In contrast to previous works that treat energy consumption and coverage as separate concerns, this study formulates a joint optimization problem that incorporates energy-aware task planning, charging station positioning, and UAV movement decisions within a single framework.

To validate the theoretical and practical relevance of the model, a case study on an earthquake scenario is conducted. This real-world application not only demonstrates the feasibility of the proposed solution but also highlights its potential to improve the resilience and adaptability of emergency communication systems. Finally, by addressing UAV coordination, energy sustainability, and adaptive coverage in a unified manner, this study makes a novel and comprehensive contribution to the literature on UAV-BS deployment in critical response operations.

Chapter 3

SOLUTION METHODOLOGY

In this section introduced the development of a Mixed-Integer Linear Programming (MILP) model that aims to optimize the deployment, movement, and energy management of UAV-based base stations in a post-disaster environment. In the following chapter, this model is tested using a case study based on Istanbul. The data used in the case study—including population density, earthquake risk distribution, and spatial segmentation using a hexagonal grid—are generated and processed through custom Python algorithms. The chapter also explains how candidate UAV deployment points and demand values are derived to simulate realistic post-earthquake communication scenarios.

3.1 Model Development

3.1.1 Assumptions Adopted in the Study

In order to create a tractable and analytically robust modeling framework within the scope of this study, several critical assumptions are introduced. These assumptions, while simplifying the real-world complexity of UAV-based communication networks, ensure that the model remains focused, scalable, and reflective of core operational dynamics in a post-disaster environment:

- **User Representation Through Demand Clusters:**

Tracking the real-time coordinates of individual users across a large metropolitan area like Istanbul poses significant logistical and computational challenges. To address this, user locations are abstracted into aggregated demand regions, with each region representing a group of users. The population sizes of these regions are not static; instead, they are allowed to vary across time intervals, acknowledging the fluidity of population movements during disaster scenarios.

- **Homogeneity of UAV Characteristics:**

All UAVs deployed in the model are assumed to be technologically identical. This includes uniformity in flight speed, battery capacity, and general performance attributes. Such standardization allows for a consistent operational framework and simplifies comparative performance analyses between deployment strategies.

- **Free Hovering Capability in the 2D Plane:**

The UAVs are considered to be rotary-wing types, which grants them the flexibility to hover at any coordinate (x, y) within the defined area of interest. There are no restrictions placed on their positioning in the airspace during active operation, and UAVs are assumed to remain stationary once positioned, unless reassigned.

- **Unlimited Wireless Transmission Capacity:**

The model assumes that there are no throughput limitations in the UAVs' wireless communication capabilities. This idealized assumption ensures that any covered region receives seamless service, allowing the study to focus on spatial coverage rather than bandwidth constraints.

- **Uniform Initial Flight Energy Levels:**

At the beginning of each operational period, all UAVs are presumed to be fully charged and ready for deployment. This assumption standardizes the start conditions across different UAVs and allows the model to evaluate strategies without discrepancies caused by variable energy levels.

- **Unrestricted Charging Station Utilization:**

The charging infrastructure is assumed to support simultaneous recharging of multiple UAVs. Locations designated as charging stations also serve as temporary idle points, where unused UAVs can wait until redeployment. This dual-purpose functionality improves logistical efficiency in managing fleet readiness.

- **Fixed Charging Time Window:**

A predetermined and consistent duration is assigned for the recharging or battery replacement process. UAVs that return to the main charging station are expected to become fully operational again after staying for this defined period. This removes uncertainties related to varying recharge rates or maintenance delays

- **Single Centralized Charging Facility:**

The model operates under the premise that one primary charging station services all UAVs. This simplification reflects a centralized infrastructure strategy and helps streamline energy management within the system.

- **Single-Point Operation per Period:**

UAVs are limited to operating in only one location during each time period. Once deployed, a UAV remains in its assigned grid until the next operational cycle, which allows for clearer tracking of coverage and performance metrics.

3.1.2 Mathematical Model

In this section introduced the development of a Mixed-Integer Linear Programming (MILP) model that aims to optimize the deployment, movement, and energy management of UAV-based base stations in a post-disaster environment.

3.1.2.1 Sets

I: possible candidate locations for drones

I^c: Charge station locations.

J: drone

T: time slot

K: demand regions

3.1.2.2 Parameters

C_{ik}: 1 if location point i is covering demand region k, 0 otherwise.

O: Maximum number of drones.

$User_{tk}$: Number of users in region k to whom service must be provided in time slot t.

S: Duration of drones in the air in terms of the number of periods when fully charged.

dis: Minimum distance between two drones to be positioned in the sky at the same time.

$d_{ii'}$: Distance between location i and location i'.

co: coefficient of charge consumption in movement.

M: relatively big value.

3.1.2.3 Decision Variables

q_j: 1 if drone j is used, 0 otherwise.

x_{ijt}: 1 if drone j is positioned at point i in time slot t, 0 otherwise.

y_{kt} : 1 if demand region k is covering in time slot t, 0 otherwise.

u_{jt}: Flight time of drone j at time t in terms of the number of remaining periods.

$h_{ii'jt}$: 1 if drone j moved at time t, 0 otherwise.

mv_{jt}: Movement distance of drone j at time t.

3.1.2.4 Objective Function

$$Max \sum_k \sum_t D_{tk} * y_{kt} - \sum_i \sum_{i'} \sum_j \sum_t h_{ii'jt} \quad (1)$$

Objective function of mathematical model - The objective is to cover the maximum number of users possible with a certain number of UAV-BS while minimizing the movement of UAV-BS.

3.1.2.5 Constraints

$$\sum_{i=1}^{I} x_{ijt} = q_j \quad \forall\, j, t \quad (2)$$

Single assignment of UAV-BS - Each UAV-BS can be assigned to only one location at any given time to avoid task overlap.

$$\sum_{j=1}^{J} x_{ijt} \leq 1 \quad \forall\, i, t: i \notin I^c \quad (3)$$

One UAV-BS per location - Only one UAV-BS can be assigned to a location; however, all UAV-BSs can be assigned to the charging station simultaneously.

$$\sum_{j=1}^{J} q_j \leq O \quad (4)$$

Limit on total UAV-BS usage - The number of UAV-BSs assigned for tasks cannot exceed the total available UAV-BSs.

$$y_{kt} \leq \sum_{i=1}^{I} \sum_{j=1}^{J} C_{ik} \, x_{ijt} \quad \forall k, t \tag{5}$$

Coverage update of demand regions - Based on UAV-BS location decisions, coverage status of the demand regions is updated in each time period.

$$x_{zj1} = 1 \quad \forall j \qquad z \in I^c \tag{6}$$

Initial positioning at charging station - All UAV-BSs must start at the charging station to ensure a controlled beginning of operations.

$$u_{j1} = S + 1 \quad \forall j \tag{7}$$

Definition of initial flight time - The initial available flight time of each UAV-BS is defined for effective energy management.

$$u_{jt} - 1 - mv_{jt} * co \geq x_{ij(t+1)} * d_{iz} * co + 1 \quad \forall i, j, t \; z \in I^c \tag{8}$$

Restriction on distant assignments - If a UAV-BS lacks sufficient battery to return to the charging station in the next period, it cannot be assigned to distant locations.

$$u_{jt} \leq u_{j(t-1)} - 1 - co * mv_{jt} + M * x_{zjt} \quad \forall j, t\colon t \geq 1 \; z \in I^c \tag{9}$$

Flight time update per period - Remaining flight time is recalculated at the beginning of each time period based on UAV-BS movements.

$$u_{jt} \geq u_{j(t-1)} - 1 - co * mv_{jt} - M * x_{zjt} \quad \forall j, t\colon t \geq 1 \; z \in I^c \tag{10}$$

Continuity of flight time update - Works with constraint (8) to ensure ongoing monitoring and management of flight time.

$$u_{jt} \leq S + M(1 - x_{zjt}) \quad \forall j, t \; z \in I^c \tag{11}$$

Flight time reset after charging - When a UAV-BS returns to the charging station, its remaining flight time is reset or replenished.

$$u_{jt} \geq S - M(1 - x_{zjt}) \quad \forall j, t \; z \in I^c \tag{12}$$

Restoration of flight capacity - Recharged UAV-BSs regain their maximum flight capacity after visiting the charging station.

$$d_{ii'} \geq dis - M(2 - x_{ijt} - x_{i'jt}) \quad \forall i,j,t \;\; i \neq i' \tag{13}$$

Minimum distance between UAV-BSs - UAV-BSs must not be positioned too close to each other to prevent signal interference and ensure communication quality.

$$h_{ii'jt} \geq \; x_{ijt} - x_{i'j(t-1)} - 1 \quad \forall i,i',j,t{:}\, i \neq i', t \geq 1 \tag{14}$$

Tracking UAV-BS movement - Tracks whether a UAV-BS moves in each time period.

$$h_{ii'jt} \leq \; x_{ijt} - x_{i'j(t-1)} + 1 \quad \forall i,i',j,t{:}\, i \neq i', t \geq 1 \tag{15}$$

Clarification of movement decisions - The system determines whether the UAV-BS has changed its position.

$$\sum_{i=1}^{I} \sum_{i'=1}^{I} h_{ii'jt} \leq 1 \quad \forall j,t{:}\, t \geq 1 \tag{16}$$

Single movement per period - A UAV-BS can make only one movement in a single period for energy efficiency.

$$mv_{jt} = \sum_{i=1}^{I} \sum_{i'=1}^{I} h_{ii'jt} * d_{ii'} \qquad \forall j,t{:}\, i \neq i', t \geq 1 \tag{17}$$

Definition of movement distance - Physical movement distances of UAV-BSs are defined to support calculations of energy and total distance.

$$q_j \; \in \; \{0,1\} \quad \forall j,t \tag{18}$$

Binary decision variables - Certain decision variables can only take binary values (0 or 1) to clearly define assignment states.

$$y_{jtk} \; \in \; \{0,1\} \quad \forall j,t,k \tag{19}$$

Binary decision variables - Certain decision variables can only take binary values (0 or 1) to clearly define assignment states.

$$h_{ii'jt} \; \in \; \{0,1\} \quad \forall j,t \tag{20}$$

Binary decision variables - Certain decision variables can only take binary values (0 or 1) to clearly define assignment states.

$$u_{jt} \geq 0 \quad \forall j, t \tag{21}$$

Non-negativity of variables - Ensures values like time, distance, and energy remain within logical, non-negative bounds.

$$mv_{jt} \geq 0 \quad \forall j, t \tag{22}$$

Non-negativity of variables - Ensures values like time, distance, and energy remain within logical, non-negative bounds.

3.2 Case Studies

3.2.1 Case 1: Comparative Deployment Analysis of UAV-Based Mobile Base Stations with Varying Fleet Sizes in a Post-Disaster Communication Scenario

UAVs, employed as mobile base stations (UAV-BS), present a compelling solution for rapidly restoring communication infrastructure in disaster-affected areas. This case study investigates and compares two deployment strategies involving 4 and 6 UAVs respectively, focusing on assignment patterns and remaining battery capacities across a 20-period planning horizon. The study builds upon an initial deployment model applied to 21 critical demand regions in Kahramanmaraş, Turkey, with the aim of maximizing user coverage while minimizing energy consumption and repositioning efforts.

3.2.1.1 Problem Context and Methodology

Both scenarios are based on a mixed-integer programming model designed to maximize dynamic user coverage while minimizing unnecessary UAV repositioning and energy consumption. The first scenario (Scenario A) uses 4 UAVs; the second (Scenario B) utilizes 6 UAVs.

Key shared parameters:

- 21 critical demand points (Kahramanmaraş districts),
- 81 candidate locations in the air (7x7 or 9x9 grid),
- 20 time periods,
- Initial charge: 10 units,

- Charge coefficient 0.01,
- Central charging station at node 57.

Simulations output UAV assignment locations and their remaining battery charge per period. These results are presented in the next section.

3.2.1.2 Computational Environment and Solution Performance

The mathematical model developed in this study is solved using the General Algebraic Modeling System (GAMS). The solution process is executed on a workstation named SIMOPT-4, equipped with an Intel(R) Core (TM) i7-7700 CPU 3.60GHz, 32 GB of RAM (usable: 31.9 GB), and a 64-bit, x64-based operating system.

In terms of computational performance, the 4-drone scenario reaches an optimal solution in approximately 5797 seconds (about 1 hour and 36 minutes), while the 6-drone scenario requires around 11438 seconds (about 3 hours and 10 minutes). The increased number of UAVs leads to greater model complexity and coverage density, which directly impacts the total runtime. This illustrates a clear correlation between model scale and computational demand.

3.2.1.3 Results and Comparative Analysis

The UAV assignment behavior over time reflects how UAVs are strategically placed to maximize coverage. As shown in Table 1 below, the assignment schedule for Scenario A (4 UAVs) spans 20 time periods.

Table 1 Assignment of UAVs Over Time (4 Drones Scenario)

UAV Location/Time	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
13		*4*	*1*			*3*		*1*	*1*	*1*										
14							*2*													
15		*2*	*2*	*1*	*4*	*2*		*4*	*4*	*4*										
22					*3*															
28			*4*	*4*						*2*										
30									*2*											
31					*2*		*1*													
32						*4*			*3*											
33				*2*	*1*					*3*										
40		*3*	*3*	*3*				*3*												
42		*1*																		
43											*4*	*4*			*4*	*4*	*4*	*4*	*4*	*4*
48											*1*	*1*	*1*	*4*		*2*	*2*	*2*	*2*	*2*
50												*2*			*3*	*3*	*3*	*3*	*3*	*3*
51													*2*	*2*						
Charge Station (57)	*1,2,3,4*					*1*	*3,4*	*2*					*3,4*	*1*	*2*					
59											*2*									
61											*3*									
68												*3*		*3*	*1*	*1*	*1*	*1*	*1*	*1*

In the 4-drone configuration, the UAVs move frequently, with noticeable returns to the charging station especially around periods 6–8 and 13–14. This dynamic adjustment was essential to maintain high coverage given limited UAV availability.

The updated experiment using 6 UAVs demonstrates a more distributed and stable assignment pattern, as seen in the following table:

Table 2 Assignment of UAVs Over Time (6 Drones Scenario)

UAV Location/Time	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
13					4	4		1	1	4										
14							4													
15		2	2	2	2	5		2	5	5	2				4				5	
22		6	6																	
28		1	1	4																
29					1		1	6	6	6										
30																1				
31		4			5															
32						6														
33		3	3	3			6													
37						1														
39				5																
40			5				3	4	2	2										
42					3	2		3	3	3										
43											5	5			2		2	6	6	6
48											1	1	4	3	5		1	5	2	1
50				6							4	4					6		3	3
51													5	6						
52																5				
Charge Station (57)	1,2,3, 4,5,6		4	1	6	3	2,5	5	4	1	6	2	1,3	4,5		6	3,5	1,2		4
59		5														2		3		
60															6					
61												6	6		1					
68											3	3	2	2	3				1	2
70														1						
71																4	4	4	4	5
77																3				

With two additional drones, the system achieved better continuity, especially during peak usage periods. Idle times were minimized, and critical demand points experienced fewer coverage gaps.

Battery efficiency plays a critical role in operational sustainability. The following table displays the remaining battery levels of each UAV in the 4-drone scenario.

Table 3 Remaining Battery Charge per Time Period (4 Drones Scenario)

UAV/Time	1	2	3	4	5	6	7	8	9	10
1	*10*	*9,32*	*7,63*	*6,25*	*4,87*	*10*	*9,4*	*8,02*	*7,02*	*6,02*
2	*10*	*8,89*	*7,89*	*6,51*	*5,13*	*3,6*	*2,41*	*10*	*9,43*	*8,05*
3	*10*	*9,58*	*8,58*	*7,58*	*6,2*	*5*	*10*	*9,58*	*8,31*	*7,12*
4	*10*	*9,03*	*7,35*	*6,35*	*4,32*	*2,9*	*10*	*8,89*	*7,89*	*6,89*
UAV/Time	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	*4,24*	*3,24*	*2,24*	*10*	*9,58*	*8,58*	*7,58*	*6,58*	*5,58*	*4,58*
2	*6,1*	*4,91*	*3,72*	*2,72*	*10*	*9,81*	*8,81*	*7,81*	*6,81*	*5,81*
3	*55,52*	*4,09*	*10*	*9,58*	*8,2*	*7,2*	*6,2*	*5,2*	*4,2*	*3,2*
4	*5,29*	*4,29*	*10*	*9,81*	*8,03*	*7,03*	*6,03*	*5,03*	*4,03*	*3,03*

The data highlights rapid consumption in some UAVs—particularly UAV 2 and 4—which required mid-horizon recharging.

In contrast, the extended 6-drone case yields smoother discharge curves:

Table 4 Remaining Battery Charge per Time Period (6 Drones Scenario)

UAV/Time	1	2	3	4	5	6	7	8	9	10
1	*10*	*8,315*	*7,315*	*10*	*8,399*	*7,13*	*5,862*	*4,324*	*3,324*	*10*
2	*10*	*7,892*	*6,892*	*5,892*	*4,892*	*3,322*	*10*	*7,892*	*6,207*	*5,207*
3	*10*	*8,194*	*7,194*	*6,194*	*5,004*	*10*	*8,575*	*7,195*	*6,195*	*5,195*
4	*10*	*8,399*	*10*	*8,315*	*6,63*	*5,63*	*4,44*	*2,839*	*10*	*8,031*
5	*10*	*8,62*	*7,195*	*6,005*	*4,736*	*3,199*	*10*	*10*	*7,892*	*6,892*
6	*10*	*8,217*	*7,217*	*5,616*	*10*	*8,315*	*7,125*	*5,365*	*4,365*	*3,365*
UAV/Time	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	*8,81*	*7,81*	*10*	*8,217*	*7,027*	*5,077*	*3,697*	*10*	*8,575*	*7,038*
2	*3,522*	*10*	*8,575*	*7,575*	*5,89*	*4,353*	*2,815*	*10*	*8,81*	*7,273*
3	*3,594*	*2,594*	*10*	*8,81*	*7,273*	*6,083*	*10*	*8,62*	*7,43*	*6,43*
4	*6,248*	*5,248*	*3,868*	*10*	*7,892*	*5,69*	*4,69*	*3,69*	*2,69*	*10*
5	*5,291*	*4,291*	*3,023*	*10*	*8,81*	*7,05*	*10*	*8,81*	*6,86*	*4,658*
6	*10*	*8,24*	*7,24*	*5,971*	*4,781*	*10*	*8,575*	*7,15*	*6,15*	*5,15*

The battery performance confirms that distributing workload across more UAVs reduces individual energy strain. UAVs returned to the charging station less frequently and had more residual energy at the end of each period.

Remaining charge data in both scenarios reveal:

- Scenario A: Faster depletion cycles, with several UAVs requiring recharge as early as period 6–8.
- Scenario B: More gradual consumption, some UAVs sustaining 10+ periods before returning to charge.

This difference demonstrates the energy conservation benefit of increasing fleet size, particularly in extended missions requiring persistent coverage.

A key metric for disaster scenarios is temporal consistency of service. With 6 UAVs, downtime in specific regions (due to recharge cycles) is minimized, ensuring that even during UAV rotation, other drones can temporarily cover vacated demand points.

This continuity is vital in post-disaster environments, where communication interruptions—even for short durations—can have life-threatening consequences.

While Scenario B clearly performs better in coverage, stability, and energy efficiency, it also implies:

- Greater logistical complexity (e.g., more UAVs to coordinate and deploy),
- Potentially higher costs (equipment, maintenance).

Thus, decision-makers must weigh these operational benefits against deployment constraints in real-world emergencies.

3.2.1.4 Discussion and Implications

This case study illustrates the scalability and robustness of the proposed optimization model under varying UAV fleet sizes. The transition from 4 to 6 UAVs:

- Increases system resilience to user density fluctuations,
- Reduces energy pressure on individual UAVs,
- Enhances service continuity across critical periods.

From a strategic planning perspective, these insights underline the importance of modular UAV infrastructure: the ability to scale up or down depending on the severity and size of the affected area.

In real-world deployments, this flexibility can be the difference between partial communication recovery and full-scale coverage—especially in regions with complex geography or dispersed population patterns.

3.2.1.5 Comparative Analysis of Coverage Efficiency in 4-Drone and 6-Drone Scenarios

In the conducted case study, two alternative deployment scenarios are evaluated in order to assess the efficiency of drone-based coverage in a post-disaster communication network. The first scenario utilizes 4 UAVs, while the second involves the deployment of 6 UAVs over a planning horizon of 20 time slots and 21 distinct regions.

As presented in Table 5, the 4-drone configuration results in a total of 174 coverage points, which are relatively concentrated within a narrower range of regions and time slots. This outcome suggests that, although operationally feasible, the 4-drone deployment may not suffice for complete and continuous coverage in high-demand post-disaster environments. The uncovered regions and time gaps observed in this configuration might lead to communication blackouts or delayed data transmission in practical applications.

Table 5 Drone-to-Region Assignments in the 4-Drone Scenario

Time\Region	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1																					
2										1	1	1	1	1	1	1			1	1	1
3												1		1	1	1	1	1	1	1	1
4										1	1	1	1	1		1	1	1		1	1
5										1	1	1	1	1		1			1	1	
6												1	1	1	1	1		1	1	1	1
7												1		1		1			1	1	
8												1		1	1	1			1	1	1
9												1	1	1	1	1		1	1	1	1
10										1	1	1	1		1		1	1	1	1	1
11	1	1		1			1	1	1	1	1										
12	1	1	1	1	1		1	1	1	1	1			1							
13	1	1	1	1	1		1		1	1											
14			1	1	1		1		1	1											
15			1	1	1		1	1	1	1	1			1							
16	1	1	1	1	1		1	1	1	1	1			1							
17	1	1	1	1	1		1	1	1	1	1			1							
18	1	1	1	1	1		1	1	1	1	1			1							
19	1	1	1	1	1		1	1	1	1	1			1							
20	1	1	1	1	1		1	1	1	1	1			1							

Conversely, the 6-drone configuration, displayed in Table 6, achieves a significantly broader spatial and temporal distribution, recording 221 coverage points in total. This enhanced coverage not only increases regional reach but also provides redundancy and reliability in communication service continuity. The 6-drone scenario manages to cover nearly all regions during peak time intervals, indicating superior flexibility and responsiveness under dynamic demand conditions.

Table 6 Drone-to-Region Assignments in the 6-Drone Scenario

Time\Region	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1																					
2				1			1		1	1	1	1	1	1	1	1	1	1	1	1	1
3										1	1	1	1	1	1	1	1	1	1	1	1
4	1						1		1	1	1	1	1	1		1	1	1		1	1
5										1	1	1	1	1	1	1	1	1	1	1	1
6										1	1	1	1	1	1			1	1	1	1
7										1	1	1	1	1		1	1	1	1	1	
8										1	1	1	1	1	1	1	1	1	1	1	1
9										1	1	1	1	1	1	1	1	1	1	1	1
10										1	1	1	1	1	1	1	1	1	1	1	1
11	1	1	1	1	1		1	1	1	1	1	1		1						1	1
12	1	1	1	1	1	1	1	1	1	1	1			1							
13	1	1	1	1	1	1	1		1	1											
14	1	1	1	1	1	1	1		1	1											
15	1	1	1	1	1	1	1	1	1	1	1	1								1	1
16			1	1	1	1	1	1	1	1						1		1			
17	1	1				1	1	1	1	1	1			1							
18	1	1		1		1	1	1	1	1	1										
19	1	1	1	1	1	1	1	1	1	1	1	1		1						1	1
20	1	1	1	1	1	1	1	1	1	1	1			1							

Overall, the comparative results underline that increasing the number of UAVs from four to six contributes markedly to improving coverage density and service reliability. Therefore, in real-world emergency response operations—especially those involving geographically dispersed and dynamically evolving user densities—the adoption of a higher number of drones can be considered a critical factor for enhancing the robustness and effectiveness of aerial communication infrastructures.

3.2.1.6 Conclusion

Through comparative analysis of two deployment scenarios, this case study validates the operational gains from extending UAV-BS fleets in post-disaster communication efforts. The enhanced coverage stability, improved battery utilization, and reduced movement intensity offered by a 6-UAV configuration present a compelling case for scalable deployment architectures.

These findings may guide future disaster communication planning efforts, enabling humanitarian agencies and governmental bodies to better prepare for high-impact events.

3.2.2 Case 2: Model Application for Post-Earthquake Communication Coverage Using UAV-Based Base Stations

To assess the practical applicability of the proposed model, a case study is conducted based on a simulated post-disaster scenario in Istanbul. As one of the most densely populated and earthquake-prone cities in Turkey, Istanbul provides a representative urban setting for testing UAV-based communication deployment. District-level population data and seismic risk indicators are integrated to generate dynamic demand distributions over time. The city map is converted into a hexagonal grid structure to enable spatial segmentation and improve coverage analysis. Candidate deployment and charging points are derived from this grid, and multiple scenarios are created by varying the number of UAVs, charging stations, and mission durations. This case study reveals the model's ability to deliver high coverage while maintaining energy efficiency and demonstrates its potential as a decision-support tool for real-time disaster response planning.

3.2.2.1 Hexagonal Grid Approach

This case study adopts a hexagonal grid structure as the foundational spatial modelling framework due to its advantages in spatial representation and coverage optimization. Unlike traditional square or triangular grids, hexagonal tiling ensures uniform adjacency, reduces overlap, and maximizes area utilization. These properties make it particularly suitable for wireless network planning applications, especially in modelling the deployment and coverage of UAV-BSs. Several studies have highlighted the effectiveness of hexagonal grids in wireless coverage modelling. For instance, [35] demonstrated that hexagonal tessellation provides better spatial continuity and minimized coverage holes in UAV-BS deployment scenarios. Similarly, [36] employed hexagonal cell structures to optimize UAV-BS placement in terms of coverage and energy efficiency. These studies provide a strong foundation for adopting the hexagonal model in this work.

The case study focuses on the Istanbul metropolitan area, selected for its high population density, complex urban structure, and significant vulnerability to seismic activity. These characteristics render Istanbul a strategically important and realistic setting for post-disaster communication planning. The city's diverse urban environment allows for a comprehensive evaluation of the efficiency and flexibility of the proposed UAV-BS deployment and task assignment model. Moreover, the availability of detailed geographical and demographic data strengthens the analytical rigor and replicability of the study. Istanbul's high seismic risk has been extensively documented in previous research and official reports. According to the JICA–İBB Earthquake Master Plan [37], a major earthquake along the North Anatolian Fault is expected to directly impact the Istanbul region, potentially causing severe human and infrastructural losses. More recent studies, such as those by KOERI [38] and AFAD [39], also highlight Istanbul's vulnerability due to its dense urbanization and proximity to active fault lines. These sources underscore the urgency and importance of developing resilient post-disaster communication systems for the city.

To enable a systematic and scalable spatial analysis, the geographical boundaries of Istanbul's 39 districts are obtained in GeoJSON format and converted into a hexagonal grid structure using Python. This conversion process facilitates consistent regional segmentation and enhances the precision of data density representation and coverage analysis. While aligning the district coordinates with the hexagonal cells, the model preserves fidelity to the original boundaries, thereby ensuring analytical consistency across regional comparisons.

Demand points are determined based on a combination of population density metrics and the strategic importance of specific urban zones that are expected to require urgent communication support in post-disaster scenarios. This demand modelling approach aims to reflect realistic disaster conditions by identifying areas where communication breakdowns could have the most critical consequences. The finalized hexagon-based coordinate dataset is exported to Excel format to support subsequent stages of statistical analysis, visualization, and modelling. This ensures transparency, reproducibility, and ease of use throughout the research process.

Figure 1 Hexagonal Grids for Istanbul

3.2.2.2 Creating Candidate Deployment Points for UAV-BS Operations

Following the integration of the hexagonal grid system over the map of Istanbul, a total of 81 distinct candidate locations are identified as potential deployment points for unmanned aerial vehicle-based base stations (UAV-BSs). These locations are not arbitrarily selected; rather, they emerge from a systematic spatial overlay where district-level coordinate data intersect with the hexagonal partitioning of the urban landscape. The selection of these points prioritizes two key criteria: the geometric centrality of each candidate within its corresponding hexagonal cell and its potential to maximize communication coverage in surrounding areas. This approach ensures that each UAV-BS unit, when deployed at a designated point, can deliver an optimal service radius with minimal overlap or blind spots—especially critical in post-disaster scenarios where uninterrupted communication is vital. The coordinate values of these candidate deployment points are programmatically derived using Python-based geospatial libraries. Once calculated, the data is structured and exported into Excel format to facilitate in-depth analysis, scenario modeling, and integration with subsequent decision-making processes. This structured and transparent methodology not only enhances analytical rigor but also ensures that the UAV deployment plan is both scalable and adaptable to real-world conditions.

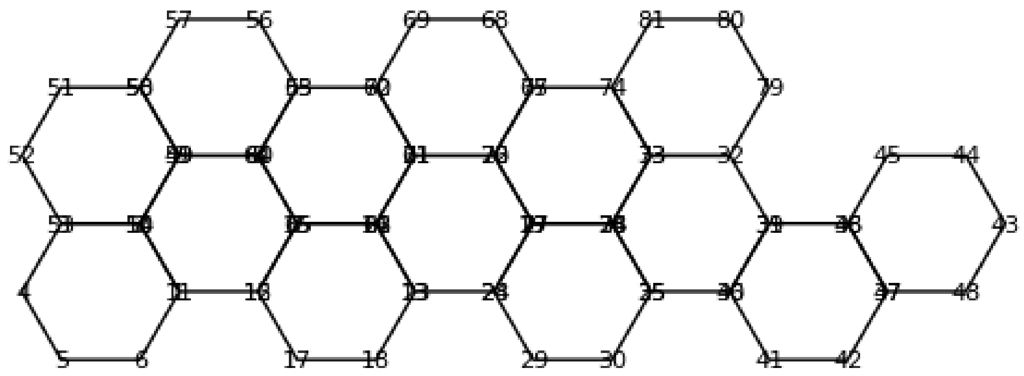

Figure 2 Possible Drones Points

3.2.2.3 Assessment of Binary and UAV-Based Coverage Capabilities

To evaluate the efficiency of drone deployments across the 81 identified candidate locations, the coverage performance of each UAV is meticulously analyzed. This analysis focuses on determining the spatial extent to which each drone can provide communication support, based on its placement within the designated hexagonal grid cells. The coverage area for each district is calculated by identifying and aggregating the coordinate values of all hexagonal cells that fall within the theoretical coverage radius of each drone. This approach allows for a detailed, cell-based representation of communication accessibility across the city. To quantify the relationship between drones and district coverage, a binary coverage matrix is developed using a Python-based algorithm. In this matrix, a value of 1 signifies that a drone placed at a specific location successfully covers a given district, whereas a value of 0 indicates the absence of coverage. This binary classification not only simplifies the evaluation of different deployment configurations but also provides a clear and scalable framework for scenario modeling under varying operational constraints.

The use of such a matrix-based structure enables rapid assessment of coverage gaps, redundancy areas, and optimization opportunities, especially in disaster-prone environments where timely and efficient communication is paramount.

Table 7 81x39 Example for Coverage

Location/Demand	1	2	3	.	.	37	38	39
1	1	1	1	.	.	0	0	0
2	1	1	0	.	.	0	0	0
3	1	1	1	.	.	0	0	0
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
80	0	0	0	.	.	0	1	1
81	0	0	0	.	.	0	0	1

3.2.2.4 Integrating Earthquake Risk and Population Density into Demand Estimation

The analytical depth of the study is significantly enhanced through the integration of population density as a core component of demand assessment, particularly in the context of a hypothetical post-earthquake communication scenario. Recognizing that densely populated areas exhibit a higher need for uninterrupted connectivity in times of crisis, population data for Istanbul's 39 districts are sourced from verified and up-to-date demographic repositories. To simulate a realistic demand environment, a custom Python algorithm is developed to synthesize both population density and assumed earthquake impact severity. Each district is assigned a potential demand value by proportionally weighing these factors, thereby generating a spatial demand distribution that mirrors probable needs during an emergency. These calculated demand scores are systematically organized and exported into Excel format, allowing for seamless integration with subsequent optimization models. This structured data serves as a fundamental input for algorithms aimed at maximizing UAV-BS coverage efficiency, with a focus on prioritizing areas of critical need. By embedding population and risk-based factors into the planning process, the study not only increases its practical relevance but also ensures that coverage strategies are socially equitable and operationally responsive in the aftermath of a disaster.

3.2.2.5 Gams Results and Detections

After the test with the Istanbul data, the duration of the model and the gap values of the model are tested against the data collected by the previous group. The results obtained from the model run for the Istanbul data are as follows: Table 3 shows the remaining charge levels of UAV-BS over specific time intervals. In general, it is observed that the charge levels of UAVs decrease over time, while energy consumption rates vary according to the type and duration of the task. For example, the charge of UAV 1 in the first time period is 11 units, but by the 10th time zone, it decreases to 2.73 units. Moreover, significant differences in the remaining charge levels between UAVs are observed, and in some cases, critical levels are reached (for instance, UAV 1's charge drops to 2.67 units in the 28th time zone). These results indicate that the remaining charge levels of UAVs are closely related to the task type and duration. Long-duration and energy-intensive tasks, for instance, cause the UAVs' charge levels to decrease rapidly, which poses a significant challenge for the continuity and efficiency of such tasks. These observations highlight the importance of energy management and task optimization in system design.

Table 8 Remaining Charge Over Time

UAV/Time	1	2	3	4	5	6	7	8	9	10	11	12	13
1	11	11	9,08	7,73	6,73	5,73	4,73	3,73	2,73	11,00	9,08	7,56	6,04
2	11	11	9,40	8,05	6,45	4,83	3,83	2,83	11	9,21	11	9,21	7,16
3	11	11	9,83	11	9,08	8,08	7,08	6,08	5,08	4,08	2,56	11,00	9,40
UAV/Time	14	15	16	17	18	19	20	21	22	23	24	25	26
1	4,69	3,69	2,69	11	9,31	8,31	7,31	6,31	4,52	11	9,31	6,72	4,13
2	5,08	3,18	11	9,21	8,21	7,21	6,21	4,75	3,13	11	9,21	7,86	6,51
3	8,05	7,05	4,91	3,74	2,44	11	9,08	8,08	6,73	5,38	4,38	3,38	2,38
UAV/Time	27	28	29	30	31	32	33	34	35	36	37	38	39
1	2,67	11,00	9,38	7,86	6,40	3,81	11,00	9,31	7,96	6,61	5,61	4,26	2,91
2	5,34	4,17	3,00	2,00	11,00	9,08	7,91	11,00	9,21	8,21	7,21	6,04	4,87
3	11	9,08	6,08	4,46	3,00	11,00	9,54	7,92	5,88	3,84	11,00	9,08	8,08

The table below shows the positions where unmanned aerial vehicles (UAVs) are deployed during specific time periods. It is observed that the UAVs cover the targeted demand regions. Additionally, the distance values between multiple UAVs are tested. Table 9 shows the locations where the UAVs are deployed for the Istanbul data. The hexagonal study conducted increases the number of possible locations for the UAVs to settle, while allowing them to cover more demand regions.

These results highlight the importance of infrastructure improvements for the efficient management of tasks. The hexagonal arrangement enables a more systematic and effective deployment of UAVs, allowing them to cover a wider area and reach more demand points. This optimization leads to significant improvements in energy and time management.

Table 9 Assignment UAVs Over Time

Location / time	1	2	3	4	5	.	.	.	.	.	36	37	38	39
1			1	2	3	.	.	.	.	.	3		3	
2						.	.	.	.	.	2	2		2
3				1	1	.	.	.	.	.	1	1		1
4						.	.	.	.	.				
5						.	.	.	.	.			1	
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
57	1,2,3	1,2,3	.	3	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
77						.	.	.	.	.				
78						.	.	.	.	.				
79			3			.	.	.	.	.				
80						.	.	.	.	.				
81						.	.	.	.	.				

The following table contains the outputs obtained from the GAMS model using the previous data. The table includes parameters such as different i (candidate locations), k (zones), the number of default charging stations, and execution time. The candidate positions (i) are varied in an ascending or descending manner. Different numbers of charging stations (e.g., 3, 10, 30, 45, 57) are tested in the model. It is observed that increasing the number of charging stations also affects the model's execution time. For instance, the operating time for a charging station with 10 locations (17656.575 seconds) is quite high, whereas the operating time for 3 charging stations is generally lower.

These results indicate that the number of charging stations significantly impacts the execution time of the model. A higher number of charging stations leads to a more complex model, resulting in longer execution times. This highlights the need to determine an optimal number of charging stations in the system design, balancing both energy efficiency and execution time.

Table 10 GAMS Result Analysis

i	k	Assuming Charge Station	Execution Time (Seconds)	Execution Time (Minutes)
20	21	3	128.971 Seconds	2 min 8.97 sec
15	10	3	1451.745 Seconds	24 min 11.74 sec
30	21	10	17656.575 Seconds	294 min 16.57 sec
30	21	3	5530.947 Seconds	92 min 10.95 sec
50	21	3	2708.475 Seconds	45 min 8.47 sec
50	21	30	1844.603 Seconds	30 min 44.60 sec
50	21	45	2753.128 Seconds	45 min 53.13 sec
70	21	45	8401.145 Seconds	140 min 1.15 sec
81	21	57	8477.802 Seconds	141 min 17.80 sec

Execution times increase significantly with the number of candidate locations and charging stations. Each model is executed to achieve a GAP of 0. For example:

- 20 candidate locations and 3 charging stations: 128.971 seconds.
- 81 candidate locations and 57 charging stations: 8477.802 seconds.

In larger-scale models (e.g., with 81 candidate locations), heuristic or meta-heuristic approaches should be explored to reduce execution times. The varying working times, depending on the number of charging stations, are an important factor for system efficiency.

These observations show that as more candidate locations and charging stations are added, the model becomes more complex, leading to increased execution times. For large-scale systems, it is evident that different optimization methods need to be applied to obtain faster solutions. Specifically, the increase in the number of charging stations results in longer execution times, which can make it more challenging to optimize the system for real-time applications.

Chapter 4

CONCLUSION AND FUTURE PROSPECTS

4.1 Conclusion

This thesis introduces an integrated planning model for the task assignment and energy optimization of UAV-BSs in post-disaster communication networks. By applying a Mixed-Integer Linear Programming (MILP) formulation, the model addresses critical challenges such as dynamic user demand, limited UAV battery life, and strategic placement of charging stations. The adoption of a hexagonal grid structure enhances spatial granularity and improves regional segmentation, allowing the model to deliver more efficient and scalable solutions in dense urban environments such as Istanbul.

Through comparative case studies based on both Kahramanmaraş and Istanbul, the model demonstrates its capability to provide high user coverage while maintaining energy efficiency across multiple time periods. The transition from a 4-UAV to a 6-UAV configuration significantly improves system resilience, continuity of service, and battery performance. The integration of real demographic data and earthquake risk distributions into the demand estimation process further validates the model's real-world applicability.

In its current form, the proposed optimization framework bridges theoretical modeling and practical deployment strategies. The results confirm that UAV-BSs can be effectively deployed to ensure continuous communication in the aftermath of a disaster. Nevertheless, the increasing computational burden in larger-scale scenarios highlights the necessity for methodological enhancements to support real-time decision-making in fast-evolving environments.

4.2 Future Prospects

Building upon the foundation laid by this study, several future research directions are envisioned to enhance the operational performance and applicability of the model. One immediate priority is the integration of heuristic and metaheuristic algorithms—such as Genetic Algorithms or Ant Colony Optimization—to reduce computational times, especially in large-scale models with numerous UAVs and deployment nodes. Such hybrid approaches may ensure near-optimal results within a timeframe suitable for real-time disaster response.

Future extensions of the model may also include heterogeneous UAV fleets with varying flight capabilities, payload capacities, and battery degradation profiles. Introducing this level of detail would improve deployment realism and support adaptive fleet management under uncertain and rapidly changing conditions.

Moreover, transforming the current model into an interactive Decision Support System (DSS) could significantly benefit emergency response operations. By linking the model to live demographic data, seismic alerts, and Geographic Information Systems (GIS), emergency planners could receive intelligent, location-specific recommendations for UAV deployment, ensuring faster recovery of communication networks.

Finally, the implementation of field pilots and collaborations with disaster management agencies, municipalities, or NGOs would provide invaluable insights into the model's practicality. These real-world validations could reveal operational challenges and further refine the solution framework to better serve vulnerable populations during crises.

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