UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
INSTITUTO DE INFORMÁTICA
PROGRAMA DE PÓS-GRADUAÇÃO EM COMPUTAÇÃO

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Providing an energy-efficient UAV Base Station positioning mechanism to improve wireless connectivity

Thesis presented in partial fulfillment of the requirements for the degree of Doctor of Computer Science

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Porto Alegre
April 2024

CIP — CATALOGING-IN-PUBLICATION

Pasandideh, Faezeh

Providing an energy-efficient UAV Base Station positioning mechanism to improve wireless connectivity / Faezeh Pasandideh. – Porto Alegre: PPGC da UFRGS, 2024.

131 f.: il.

Thesis (Ph.D.) – Universidade Federal do Rio Grande do Sul. Programa de Pós-Graduação em Computação, Porto Alegre, BR–RS, 2024. Advisor: Edison Pignaton de Freitas; Co-advisor: Joao Paulo Javidi da Costa.

1. UAV/drone placement problem. 2. Non-linear optimization problem. 3. Optimization algorithms. 4. Wireless connectivity. I. Pignaton de Freitas, Edison. II. Javidi da Costa, Joao Paulo. III. Título.

ACKNOWLEDGEMENTS

I extend my deepest gratitude to my advisors, Prof. Dr. Edison Pignaton de Freitas, and Prof. Dr.-Ing. João Paulo J. da Costa, for their exceptional guidance, unwavering support, and invaluable mentorship throughout my doctoral journey. Their expertise and encouragement have been instrumental in shaping this thesis.

To my loving husband, whose patience, understanding, and unwavering support sustained me through the highs and lows of this academic pursuit, I owe immeasurable thanks. Your belief in me never wavered, and I am endlessly grateful.

My heartfelt appreciation goes to my family for their boundless love, encouragement, and unwavering belief in my abilities. Your support has been the cornerstone of my success.

I am indebted to the Universidade Federal do Rio Grande do Sul (UFRGS), and Hamm-Lippstadt University of Applied Sciences (HSHL) for providing an academic environment and resources necessary for the completion of this thesis.

Thank you to all those who have contributed to my journey, whether through direct assistance, discussions, or moral support. Your impact has been profound and deeply appreciated.

ABSTRACT

In an era marked by the omnipresence of wireless communication, the need for exceptional connectivity has experienced an unprecedented surge. The evolution towards Sixth-Generation (6G) networks has not only emphasized ubiquitous communication but also demanded remarkably high data rates and reliability, setting the stage for revolutionary advancements. The impending landscape of communication technologies, such as Vehicular Ad-hoc Networks (VANETs), presents unique challenges and opportunities, compelling a paradigm shift in wireless connectivity strategies. This study addresses the challenge of enhancing wireless connectivity by presenting an innovative solution for Unmanned Aerial Vehicles (UAVs) as base stations (BS), thereby exploring the concept of UAV-BSs. This study provides a Mixed-Integer Non-Linear Programming (MINLP) energy-efficient optimization model to position UAV-BSs based on real-time demand and network conditions adaptively. Traditional optimization methods often face challenges in handling the complex and dynamic nature of UAV-BSs deployment. To overcome this limitation, a novel algorithm combines the strengths of the JAYA, a population-based optimization algorithm inspired by social behavior for solving mathematical optimization problems, and the K-means clustering technique. Through extensive experimentation and comparative analysis, the performance of the optimization model and the enhanced JAYA-based algorithm is evaluated, showcasing their effectiveness in maximizing network coverage and connectivity while minimizing the power consumption of UAV-BSs. The results demonstrate that this approach outperforms other methods regarding UAV-BS placement accuracy, lower power consumed by UAV-BSs, packet loss rate, and latency. Furthermore, the algorithm exhibits adaptability to varying network conditions, making it a valuable tool for optimizing UAV-BS locations in dynamic environments.

Keywords: UAV/drone placement problem. Non-linear optimization problem. Optimization algorithms. Wireless connectivity.

Posicionamento energeticamente eficiente de Estações-Base Montadas em VANTs para melhoria de conectividade em redes sem fio

RESUMO

Em uma era marcada pela onipresença da comunicação sem fio, a necessidade de conectividade excepcional sofreu um aumento sem precedentes. A evolução para as redes de sexta geração (6G) não só enfatizou a comunicação onipresente mas também exigiu taxas de dados e confiabilidade extremamente altas, preparando o terreno para avanços revolucionários. O cenário iminente O cenário iminente das tecnologias de comunicação, como as redes ad-hoc veiculares (VANETs), apresenta desafios e oportunidades oportunidades únicas, exigindo uma mudança de paradigma nas estratégias de conectividade sem fio. Este documento aborda o desafio de aprimorar a conectividade sem fio, apresentando uma solução inovadora para veículos aéreos não tripulados (UAVs) como estações de base (BS), explorando assim o conceito de UAV-BS. Este estudo apresenta um modelo de otimização com eficiência energética de programação não linear de inteiro misto (MINLP) para posicionar os UAV-BSs com base na demanda em tempo real e nas condições da rede de forma adaptativa. Os métodos tradicionais de otimização tradicionais geralmente enfrentam desafios para lidar com a natureza complexa e dinâmica da implantação de UAV-BSs. Para superar essa limitação, um novo algoritmo combina os pontos fortes do JAYA , um algoritmo de otimização baseado em população inspirado no comportamento social para resolver problemas de otimização matemática, e a técnica de agrupamento K-means. Por meio de experimentos extensivos e análise comparativa, o desempenho do modelo de otimização e do algoritmo aprimorado baseado no JAYA é avaliado, demonstrando sua eficácia em atingir os objetivos de maximizar a cobertura e a conectividade da rede e, ao mesmo tempo, minimizar o consumo de energia dos UAV-BSs. consumo de energia dos UAV-BSs. Os resultados demonstram que essa abordagem supera outros métodos em termos de precisão de posicionamento de precisão, menor consumo de energia pelos VANTs-BSs, taxa de perda de pacotes e latência. Além disso, o algoritmo apresenta adaptabilidade a condições de rede variáveis, o que o torna uma ferramenta valiosa para otimizar a localização de UAV-BSs em ambientes dinâmicos.

Palavras-chave: Problema de posicionamento de UAV/drone. Problema de otimi-

zação não linear. Algoritmos de otimização. Conectividade sem fio .

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LIST OF ABBREVIATIONS AND ACRONYMS

UAV	Unmanned Aerial Vehicle
FANET	Flying Ad Hoc Network
IoT	Internet of Things
DBS	Drone-mounted base station
BS	Base station
UAV-BS	UAV-mounted BSs, UAVs as BS
ML	Machine learning
AI	Artificial intelligence
DL	Deep learning
MIMO	Massive multiple-input multiple-output
WPT	Wireless power transfer
SDN	Software Defined Network
NFV	Network function Virtualization
A2A	Air-to-air channel
A2G	Air-to-ground
QoS	Quality of Service
MINLP	Mixed-Integer Non-Linear Programming
PSO	Particle Swarm Optimization

CONTENTS

1 INTRODUCTION

With the advent of Sixth-Generation (6G) networks aiming to establish pervasive wireless connectivity worldwide, there arises a considerable challenge to meet the escalating demands for high-quality and ubiquitous wireless services within current cellular networks. Unmanned Aerial Vehicles (UAVs) exhibit exceptional flexibility, mobility, and advantageous line-of-sight channels, thereby enhancing terrestrial communications in the context of 6G networks. The emergence of UAVs as a technology capable of delivering seamless wireless connectivity becomes pivotal, especially in scenarios where conventional ground-based Base Stations (BSs) might encounter limitations in providing efficient coverage and capacity. Instances of such scenarios encompass emergency communications and responses to natural disasters in densely populated urban areas. UAV-BS can play both complementary and, enabling roles in 6G networks.

- Complementary Role: In this view, the work leveraging UAV-BSs is seen as complementary to 6G. It enhances and extends the capabilities of 6G networks by addressing specific challenges and limitations encountered by traditional ground-based infrastructure. While 6G aims for pervasive wireless connectivity worldwide, it may face obstacles in achieving this goal in certain scenarios, such as densely populated urban areas or during emergency situations. The use of UAV-BSs in such scenarios provides an additional layer of flexibility and mobility, enabling the network to adapt and respond to dynamic conditions effectively. By deploying aerial relay nodes-mounted BSs, this work contributes to extending coverage, enhancing capacity, and improving the quality of wireless services in areas where conventional infrastructure may struggle to meet demands. This augmentation of 6G capabilities through UAV-BS technology ensures that the promises and objectives of 6G can be fulfilled more comprehensively and efficiently.

- Enabling Role:

  In contrast, the enabling role perspective considers the integration of UAV-BS technology as foundational to the very concept of 6G itself. It views UAV-BSs not just as supplements to existing infrastructure but as essential components that enable the realization of pervasive wireless connectivity worldwide. In this view, UAV-BS technology addresses the fundamental challenges and requirements of 6G networks, playing a crucial role in shaping their architecture and capabilities.

By leveraging UAVs to deploy UAV-BSs, this study becomes integral to establishing and maintaining seamless wireless connectivity, particularly in scenarios where conventional infrastructure is insufficient or impractical. UAV-BSs provide unique advantages such as enhanced mobility and line-of-sight channels, which are essential for overcoming obstacles and ensuring reliable communication in diverse environments. Therefore, the integration of UAV-BS technology is not merely complementary but pivotal in achieving the overarching objectives of 6G networks. This work's contribution to 6G lies in its ability to leverage UAV-BSs effectively to optimize throughput, enhance coverage, and manage energy constraints. Whether seen as complementary or enabling, the integration of UAV-BS technology aligns with the goals and promises of 6G networks, ultimately facilitating the realization of pervasive wireless connectivity worldwide.

One of the paramount challenges in this domain is the efficient deployment of aerial relay node-mounted BSs, which requires optimizing throughput while managing the stringent energy constraints inherent to UAVs (PEREIRA et al., 2023; PASANDIDEH et al., 2022).

This chapter serves as an introduction to the thesis, setting the stage for the exploration of UAV positioning in wireless networks. Section 1.1 contextualizes the research, providing the background and context necessary to understand the scope of the study. It may cover details such as the evolution of wireless networks, the emergence of UAVs as BS, and the challenges associated with their optimization. Section 1.2 shows the primary goals of UAV-BS placement problem, including maximizing coverage, minimizing signal interference, optimizing network capacity, ensuring Quality of Service (QoS), and reducing power consumption. Section 1.3 outlines the specific research problems addressed in this thesis. It details the challenges and gaps in current methodologies, potentially encompassing issues related to connectivity, coverage optimization, power consumption, and other pertinent aspects of UAV-BS deployment in wireless networks. Section 1.4, focuses on the problem statement and research motivation, identifying gaps in current UAV-BS placement strategies and examining real-world applications and industries benefiting from optimized UAV-BS deployment. It discusses the potential impact of enhanced UAV-BS placement on network performance, coverage, and reliability. Additionally, Section 1.5 delves into the motivations driving this research, elucidating the objectives, goals, and intended contributions. Lastly, Section 1.6 provides an overview of the thesis structure, outlining the subsequent chapters and their respective contents.

Throughout this thesis, the emphasis lies on utilizing optimization methodologies to strategically position UAVs as BS, enhancing network coverage, improving wireless connectivity, and addressing the critical aspect of power consumption optimization, thereby contributing to the advancement of wireless network technologies.

1.1 Contextualization

In recent years, designing the collaborative systems of UAVs commonly known as drones have become a major research topic in different areas, especially in robotics and artificial intelligence (AI) (SULTAN et al., 2021; CHEN et al., 2018). Based on available statistics[1], the worldwide commercial UAV market size is growing. Around 1.1 billion dollars were invested in the aerial guided system industry in 2020. The global commercial UAV market is expected to reach *58.4* billion dollars in 2026. The significant investments in the aerial guided system industry shows that UAVs are becoming more common in all-day applications.

Recently, different civilian and military applications have been implemented using multi-UAV systems in which there is a swarm or formation of small UAVs. This approach brings together the concept of Flying Ad hoc Network (FANET) of UAVs which allows a group of UAVs to communicate and cooperate towards completing their mission without human intervention. To accomplish their missions, the swarm of UAVs moves freely in the environment using different types of mobility models, which is an aspect that takes into account both the dynamics of the UAV network and the physical characteristics of the UAV platforms. It is important to notice that this study refers to the word "FANET" as a network of UAVs (UAV-FANETs) and uses FANETs, UAV networks, UAV-networked systems, UAV-based networks, and networked UAV-systems interchangeably referring to the same concept.

Not only the continuous advance of the hardware has drastically impacted the FANETs of UAVs, but also the development of software, in particular in the area of AI, has been crucial (Garaffa et al., 2021). This advance benefits FANETs

[1]https://www.statista.com/statistics/1117058/global-commercial-drone-investments/

used in different application domains. As the FANETs become more intelligent, they manage to interact and make part of other systems, such as Cloud-based ones and IoT Systems. In addition to the existing challenges in traditional FANETs, new issues arise, such as bottlenecks, latency due to centralized processing, lack of offline processing, and security issues. In this context, Machine Learning (ML) approaches offer promising models in the AI domain to address these challenges with deep learning and reinforcement learning-based solutions.

As FANETs have been adopted by many industries, a deep insight into challenges, and perspectives in FANETs are important subjects that need to be studied.

One of the paramount challenges in this domain is the efficient deployment of aerial relay node-mounted BSs, which requires optimizing throughput while managing the stringent energy constraints inherent to UAVs (PEREIRA et al., 2023; PASANDIDEH et al., 2022). The UAV-BS placement problem, which is to determine the optimal locations for deploying UAV-BSs to achieve specific objectives, such as maximizing coverage of an area/ number of served users (Fahim; Gadallah, 2020), (ZAHEDI et al., 2020), (Akram et al., 2020), (SHAKOOR et al., 2021), (CHERIF et al., 2020), (Chaalal; Reynaud; Senouci, 2020), (TAREKEGN et al., 2022), (WANG et al., 2022), (DAI et al., 2022), (WU et al., 2022); improving wireless connectivity between UAV-BSs and ground nodes (Fahim; Gadallah, 2020) (ZAHEDI et al., 2020) (Akram et al., 2020) (SHAKOOR et al., 2021) (CHERIF et al., 2020) (Chaalal; Reynaud; Senouci, 2020), (TAREKEGN et al., 2022), (WANG et al., 2022), (DAI et al., 2022), (WU et al., 2022),(SHAKOOR et al., 2021), (Zhang; Ansari, 2020) (Zhong et al., 2020), (Vashisht; Jain; Mann, 2019), (Cicek et al., 2020), (Guo et al., 2019), and (YOU et al., 2020); minimizing travel time between points; maximizing network profit (Cicek et al., 2020); and the spectral efficiency of the whole system (Guo et al., 2019).

Numerous research studies have explored the application of UAV-BSs to enhance wireless communication by examining UAV-BS deployment strategies and resource allocation schemes (Fahim; Gadallah, 2020)-(YOU et al., 2020). However, several ongoing challenges and constraints persist in the realm of UAV-BS placement. This problem centers on identifying the most advantageous positions for deploying UAVs as BS to attain particular goals, including the maximization of coverage, minimization of signal interference, optimization of network capacity, enhancement of QoS metrics, and reduction of energy consumption.

1.2 Goals

UAVs utilized as BSs have emerged as a prominent solution for enhancing wireless communication networks. The placement of UAV-BS involves strategically positioning these aerial units to achieve various objectives related to network performance. The primary goals encompass maximizing coverage, minimizing signal interference, optimizing network capacity, ensuring QoS, and reducing power consumption, as described in the following:

- Maximization of Coverage: One of the fundamental objectives in UAV-BS placement is to maximize the coverage area of wireless networks. This involves a meticulous process of identifying strategic positions for UAV-BS deployment to ensure extensive and efficient coverage for network users. The goal is to establish an optimized spatial arrangement of UAV-BS units that effectively extends the coverage footprint, reaching a larger geographical area while maintaining reliable connectivity and communication services (MOZAFFARI et al., 2019a). Achieving comprehensive coverage entails a multifaceted approach; Geospatial Planning, User Distribution and Density, Signal Propagation and Quality, and Dynamic Adaptability.

- Minimization of Signal Interference: Another critical aspect of UAV-BS placement is the reduction of signal interference within the network. Identifying optimal locations for UAV-BS helps minimize interference, thereby enhancing the reliability and efficiency of communication links (AL-HOURANI; KANDEEPAN; JAMALIPOUR, 2014a). Signal interference poses a significant challenge in wireless communication systems, affecting the quality and reliability of transmissions. By strategically locating these aerial base stations, engineers aim to *reduce Co-Channel interference*, *mitigate Multi-Path effects*, and *address interference from external sources.*

- Optimization of Network Capacity:

  Effective placement of UAV-BS aims to optimize the network capacity, ensuring efficient utilization of resources. Research focuses on deploying UAV-BS in strategic locations to enhance the overall capacity of the wireless network (ZENG; WU; ZHANG, 2016). By carefully selecting and situating the UAV-BSs, the objective is to bolster connectivity, reduce interference, and effectively cater to varying demand densities across different areas within the network. Furthermore, the utilization of UAV-BS enables dynamic coverage extension and targeted support, particularly in scenarios with high mobility or areas lacking traditional infrastructure. This approach not only amplifies the network's overall efficiency but also facilitates improved service provisioning, ensuring a more robust and reliable wireless communication ecosystem.

- Enhancement of Quality of Service (QoS) Metrics:

  UAV-BS placement also focuses on improving QoS metrics such as latency, reliability, and throughput. Strategic positioning of UAV-BS influences QoS parameters, ensuring a better user experience (YAN; VUCETIC; HANLY, 2019). By strategically locating UAV-BS, there is a direct influence on reducing latency, enhancing reliability, and augmenting throughput, all of which collectively contribute to delivering superior service quality within the wireless network.

- Reduction of Energy Consumption:

  Efficient UAV-BS placement contributes to reducing the energy consumption of wireless networks. Optimal deployment strategies help in conserving energy while maintaining network performance (WU; ZENG; ZHANG, 2018). Furthermore, by optimizing deployment strategies and minimizing unnecessary energy expenditure, such as excessive hovering or inefficient routing, networks can achieve enhanced longevity, improved reliability, and reduced operational expenses.

1.3 Research Problems

The investigation into solutions for the placement problem concerning UAVs has yielded promising results and considerable benefits across various domains. However, this pursuit is not without its challenges, encompassing critical facets such as energy-efficient deployment, dynamic environment adaptation, scalability and mobility, and real-time optimization. Despite substantial progress in tackling these challenges in recent years, several pertinent issues remain unresolved. Therefore, this study aims to delve deeper into these persisting challenges and seeks to address specific research questions to further advance the field of UAV-BS deployment. The following are the key research questions this work endeavors to explore and resolve

Research Question #1: What techniques, optimized algorithms, and data structures can be employed to mitigate wasted power consumption in achieving optimal UAV-BS placement?

To mitigate UAV-BS power wastage in optimal placement challenges, various techniques and algorithms have been proposed. One approach involves using energy-aware optimization algorithms that consider UAV-BS flight paths and task scheduling to minimize energy consumption while maintaining network coverage and service quality (ZHONG et al., 2021). Additionally, employing efficient data structures such as spatial indexes or graph-based representations aids in quickly accessing and processing spatial information, optimizing route planning, and reducing UAV-BS energy expenditure during navigation and communication tasks (DING et al., 2020). Furthermore, the implementation of machine learning-based predictive models enables proactive decision-making regarding UAV-BS movement and resource allocation, contributing to energy-efficient deployment strategies (LYU et al., 2020).

Research Question #2: What are the adaptive algorithms or optimization techniques that account for real-time environmental factors such as weather conditions, terrain variations, or fluctuating user demands, aiming to optimize UAV-BS placement and energy consumption without compromising on network quality? and how can they be improved?

Adaptive algorithms and optimization techniques that consider real-time environmental factors for optimizing UAV-BS placement and energy consumption while maintaining network quality often include dynamic programming-based approaches, reinforcement learning frameworks, and heuristic-based algorithms. Dynamic programming techniques adapt UAV-BS paths considering weather changes, terrain constraints, and dynamic user demands to optimize energy consumption and network quality (ABDOLI; AL., 2020). Reinforcement learning models, such as Q-learning or Deep Q-networks, enable UAV-BSs to make real-time decisions by learning from environmental feedback, allowing for adaptive trajectory planning and resource allocation (ZHAO; AL., 2021). Additionally, metaheuristic-based algorithms, such as genetic algorithms or particle swarm optimization, iteratively adjust UAV-BS positions based on real-time environmental data to achieve energy efficiency without compromising network performance (NAWROCKI; AL., 2021). Improving these techniques involves enhancing the learning capabilities of reinforcement models with larger and more diverse environmental datasets, refining metaheuristic algorithms for faster convergence, and integrating multi-objective optimization strategies for balancing conflicting objectives in real-time UAV-BS placement scenarios.

1.4 Problem Statement and Research Motivation

In this section, the motivation is explored behind research endeavors focused on optimizing UAV-BS deployment, driven by the ambition to transform communication networks, especially in situations where conventional infrastructure proves insufficient or unfeasible. This field of study presents significant potential owing to the distinctive capabilities of UAVs, offering adaptable, swiftly deployable, and customizable communication services on demand.

1.4.1 Identification of the gaps in current UAV-BS placement strategies

The pursuit of optimizing UAV-BS placement strategies for efficient and effective communication networks remains a focal point in contemporary research. Despite remarkable advancements, several critical gaps and limitations persist in current approaches. Notably, these gaps encompass challenges associated with dynamic environmental conditions, stringent regulatory compliance, scalability concerns, and shortcomings in adaptive resource allocation methodologies. Addressing these gaps is crucial to unlocking the full potential of UAV-BSs in augmenting communication infrastructures. The identification and comprehension of these limitations provide a cornerstone for refining existing strategies and devising novel approaches in UAV-BS placement optimization research.

- *Limited Consideration for Dynamic Environmental Changes:* Current placement strategies often lack adaptability to rapidly changing environmental conditions such as weather, wind patterns, and other atmospheric factors, impacting the reliability and efficiency of UAV-BS deployment (ZHANG; AL., 2021).

- *Insufficient Adaptation to User Mobility and Traffic Dynamics:* Strategies may overlook the dynamic movement of users and fluctuating traffic demands, leading to sub-optimal placement and inadequate coverage in areas with varying user densities (MOZAFFARI; AL., 2016).

- *Inadequate Handling of Interference and Network Congestion:* Current strategies may not sufficiently address interference management among multiple UAV-BSs or efficiently mitigate network congestion, affecting communication quality and network performance (MOZAFFARI; AL., 2017).

- *Scalability and Complexity of Optimization Algorithms:* Scalability issues in optimization algorithms used for UAV-BS placement strategies might arise with an increasing number of UAV-BSs and users, impacting the computational efficiency and real-time adaptability (AL-HOURANI; KANDEEPAN; JAMALIPOUR, 2014a).

- *Energy Efficiency and Flight Duration Constraints:* Strategies might not effectively balance energy efficiency while optimizing UAV-BS placement, potentially leading to limited flight duration and compromised operational effectiveness (MOZAFFARI; AL., 2016).

1.4.2 Real-world applications and industries benefiting from optimized UAV-BS deployment

Optimized UAV-BS deployment has significant implications across various real-world applications and industries. These deployments offer enhanced connectivity, improved services, and novel solutions in sectors where traditional communication infrastructure might be insufficient or unavailable. In this section, some key industries and applications are provided, benefiting from optimized UAV-BS deployment, along with explanations of how optimal placement affects these applications.

a. *Disaster Management and Emergency Response:*

   - *Application:* During natural disasters or emergencies, UAV-BSs play a vital role in establishing temporary communication networks for rescue operations, coordination among responders, and providing connectivity to affected areas (ZHANG; AL., 2021).

- *Impact of Optimal Placement:* Efficiently positioned UAV-BSs can rapidly establish communication links, cover affected regions, and ensure connectivity for emergency services and affected populations. Optimal placement enhances network coverage and reliability in dynamic and challenging environments (ZHANG; AL., 2021).

b. *Precision Agriculture and Monitoring:*

- *Application:* In agriculture, UAV-BSs enable real-time data collection, remote sensing, and monitoring of crop health, allowing for precise and targeted interventions (MOZAFFARI; AL., 2017).
- *Impact of Optimal Placement:* Strategically positioned UAV-BSs ensure continuous and reliable connectivity, facilitating data transmission from agricultural sensors and drones. This enables efficient data analysis and decision-making for precision farming (MOZAFFARI; AL., 2017).

c. *Telecommunications and Connectivity in Remote Areas:*

- *Application:* In remote regions lacking traditional infrastructure, UAV-BSs offer a means to establish temporary communication networks for remote communities, expeditions, or events (MOZAFFARI; AL., 2016).
- *Impact of Optimal Placement:* Well-placed UAV-BSs extend network coverage, ensuring reliable connectivity in remote areas, fostering economic development, and enabling access to essential services (MOZAFFARI; AL., 2016).

d. *Surveillance and Public Safety:*

- *Application:* UAV-BSs aid in surveillance, law enforcement, and public safety by providing aerial coverage for monitoring events, crowd control, and enhancing situational awareness (LIU; ZHANG; ZHOU, 2021).
- *Impact of Optimal Placement:* Optimal UAV-BS placement ensures comprehensive and efficient coverage, enhancing data transmission for real-time surveillance and emergency response, thereby improving public safety (LIU; ZHANG; ZHOU, 2021).

e. *Media Coverage and Entertainment Events:*

- *Application:* UAV-BSs facilitate media coverage during events, concerts, or sports, providing high-quality live streaming, enhancing coverage, and ensuring reliable communication (MOZAFFARI; AL., 2016).

- *Impact of Optimal Placement:* Strategically positioned UAV-BSs enable seamless connectivity, enhancing the quality and reliability of live broadcasting, supporting real-time data transmission from multiple viewpoints (MOZAFFARI; AL., 2016).

1.4.3 The potential impact of improved UAV-BS placement on network performance, coverage, and reliability

Improved UAV-BS placement holds substantial promise for enhancing network performance, coverage, and reliability across diverse applications. Optimal positioning of UAV-BSs directly influences the overall network performance by extending coverage to underserved areas, enhancing signal strength, and mitigating coverage gaps. A strategic deployment of UAV-BSs allows for dynamic adaptation to user demands, enabling better load balancing, reduced interference, and improved spectral efficiency. This enhanced placement not only bolsters connectivity but also significantly augments the reliability of communication networks, particularly in scenarios such as disaster response, remote area connectivity, and mission-critical operations.

Improved UAV-BS placement significantly enhances network performance by optimizing coverage, reducing latency, and boosting throughput. Strategic positioning ensures wider coverage, extending connectivity to remote or underserved areas. For instance, in disaster management scenarios, optimally placed UAV-BSs facilitate real-time communication among rescue teams, minimizing response times and enabling efficient coordination, as evidenced by (ZHANG; AL., 2021). Furthermore, reduced signal interference and stronger signal strength from well-positioned UAV-BSs enhance reliability, ensuring consistent connectivity, and fostering seamless data transmission. This improved network performance is crucial not only in emergency situations but also in applications like precision agriculture, where optimized UAV-BS placement enables real-time data transmission for monitoring and management practices (MOZAFFARI; AL., 2016).

1.5 Contributions

This research study presents two pivotal contributions in the realm of UAV-BS deployment optimization. The first and main contribution lies in formulating an optimal UAV-BS placement model that incorporates non-linear optimization problems. This model takes into account the intricacies of power consumption, strategically placing UAV-BSs while adhering to energy constraints.

The second contribution delves into a comprehensive study aimed at solving the aforementioned mathematical model. By employing advanced mathematical techniques and algorithms, this research explores effective methodologies to efficiently solve the complex non-linear optimization problem associated with UAV-BS placement. These contributions collectively offer a novel approach towards optimizing UAV-BS deployment by considering power consumption constraints and proposing viable solutions to the resultant mathematical model, thereby enriching the landscape of UAV-BS deployment strategies.

The contributions can be elucidated as follows:

- Formulating a robust representation of the energy-aware UAV-BS placement problem as a Mixed-Integer Non-Linear Programming (MINLP), enabling the simultaneous integration of diverse objectives and constraints. Unlike some of the previous works, which neglect considerations of energy efficiency and fail to integrate diverse objectives into their optimization models, this approach offers a comprehensive solution. Employing MINLP, enables the simultaneous integration of various objectives and constraints, thereby addressing critical issues such as energy efficiency and accommodating diverse optimization goals.

- Unlike previous studies, which overlook the dynamic environmental factors, this research incorporates a comprehensive range of constraints related to UAV-BS rotor specifications, communication range, flying speed, as well as environmental variables such as wind speed and direction, alongside UE specifications and other pertinent limitations. By assimilating these intricate parameters and restrictions into the devised model, the research ensures a nuanced understanding of the physical capabilities of UAV-BS rotors while adhering to communication thresholds over specified distances and accommodating diverse flying speeds amidst dynamic environmental factors such as wind speed, and direction. Moreover, the model extends its scope to encompass the unique requirements and capabilities of UEs, integrating these constraints to develop a comprehensive framework that accurately reflects real-world conditions and operational limitations, thereby significantly enhancing the applicability and robustness of UAV-BS systems in dynamic environments.

- The optimization process for the suggested UAV-BS placement model involves a meticulous examination across multiple performance metrics. These encompass a comprehensive evaluation, not limited to, but inclusive of coverage, capacity, energy consumption, and the fulfillment of QoS prerequisites. This intricate analysis allows for a holistic approach, ensuring that the placement of UAV-BSs is not only strategically positioned but also attuned to meet diverse operational needs. The optimization procedure is aimed at achieving an equilibrium where the placement configuration significantly enhances coverage areas, maximizes network capacity, minimizes energy usage, and concurrently meets the stringent QoS demands essential for seamless and reliable network performance.

- Introduction of a meta-heuristic algorithm, namely PSO, and JAYA, designed to determine optimal UAV-BS locations. These algorithms represent innovative methods in the realm of UAV-BS location optimization, promising enhanced performance and accuracy in finding the most suitable deployment positions for these UAV-BSs. Contrary to existing approaches, these algorithms offer innovative solutions to the optimization of UAV-BS deployment, addressing the limitations of previous methods. By improving PSO and JAYA, this contribution enhances the efficiency and accuracy of determining optimal UAV-BS locations, thus offering a promising avenue for improved performance in wireless communication networks.

- Given the absence of comprehensive datasets in the current literature, required datasets are provided for UAV-BSs. These datasets are meticulously structured to encompass crucial features tailored to different sets of UAV-BSs. Furthermore, both the datasets and the associated data generation codes have been made readily accessible, aiming to offer fellow researchers invaluable, multi-dimensional data resources for their investigations and analyses.

- The validation process of the derived analytical model involves conducting extensive numerical analyses that draw inspiration from Monte Carlo simulations. These simulations serve to reinforce and affirm not only the applicability but also the reliability of the model. By subjecting the model to rigorous numerical scrutiny akin to Monte Carlo simulations, the aim is to substantiate its robustness and ensure its effectiveness across various scenarios and conditions. This validation methodology provides a comprehensive assessment, solidifying confidence in the analytical model's accuracy and suitability for practical application.

1.6 Outline

The rest of this thesis is organized as follows. Chapter 2 delves into the background and related work, starting with an exploration of the definition and significance of UAV-BS in wireless communication networks. This section reviews the historical evolution and advancements in UAV-BS technology for communication purposes, outlines principal use cases of UAV-BS placement, and provides an overview of existing deployment strategies along with their limitations. It discusses conventional approaches, including analytical techniques, heuristic, metaheuristic-based approaches, and learning-based methodologies. Additionally, it highlights the challenges and complexities involved in optimizing UAV-BS placement. Chapter 3 introduces the system model, presenting the network model, main assumptions, and the model for UEs' mobility. It formulates the placement problem, linearizes the optimization problem, and proposes a PSO-based algorithm for the coverage module model. Furthermore, it refines the placement problem formulation for improved analysis. Chapter 4 details the proposed UAV-BS placement strategy, presenting the designed solution, conducting a complexity analysis, and describing the data generation process. Chapter 5 focuses on performance evaluations, outlining a simulated scenario, experimental design, results, and discussions. It includes algorithms for reference and evaluates their performance. Finally, Chapter 6 offers a conclusion summarizing the key findings and potential future research directions. It also includes a section on publications and a comprehensive list of references citing the sources used throughout the thesis.

2 BACKGROUND AND RELATED WORK

Within this chapter, an in-depth foundation is laid out to facilitate comprehension of this thesis's content. The opening section delves into the definition and profound significance of UAV-BS within the framework of wireless communication networks in Section 2.1, and exploration begins by tracing the historical evolution of UAV technology specifically tailored for communication purposes. This historical contextualization serves as a backdrop against which the advancements in this field are highlighted.

In Section 2.2, an extensive overview is presented, elucidating the existing strategies for UAV-BS deployment and their associated limitations. The exploration of these strategies encompasses various categories: focusing on conventional approaches employing analytical techniques, heuristic and metaheuristic-based methodologies, and learning-based approaches. This comprehensive overview aims to provide a nuanced understanding of the existing strategies and their respective constraints, laying the groundwork for the subsequent introduction of innovative methodologies in this field.

Moving forward, the subsequent Section 2.3 meticulously addresses the multifaceted challenges and intricacies associated with optimizing the placement of UAV-BS. This exploration involves an extensive examination of the complexities involved in strategically positioning UAV-BS within wireless communication networks. It delineates the technical, logistical, and operational hurdles that impede the seamless and efficient integration of these stations, thus forming a crucial part of the foundational knowledge essential for comprehending the research landscape.

2.1 Definition and significance of UAV-BS in wireless communication networks

UAV-BSs refers to UAVs as aerial base stations in wireless communication networks. These UAVs, commonly known as drones, are equipped with communication and networking capabilities, such as antennas, transceivers, and computational resources to establish wireless communication links with ground devices. They have garnered significant attention due to their mobility, flexibility, and ability to rapidly deploy and cover areas where traditional fixed-base stations might be impractical or unavailable.

The significance of UAV-BS in wireless communication networks is evident in their pivotal role, as they offer unparalleled advantages that significantly enhance connectivity, capacity, and responsiveness within modern wireless communication systems.

- *Enhanced Connectivity and Coverage:* UAV-BSs facilitate rapid deployment in areas devoid of network coverage or struck by emergencies such as natural disasters. By extending coverage to remote or underserved regions, they enable connectivity for users otherwise deprived of access to communication networks (ZENG; ZHANG; LIM, 2019).

- *Improved Capacity and Throughput:* In congested areas or during high-demand events, UAV-BSs alleviate network congestion by offloading traffic, thus enhancing network capacity and throughput. Their provision of additional network resources proves beneficial, particularly in crowded settings such as events or concerts (MOZAFFARI et al., 2019b).

- *Dynamic Deployment and Mobility:* The inherent mobility of UAV-BSs allows for swift repositioning based on changing connectivity demands. This dynamic deployment proves invaluable in scenarios requiring temporary coverage, including search and rescue operations, surveillance, or public events (ZENG; ZHANG; LIM, 2019).

- *Emergency Response and Disaster Recovery:* During emergencies or natural disasters when terrestrial infrastructure may be impaired, UAV-BSs swiftly establish temporary communication links. This capability aids in facilitating coordination among emergency responders and contributes significantly to disaster recovery efforts (ZENG; ZHANG; LIM, 2019).

- *Reliable Communication for IoT and Critical Applications:* UAV-BSs offer reliable and low-latency communication services, crucial for various Internet of Things (IoT) applications, especially in critical sectors such as agriculture, healthcare, and logistics (MOZAFFARI et al., 2019b; AL-HOURANI; KANDEEPAN; JAMALIPOUR, 2014b).

2.1.1 Historical evolution and advancements in UAV technology for communication purposes

The historical evolution of UAV technology for communication purposes has been marked by significant advancements in both hardware and communication systems, transitioning from basic reconnaissance and data transmission to highly sophisticated autonomous systems with diverse applications in military and civilian domains. UAVs have seen a significant evolution in their technology, especially concerning communication purposes. They have transitioned from simple remote-controlled aircraft to highly sophisticated systems capable of performing a wide array of tasks, including communication relay, surveillance, and data transmission. This evolution has been shaped by various advancements in technology and the increasing demand for efficient and reliable communication systems. Below is a detailed exploration of the historical evolution and advancements in UAV technology for communication purposes.

- *Early Development and Military Applications:* UAV technology traces its roots back to the early 20th century, with initial developments in the form of remotely piloted aircraft during World War I and World War II. These early UAVs were primarily used for reconnaissance and communication purposes, enabling military forces to gather information and transmit data without risking human lives (BOUCHER; SILVA, 2018).

- *Advancements in Communication Systems:* With advancements in electronics and communication technologies, UAVs started incorporating more sophisticated communication systems. These systems included improved data links, encryption methods, and better antennas, allowing for enhanced communication capabilities over longer distances (SINGH; SINHA, 2019).

- *Integration of Satellite Communication:* The integration of satellite communication greatly expanded the operational range and communication capabilities of UAVs. By utilizing satellite links, UAVs could communicate beyond line-of-sight and operate in remote areas without relying solely on ground-based communication systems (IKUNO; BARROS, 2016).

- *Emergence of Autonomous UAVs:* Advancements in artificial intelligence and autonomous systems led to the development of UAVs capable of autonomous operation. These UAVs could now execute complex communication tasks, adapt to changing environments, and make real-time decisions, further enhancing their effectiveness in communication missions (RABBATH; KIRUBARAJAN, 2017).

- *Applications in Civilian Sectors:* UAVs have found applications beyond the military, including in civilian sectors such as disaster management, agriculture, and telecommunications. In the realm of communication, UAVs are used for providing temporary communication infrastructure in remote or disaster-stricken areas where conventional systems are damaged or unavailable (MERZ, 2020).

- *Continued Technological Advancements:* Ongoing research and development continue to focus on improving UAV communication capabilities. These efforts involve exploring advanced communication protocols, better integration with 5G and future networks, as well as miniaturization of communication hardware for smaller UAVs with increased functionalities (LIU; ZHANG; ZHOU, 2021).

2.1.2 Principal use cases of the UAV-BS placement problem

The main use cases for UAV-mounted BSs placement problem can be summarized as follows:

- **Use Case 1: coverage enhancement for short-term events:** An illustrative application scenario involves addressing temporary events such as concerts and sporting events, depicted in Figure 2.1, where a substantial surge in connectivity, throughput, and data rate demands arises due to a large audience. In such instances, investing in a complete infrastructure solely for these events may not be cost-effective. Leveraging UAV-BSs emerges as a promising solution to meet temporary communication needs. Once the event concludes, these UAVs can return to their stations, eliminating the necessity for substantial investments in fibers, antennas, and the installation of a permanent infrastructure. This approach provides an efficient and economical means to address the heightened communication requirements during such events without incurring extensive, long-term expenses. This scenario prioritizes accommodating a surge in connectivity, throughput, and data rate demands during temporary events. The primary focus in such scenarios is on providing sufficient throughput to handle the increased communication requirements efficiently. The temporary nature of these events means that cost-effectiveness and flexibility are crucial, and the ability to quickly deploy and reposition UAV-BSs is essential. Regarding UEs' mobility model for short-term events such as concerts and sporting events, where there is a large audience gathered in a relatively confined area, the movement of UEs can often resemble queues or organized lines rather than random patterns. Employing a mobility model that simulates such queue-like behavior would better capture the dynamics of UEs movement during these events, leading to more accurate predictions of where the UAV-BSs should be positioned to optimize coverage and capacity.

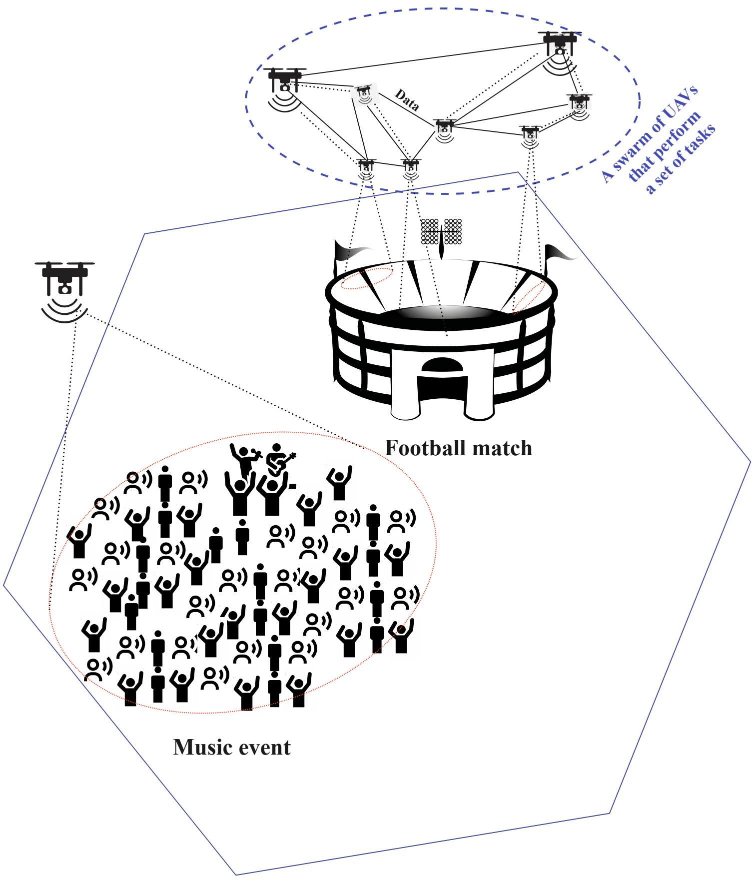


Figure 2.1 – Coverage enhancement for temporary crowded events

- **Use Case 2: coverage enhancement for temporary unavailable infrastructure :**

  In unforeseen situations such as natural or human-made disasters—such as floods, severe storms, landslides, earthquakes, forest fires, or emergency accidents—as illustrated in Figure 2.2, terrestrial networks might suffer breakdowns, rendering them out of service due to equipment damage or power failures. Here, UAV-BSs emerge as crucial tools to swiftly and effectively restore communication. Multiple UAV-mounted BSs can be deployed to the affected areas, facilitating the rapid provision of temporary wireless communication services, and aiding in the quick reconstruction of communication infrastructure. to target regions to provide temporary wireless communication services. In this scenario, low latency and rapid deployment are critical to ensure effective communication during crisis situations. The priority here is on providing reliable and resilient communication services to areas where terrestrial networks have become unavailable due to damage or power failures. In terms of UEs' mobility model, in emergency scenarios such as natural disasters or accidents where terrestrial networks may be disrupted, UEs tend to move in random directions as they seek safety or assistance. Therefore, a mobility model such as the random way point model would be appropriate to simulate the unpredictable movements of users during such events, enabling UAV-BSs to dynamically adjust their positions to provide effective coverage where it is most needed.

- **Use Case 3: coverage enhancement for rural areas:**

  In rural and low-income areas, the absence of network infrastructure persists due to the high expenses associated with deploying traditional network systems, coupled with the limited potential for profits. A promising solution to bolster cellular coverage in these regions involves the utilization of UAV-BSs as opposed to the costly terrestrial BSs. Rural areas generally lack tall buildings, and the demand for network traffic is notably lower compared to urban areas. Consequently, the need for frequent spatial repositioning of UAVs is minimized, making continuous adjustments unnecessary. While the demand for network traffic in rural and low-income areas may be lower compared to urban areas, providing reliable coverage is essential. The focus here is on achieving broad coverage with minimal infrastructure investment, making continuous adjustments unnecessary. Throughput and coverage are important, but cost-effectiveness and adaptability to the rural environment are paramount. In rural areas with low population density and limited mobility patterns, UEs

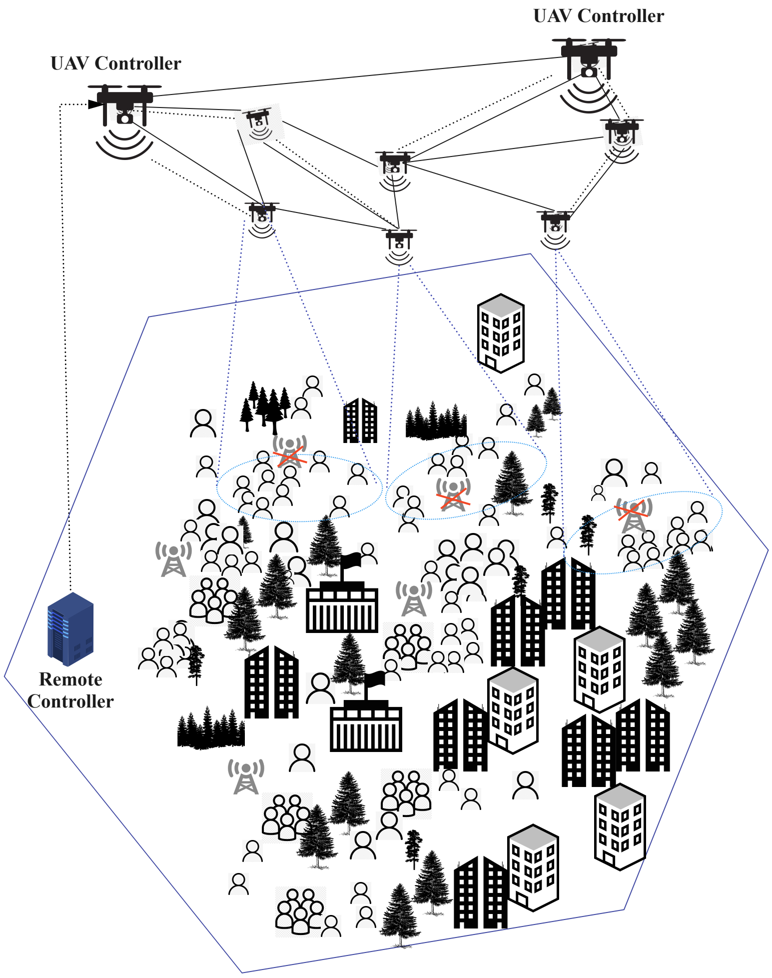


Figure 2.2 – Coverage enhancement for temporary unavailable infrastructure

may move in relatively random directions within their local vicinity. The random walk mobility model would be suitable for capturing this behavior, as it allows UAV-BSs to adapt to the sporadic movement of UEs while ensuring continuous coverage over the vast rural landscape.

- **Use Case 4: coverage enhancement for high data rate applications in urban areas with lack of infrastructure:**

  Several emerging applications necessitate exceptionally high data throughput. As depicted in Figure 2.3, an example is the utilization of autonomous vehicles (AVs) navigating city streets, where occupants engage with augmented or virtual reality interfaces inside the vehicle. These applications demand several gigabytes per second of data transmission, a feat that exceeds the capabilities of the existing 5G network infrastructure. A promising solution to meet such demanding data rate requirements involves leveraging Millimeter-

Wave (mmWave) Beam-forming enabled UAV communications, particularly in high-traffic scenarios. One of the promising solutions is to use mmWave Beam-forming enabled UAV communications in such high-traffic scenarios. In this scenario, the emphasis is on achieving exceptionally high data throughput to meet the demands of these emerging applications. Regarding the user mobility model, in urban areas with high data rate demands, such as those involving AVs and augmented reality interfaces, users often move along predefined routes or grids, especially in areas with dense traffic and infrastructure. The Manhattan Grid mobility model, which simulates movement along city streets in a grid-like fashion, would be well-suited for modeling the movement patterns of users in these scenarios. It enables UAV-BSs to anticipate and adapt to the predictable trajectories of high-demand users, ensuring optimal coverage and capacity for data-intensive applications.

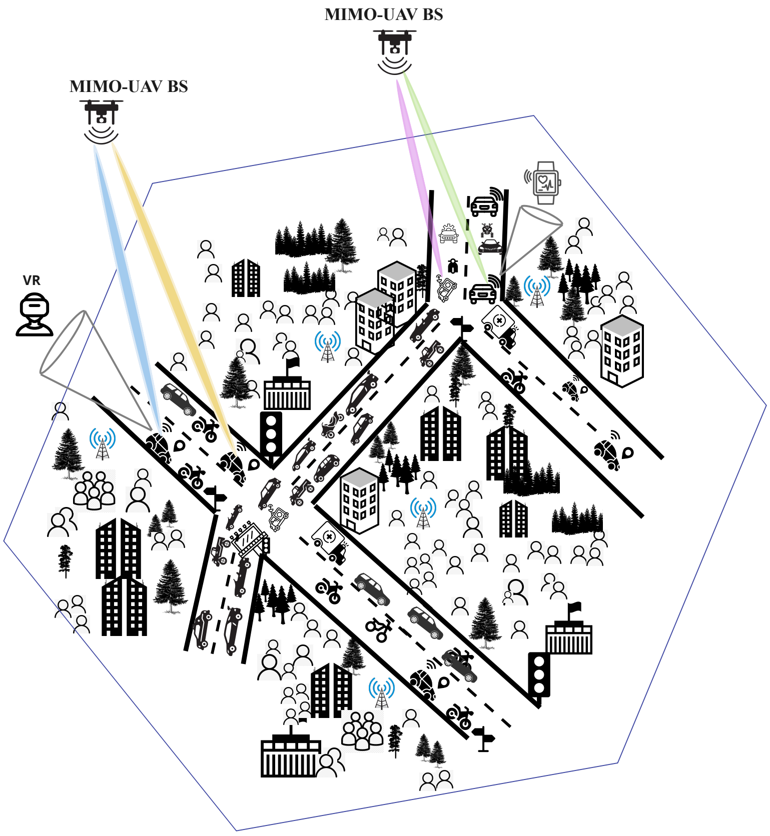


Figure 2.3 – Coverage enhancement for high data rate applications in autonomous vehicles (AVs) with lack of infrastructure

In summary, while each use case may share some common features such as the utilization of UAV-BSs for coverage enhancement, their specific characteristics and priorities vary significantly based on the application scenario. Through-

Table 2.1 – The importance of latency, throughput, coverage, cost-effective, and other factors in each use case scenario.

Use Case	**Low Latency?**	**High Throughput?**	**Broad Coverage?**	**Economic efficiency**	**Other Important Factors**	**Mobility model**
1	Yes	Yes	Moderate	High	Flexibility	Queue based mobility model
2	No	Moderate	High	High	Reliability	Random waypoint model
3	Yes	Moderate	High	High	Adaptability	Random walk mobility model
4	Yes	Yes	Moderate	Low	Compatibility	Manhattan Grid mobility model

put, latency, coverage, cost-effectiveness, and adaptability to different environments emerge as key factors influencing the design and implementation of UAV-BS solutions in each scenario. Table 2.1, illustrates the importance of various factors, and the recommended mobility models in each use case scenario.

2.2 Overview of existing UAV-BSs deployment strategies and their limitations.

UAV-BSs hold promise in expanding communication coverage, especially in challenging terrains and emergencies. Multiple deployment strategies exist for UAV-BS, encompassing static, mobile, relay-assisted, swarm, and hybrid deployments. Static deployment offers stability but lacks adaptability to dynamic demands, while mobile strategies provide flexibility despite energy consumption and connectivity issues. Relay-assisted deployment enhances coverage but faces limitations in mobility and transition. Swarm deployment provides redundancy but demands intricate coordination. Hybrid methods offer adaptability but increase management complexity. Common limitations encompass energy constraints, regulatory challenges, spectral efficiency issues, and coordination overhead. Addressing these challenges necessitates innovative solutions in energy efficiency, advanced protocols, trajectory planning, and regulatory support to fully harness UAV-BS potential in communication networks (LIU; ZHANG; ZHOU, 2021), (MOZAFFARI et al., 2019a).

According to Figure 2.4, optimization of UAV-BS placement for energy efficiency involves diverse methodologies across traditional, machine learning, optimization algorithms, and hybrid strategies. Traditional approaches such as trial and error leverage heuristic-based strategies or grid-based searches to intuitively place UAV-BSs in ways that efficiently cover target areas, aiming to reduce energy consumption. Analytical methods, such as Optimization Models and Game Theory Models, employ mathematical formulations to precisely determine optimal UAV-BS placements considering factors like coverage, interference, and energy trade-offs. These methods strive to minimize energy consumption while ensuring effective communication coverage.

Machine learning-based techniques, including Supervised Learning (utilizing regression and classification models), Unsupervised Learning (employing clustering and anomaly detection), and Deep Learning (utilizing RNNs and CNNs), contribute significantly. These approaches learn from data patterns to predict energy usage, detect efficient spatial placements, or uncover complex spatial and temporal patterns for optimized UAV-BS deployment, thereby enhancing energy efficiency.

Reinforcement Learning, particularly via Markov Decision Processes, allows UAVs to learn optimal placement policies through interactions with the environment, aiming to minimize energy consumption while ensuring effective coverage. Optimization algorithms such as Greedy Algorithms and Metaheuristic Algorithms (e.g., GA, PSO, Simulated Annealing) explore search spaces to find near-optimal solutions that consider energy efficiency in UAV-BS placement.

Hybrid approaches integrate traditional methods with machine learning, offering a blend of mathematical precision and pattern recognition for optimal UAV-BS placement.

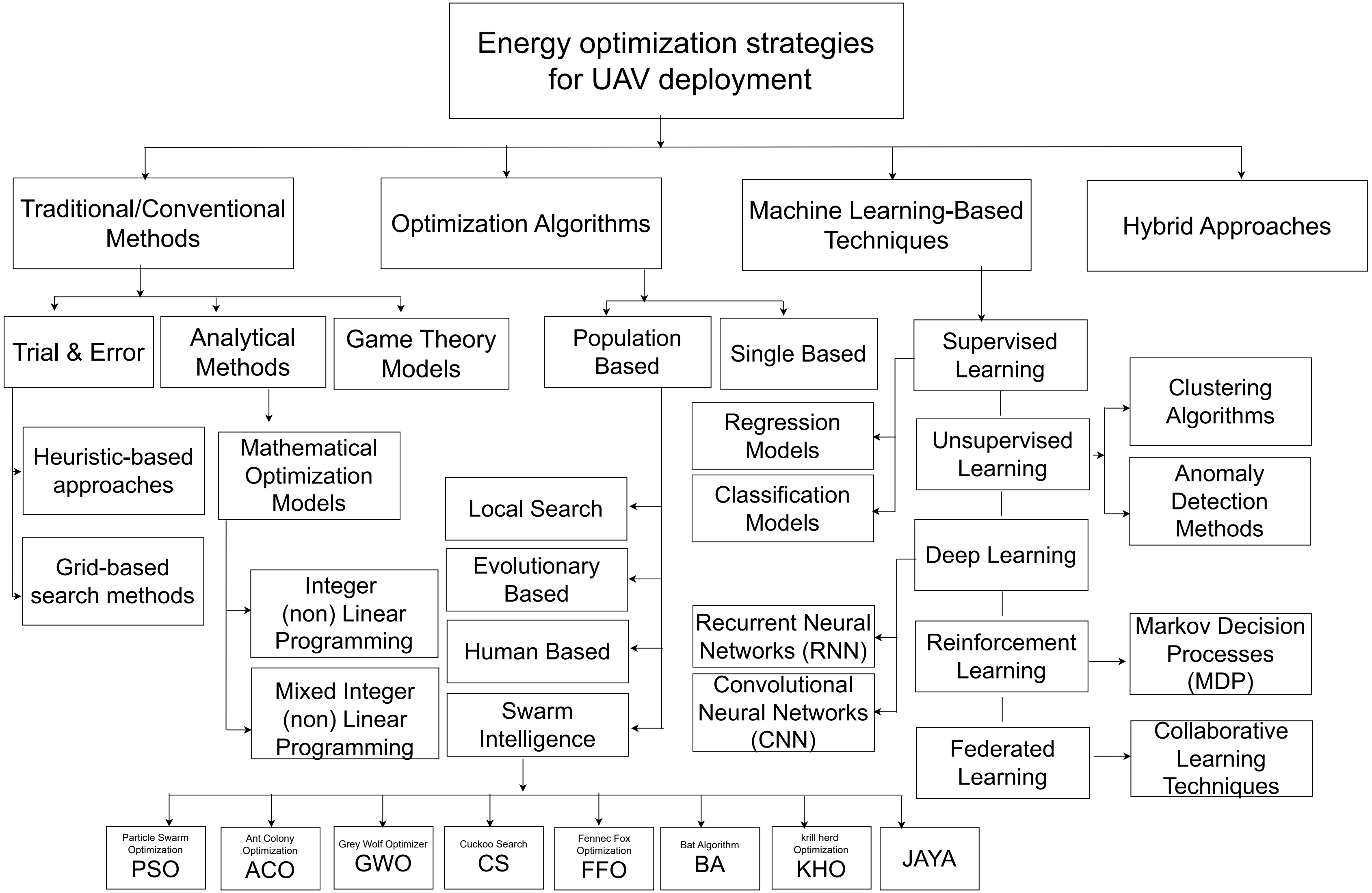


Figure 2.4 – A high-level overview of diverse approaches to optimizing energy in UAV-based communication systems.

2.2.1 Conventional Approaches: Analytical techniques

In this approach, a mathematical model is created that represents the problem, and the optimal solution is found by solving the mathematical equations using optimization techniques such as linear programming, integer programming, or nonlinear programming.

In (ALZENAD et al., 2017), authors propose the UAV-BS deployment in the horizontal dimension as a circle placement problem and a smallest enclosing circle problem. They consider two scenarios where the UAV-BS is placed in a 2D location and in a three-dimensional (3D) Location. The number of users covered and the power consumed in the BSs is 16 percent. However, this can limit the flying time of the UAV. In this paper the authors focus only on the power consumed in the BS, adopting the energy for efficient utilization. The UAV-BS can be rapidly deployed when a BS failure occurs because it can adjust to any kind of scenario to provide wireless. However, this should be deployed in an area where it can maximize the number of users covered. The solution that is achieved is to place the UAV-BS in a way that can cover a wide range of users while using less transmit power proposing a UAV-BS 3D method placement. The UAV is placed in a vertical way from his horizontal which will simplify any loss of optimality. Evaluating the proposed method for any levels of user heterogeneity, and saving power can lead to highly heterogeneous scenarios.

In (LI et al., 2019), the authors proposed the idea of UAV relay deployment for maximizing system energy efficiency in a Space-Air-Ground Internet of Remote Things (SAG-IoRT) network. In a SAG-IoRT network, because access to smart devices can not be reached by ground access networks because of strong conditions (deserts, forests, etc) the power consumption is limited, this is why the UAV helps connection directly with the satellites and cope with challenges for IoRT networks. Smart devices are also distributed in remote areas to monitor or sense but this cannot be served by ground access networks. The idea of this paper is to investigate the energy-efficient resource for the use of Space Air Ground Internet of Things and maximize the system energy by using some channels selection, power upLink transmission, and UAV deployment. They divide the main problem into two subproblems. In the first sub-problem, the optimal sub-channel selection and power control policy are obtained by given UAV relay deployment. In the second subproblem, UAV relay deployment policy is obtained based on the first sub-problem. Then, iterating two sub-problems to obtain the maximum system energy efficiency. The UAV perfect placement is given by the Lagrangian method and the UAV relays deployment by successive convex approximation (SCA).

UAV-BSs can tilt their directional antenna at an adjustable angle to serve the GUs, however, a UAV-BS has a limited amount of available onboard power. In (YOU et al., 2020), the authors propose an energy-efficient 3D positioning to reduce the total energy consumption (TEC) of the UAV-Bs that is the energy required by a UAV-BS to move from its point of origin to its 3D destination and complete the provision of data services to all GUs in a given area. TEC includes propulsion power and communication power. The authors solve the 2D placement problem using the gradient descent method (GDA) The proposed simulation shows that the GDA performs quite similarly to the comprehensive 2D search strategy in finding the ideal UAV BS placement. Also compared to benchmark methods, the proposed antenna tilting approach leads to significant energy savings. Extending a system model to operate with multiple UAV-BS and considering the different wireless channel conditions/variations and a UAV-BS trajectory problem removes some limitations of the idea that optimal 3D placement requires different throughput requirements and GU densities.

In (WANG; HU; CHEN, 2020), the authors examined the energy efficiency of a DBS that provides wireless coverage for ground users (GUs). They formulate a DBS placement problem that minimizes the average transmit power of the DBS. The influence of the elevation angle on the additional path loss of the Air to Ground (AtG) connection is introduced using the statistical path loss model. They first, consider a case where the DBS allocates the same transmit power to each user. Then a decoupling-based placement algorithm is proposed to get the optimal DBS location. Further, if the case is considered without assuming the same transmit power for each user, an SCA-based DBS placement algorithm is proposed to obtain the DBS location. Simulation results show that increasing the drone altitude can achieve the line-of-sight spread (LoS) advantage of the AtG connection, resulting in power savings from the proposed algorithms. DBSs are extremely helpful for various scenarios. In the event of an emergency, the ground base station may become overloaded due to an increase in the number of users over time. It is difficult to provide the ground infrastructure in a short time. A DBS can serve as an air access point to serve these transient users.

In (BABU; PAPADIAS; POPOVSKI, 2020), the authors propose to place multiple Air Access Points (AAPs) in the target area in an energy-efficient manner and serve as an airborne base station for uplink communications from a variety of UEs. Analytically, the inter-cell interference and the energy consumption of the AAPs are taken into account to determine the ideal energy-efficient vertical position of the AAPs worldwide. The energy-efficient flight altitude of AAPs is determined and the multi-level regular polygon-based placement method is used to solve the optimal horizontal placement problem; it is presented as a circular packing problem for maximum packing density. Finding the ideal vertical positioning of the AAPs can be decomposed into identical and separate vertical positioning challenges for individual AAPs when considering AAPs with non-overlapping coverage areas. Since the problem of vertical positioning of the independent AAPs has been solved, all AAPs will float at an energy-efficient height. Here they consider an uplink orthogonal communication between the associated AAP and the UEs. Future research will expand the study to include downlink UAV communications with non-uniformly distributed UEs and full coverage of the required range through carefully managed overlap across AAP coverage areas.

Using UAV in AtG communication currently poses two main problems: energy consumption, and the jitteriness of the UAVs, which could be caused by airflow and body vibration of the UAV. Authors in (WU et al., 2020) investigate secure communication in a secured downlink AtG communication system using UAV-BS, with consideration of security, energy consumption, and the impact of UAV jitter. In this paper, the BS is set to simultaneously transmit a secured signal ("legitimate signal" as in the paper) to a legitimate user and artificial noise signal to an eavesdropper. To achieve better power consumption while still maintaining security, a joint beamforming design for both signals is formulated as a non-convex optimization problem. For the worst-case scenario of UAV jittering, constraints such as the minimum data rate of the secured channel being above a given threshold and the maximum data rate of the eavesdropping channel being below the other threshold, are considered. The experimental results demonstrate the impact of key system parameters on power saving under secure transmission requirements and UAV jitter.

Traditionally, UAV-based communication has been impacted by weather conditions. Authors in (MUTHANNA et al., 2022) propose a new approach for positioning and path planning of UAV to improve the QoS, reliability, and energy efficiency in UAV communications with consideration of the impact of the weather. A Cerebral Long Short-Term Memory (C-LSTM) model is utilized to predict weather conditions, then cell-based partitioning of emergency areas is carried out, and the A3C algorithm is used to decide the number and position of UAVs for optimal coverage and minimal transmission power. The path planning of UAVs is optimized using the Mayfly Optimization Algorithm (MOA). The proposed approach is evaluated using performance metrics such as coverage ratio, cell coverage, delay, path gain, number of collected packets, UAV transmit power and energy consumption. The results of the evaluation demonstrated its efficiency in improving the performance of UAV communications in adverse weather conditions.

Authors in (GUO et al., 2022), propose UAV-BS location optimization to deliver the required minimum bit rates to the GUs. They divide the 3D location optimization problem into two subproblems, the horizontal coordinates and the height optimization subproblem. The authors optimize the horizontal coordinates by using the CVX toolbox and converting the height optimization subproblem into the elevation angle optimization problem. In this paper, authors took the average of the sum of the transmission rate of ground node (GN) and provide the same Bit rates to all GN in the range of UAV-BS.

In (MARANI; MIRREZAEI; MIRZAVAND, 2023) authors cover two types of users, in this paper author increases the coverage area and rate for Downlink Users(DU) by randomizing their movement using Gauss-Markov random moment and using Rayleigh fading communication channel for the D2D Transmitter Receiver pair. To achieve the requirements, the author calculates the maximum radius for the drone using a new method based on the Global Positioning System (GPS) and then they calculate the optimal position for the drone using a non-real-time algorithm. It is assumed that drones know the location of users in advance therefore using this the optimum position of UAV is achieved.

In (IQBAL; AHMAD; KALEEM, 2022) authors propose a method to optimize the power consumption of drones in disaster-stricken areas to increase the performance time using relay drones. In this paper, the working BS is to be assumed to be placed at 10x times the range of the Observation UAV (O-UAV) (drone covering the area) such as if O-UAV can cover 500m then the BS is located at 5000 m. Therefore to optimize power consumption, Relay UAV (R-UAV) is placed between

O-UAV and BS, here author proposed the method for optimal R-UAV placement. The authors assume that the link rates of O-UAV and R-UAV are equal to the link rates of R-UAV and BS, thus allowing them to convert the non-convex optimization problem into a convex optimization problem. This problem is then solved using the Interior point polynomial algorithm, and after the simulation, it is shown that using an optimized R-UAV position the power consumption can be reduced thus increasing the flight time of UAV over the area.

2.2.2 Conventional Approaches: Heuristic and Methaheuristic-based approaches

Metaheuristic-based approaches are problem-solving techniques that use iterative search algorithms to find optimal or near-optimal solutions to UAV placement optimization problems. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Cuckoo Search (CS), and Ant Colony Optimization (ACO) are powerful problem-solving techniques that can be used to solve the UAV-BS placement problem (PASANDIDEH et al., 2022; PASANDIDEH et al., 2023a).

In (PASANDIDEH et al., 2023a), the authors propose an improved PSO algorithm to solve the DBS placement problem. They provide a MINLP formulation problem in which the DBSs location and the optimal number of DBSs are jointly obtained using the proposed method which is based on the integration of PSO and K-means algorithms. A custom communication protocol (CCP) is also proposed for data exchange between the UEs and the network controller. The proposed algorithm provides a low latency and packet loss rate of UEs while maximizing UE coverage. However, the presented mathematical model overlooks the power consumption aspect of the UAV-BSs, and the examined scenarios are confined to a restricted number of UEs.

In (YU et al., 2022), authors introduce the backhaul aware bandwidth allocation and DBS placement (BROAD) algorithm, utilizing GA to allocate available bandwidth to UEs and determine the placement of UAV-BSs considering LOS communication with the Macro Base Station (MBS). The authors propose to use Free Space Optic (FSO) as a backhaul solution between UAV-BS and MBS. According to (YU et al., 2022), using UAV-BS with the usual backhaul in a disaster-stricken area where MBS is more than 10 km away will result in low link capacity. FSO offers data rates from Gbps to Tbps over several kilometers. However, maintaining accurate optical alignment between the FSO transmitter at the MBS and the FSO receiver at the UAV-BS is challenging due to potential UAV-BS movement and vibration in the air. While high-precision Acquisition, Tracking, and Pointing (ATP) systems ensure alignment, their weight accelerates UAV-BS battery drainage. To address this, the authors suggest employing Simultaneous Wireless Information and Power Transfer (SWIFT) technology for FSO.

In (LAI; CHEN; WANG, 2019), the authors model the UAV-BS placement problem as a knapsack problem in the area with respect to the network traffic requirements and UE density in the area, unlike other methods that try to cover the maximum area using UAV-BS. In the proposed algorithm, which is designed based on the concept of the GA, the authors have suggested different network ranges of drones with respect to user equipment (UE) density providing them with guaranteed data rates and reducing the transmission power. The proposed density-aware 3D UAV-BS placement algorithm selects three random UEs and then obtains the circumference which is the range of UAV-BS. The smaller the area higher bit rates are provided to the UE.

The findings of (ISLAM et al., 2022) reveal that the proposed solution effectively predicts vehicle traffic patterns to optimize UAV height settings. This article employs the PSO algorithm to determine the optimal UAV deployment positions across the entire network, taking into account factors such as vehicle density, heading direction, and prior coverage data. Subsequently, PSO is iteratively applied to ascertain the ideal number of UAVs needed to meet a predefined network coverage threshold. The simulation results demonstrate that the proposed scheme, known as the collaborative network coverage enhancement scheme (CONEC), significantly enhances vehicular ad-hoc network (VANET) performance in terms of key metrics including packet delivery ratio (PDR), hop counts (HOPs), end-to-end delay (EED), and throughput when compared to its counterparts.

Authors in (SHAKHATREH et al., 2021) formulate the problem of optimal placement of UAVs as air base stations to maximize the total throughput of wireless devices. Authors find the location of the UAVs, using PSO algorithm, then the total throughput of the UAVS is achieved using three different approaches, (1) the equal power allocation approach, (2) the water filling approach, and (3) the modified water filling approach. Authors in (ABU-BAKER et al., 2023) also use the PSO and GA for clustering wireless sensor networks (WSNs), and for optimal search with the aim of increasing battery life, respectively.

In (OUAMRI et al., 2022), the authors address the challenge of UAV placement utilizing the GWO algorithm. The primary goal of their research is to optimize coverage. The study presents simulation results for a scenario involving 10 UAVs and 200 UEs, yielding a reported coverage rate of 85%. However, the authors overlook the significant factors of the blocking effect and overlap between drones, which are crucial considerations for effective handoff mechanisms.

In (MANDLOI; ARYA, 2023), the authors explore the optimal utilization of UAVs in scenarios characterized by damaged environments or lacking communication infrastructure. While the primary focus is on determining the ideal quantity of UAVs, the model encompasses several distinct stages, with the optimal deployment and placement of these UAVs representing key objectives within the research. This paper delineates three crucial steps: the application of the k-means technique, formulation procedures, and the utilization of a fuzzy-based genetic algorithm. Since metaheuristic methods are utilized, an outline of studies employing metaheuristic approaches to optimize power consumption in UAV-based communication systems is provided by Table 2.2. The proposed method, illustrated in Table 2.2, considers all these specified objectives.

Table 2.2 – Summary of key characteristics in metaheuristic-based studies

References	Methods	Coverage	Connectivity	Energy	Latency
(PASANDIDEH et al., 2023a)	PSO	✓	✓		✓
(YU et al., 2022)	BROAD (Heuristic)	✓	✓		
(LAI; CHEN; WANG, 2019)	GA	✓	✓	✓	
(ISLAM et al., 2022)	PSO	✓			✓
(SHAKHATREH et al., 2021)	PSO	✓	✓		
(ABU-BAKER et al., 2023)	PSO + GA			✓	
(OUAMRI et al., 2022)	GWO	✓			
This work	JAYA	✓	✓	✓	✓

2.2.3 Learning-based approaches

ML-based approaches can also be used to solve UAV placement optimization problems. In this approach, ML techniques such as Supervised and Unsupervised Learning, Deep Learning (DL), and Reinforcement Learning (RL) are trained on historical data to learn patterns and make predictions about optimal UAV placement strategies.

In (NOH; JEON; CHAE, 2020), authors propose an ellipse clustering algorithm for optimizing the deployment of UAVs as base stations. The algorithm maximizes user coverage probability and minimizes transmit power to lower inter-cell interference by adjusting its antenna half-power beamwidth, orientation, and 3D location to minimize path loss for cell-edge users. As simulations were carried out, the results demonstrated that when compared to conventional algorithms, such as the circle-packing approach, the proposed solution can achieve high system throughput and coverage while using less transmit power. This allows an efficient deployment of multiple UAVs while maintaining QoS for the users.

The challenge regarding UAV base station positioning increases when the UAVs are forced to change their heights, which can affect channel conditions and coverage. In (SHAKOOR et al., 2021), authors address this problem by jointly optimizing UAV positioning and path-loss compensation factor, which can maximize coverage in uplink transmission. Path-loss compensation factor is also optimized for different heights of UAV deployment. Simulation results demonstrate that this approach improves both range and throughput.

In (LIU et al., 2018), authors propose a novel highly energy-efficient Deep Reinforcement Learning (DRL) method for controlling a group of UAV base stations while maintaining coverage and connectivity. This DRL-based method is called DRL-EC3. This proposed method considers communication coverage, fairness, energy consumption, and connectivity to maximize a novel energy efficiency function. The environment and its dynamics are learned, then decisions can be made with the help of two deep neural networks. Simulations have been carried out and show that the proposed method outperforms two commonly used baseline methods.

In (MOUSTAFA; ALYAHFOUFI; ABBAS, 2022), the authors present an advanced multi-UAV deployment algorithm designed to optimize power efficiency while minimizing latency. The intended application is within a hazardous industrial area measuring 40m by 40m, where the algorithm aims to establish communication with 20 randomly distributed IoT devices. Unlike prior studies that focused on singular UAV systems or a limited number of IoT devices, this paper targets the deployment of the fewest energy-efficient UAVs necessary to efficiently communicate with a larger set of IoT devices. The investigation encompasses metrics such as the quantity of UAVs required, energy consumption per UAV, and the needs of the IoT devices, considering each as individual parameters. To tackle this challenging optimization problem, the study introduces a real-time methodology that leverages k-means clustering and a novel activity selection algorithm. These innovative approaches collectively address the NP-hard nature of the optimization problem, offering a promising solution for practical deployment in complex environments. In in (LIU et al., 2022), a Proximal Stochastic Gradient Descent (ProxSGD) based algorithm proposed for optimizing UAV placement in a wireless cellular network scenario, considering Ground-to-Ground (G2G) and A2G access links. The primary objective is to maximize fair coverage while minimizing energy consumption, and adhering to backhaul and bound constraints. Evaluation metrics include region coverage ratio, fairness index, and energy usage. The algorithm is tested in a rectangular region with 106 BSs and 10201 ground samples. Monte Carlo simulations placed UAVs randomly, revealing that the coverage versus average energy consumption converges optimally with 175 UAVs. Validation is confirmed through the incremental increase in the region coverage ratio, affirming the optimization's validity. ProxSGD's efficiency was then compared with Simulated Annealing Algorithm (SAA), GA, and PSO, demonstrating superior convergence speed over these algorithms.

In (QI et al., 2022), authors propose a resource allocation strategy in the UAV-assisted vehicular network that also handles spectrum sharing. Factors that affect QoS and energy efficiency such a content placement, spectrum allocation, co-channel link pairing, and power control are optimized in this study. The authors consider a scenario where a UAV can transmit cached content files to vehicular users over UAV-to-vehicle (U2V) links. Simultaneously vehicle-to-vehicle (V2V) links can reuse the U2V spectrum for safety-critical message exchanges. UAVs are assumed to be static and on a fixed altitude. In a realistic scenario, this is rarely the case. However, it is formulated as a MINLP problem that is then solved by the utilization of both a Hungarian Algorithm and a DDQN. The Hungarian Algorithm is employed to improve the convergence speed of the DDQN. Evaluation metrics include UAVs energy efficiency in scenarios such as different numbers of vehicles, maximum transmission power for U2V-UEs, and different weight values. Additionally, the change in Q values is also used to evaluate the RL methods. They were able to significantly improve the energy efficiency of their UAVs while proving the Hungarian Algorithm significantly speeds up the convergence as compared to a traditional DQN method.

In (SUN et al., 2023), a UAV-Net+ is introduced to deploy and schedule a set of UAV Base Stations. UAV-Net+ can provide high-quality connectivity while accounting for dynamic traffic demands and UAV path planning that considers the energy constraints. A 3D terrain is divided into a set of grid cells where the model runs a Ray Tracing simulation to obtain Signal-to-noise ratio (SNR) values. These are used to create a 3D SNR heat map. Since it is sensitive to a few centimeters of error, the region is then further divided into a set of chunks whose size is larger than a grid cell. The chunks are then selected by the next algorithm. A 3D convolutional DRL-based Chunk Selection algorithm selects an optimal subset of chunks to determine a small search space for UAVs. Then the energy-aware DRL-based Chunk Search Algorithm considers the impact of multiple factors to determine the long-term benefits of different task choices. This is then used to plan the paths that can cover all the selected chunks to complete certain tasks. These tasks include SNR measurements, providing network services and efficiently recharging. Effective Throughput is introduced as an evaluation metric that selects grid cells that can provide a higher throughput to each client as a candidate for UAV base station placements. The algorithms intend to maximize the effective throughput for each grid and select the chunks according to this metric. It is NP-hard and greedy. These algorithms are verified in a real-world environment namely Beijing Happy Value and it was found that UAV-Net+ outperforms similar models.

Table 2.3 summarizes the main aspects of the revised relevant related work.

Table 2.3 – Summary of main characteristics of some of related studies

Reference	Addressed Problem	Centralized?	Proposal
(Akram et al., 2020)	To minimize UAV-BSs while maximizing served users	no	Classical Branch and Bound search (RINS)
(Zhong et al., 2020)	To maximize users' data-rate requirements	no	Genetic algorithm (GA)
(Cicek et al., 2020)	To maximize network profit (throughput, latency, coverage)	no	Golden Section Search (GSS) algorithm
(Chaalal; Reynaud; Senouci, 2020)	To maximize users' coverage	no	Social Spider algorithm
(Guo et al., 2019)	To maximize spectral efficiency of the system	no	Deep reinforcement learning algorithm (DQN)
(TAREKEGN et al., 2022)	To maximize communication coverage and network connectivity	yes	Deep reinforcement learning (DRL)
(WANG et al., 2022)	On-demand coverage with minimum power consumption	yes	Centralized multi-agent Q-learning
(DAI et al., 2022)	Optimize coverage and utility	no	Multi-agent collaborative environment learning
(WU et al., 2022)	To maximize average spectrum efficiency	no	Federated multi-agent deep deterministic policy gradient (F-MADDPG)
(ALFAIA et al., 2022)	To improve service quality in regions supported by UAV-BS	no	Prediction machine learning algorithm
(Bozkaya; Canberk, 2020)	To maximize covered users and communication quality	yes	Nearest neighbour weighted interpolation method
(Pan et al., 2019)	To maximize data rate utility among overall users	yes	Successive convex optimization (SCO) and modified ADMM techniques
(Pan et al., 2018)	To maximize number of covered users	yes	Bisection search and CCCP methods
(Vashisht; Jain; Mann, 2019)	To provide continuous connectivity between various UAVs	yes	Grey Wolf Optimizer (GWO)
(PASANDIDEH et al., 2023a)	To provide maximum user coverage with minimum latency and packet loss	yes	Improved k-means based PSO algorithm
This work	To provide maximum connectivity and minimum power consumption	yes	Improved k-means based JAYA algorithm

2.3 Challenges and complexities involved in optimizing UAV-BS placement

UAV-BS placement problem is a challenging research issue that requires further investigation. Currently, there are several challenges and potential future research directions for addressing this problem that are shown in Figure 2.5.

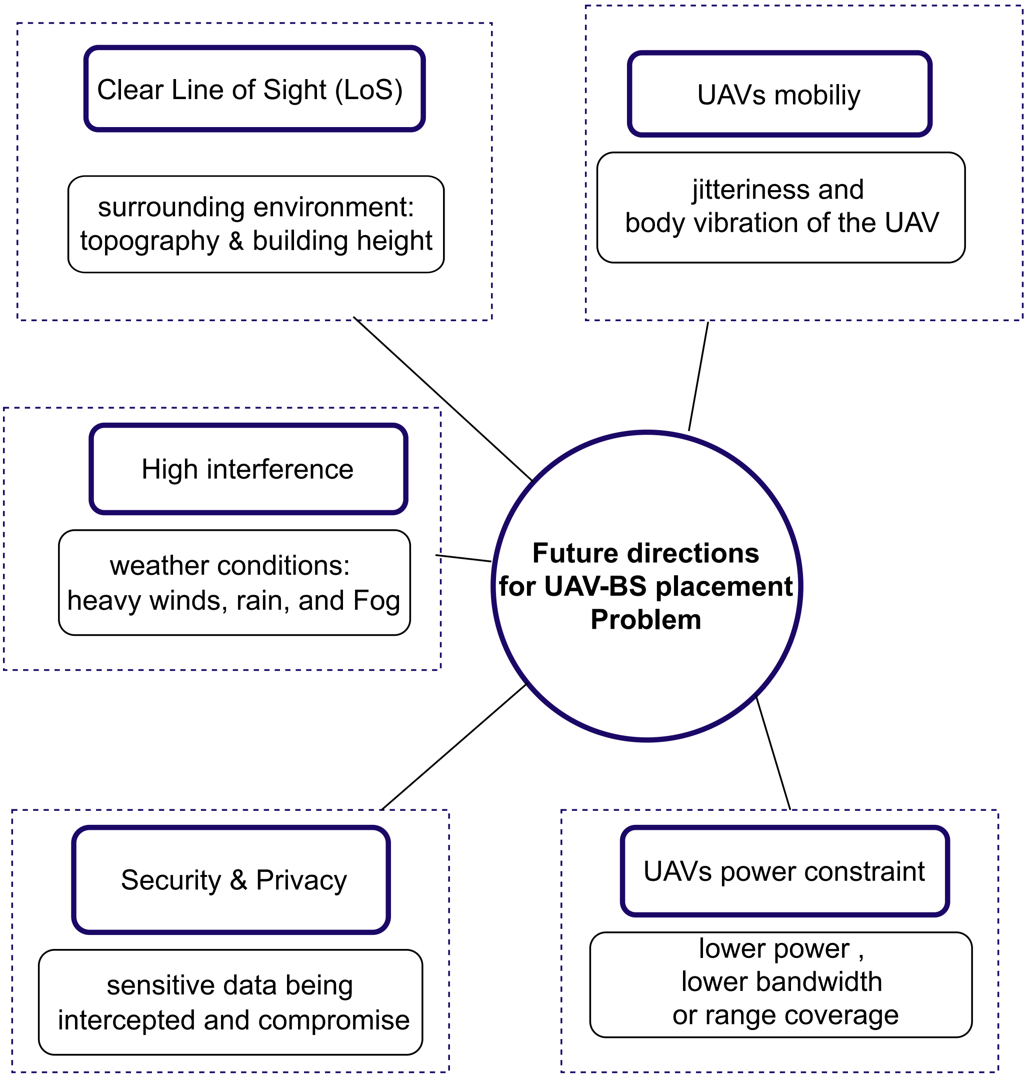


Figure 2.5 – Future research directions for UAV-BS placement problem

One main challenge is ensuring a clear LoS between the devices. Since UAVs usually operate at high altitudes, there can be multiple obstructions such as buildings, trees, or other tall structures that can interfere with the LOS, which leads to connectivity issues (GAPEYENKO et al., 2021). Therefore, the base station placement problem should consider the surrounding environment, including topography and building height.

Another challenge is high interference among nodes. The frequency bands used for UAV communication may be crowded with other wireless devices, especially in urban areas, leading to interference and signal degradation. Not only wireless devices, but weather can also be a source of interference. Harsh weather conditions such as heavy winds, rain, and fog can interfere with communication and cause connectivity issues (MUTHANNA et al., 2022). The base stations therefore should be designed to minimize the impact of wireless interference as well as harsh weather conditions.

In addition, another challenge is the mobility of the UAVs themselves. UAVs are mobile and can move quickly from one point to another, therefore it can be challenging to provide good coverage. The nature of flying UAV can also lead to jitteriness caused by airflow and body vibration of the UAV (WU et al., 2020), which should be taken into account.

In addition to these challenges, power constraint is another major difficulty. UAVs have limited battery life, which means that the UAV-BS must be designed to operate on low power consumption. It can be challenging because low-power communication technologies may not have the necessary bandwidth or range coverage required for effective communication (WANG; HU; CHEN, 2020).

The placement of UAV base stations can have significant security and privacy implications. Therefore, it is essential to consider security and privacy concerns when designing placement algorithms (RODRIGUES et al., 2019). Unauthorized access to the UAV's communication can lead to sensitive data being intercepted and compromised. This is a matter of grave concern if the UAV-BS is being deployed in critical applications such as security, surveillance, or defense.

3 SYSTEM MODEL

Within this chapter, a detailed exploration of the network model delineated in Section 3.1 is embarked upon. This model serves as the foundational framework for the subsequent analysis and evaluations conducted in this study. It encapsulates the intricate interconnections, node behaviors, and communication protocols essential to comprehending the dynamics of UAV-assisted networks. Section 3.1.1 elucidates the primary assumption that underlies and drives the investigation undertaken in this research. This assumption acts as a guiding principle, shaping the direction of the study and influencing the subsequent methodologies employed.

Section 3.1.2 represents a critical segment wherein various mobility models applicable in UAV-assisted networks are systematically delineated. Each model's distinct characteristics, advantages, and limitations are scrutinized to underscore the rationale behind the selection of the random walk mobility model for this study. The inherent stochastic nature and adaptability of the random walk model align closely with the dynamic nature of UAV-assisted networks, making it a suitable choice for simulating realistic user mobility patterns. Furthermore, a comprehensive justification for opting for this specific mobility model is presented, emphasizing its relevance and applicability to the research objectives.

Concluding this in-depth exploration, Section 3.2 provides an exhaustive explanation encompassing both historical and contemporary mathematical optimization models proposed for addressing placement challenges in UAV-assisted networks. This section meticulously dissects the objective functions and constraints embedded within these models. It offers detailed insights into their operational mechanisms, shedding light on the evolution of optimization strategies from earlier proposals to current methodologies. Additionally, it examines the efficacy of these models in addressing the complexities inherent in optimizing UAV-BS placements, thereby providing a comprehensive understanding of their strengths and limitations within varying network contexts.

3.1 Network Model:

The problem of determining the optimal positions remains an ongoing challenge, UAV-BSs are commonly referred to as the placement problem, which this study investigates. The network model comprises multiple low-altitude UAV-BSs and a group of mobile UEs within an environment designed to simulate a dynamic flying ad-hoc network. The mobility pattern of the UEs is governed by the Random Walk mobility model, characterized by a varying speed range, reflecting the unpredictable movement patterns akin to real-world scenarios.

Throughout the performed simulation, which comprises 10 discrete time steps (T=10), each representing a unit of time, computations are performed and UAV-BS placement is dynamically adjusted in response to evolving UEs positions and requirements. This ensures that the placement of UAV-BSs accurately reflects real-world scenarios, effectively capturing the dynamic mobility of UEs. For instance, at time0, one unit of time is considered, with subsequent times representing increasing duration. The time step increment, dt=1, denotes the duration of each step, commonly expressed in seconds, minutes, or other relevant intervals. Considering a flight duration constraint of 20 minutes for UAVs equipped with batteries lasting between 15 to 30 minutes, the 2-minute time unit proves pivotal for realistic flight operations, aligning with the limited mobility of commercial UAVs. This constraint facilitates practical simulations wherein users engage in data transfer operations within these constrained flight windows.

An important scenario demanding adaptability, reliable connectivity, and minimal latency occurs within 6G networks during natural disasters, such as severe storms. This situation showcases the utilization of UAV-BSs as macro cells, operating as 5G and beyond infrastructure, especially in areas that have incurred damage, as depicted in Figure 3.1. The illustration in Figure 3.1 demonstrates that terrestrial Base Stations (BS_k) might become inoperative due to equipment damage or power issues. In such cases, UAV-BSi can be deployed at $(x_{i,t}^{\mathrm{UAV-BS}}, y_{i,t}^{\mathrm{UAV-BS}}, h_{i,t}^{\mathrm{UAV-BS}})$ at time t. This deployment serves to enhance relief efforts and amplify radio communication capacities for UE_j situated at $(x_{j,t}^{UE}, y_{j,t}^{UE})$ within the radius of UAV-BSi, which measures $R_t^{\mathrm{UAV-BS}}$ at time t. The coordinates $(x_{i,t}^{\mathrm{UAV-BS}}, y_{i,t}^{\mathrm{UAV-BS}}, h_{i,t}^{\mathrm{UAV-BS}})$ are determined using an optimization model for placement. Additionally, the optimization model includes essential variables such as $\theta_{i,j,t}^{\mathrm{UE}}$, representing the elevation angle between $\mathrm{UAV\text{-}BS}_i$ and UE_j at time t, and $dist_{i,j,t}^{UAV-UE}$, which denotes the distance between UE_j and the projection of $\mathrm{UAV\text{-}BS}_i$ on the X-axis at time t. As BS_k is non-operational, there exists no backhaul link between UAV-BSi and BS_k. At this moment, $\mathrm{UAV\text{-}BS}_i$ directly communicates with UE_j at time t using an access link.

In a UAV-BS placement formulation, the elevation angle, $\theta_{i,j,t}^{\mathrm{UE}}$ between UAV-BS$_i$ and UE$_j$ significantly affects both the path Loss and data rate Constraints within the model. The path loss between the UAV-BS and UE is influenced by the elevation angle, with smaller angles generally resulting in reduced path loss due to improved line-of-sight conditions. Consequently, the path loss constraint in the model may vary depending on the elevation angle, potentially allowing for more flexible placement of UAV-BSs to meet desired signal strength requirements. Moreover, the elevation angle impacts the achievable data rate between the UAV-BS and UE, as it affects the signal strength and quality. Higher elevation angles typically lead to higher data rates due to stronger signal reception. Therefore, the data rate constraint in the model may also be influenced by the elevation angle, potentially enabling optimization of UAV placement to ensure adequate data rate coverage across the network. Incorporating elevation angle considerations into the UAV placement formulation allows for more accurate modeling of path loss and data rate constraints, ultimately leading to improved performance and efficiency in UAV-BS deployment.

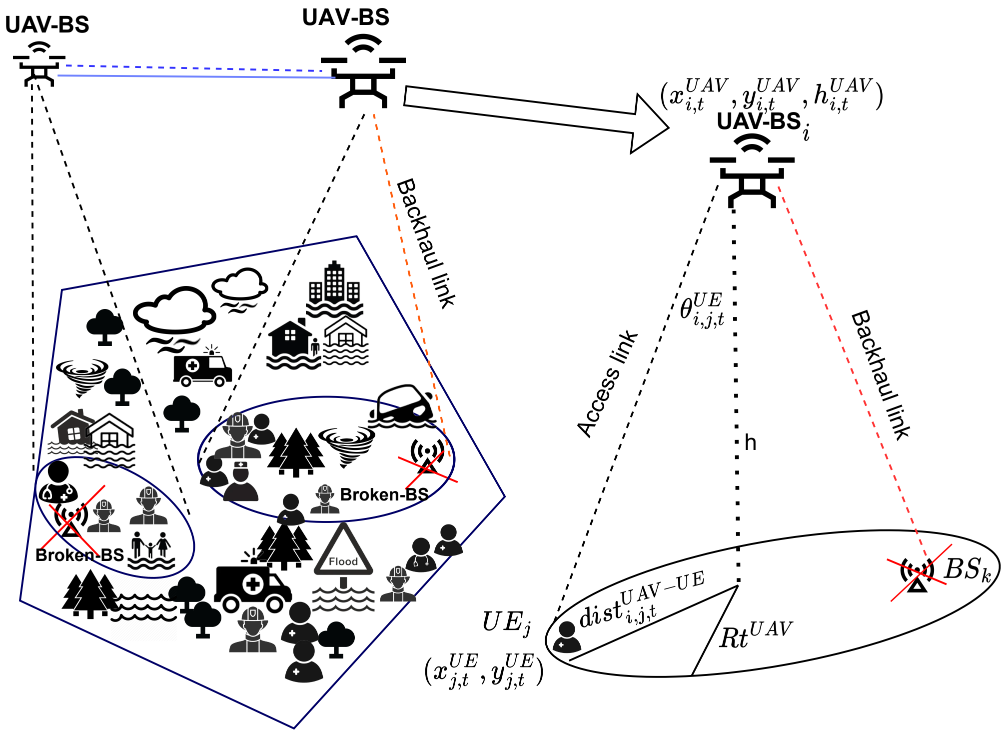


Figure 3.1 – The deployment of UAV-BSs as resilient infrastructure in 6G networks during natural disasters.

3.1.1 Main assumption:

Below are the refined assumptions outlined in the proposed work:

- The operational environment for the UAV-BSs spans across an area of 2 square kilometers.
- UAV-BSs possess varied communication ranges (R_t^{UAV}) and capacities.
- The data requirement rate for UEs varies at each time step, determined randomly for each UE.
- Each node (comprising UAV-BSs and UEs) is assigned a unique identifier for network distinction.
- All UEs maneuver based on a Random Walk mobility model, with speeds ranging from 5 to 100 km/h.
- The communication setup assumes direct single-hop communication between UEs and UAV-BSs.
- Vertical speed of UAV-BSs is assumed to remain unaffected by wind speed and direction.
- Ground Base Stations (GBS) and the backhaul links between UAV-BSs and BSs are not considered in this context.

Table 3.1 show the list of notations used in this work and the problem optimization formulation.

3.1.2 UEs mobility model:

In UAV-assisted networks, user mobility models simulate the movement patterns of users or devices within the network. These models are crucial for understanding and predicting the behavior of users, which is essential for designing efficient network protocols and algorithms. Several user mobility models are used in UAV-assisted networks (BOUVRY; THOMAS, 2005; BISWAS; TATCHIKOU; DION, 2006; AKYILDIZ; WANG; WANG, 2005), including:

Table 3.1 – Summary of sets, parameters, variables

Abbreviation	**Description**	**Values**
Sets		
I, J, T	Set of UAV-BSs, Set of UEs, Set of Times	$\{2, 3, 5, 10\}$, $\{50, 75, 150\}$, $\{1, 2, ..., 10\}$
Scalars		
w_1/w_2	Weight coefficients ($w_1 + w_2 = 1$)	$0.5, 0.5$
dt, P_c	Time step, Circuit power	1, $56W$
P_0, P, U_{tip}	Constant P_0, Transmit power, Tip speed	38 dBm, 200
V_0, ρ, τ_t	Mean rotor induced velocity, Air density, Normalized traffic load	7.2, $1.225\,\mathrm{kg/m^3}$, 1
η, Ω, R	Amplifier Efficiency, Blade angular velocity, Rotor radius	2.6, $400\,\mathrm{rad/s}$, $0.5\,\mathrm{m}$
A, W, T	Rotor disc area, UAV-BS weight, Rotor thrust	$0.79\,\mathrm{m}^2$, $100N$, 100
c, C_r, s	Blade length, Thrust coefficient, Rotor solidity	0.0196, 0.001195, 0.05
$x_{\mathrm{Min}}/x_{\mathrm{Max}}$, $y_{\mathrm{Min}}/y_{\mathrm{Max}}$, $h_{\mathrm{Min}}/h_{\mathrm{Max}}$	Min/Max coordinates in area	$0 - 2000$m, $0 - 2000$m, $0 - 1000$m
S_{FP}, $\widetilde{k}$	Fuselage area, Thrust-to-weight ratio	$0.0118\,\mathrm{m}^2$, 1
Parameters		
V_t^{Wind}, θ_t^{Wind}	Wind speed, Speed angle	-
$x_{i,t}^{UAV-BS,initial}$, $y_{i,t}^{UAV-BS,initial}$, $h_{i,t}^{UAV-BS,initial}$	Initial coordinates and altitude	-
P_i, $B_{i,j}$, $P_{i,j}$	Constants, Bandwidth, Transmit power	-
R_t^{UAV}, $x_{j,t}^{UE}$, $y_{j,t}^{UE}$	Coverage radius, UE coordinates	$400 - 500$m, $0 - 2000$m, $0 - 2000$m
Variables		
$V_{i,t}^{Vertical}$, $V_{i,t}^{Horizontal}$	Vertical and horizontal speeds	-
$P_{i,t}^{Vertical}$, $P_{i,t}^{Horizontal}$	Power consumption	-
$V_{i,t}^{X}$, $V_{i,t}^{Y}$	Horizontal speed in axes	-
$x_{i,t}^{UAV-BS}$, $y_{i,t}^{UAV-BS}$, $h_{i,t}^{UAV-BS}$	Coordinates and altitude	-
$P_{i,t}^{Total}$, $dist_{i,j,t}^{UAV-UE}$	Total power consumption, Distance	-
$\theta_{i,j,t}^{UE}$, ${}_{i,j,t}^{UE}$	Elevation angle, Data rate requirement	-
Binary Variables		
I_i^{UAV-BS}, $I_{i,j,t}^{UE}$	UAV-BS location, UE association	$\{0, 1\}$

- *Random Waypoint Model:* Users move randomly within a defined area. They randomly select a destination and move towards it at a constant speed. Once they reach the destination, they pause for a certain period before selecting a new destination.

- *Gauss-Markov Mobility Model:* Users move based on a correlated random process. It incorporates both randomness and correlation in mobility by considering the previous position and velocity of the users.

- *Group Mobility Model:* It simulates the movement of users in groups or clusters. Users within the same group move together, possibly following a certain pattern or behavior.

- *Nomadic Community Mobility Model:* This model represents users' movements in a way that captures the behavior of communities or groups of users who frequently move together but might occasionally split or merge.

- *Random Walk Model:* It is a widely used mobility model in network simulations, emulates user movements within a specified area by employing a two-step process. Initially, users choose random destinations within the designated area, setting the direction and speed to reach these points. They traverse the space at a consistent pace until reaching the targeted destination. Upon arrival, users pause for a predefined duration before selecting a new random destination to proceed towards, restarting the cycle. This model's simplicity allows it to capture diverse movement patterns, including abrupt changes in direction and velocity, reflecting real-world scenarios where users navigate randomly within a defined space, making it valuable for evaluating network protocols and algorithms in UAV-assisted networks.

Each model has its own characteristics, advantages, and complexities. The choice of a particular mobility model in a UAV-assisted network depends on various factors such as the application scenario, required simulation accuracy, and the level of detail needed in modeling user movements.

The Random Walk Model is selected in this study for UEs due to several reasons:

- Realistic Representation: It provides a simple yet more realistic representation of random movement patterns exhibited by users in certain scenarios.

- Simulation Flexibility: The model is flexible and straightforward to implement, making it suitable for simulating a wide range of user behaviors.

- Captures Unpredictability: In certain situations, such as in urban environments or crowded areas, users might not follow predefined paths but instead move in unpredictable ways. The Random Walk Model can simulate such behavior effectively.

Figure 3.2 shows the initial distribution of the UEs at time 0. Additionally, Figures 3.3, 3.4, and 3.5 illustrate the movement paths of UEs 4, 10, and 26 across 10 discrete time steps, utilizing the Random Walk mobility model. This model is distinguished by a fluctuating speed range spanning from 5 to 100 kilometers per hour. Additionally, the movement trajectories of all UEs involved in each experiment are accessible for analysis.

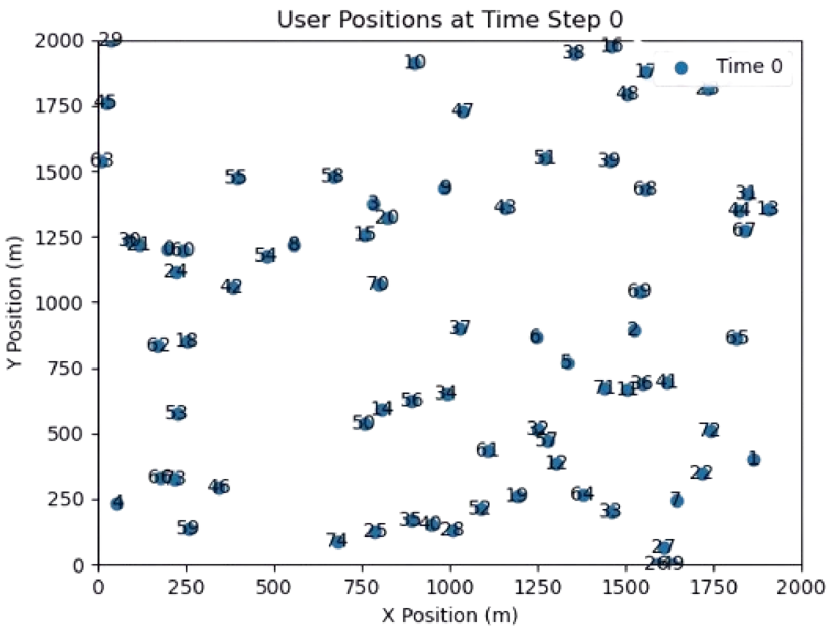


Figure 3.2 – UEs' distribution at time 0, experiments with 75 UEs

3.2 Placement Problem Formulation

In this thesis, two formulations for UAV-BS placement have been proposed. Figure 3.8 shows the big picture of the previous and current mathematical optimization models. The problem formulation depicted on the left side of Figure 3.8

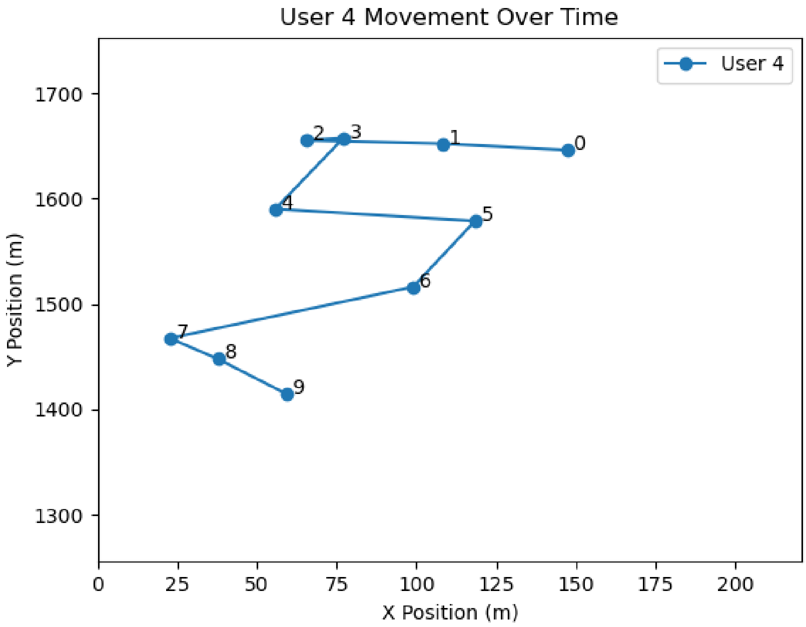


Figure 3.3 – The movement path of UE 4 in 10 consecutive time intervals

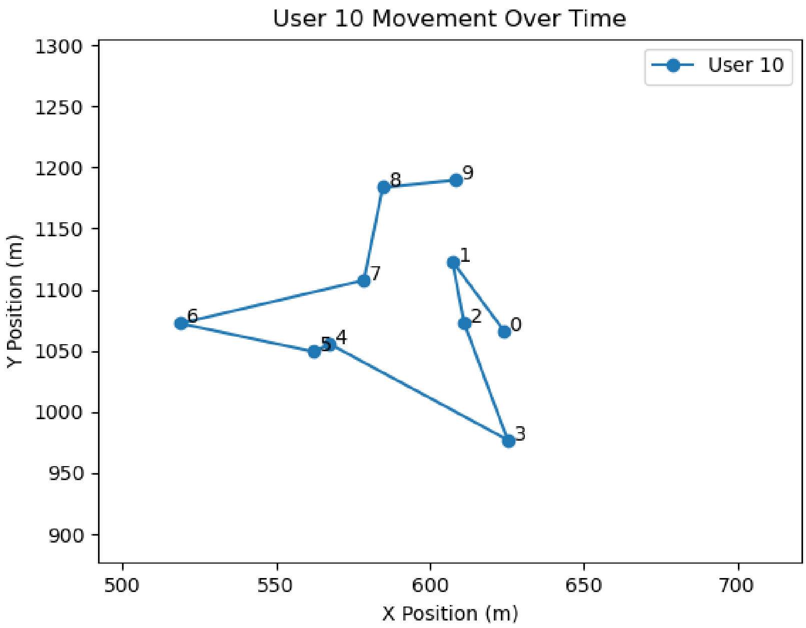


Figure 3.4 – The movement path of UE 10 in 10 consecutive time intervals

represents the initial model proposed in (PASANDIDEH et al., 2023a), which was addressed using an enhanced PSO-based algorithm. On the right side, the problem formulation illustrates the improved and currently proposed model, solved using the JAYA algorithm. Both models share common constraints, such as those pertaining to meeting UEs' QoS, boundary limitations, and the assignment of UEs to UAV-

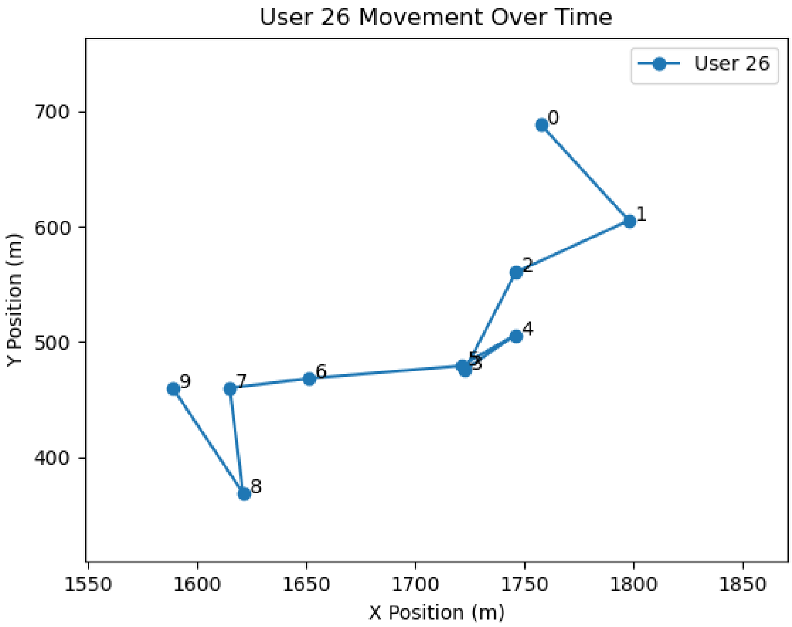


Figure 3.5 – The movement path of UE 26 in 10 consecutive time intervals

BSs. However, the improved model incorporates additional constraints, particularly those related to power consumption.

In this section, elaboration is provided on the initial problem placement as documented in (PASANDIDEH et al., 2023a), which is detailed in section 3.2.1. Following this, in section 3.2.2, the enhancements made to the model are delineated.

In this section the initial problem placement that published in (PASANDIDEH et al., 2023a) is explained in section 3.2.1, then in section 3.2.2 the improved model is explained.

3.2.1 Initial placement problem formulation

In (PASANDIDEH et al., 2023a), firstly an improved PSO-based placement algorithm is proposed to find the minimum number of DBSs and their optimal locations. An initialization approach that estimates the initial value of the number of DBSs is provided by employing a K-means clustering-based scheme in the PSO algorithm to improve the performance. A custom communication protocol was also developed for exchanging the users' main data between users and the network controller.

The initial number of required DBSs ($NDBS$) to start serving a set of users in an area can be defined as the total number of users in the network divided by the maximum number of users that each DBS covers (PASANDIDEH et al., 2023a). Then using intelligent algorithms, the optimal number of DBSs can be estimated. Considering the maximum number of users that a DBS can serve, M_i,

$$NDBS = \frac{TotalUsers}{M_i} \tag{3.1}$$

Considering the sum of data rate requirements of users, T and the capacity of the DBS, *Capacity* then:

$$M_i = \left\lfloor \frac{T}{Capacity} \right\rfloor \tag{3.2}$$

Therefore, the optimization problem is formulated as follows:

$$min_{x_{di},y_{di},h,X_{ij}} \sum_{i=1}^{NDBS} \sum_{j=1}^{M} E[w_{ij}]X_{ij} \tag{3.3}$$

Subject to

$$R_{ij} \geq T_j : \forall j \in M \tag{3.4}$$

$$\sum_{j \in M} R_{ij} \leq Capacity \tag{3.5}$$

$$x_{min} \leq x_{di} \leq x_{max} \tag{3.6}$$

$$y_{min} \leq y_{di} \leq y_{max} \tag{3.7}$$

$$h_{min} \leq h \leq h_{max} \tag{3.8}$$

$$\sum_{i=1}^{NDBS} X_{ij} \leq 1 : \forall \in \{1, 2, ..., M\} \tag{3.9}$$

$$\sum_{j=1}^{M} B_{ij} = B_{max} \tag{3.10}$$

$$\sum_{j=1}^{M} p_{ij} = P_{max} \tag{3.11}$$

$$r_{di} < r_{max} : i \in \{1, 2, ..., NDBS\} \tag{3.12}$$

The problem formulated by (3.3) aims to minimize the number of required DBSs (NDBS) by minimizing the waiting time of the users in the queue. $E[w_{ij}]$ is the waiting time of user j in the queue inside the DBS i. X_{ij} is a binary variable ($X_{ij} \in \{0, 1\}$) that determines if user j is covered by DBS i or not. A user can be served by a DBS if horizontal euclidean distance between the user and DBS is less than or equal to DBS's coverage radius (r_{di}):

$$X_{ij} = \begin{cases} 1 & \text{if } \sigma_{ij} \leq r_{di} \\ 0 & \text{if } \sigma_{ij} > r_{di} \end{cases} \tag{3.13}$$

Constraint (3.4) indicates that QoS requirement of each user should be satisfied which R_j is the data rate between user j and DBS and T_j is the data requirement of user j. Constraint (3.5) shows that total data rate of all covered users served by one DBS cannot exceed the data rate capacity of that DBS. Constraints (3.6), (3.7), and (3.8) indicate the placement region of the 3D coordinates of DBSs which $x_{min}, x_{max}, y_{min}$ and y_{max} are limits of the area and h_{min} and h_{max} are the minimum and maximum altitude of a DBS allowed to reach. Constraint (3.9) ensures that each user should be served at most by one DBS. Constraint (3.10) and (3.11) show the resource limitation which B_{ij} is bandwidth allocated by DBSi for user j and p_{ij} is transmission power allocated by DBS i for user$j$. Constraint (3.12) indicates that radii of DBSs i (r_{di}) is no longer than the maximum radii.

3.2.1.1 Linearizing the optimization problem

The problem P, which is the constraint-based mixed-integer programming problem, can be reformulated as:

$$\begin{aligned} f(x_{di}, y_{di}, h, NDBS) = min_{x_{di}, y_{di}, h} \sum_{i=1}^{NDBS} \sum_{j=1}^{M} E[w_{ij}] X_{ij} \\ + Constraints. \end{aligned} \tag{3.14}$$

where $f(x_{di}, y_{di}, h, NDBS)$ is the unconstrained cost function and $Constraints$ can be shown as:

$$Constraints = \Phi * (\sum_{k=1}^{9} \alpha_k + (P_{max} - \sum_{j=1}^{M} p_{ij}) \\ +(B_{max} - \sum_{j=1}^{M} b_{ij})) \tag{3.15}$$

According to problem P (3.3), the constraints (3.4-3.12) contain equals signs and comparison operators. Regarding the equals sign, a large number (Φ) needs to be multiplied by the subtraction value of the expressions on the two sides of the equals sign, and the result needs to be added to the cost function. In this case the $\Phi * (P_{max} - \sum_{j=1}^{M} p_{ij})$ and $\Phi * (B_{max} - \sum_{j=1}^{M} b_{ij})$ are added into the cost function. Regarding comparison operators, in this case greater than or equal to (>=) and less than or equal to (=<) , the subtraction value of both sides of the equation is not highly important, but satisfying the equation is essential. Thus, a new binary variable α_k is defined to determine whether the given equation is satisfied:

$$\begin{cases} \alpha_k = 1 & if the equation is not satisfied \\ \alpha_k = 0 & Otherwise \end{cases} \tag{3.16}$$

when the equation is not satisfied a penalty value should be imposed to the cost function. Therefore ($\alpha_k * \Phi$) is added into the cost function.

3.2.1.2 Proposed PSO-Based Algorithm for coverage module model

PSO is a computational method that optimizes a problem by iterative enhancing the candidate solution and discovering the global optimum. In this study, PSO algorithm optimizes the placement problem of UAV-BSs by using the sets of candidate UAV-BSs positions called particles and moving the swarm of particles, which represent potential solutions, around in the search-space according to simple mathematical formulae over the particle's position, velocity, and cost value. Each particle's movement is influenced by the best position the particle has experienced (local best position) and the best position that all the particles have experienced (global best position). Therefore, each particle (UAV-BS) adjusts its flight according to its own flying experience and companion's flying experience. This is expected to move the swarm toward the best solutions (SILVA et al., 2019), (PASANDIDEH et al., 2021).

However, PSO suffers from trapping in the local minimum or finding the best global minimum in some problems. The particles are not successful to cover the entire search space, as they are distributed randomly in initialization phase using Gaussian or uniform distribution. It is expected that by improving the initialization phase, the final results of PSO would be more accurate. Therefore, it is important to improve the initial population generation phase to cover the feasible space properly. There are some investigations that take advantage of other optimization methods to reinforce the exploitation and exploration phases of the PSO algorithm, such as (GARG, 2016; K.S.; MURUGAN, 2017; PSOSCALF. . . , 2018). Authors in (DONG et al., 2012; XIANG; LIAO; WONG, 2007) try to improve the population initialization step. In the following, the proposed PSO-Based algorithm is explained in detail.

The first step of the PSO algorithm is to initialize the PSO parameters, including, acceleration coefficients (c_1, c_2),random vectors (r_2, r_2) and inertia weight (w), and the number of population (*npop*) which is the number of UAV-BS($NDBS$). The basic PSO algorithm randomly determines these parameters. However, they can be initialized more accurately to enhance the PSO parameters. Regarding *npop* (the number of UAV-BSs if the scheme starts with one UAV-BS it is not desirable as the number of PSO iterations will increase. Thus a more accurate number of UAV-BSs is needed to reduce the number of PSO iterations.The next step is to initialize the positions of UAV-BS (particles). The initial generation is commonly randomly generated in the PSO algorithm. However, such random initialization suffers from less satisfactory performance. More specifically, the K-means clustering-based algorithm can be employed to determine the initialized positions of the UAV-BSs in the area.

The goal of the PSO algorithm is to locate the UAV-BSs in a two-dimensional (2D) plane and find (x_{di}, y_{di}) based on the linearized optimization problem in Section 3.2.1.1. After calculating the cost function for each particle , then current PSO iteration time, particle's local best, and global best are updated based on this function. Next, the velocity of UAV-BSs located at the new positions is updated and the velocity limits (v_{min} and v_{max}) are applied. To make sure that all the particles stay inside the search space, velocity mirror effects are avoided which means if a particle is outside the search space, it should be moved back inside. After updating the personal and global best of each UAV-BS, the PSO algorithm will terminate if the swarm meets the termination criteria. If it terminates, the optimal position of the DBS is obtained then check if the waiting time of the users in the queue is minimized or not. If it is not minimized, it is realized that the number of DBSs is not sufficient, then this number is increased by one, and perform the steps from scratch.

a) Improved population initialization phase

In the original PSO algorithm, the particles are distributed randomly in the initialization phase. The proper initialization of the first-generation particles can improve the performance of the PSO algorithm. A K-means-based clustering method can be proposed as an initialization method to generate the positions of the first-generation particles (UAV-BSs).

- **k-means:** More specifically, the K-means algorithm is an iterative algorithm that tries to partition data points (users) into K pre-defined distinct non-overlapping clusters where each user belongs to only one cluster. It assigns users to a cluster such that the sum of the squared distance between the users and the cluster's centroid is at the minimum (KRISHNA; MURTY, 1999). The centroid is the arithmetic mean of all the users that belong to that cluster. The Cluster head or centroid, in this case, refers to the DBS.

  The following problem has to be solved:

$$min_x \sum_{j=1}^{TotalUsers} \sum_{k=1}^{K} x_{jk} \left\| U_j - \mu_k \right\|^2 \tag{3.17}$$

  subject to

$$\sum_{k=1}^{K} x_{jk} = 1 \forall j \tag{3.18}$$

$$\mu_k = \frac{\sum_{j=1}^{TotalUsers} x_{jk} U_j}{\sum_{j=1}^{TotalUsers} x_{jk}} \tag{3.19}$$

$$x_{jk} \in \{0, 1\} \, \forall j, k \tag{3.20}$$

  Where x_{jk} is a binary varible determines if user j belongs to cluster k ($x_{jk} = 1$) or not ($x_{jk} = 0$). U_j and μ_k are the coordinates of jth user and the centroid of user j's cluster, respectively. They are both located in $\mathbb{R}^d$, where d is the dimensional of users. Constraint (3.18) indicates that each user should be assigned to exactly one cluster. Constraint (3.19) shows that the coordinates of centroid of cluster k depend on values of x_{jk} and U_j variables. The problem (3.17) which contains these non-linear constraints can be rewritten as the following problem:

$$min_x \sum_{j=1}^{TotalUsers} \sum_{k=1}^{K} x_{jk} \left\| U_j - y_k \right\|^2 \tag{3.21}$$

subject to

$$\sum_{k=1}^{K} x_{jk} = 1 \forall j \tag{3.22}$$

$$\mu_k = \frac{\sum_{j=1}^{TotalUsers} x_{jk} U_j}{\sum_{j=1}^{TotalUsers} x_{jk}} \tag{3.23}$$

$$x_{jk} \in \{0, 1\} \, \forall j, k \tag{3.24}$$

$$y_k \in \mathbb{R}^d \forall k \tag{3.25}$$

The problem represented in (3.21) shows that instead of minimizing the distance to centroids (μ_k), the idea is to minimize the distance to just any set of points (y_k) that will give a better solution based on results. It turns out that these points are exactly the centroids. To solve the objective function, first the values for y_k variables are fixed and the optimal values for x_{jk} variables are found, then the values of x_{jk} variables are fixed, and the optimal values for y_k variables are found.

The proposed algorithm is shown in Algorithm 1. As can be observed in the algorithm, the positions of the users X_U is considered as an input.

The output is the optimal position and optimal number of DBSs, respectively, X_D and $NDBS^*$ resulted by the proposed algorithm. After calculating the initial value of $NDBS$ according to (3.1), the initial positions of the particles (UAV-BSs) are generated using the k-means algorithm. The PSO parameters

Algorithm 1: Proposed algorithm.

Input: X_U.
Output: X_D and $NDBS^*$.
1: Calculate the initial value of $NDBS$ according to (3.1).
2: Generate first generation:$initPosDBS = k - means(NDBS)$
3: **repeat**
4:     **for** *each particle* (DBS) **do**
5:         **Initialize PSO parameters:** Initialize w, c_1 and c_2 according to (Paul; De; Dey, 2020), and r_1, r_2 and *velocity*
6:         Calculate the $Cost\ function$.
7:         Update p_best and g_best.
8:     **repeat**
9:         **for** *each particle* DBS **do**
10:             Update *velocity*
11:             Update DBS *velocity limit*.
12:             Update $Costfunction$.
13:             Update p_{best} and g_{best}.
14:     **until** *The swarm met the termination criteria*;
15:     $X_D \leftarrow g_{best}$;
16:     $NDBS^* \leftarrow NDBS$;
17:     $++NDBS$
18: **until** *The* $E[w_{ij}]$ *is obtained*;

including w, c_1 and c_2 are initialized according to 3.1, the remaining parameters such as r_1, r_2 and *velocity* are initialized in line 5. Finally the personal best and global best are updated. Then the PSO algorithm iteratively runs updating the velocity and the velocity limit of the particles (line 11 and line 12). The cost function is obtained by the formulation provided in (3.14) and updated in line 13. Then PSO updates the individual local best solution of particles. The global solution is continuously updated (line 14), as well. The repetition finishes if the swarm met the termination criteria. Then the output of the algorithm X_D and $NDBS^*$ is obtained. Finally, if the $E[w_{ij}]$, the waiting time of $user_j$ in the queue inside the DBS_i, is satisfied, the algorithm terminates, otherwise, the algorithm run from scratch with one more DBS ($NDBS++$).

The simulation results show impressive performance of the proposed PSO-based scheme in which low packet loss and latency. It also indicates that all the users in the considered scenario are covered by the UAV-BSs. Nevertheless, the mathematical model put forward lacks consideration for the power consumption of the DBSs, and the tested scenarios exclusively encompass a limited count of users.

In light of the landscape presented, this study introduces an approach aimed at covering power and connectivity concerns by proposing an improved optimization model.

3.2.2 Improved placement problem formulation

Figure 3.6 provides an overview of the entire system architecture. As depicted in this figure, the forthcoming section will delve into a comprehensive discussion of the mathematical optimization model. This model considers various specifications, including the UAV-BS rotor characteristics, horizontal and vertical motor speeds, wind speed and direction, data rate requirements of UEs, and the trajectory of UEs at each time step, and consequently provides optimal or near-optimal positioning of the UAV-BSs across diverse experiments.

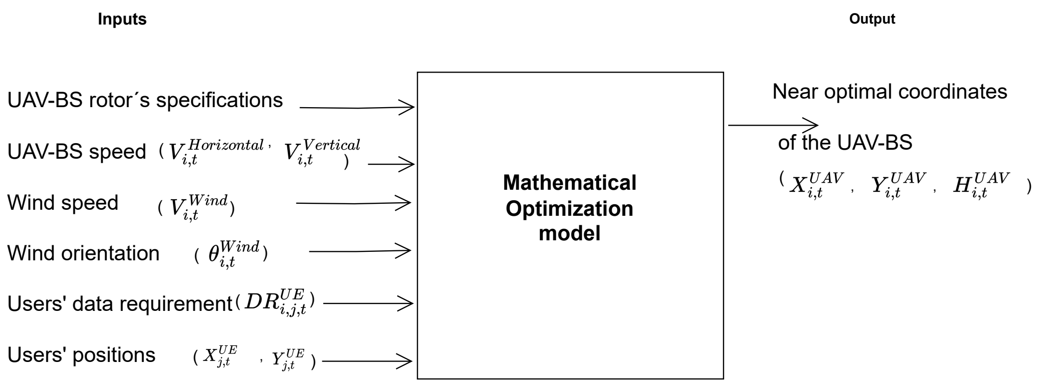


Figure 3.6 – Overall view of proposed system

In this section, an optimization model is formulated. The optimization model aims to achieve two primary objectives concurrently. The initial goal is to minimize the power consumption related to the movement and to the communication ($P_{i,t}^{\text{Total}}$) utilized by UAV-BSs, and the second objective is to reduce the number of uncovered UEs ($I_{i,j,t}^{\text{UE}}$).

$$f_1 = \sum_{i}^{I} \sum_{t}^{T} \mathrm{P}_{\mathrm{i,t}}^{\mathrm{Total}}, \forall i, t \tag{3.26}$$

$$f_2 = -\sum_{i}^{I} \sum_{j}^{J} \sum_{t}^{T} I_{i,j,t}^{\text{UE}}, \forall i, j, t \tag{3.27}$$

$$\min f = w_1 \cdot f_1 + w_2 \cdot f_2 \tag{3.28}$$

$$w_1 + w_2 = 1 \tag{3.29}$$

The function f_1 shown in (3.26), computes the sum of the total power consumption of each UAV-BS across all time steps. This function encapsulates the objective of minimizing the overall power usage of the UAV-BSs throughout the specified time horizon. The symbol $\sum_i^I$ denotes a summation over all I UAV-BSs. Similarly, $\sum_t^T$ represents a summation over all T time steps. $P_{i,t}^{Total}$ signifies the total power consumption of UAV-BS$_i$ at time step t. Function f_2 in (3.27) represents the total count of uncovered UEs. The negative sign preceding the summation implies that the objective is to minimize this metric, aiming to reduce the number of UEs left uncovered ($I_{i,j,t}^{UE} = 0$). Function f in (3.28) that can be referred to as the problem itself, represents the combination of the two objectives f_1 and f_2 into a single objective function min f by assigning weights w_1 and w_2 to each objective. Constraint (3.29) ensures that the weights are properly normalized, meaning w_1 and w_2 must sum up to 1.

The constraints pertaining to the proposed optimization problem can be classified into several categories: mobility-related constraints, power consumption constraints, path loss and UEs' data rates, and operational constraints.

A: Mobility Constraints:

When factoring in the mobility constraints of UAV-BSs such as limiting boundaries, setting UAV-BSs' start points, and UAV-BSs speed, it is crucial to design assignments that optimize mission success while adhering to these constraints. The vertical and horizontal speeds of UAV-BSs have a significant impact on their mobility and performance. These speeds are key parameters that influence the UAV-BS's ability to navigate, carry out missions, and adapt to different scenarios. In addition, defining clear boundaries within which UAV-BSs can operate is essential to ensure safety, security, and regulatory compliance.

$$V_{i,t}^{\text{Vertical}} = \frac{h_{i,t}^{\text{UAV-BS}} - h_{i,t-1}^{\text{UAV-BS}}}{dt}, \forall i, t \tag{3.30}$$

$$V_{i,t}^{\text{X}} = \frac{x_{i,t}^{\text{UAV-BS}} - x_{i,t-1}^{\text{UAV-BS}}}{dt} + V_{i,t}^{Wind} cos(\theta_t^{Wind}) I_{i,t}^{\text{UAV-BS}}, \forall i, t \tag{3.31}$$

$$V_{i,t}^{\mathrm{Y}} = \frac{y_{i,t}^{\mathrm{UAV-BS}} - y_{i,t-1}^{\mathrm{UAV-BS}}}{dt} + V_{i,t}^{\mathrm{Wind}} sin(\theta_t^{\mathrm{Wind}}) I_{i,t}^{\mathrm{UAV-BS}}, \forall i, t \tag{3.32}$$

$$V_{i,t}^{\mathrm{Horizontal}} = \sqrt{\left(V_{i,t}^{\mathrm{X}}\right)^2 + \left(V_{i,t}^{\mathrm{Y}}\right)^2}, \forall i, t \tag{3.33}$$

$$V_{i,t} = \sqrt{\left(V_{i,t}^{\mathrm{Vertical}}\right)^2 + \left(V_{i,t}^{\mathrm{Horizontal}}\right)^2}, \forall i, t \tag{3.34}$$

$$x_{i,t}^{\mathrm{UAV-BS}} = x_{i,t}^{\mathrm{UAV-BS,Initial}} \cdot I_{i,t}^{\mathrm{UAV-BS}}, \forall i, t = 0 \tag{3.35}$$

$$y_{i,t}^{\mathrm{UAV-BS}} = y_{i,t}^{\mathrm{UAV,Initial}} \cdot I_{i,t}^{\mathrm{UAV-BS}}, \forall i, t = 0 \tag{3.36}$$

$$h_{i,t}^{\mathrm{UAV-BS}} = h_{i,t}^{\mathrm{UAV-BS,Initial}} \cdot I_{i,t}^{\mathrm{UAV-BS}}, \forall i, t = 0 \tag{3.37}$$

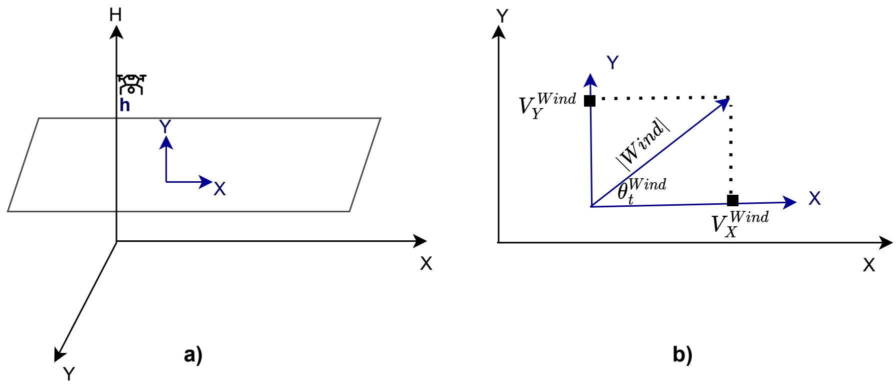
$$x^{\mathrm{Min}} \leq x_{i,t}^{\mathrm{UAV-BS}} \leq x^{\mathrm{Max}}, \forall i, t \tag{3.38}$$

$$y^{\mathrm{Min}} \leq y_{i,t}^{\mathrm{UAV-BS}} \leq y^{\mathrm{Max}}, \forall i, t \tag{3.39}$$

$$h^{\mathrm{Min}} \leq h_{i,t}^{\mathrm{UAV-BS}} \leq h^{\mathrm{Max}}, \forall i, t \tag{3.40}$$

Constraint (3.30) indicates the vertical speed of the UAV-BSi at time t on the vertical axis, assuming the wind speed and direction do not impact the vertical speed. Constraints (3.31), and (3.32) show the horizontal speed of the UAV-BSi at time t in X-axis, and Y-axis, respectively, considering wind speed and orientation. Constraint (3.33) shows the horizontal speed of the UAV-BSi at time t.

The Euclidean relation between vertical and horizontal speeds form the total speed of the UAV-BSi at time t, shown in constraint (3.34). The logic behind the constraints (3.31) to (3.34) is shown in Figure (3.7). Based on Figure (3.7), the speed of UAV-BSi at time t can be calculated, and it is located at coordinates $(x_{i,t}^{UAV}, y_{i,t}^{UAV}, h_{i,t}^{UAV})$ in both the horizontal and vertical dimensions. The speed of UAV-BS during vertical flight is equivalent to the distance traveled along the vertical (h) axis, as indicated in constraint (3.30). As Figure (3.7) shows, for horizontal flight,



$$V_{i,t}^{Vertical_H} = \frac{h_{i,t}^{UAV} - h_{i,t-1}^{UAV}}{dt}$$

$$V_{i,t}^{Horizontal_X} = \frac{x_{i,t}^{UAV} - x_{i,t-1}^{UAV}}{dt} + V_X^{Wind}$$

$$V_{i,t}^{Horizontal_Y} = \frac{y_{i,t}^{UAV} - y_{i,t-1}^{UAV}}{dt} + V_Y^{Wind}$$

$$V_X^{Wind} = V_{i,t}^{Wind} cos(\theta_t^{Wind}) I_{i,t}^{UAV}$$

$$V_Y^{Wind} = V_{i,t}^{Wind} sin(\theta_t^{Wind}) I_{i,t}^{UAV}$$

Figure 3.7 – Speed and direction of wind in power model

one can project the motion of a UAV-BS onto a 2D plane to calculate the speed of the UAV-BS along the x-axis (constraint (3.31) and y-axis (constraint (3.32), taking into account the effect of wind speed ($V_{i,t}^{Wind}$) and direction (θ_t^{Wind}). Finally, constraint (3.33) illustrates the horizontal speed of the UAV-BS.

Constraints (3.35), (3.36), and (3.37) define the initial values of UAV-BS coordinates. Constraints (3.38), (3.39), and (3.40) the spatial boundaries within which the 3D coordinates of UAV-BSs have to lie. The x^{min}, y^{min},h^{min}, and x^{max}, y^{max} specify the minimum and maximum allowable x, y, and h for a UAV-BS.

B: Power Consumption Constraints:

The power consumption of UAV-BSs can be broken down into four main components (ALOQAILY et al., 2022), (OMONIWA; GALKIN; DUSPARIC, 2022), (REN et al., 2023) :

- *Motor power:* This component, also referred to as propulsion power, which is the most significant portion of power consumption, covers the power required for various UAV-BS movements, including horizontal and vertical motion, landing, take-off, and hovering. A connection exists between UAV-BS' speed, wind speed, and direction, but it is noteworthy that many studies overlook how wind factors affect UAV-BS speed and motion. When the UAV-BS faces substantial headwinds, it might necessitate extra power consumption, resulting in faster battery drainage and a decrease in the duration of flight.

Conversely, when flying with tailwinds, the UAV-BS can prolong its flight time because it needs less power to operate (THIBBOTUWAWA et al., 2019).

- *Communication-related power:* This component pertains to the energy used for data transmission and reception at the UAV-BS.

- *Sensing and processing powers:* While this factor exists, their power consumption is minimal and is neglected in the proposed power model.

These components collectively make up the power consumption of UAV-BSs, with motor power and communication-related power being the most prominent factors.

$$\begin{aligned} P_{i,t}^{\text{Horizontal}} &= P_0 \left(1 + \frac{\left(V_{i,t}^{\text{Horizontal}}\right)^2}{\Omega^2 R^2} \right) \\ &+ P_i \widetilde{\kappa} \left(\sqrt{\widetilde{\kappa}^2 + \frac{\left(V_{i,t}^{\text{Horizontal}}\right)^4}{4V_0^4}} - \frac{\left(V_{i,t}^{\text{Horizontal}}\right)^2}{2V_0^2} \right)^{\frac{1}{2}} \\ &+ \frac{\rho}{2} S_{FP} \left(V_{i,t}^{\text{Horizontal}}\right)^3, \quad \forall i, t \end{aligned} \tag{3.41}$$

Constraint (3.41) shows the closed-form expression of UAV-BS power consumption model in horizontal flight, which is provided based on the formula given in (ZENG; XU; ZHANG, 2019). In constraint (3.41), the first two terms represent the blade profile power and induced power during forward flight, respectively. The third term signifies the parasite's power. These terms are contingent on the horizontal speed $V_{i,t}^{Horizontal}$.

$$P_{i,t}^{\text{Vertical}} = P_0 + P_i + \frac{1}{2} R_T V_{i,t}^{\text{Vertical}} + \frac{R_T}{2} \sqrt{\left(V_{i,t}^{\text{Vertical}}\right)^2 + \frac{2R_T}{\rho A}}, \forall i, t \tag{3.42}$$

constraint (3.42) shows the vertical flight of the UAV-BSs, which is extracted from (GONG et al., 2023). R_T represents the rotor thrust, while the other parameters remain consistent with those previously introduced. The Thrust-to-weight ratio $\widetilde{\kappa}$ in (3.41) is equal to $\frac{R_T}{W} \simeq 1$ which means ($R_T \simeq W$), based on this (3.41) and (3.42) that show the horizontal, and vertical power consumption of the UAV-BSi at time t, respectively, can be simplified as follows:

$$
\begin{aligned}
P_{i,t}^{Horizontal} &= P_0\left(1+\frac{(V_{i,t}^{Horizontal})^2}{\Omega^2R^2}\right)\\
&+P_i\left(\sqrt{\frac{(V_{i,t}^{Horizontal})^4}{4V_0^4}}-\frac{(V_{i,t}^{Horizontal})^2}{2V_0^2}\right)^{\frac{1}{2}}\\
&+\frac{\rho}{2}S_{FP}(V_{i,t}^{Horizontal})^3,\quad \forall i,t
\end{aligned}
\tag{3.43}
$$

$$
P_{i,t}^{Vertical}=P_0+P_i+\frac{1}{2}W_iV_{i,t}^{Vertical}+\frac{W_i}{2}\sqrt{\left(V_{i,t}^{Vertical}\right)^2+\frac{2W_i}{\rho A}},\forall i,t \tag{3.44}
$$

$$
P_{i,t}^{Comm}=P_c+\tau_t\eta P,\forall i,t \tag{3.45}
$$

$$
P_{i,t}^{Total}=P_{i,t}^{Horizontal}+P_{i,t}^{Vertical}+P_{i,t}^{Comm},\forall i,t \tag{3.46}
$$

The power consumption resulting from communication, which is extracted from (ABUBAKAR et al., 2023), is shown in (3.45), where the P_c shows the circuit power, τ_t, η and P depict normalized traffic load, amplifier efficiency, and transmit power, respectively.

The total power is shown in Constraint (3.46) which is the summation of horizontal, vertical movement power, and consumption power.

C: Path Loss and Data Rate Constraints:

The deployment of UAV-BS has dual repercussions, impacting both the coverage area available to UEs and the reliability of AtG communication links. Within the realm of AtG path loss simulation, a variety of channel models can be found in the literature (SMITH; JOHNSON, 2020), (LEE; GARCIA, 2018), and (BROWN; WILLIAMS, 2019). In this paper, the channel model detailed in (Qiu et al., 2020) is specifically chosen due to its proven track record of performance.

Depending on the prevailing propagation conditions, AtG communication links can be classified as either LoS or NLoS. The probability of establishing a LoS connection between the receiver and transmitter holds significant importance as it directly shapes the power utilization by UEs. The likelihood of achieving a LoS connection between an UE and a UAV-BS is contingent upon factors such as building density, the UE's geographical position, and the elevation angle of the UAV-

BS in relation to both the UE and itself. To compute the probabilities of both LoS and NLoS connections between UEj and UAV-BSi, the calculations adhere to the methodology delineated in (Qiu et al., 2020).

The data rate between UEj and UAV-BSi can be calculated as follows based on the path loss model provided in (Qiu et al., 2020):

$$DR_{i,j,t}^{\mathrm{UE}} = B_{ij} \times \log_2 \left(1 + \frac{p_{ij} \times 10^{\frac{-\zeta_{ij}}{10}}}{B_{ij} \times \varepsilon^2} \right), \forall i, j, t \tag{3.47}$$

where B_{ij} and p_{ij} are sub-channel bandwidth, transmit power allocated by the UAV-BSi to UEj and ε^2 is the noise power spectral density of the Zero-mean white Gaussian noise at the receiver. ζ_{ij} represents the average path loss between UEj and UAV-BSi, determined through the methodology detailed in (Qiu et al., 2020).

D: Operational Constraints:

Using operational constraints, the assignment of UEs is limited based on their proximity to at most one UAV-BS at each time step to ensure reliable communication or service. The total data rate or resource demands of the UEs assigned to a UAV-BS are ensured not to exceed the capacity or capabilities of the UAV-BS. Collision avoidance between UAV-BSs is ensured by monitoring and maintaining the minimum safe distance between them.

$$\begin{aligned}\left(x_{i,t}^{\mathrm{UAV-BS}} - x_{j,t}^{\mathrm{UE}}\right)^2 + \left(y_{i,t}^{\mathrm{UAV-BS}} - y_{j,t}^{\mathrm{UE}}\right)^2 \leq \left(R_t^{\mathrm{UAV-BS}}\right)^2 + \Big(\left(x^{\mathrm{Max}} - x^{\mathrm{Min}}\right)^2 \\ + \left(y^{\mathrm{Max}} - y^{\mathrm{Min}}\right)^2 + \left(h^{\mathrm{Max}} - h^{\mathrm{Min}}\right)^2\Big) \cdot \left(1 - I_{i,j,t}^{\mathrm{UE}}\right), \forall i, j, t\end{aligned} \tag{3.48}$$

$$\sum_{I}^{i} \sum_{J}^{j} \sum_{T}^{t} I_{i,j,t}^{\mathrm{UE}} \leq 1, \forall i, j, t \tag{3.49}$$

$$\sum_{i}^{I} \sum_{j}^{J} \sum_{t}^{T} DR_{i,j,t}^{\mathrm{UE}} \leq Capacity_i^{\mathrm{UAV-BS}}, \forall i, j, t \tag{3.50}$$

$$\left(x_{i,t}^{\mathrm{UAV-BS}} - x_{k,t}^{\mathrm{UAV-BS}}\right)^2 + \left(y_{i,t}^{\mathrm{UAV-BS}} - y_{k,t}^{\mathrm{UAV-BS}}\right)^2 + \left(h_{i,t}^{\mathrm{UAV-BS}} - h_{k,t}^{\mathrm{UAV-BS}}\right)^2 \geq D^{\mathrm{Crash}}, \forall i, k, t \tag{3.51}$$

Constraint (3.48) indicates that UEj should be within the coverage range of UAV-BSi. In other words, the 2D distance between connected UEj and the projection of UAV-BSi on the X-axis at time t should be equal or less than the coverage range of UAV-BSi, and the area boundaries. Constraint (3.49) says that each ground UEj should be served at most by one UAV-BS at location i. Constraint (3.50) shows that the total data rate of all covered UEs by one UAV-BSi (the capacity of the wireless link between UAV-BSi and UE j) at time t cannot exceed the maximum data rate capacity of that UAV-BS. Constraint (3.51) shows to avoid collisions among the UAV-BSs during movement, the distance between each pair of UAV-BSs (i,k) at time t, must be more than a threshold.

Previousoptimimization problem

$$min_{x_{di},y_{di},h,X_{ij}} \sum_{i=1}^{NDBS} \sum_{j=1}^{M} E[w_{ij}]X_{ij}$$

Subject to:

1) $R_{ij} \geq T_j : \forall j \in M$

2) $\sum_{j \in M} R_{ij} \leq Capacity$

3) $x_{min} \leq x_{di} \leq x_{max}$

4) $y_{min} \leq y_{di} \leq y_{max}$

5) $h_{min} \leq h \leq h_{max}$

6) $\sum_{i=1}^{NDBS} X_{ij} \leq 1 : \forall \in \{1, 2, \ldots, M\}$

7) $\sum_{j=1}^{M} B_{ij} \leq B_{max}$

8) $\sum_{j=1}^{M} p_{ij} \leq P_{max}$

9) $r_{di} < r_{max} : i \in \{1, 2, \ldots, NDBS\}$

Current optimimization problem

$$min[f_1, f_2]$$

$$f_1 = \sum_{i}^{I} \sum_{t}^{T} P_{i,t}^{Total} \quad , \quad f_2 = -\sum_{i}^{I} \sum_{j}^{J} \sum_{t}^{T} I_{i,j,t}^{User}$$

Subject to:

Mobility Constraints:

1) $V_{i,t}^{Vertical} = \frac{h_{i,t}^{UAV} - h_{i,t-1}^{UAV}}{dt}, \forall i, t$

2) $V_{i,t}^{X} = \frac{x_{i,t}^{UAV} - x_{i,t-1}^{UAV}}{dt} + V_{i,t}^{Wind} cos(\theta_t^{Wind}) I_{i,t}^{UAV}, \forall i, t$

3) $V_{i,t}^{Y} = \frac{y_{i,t}^{UAV} - y_{i,t-1}^{UAV}}{dt} + V_{i,t}^{Wind} sin(\theta_t^{Wind}) I_{i,t}^{UAV}, \forall i, t$

4) $V_{i,t}^{Horizontal} = \sqrt{\left(V_{i,t}^{X}\right)^2 + \left(V_{i,t}^{Y}\right)^2}, \forall i, t$

5) $V_{i,t} = \sqrt{\left(V_{i,t}^{Vertical}\right)^2 + \left(V_{i,t}^{Horizontal}\right)^2}, \forall i, t$

6) $x_{i,t0}^{UAV} = x_{i,t}^{UAV,Initial} * I_{UAV}^{i,t}, \forall i, t = 0$

7) $y_{i,t0}^{UAV} = y_{i,t}^{UAV,Initial} * I_{UAV}^{i,t}, \forall i, t = 0$

8) $h_{i,t0}^{UAV} = h_{i,t}^{UAV,Initial} * I_{UAV}^{i,t}, \forall i, t = 0$

9) $x^{Min} \leq x_{i,t}^{UAV} \leq x^{Max}, \forall i, t$

10) $y^{Min} \leq y_{i,t}^{UAV} \leq y^{Max}, \forall i, t$

11) $h^{Min} \leq h_{i,t}^{UAV} \leq h^{Max}, \forall i, t$

Power Constraints:

12) $P_{i,t}^{Horizontal} = P_0 \left(1 + \frac{\left(V_{i,t}^{Horizontal}\right)^2}{\Omega^2 R^2}\right) + P_i \left(\sqrt{\frac{\left(V_{i,t}^{Horizontal}\right)^4}{4V_0^4}} - \frac{\left(V_{i,t}^{Horizontal}\right)^2}{2V_0^2}\right)^{\frac{1}{2}} + \frac{\rho}{2} S_{FP} (V_{i,t}^{Horizontal})^3$

13) $P_{i,t}^{Vertical} = P_0 + P_i + \frac{1}{2} W_i V_{i,t}^{Vertical} + \frac{W_i}{2} \sqrt{\left(V_{i,t}^{Vertical}\right)^2 + \frac{2T}{\rho A}}$

14) $P_{i,t}^{Total} = P_{i,t}^{Horizontal} + P_{i,t}^{Vertical}$

Operational Constraints:

15) $\left(X_{i,t}^{UAV} - x_{j,t}^{Usre}\right)^2 + \left(y_{i,t}^{UAV} - y_{j,t}^{Usre}\right)^2 \leq \left(R_t^{UAV}\right)^2 + \left(\left(x^{Max} - x^{Min}\right)^2 + \left(y^{Max} - y^{Min}\right)^2 + \left(h^{Max} - h^{Min}\right)^2\right) * \left(1 - I_{i,t}^{User}\right)$

16) $\sum_{I}^{i} \sum_{J}^{j} \sum_{T}^{t} I_{i,j,t}^{User} \leq 1$

17) $\sum_{i}^{I} \sum_{j}^{J} \sum_{t}^{T} DR_{i,j,t}^{User} \leq Capacity_i^{UAV}$

18) $\left(X_{i,t}^{UAV} - x_{k,t}^{UAV}\right)^2 + \left(y_{i,t}^{UAV} - y_{k,t}^{UAV}\right)^2 + \left(h_{i,t}^{UAV} - h_{k,t}^{UAV}\right)^2 \geq D^{Crash}$

Figure 3.8 – Overall view of previous and proposed optimization models.

4 THE PROPOSED UAV-BS PLACEMENT STRATEGY

This chapter initiates by providing a comprehensive overview and description of the proposed approach, diving into the fundamental aspects outlined in Section 4.1. Specifically, it delves into the application of the JAYA algorithm, elucidating its relevance and effectiveness in addressing the optimization model proposed for determining optimal positions for the UAV-BSs. The focus lies on highlighting how the JAYA algorithm acts as a pivotal tool in achieving near-optimal solutions within the context of optimizing UAV-BS deployment.

Moreover, within this section, a thorough exploration is undertaken to showcase the efficacy of the JAYA algorithm in efficiently solving the complex optimization model. The discussion revolves around elucidating its iterative nature, adaptive characteristics, and its inherent ability to converge toward solutions that are notably close to the optimal ones. Insights into how this algorithm effectively navigates the multifaceted parameters and constraints inherent in the optimization model are also delineated, providing a comprehensive understanding of its application in this specific scenario.

Following the comprehensive overview, the chapter proceeds to present a meticulous and detailed complexity analysis. This analysis aims to provide a deeper understanding of the computational resources and time requirements involved in employing the JAYA algorithm for solving the optimization problem related to UAV-BS placement. The complexity analysis meticulously examines the algorithm's computational demands, culminating in establishing an overall time complexity of $O(n^2)$. This insight into the computational intricacies not only enriches the understanding of the algorithm's performance but also assists in gauging its feasibility for real-world deployment scenarios.

Moving forward in the chapter, the emphasis shifts to Section 4.3, which meticulously delineates the steps involved in generating the requisite dataset for the proposed optimization framework. This section elaborates on the intricacies of the data generation process, encompassing the various parameters, models, and simulations employed to create a comprehensive dataset representative of real-world conditions. By elucidating the data generation methodology in detail, this section ensures a thorough comprehension of the inputs used in the subsequent phases of the study, ultimately contributing to the reliability and robustness of the proposed approach.

4.1 Designed Solution

Problem (3.28) is a MINLP optimization problem that minimizes the movement and communication powers consumed by UAV-BSs, while minimizing the number of uncovered UEs. Such a problem can be solved using different techniques. Metaheuristic-based approaches are one of the problem-solving techniques that use iterative search algorithms to find optimal or near-optimal solutions to UAV placement optimization problems. GA, PSO, GWO, CS, ACO, and JAYA are powerful problem-solving techniques that can be used to solve the UAV-BS placement problem (PASANDIDEH et al., 2023a; PASANDIDEH et al., 2021; PASANDIDEH et al., 2022; ZITAR et al., 2022).

The Jayatilaka (JAYA) algorithm is a relatively new optimization algorithm used for solving optimization problems. It was introduced by Dr. R. V. Jayatilaka in 2016. This algorithm is inspired by the behavior of social hierarchies and dynamics within a group. The JAYA algorithm falls under the category of metaheuristic optimization techniques, specifically designed for solving continuous optimization problems (JAYATILAKA, 2016). The primary idea behind the JAYA algorithm is to improve the solutions iteratively by simulating the natural process of improvement within a society. It operates on the concept of two main phases: exploration and exploitation. During the exploration phase, potential solutions are sought, while the exploitation phase concentrates on refining these solutions.

The main reason for using JAYA as the meta-heuristic algorithm in this context is its simplicity, efficiency, and effectiveness in optimization tasks. Unlike some other meta-heuristic algorithms, JAYA does not require the specification of specific parameters such as population size or mutation rates, which simplifies its implementation process. Instead, it operates by continually improving solutions until convergence is achieved, iteratively replacing inferior solutions with superior ones. This approach not only simplifies the implementation but also leads to fast convergence towards global or near-optimal solutions. Moreover, JAYA's deterministic behavior ensures consistent results for the same problem and input, enhancing its reliability and usability in UAV-assisted applications. Additionally, JAYA is faster and more memory-efficient compared to other meta-heuristic algorithms, further solidifying its suitability for the task at hand.

One of the primary challenges in using JAYA for UAV-BS placement problems is its simplicity and lack of parameterization, which may limit its ability to effectively explore the complex solution space inherent in such optimization tasks. However, incorporating k-means clustering alongside JAYA can mitigate some of these limitations by providing a more structured approach to initial solution generation. K-means clustering helps in dividing the search space into clusters, thereby guiding JAYA to focus on specific regions of interest. By initializing the population with centroids obtained from k-means clustering, JAYA can start the optimization process with a diverse set of candidate solutions, potentially enhancing the exploration of the solution space and improving the likelihood of finding optimal or near-optimal UAV-BS placements. This combination leverages the simplicity and efficiency of JAYA while harnessing the structured initialization provided by k-means clustering to overcome some of the challenges associated with UAV placement optimization.

After initializing the parameters of both the optimization problem and the JAYA algorithm, the first potential locations for UAV-BSs are found at time 0 ($x_{i,t}^{UAV-BS,initial}$, $y_{i,t}^{UAV-BS,initial}$, $h_{i,t}^{UAV-BS,initial}$), using k-means clustering.

Figure 4.1 depicts the flowchart of the JAYA algorithm for the MINLP UAV-BS placement optimization problem, offering a comprehensive overview consistent with the algorithm outlined in Algorithm 2. After formulating the placement problem according to the flowchart provided in Figure 4.1, parameters such as population size, the number of iterations, variables, and termination criteria need to be set. Subsequently, the solutions, denoted as coordinates for UAVs, within the population are ranked, distinguishing the best and worst solutions. The refinement of new solutions involves utilizing equations 4.1, 4.2, and 4.3 that represent iterative updates for optimizing the coordinates ($X_{i,t,New}^{UAV-BS}$, $Y_{i,t,New}^{UAV-BS}$, and $H_{i,t,New}^{UAV-BS}$) of UAV-BS placements in proposed optimization process. Each equation set delineates how the new coordinates (denoted as New) are recalculated based on the current coordinates ($Current$), the best coordinates ($Best$), and the worst coordinates ($Worst$). The process involves adjusting the UAV-BS coordinates iteratively until convergence or a specific criterion is achieved. The parameter r acts as a scaling or step factor in this updating process. If an improved solution is found, it replaces the previous solution; otherwise, the algorithm reverts to the previous solution. Once all solutions in the population have been evaluated, and if the iteration count reaches N, a check for the termination condition occurs. If met, the best or optimal solutions (UAV-BS coordinates) are returned; otherwise, the process continues with a new iteration.

$$X_{i,t,New}^{\text{UAV-BS}} = X_{i,t,Current}^{\text{UAV-BS}} + r \cdot (X_{i,t,Best}^{\text{UAV-BS}} - \left|X_{i,t,Current}^{\text{UAV-BS}}\right|) \quad - r \cdot (X_{i,t,Worst}^{\text{UAV-BS}} - \left|X_{i,t,Current}^{\text{UAV-BS}}\right|) \tag{4.1}$$

$$Y_{i,t,New}^{\text{UAV-BS}} = Y_{i,t,Current}^{\text{UAV-BS}} + r \cdot (Y_{i,t,Best}^{\text{UAV-BS}} - \left|Y_{i,t,Current}^{\text{UAV-BS}}\right|) \quad - r \cdot (Y_{i,t,Worst}^{\text{UAV-BS}} - \left|Y_{i,t,Current}^{\text{UAV-BS}}\right|) \tag{4.2}$$

$$H_{i,t,New}^{\text{UAV-BS}} = H_{i,t,Current}^{\text{UAV-BS}} + r \cdot (H_{i,t,Best}^{\text{UAV-BS}} - \left|H_{i,t,Current}^{\text{UAV-BS}}\right|) \quad - r \cdot (H_{i,t,Worst}^{\text{UAV-BS}} - \left|H_{i,t,Current}^{\text{UAV-BS}}\right|) \tag{4.3}$$

Algorithm 2 utilizes the JAYA algorithm to optimize the placement of UAV-BSs in more detail. It takes as input the following parameters: UE positions, their required data rates, UAV-BS speed during horizontal and vertical flights, UAV-BS capacity, coverage radius, rotor specifications, area boundaries, wind speed, and wind orientation. It initializes both the optimization problem and JAYA algorithm parameters. Employing k-means clustering, it generates the initial potential locations of UAV-BSs at time 0 ($x_{i,t}^{UAV-BS,initial}$, $y_{i,t}^{UAV-BS,initial}$, $h_{i,t}^{UAV-BS,initial}$). Subsequently, objective functions f_1, f_2, and f are computed based on constraints (3.26), (3.27), and (3.28) respectively. After sorting the solutions to identify the best and worst ones ($x_{i,t,Best}^{UAV-BS}$, $y_{i,t,Best}^{UAV-BS}$, $h_{i,t,Best}^{UAV-BS}$, and $x_{i,t,Worst}^{UAV-BS}$, $y_{i,t,Worst}^{UAV-BS}$, $h_{i,t,Worst}^{UAV-BS}$), the algorithm initiates a loop, iterating up to a maximum count, K. For each I UAV-BS, J UEs, and T time step, new solutions refine UAV coordinates using JAYA's equations in lines 11-13. Improved solutions replace current ones if found. Finally, in lines 18-22, it checks for the termination condition, halting and returning the optimal UAV-BS coordinates if the maximum iterations are reached; otherwise, it continues until convergence, consistently refining UAV-BS placements based on the predefined objectives and constraints.

Algorithm 2: Proposed algorithm.

Input: $x_{j,t}^{\mathrm{UE}}, y_{j,t}^{\mathrm{UE}}$, $DR_{i,j,t}^{\mathrm{UE}}$, $V_{i,t}^{\mathrm{Vertical}}$, $V_{i,t}^{\mathrm{Horizontal}}$, $Capacity_i^{\mathrm{UAV-BS}}$, $R_t^{\mathrm{UAV-BS}}$, $(x^{\mathrm{Min}}, x^{\mathrm{Max}})$, $(y^{\mathrm{Min}}, y^{\mathrm{Max}})$, $(h^{\mathrm{Min}}, h^{\mathrm{Max}})$, V_t^{wind}, and θ_t^{wind}

Output: $x_{i,t}^{\mathrm{UAV-BS}}$, $y_{i,t}^{\mathrm{UAV-BS}}$, $h_{i,t}^{\mathrm{UAV-BS}}$

Initialize the problem parameters
Generate first generation using k-means.
Compute objective functions$f_1, f_2, and\ f$.
Sort the population
$k = 1$
repeat
    for $i = 1,...,I$ **do**
        for $j = 1,...,J$ **do**
            for $t = 1,...,T$ **do**
                Set $r \in [0, 1]$
                Calculate $X_{i,t,New}^{U\mathrm{UAV-BS}}$ according eq. 4.1
                Calculate $Y_{i,t,New}^{\mathrm{UAV-BS}}$ according eq. 4.2
                Calculate $H_{i,t,New}^{\mathrm{UAV-BS}}$ according eq. 4.3
    Update process
    if $f(X_{i,t,New}^{\mathrm{UAV-BS}}) \leq f(X_{i,t}^{\mathrm{UAV-BS}})$ **then**
        $f(X_{i,t}^{\mathrm{UAV-BS}}) = f(X_{i,t,New}^{\mathrm{UAV-BS}})$
    if $f(Y_{i,t,New}^{UAV}) \leq f(Y_{i,t}^{\mathrm{UAV-BS}})$ **then**
        $f(Y_{i,t}^{\mathrm{UAV-BS}}) = f(Y_{i,t,New}^{\mathrm{UAV-BS}})$
    if $f(H_{i,t,New}^{UAV}) \leq f(H_{i,t}^{\mathrm{UAV-BS}})$ **then**
        $f(H_{i,t}^{\mathrm{UAV-BS}}) = f(H_{i,t,New}^{\mathrm{UAV-BS}})$
    $k+ = 1$
until $k = K$ *: The maximum number of iterations (K) is reached*;

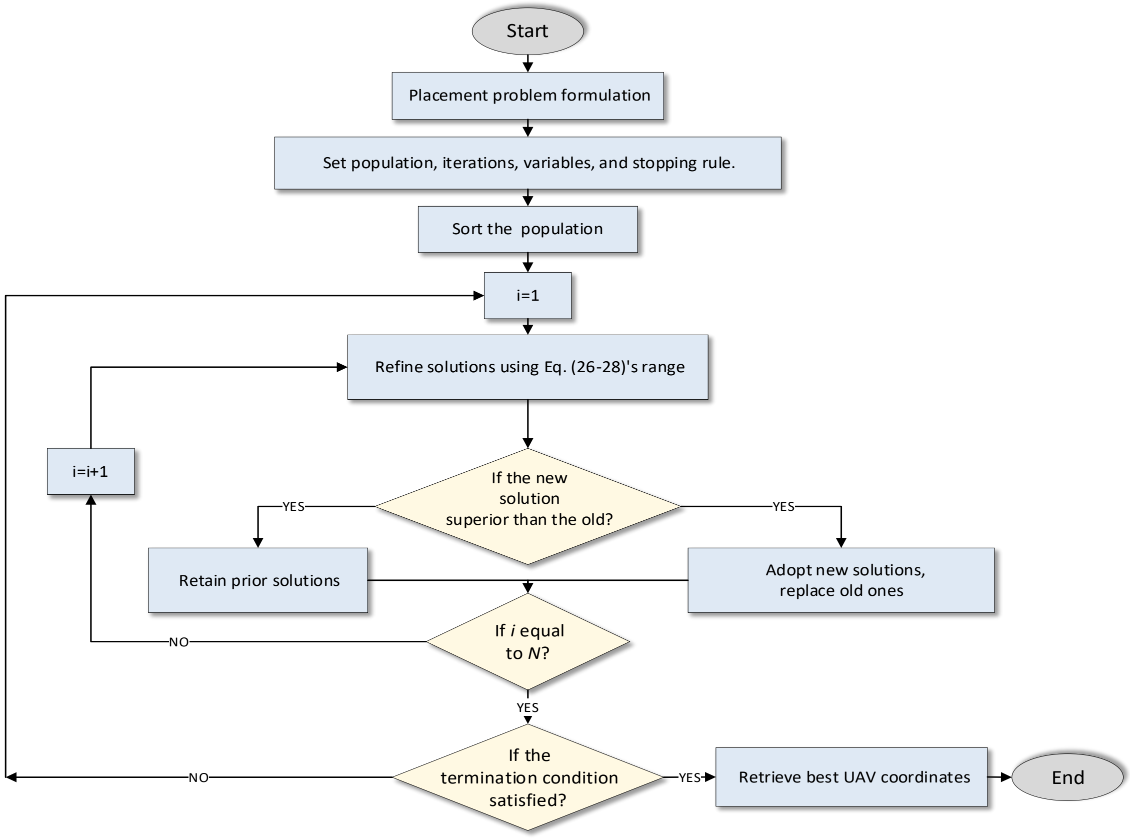


Figure 4.1 – JAYA algorithm for MINLP UAV-BS placement optimization problem.

4.2 Complexity Analysis

JAYA algorithm lacks a definitive time complexity akin to traditional algorithms due to its adaptive nature. Nevertheless, its computational complexity can be measured in terms of iterations or function evaluations, influenced by factors such as problem complexity, population size, and termination conditions. Despite this variability, the JAYA algorithm is esteemed for its simplicity and efficacy, often outperforming other metaheuristic algorithms in terms of convergence speed. Its approach involves iteratively evaluating objective functions for population members, and updating their positions based on certain rules until termination conditions are met. Evaluation of the algorithm's complexity typically occurs through empirical experimentation on specific problems to gauge convergence speed and solution quality. The time complexity of the proposed JAYA-based optimization algorithm is provided as follows:

- *Variable Initialization:* This section initializes various variables based on the data read from the file. The time complexity of initializing these variables is

$O(I+J)$, where I is the value of the "UAV-BS" set variable, and J is the value of the "UE" set variable. Considering the total number of elements processed as $n = \max(I, J)$, the time complexity expressed as $O(I+J)$ can equivalently be represented as $O(n)$. This transition to $O(n)$ clarifies that the computational complexity depends on the larger of the two variables, I and J, encapsulated by the variable 'n'. This representation emphasizes that 'n' serves as a unified measure that accounts for the overall workload determined by the maximum between I and J loops.

- *Population Initialization :* The time complexity of this section depends on the size of the population, which is determined by the values of I, and J. Considering that I and J are indicative of the population's size, the total number of elements processed is best represented by $n = I \times J$, with the larger value between I and J determining the population size. Therefore, the time complexity of this section is $O(I \times J)$, which can also be represented as $O(n^2)$, assuming $n = max(I, J)$.

- *Function Evaluation:* This section evaluates the objective functions for the population variables. The time complexity of this section depends on the size of the population and the calculations performed in the objective functions. In this case, it involves nested loops over I, J, which results in a time complexity of $O(I \times J)$ or equivalently $O(n^2)$.

  Overall, the time complexity of the given program is dominated by the population initialization and function evaluation sections, which both have a time complexity of $O(I \times J)$ or $O(n^2)$. As for the computational intensity of the code, it depends on the specific values of I and J. If these values are relatively small, the code should be computationally feasible to run on UAV-BSs. However, if the values are large, the code might become computationally intensive and may require more powerful computational resources to execute in a reasonable amount of time.

4.3 Data Generation

The input data fields are provided in Table 4.1. The number of rows for each field is determined by the lower indexes of each field. For example, in the first

Table 4.1 – Data generation parameters

Data parameters	Descriptions
V_t^{wind}	the speed of wind (1-21 km/h)
θ_t^{wind}	wind orientation (0-360°)
$Capacity_t^{UAV}$	UAV-BS capacity (400-600 MB)
$Radius_i^{UAV}$	UAV-BS coverage radius (400-500 meters)
$DR_{i,j,t}^{UE}$	UE data requirement (100-200 MB)
$X_{j,t}^{UE}$	X-coordinate of UEs (0-2000 meters)
$Y_{j,t}^{UE}$	Y-coordinate of UEs (0-2000 meters)
$Id_{j,t}^{UAV}$	UAV-BS ID number
Id_{UE}^{j}	UE ID number
I, J, T	Sets of UAV-BSs, UEs, and time steps
x^{min}, x^{max}, y^{min}, y^{max}, h^{min}, h^{max}	Minimum and maximum allowable area boundaries (same for all experiments)

scenario, experiment two, where there are 5 UAV-BSs (I=5) and 75 UEs (J=75) over 10-time steps (T=10), the number of rows for the variables V_t^{wind} and θ_t^{wind} is 10. These two variables are related to the time index, which is denoted as 't' and ranges from 1 to 10. Considering there are 75 UEs (indexed from 1 to 75) and 10-time steps, there is indeed a total of 750 rows in the dataset for both $X_{j,t}^{UE}$ and $Y_{j,t}^{UE}$ fields. For the field $DR_{i,j,t}^{UE}$, there are 5 UAV-BSs, 75 UEs, and 10-time steps, resulting in a total of 3750 (5 × 75 × 10) rows in the dataset.

A Python script is employed to generate the initial dataset with the mentioned fields, for each of the four experiments. In a manner akin to a Monte Carlo simulation, 1000 distinct variations of the initial dataset are generated for each experiment. This approach enables the model to be executed on each data variation, the resulting outputs observed, and subsequently, an average of these outputs computed. Due to the considerable computational demands associated with high dimensions for I, J, and T, the model is executed solely on the first 10 dataset variations for each experiment, evaluating their outputs. The average of these 10 files is then computed, resulting in a single file representing the average data. Subsequently, the simulation is run just once on this average data. It is observed that the output of running the simulation 10 times and averaging the results is equivalent to running the simulation once on the average data. This approach allows the conservation of computational resources while maintaining the accuracy of the results. Based on the analysis, the simulation is performed using the average dataset derived from the 1000 variations, and the resulting outputs are documented.

5 PERFORMANCE EVALUATIONS

The proposed framework and its components were meticulously constructed utilizing the Python programming language, showcasing a cohesive integration of the network architecture, optimization model, and algorithmic processes. Within the realm of Python, the simulation setup was realized through the implementation of a specialized network architecture leveraging the robust capabilities of the Pyomo optimization library (Hart et al., 2011). This Python-based framework seamlessly amalgamated several critical facets, including data preprocessing, the formulation of intricate mathematical optimization models, and the utilization of the JAYA-based algorithm, thereby establishing a comprehensive and efficient system. It is worth mentioning that a detailed presentation of the results for the initial PSO-based placement problem formulation can be found in (PASANDIDEH et al., 2023a).

To provide a detailed understanding of the simulation procedures, Section 5.1 of this chapter intricately delineates the simulated scenario. Herein, a comprehensive overview of the simulation setup, encompassing the conditions employed, is meticulously presented. Furthermore, the experimental design is comprehensively explored in Section 5.2. This section meticulously outlines the myriad factors under consideration and elucidates the methodological approach adopted for conducting the experiments. Each factor's variation and its subsequent impact on the aforementioned metrics were scrutinized and analyzed methodically.

The culmination of these rigorous experimental procedures is expounded upon in Section 5.3. This section encapsulates the findings gleaned from the conducted experiments, presenting comprehensive insights and results derived from the meticulous evaluation of the simulated scenarios and experimental designs detailed earlier. Section 5.4 presents the comparison of the proposed method with the baseline papers in terms of packet loss, latency, and movement power consumption of UAV-BSs. Following this, Section 5.5 discusses how the proposed methods guarantee the correctness of the models, the techniques employed to ensure the correctness of both the models and implementations, and addresses the challenges associated with implementing this work in the real world. Additionally, it provides a statement elucidating the limitations of the work.

5.1 Simulated Scenario

Consider a scenario where terrestrial BSs may become inoperative due to equipment damage or power failure. In such situations, UAV-BSs can play a vital role in swiftly and efficiently restoring communication services. Multiple UAV-mounted BSs are deployed to target regions, offering temporary wireless communication services. One of the use cases arises when there is a fundamental need for flexibility, reliable access, and low latency within the framework of 6G networks. In response, UAV-BSs can function as macrocells, serving as 5G or 6G infrastructure in urban settings and presenting a potential solution for advancing 6G, as highlighted in (BAJRACHARYA et al., 2022). These UAV-BSs assume a critical role during natural disasters, such as severe storms, thereby enhancing relief efforts and radio communication capabilities. Notably, the aftermath of Hurricane Katrina in the United States underscored the imperative need for such communication enhancements. Furthermore, UAV-BSs can ameliorate the consequences of unnatural disasters, such as war or fires, which can disrupt radio communication and internet access, as explored in (PARVARESH; KANTARCI, 2023) and (LIAO; FRIDERIKOS, 2022). The research aims to delve into these scenarios through simulation. In figure 5.1, two scenarios depicting natural and unnatural disasters are presented. UAV-BSs can effectively contribute to these disaster situations, and in this simulation, these scenarios are modeled to represent real-world situations where UAV-BSs are utilized.

5.2 Experimental Design

The implementation of a comprehensive full factorial experiment requires meticulous planning and systematic structuring to evaluate the dynamics between UEs and UAV-BSs in communication networks. Based on Figure 5.2, this study investigates the impact of varying quantities of UEs (50, 75, 150) and UAV-BSs (2, 3, 5, 10) on critical performance metrics including packet loss, throughput, latency, movement, and communication power of UAV-BSs.

The choice of the specific number of UEs in the performed experiments was driven by the necessity to ensure meaningful comparisons with baseline studies, as evidenced in previous research (PASANDIDEH et al., 2023a) and (MANZOOR;

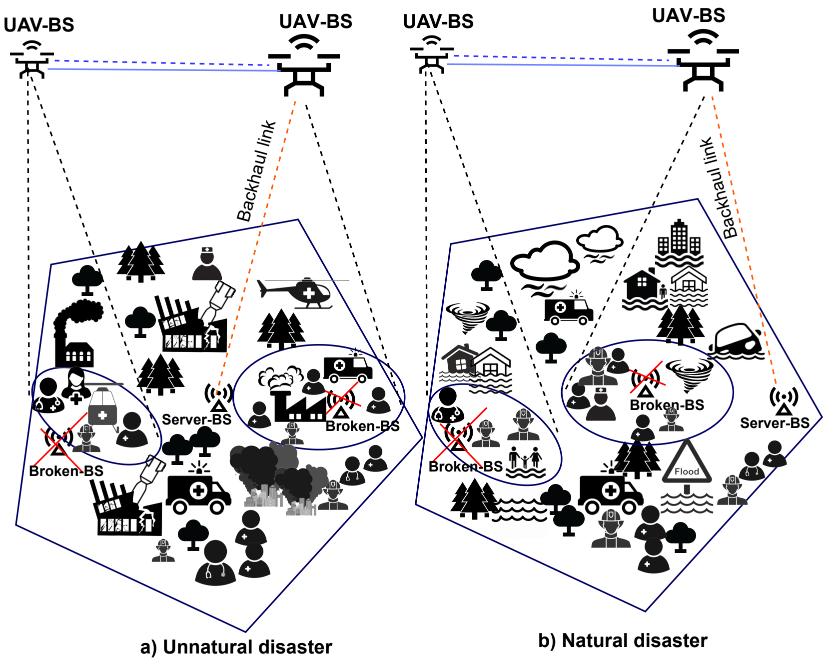


Figure 5.1 – Scenarios for unnatural disaster (war), and natural disaster (flood).

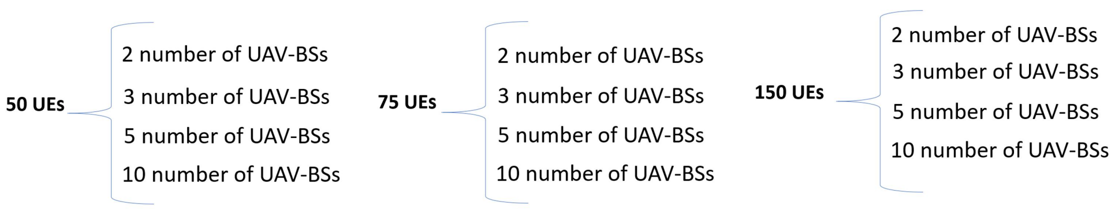


Figure 5.2 – The implementation of a comprehensive 12 factorial experiments.

KIM; HONG, 2019). However, it is acknowledged that the numbers used may appear lower when compared to the scenarios described, such as the example of 50,000 people attending a football match in a stadium. It is important to clarify that the designed experiments are simplifications of the provided use case scenarios. To address this concern, additional tests were conducted on larger sets of UEs, encompassing combinations of UAV-BSs and time steps. These tests included UEs ranging from 500 to 1000 and varying numbers of UAV-BSs (2, 3, 5, 10). Despite the reasonable results obtained, it is crucial to highlight that increasing the number of UEs led to higher computational demands, resulting in longer running times due to the heightened requirement for computational resources. Additionally, covering the expanded set of UEs necessitated a greater number of UAV-BSs. While designed experiments may not directly mirror the scale of real-world scenarios, they provide valuable insights into the performance of the proposed system under varying conditions and help lay the groundwork for further investigation and optimization. To tackle large-scale scenarios involving thousands of UEs more efficiently, future work will focus on developing algorithms tailored to such contexts.

The experiment design involves conducting 12 distinct trials, systematically controlling and manipulating the independent variables to observe their effects on the dependent variables. The experimental design matrix comprises two separate dimensions: one where the number of UAV-BSs remains constant while the number of UEs fluctuates, and another where the number of UEs is fixed while varying the quantity of UAV-BSs. To execute the experiments effectively, each trial isolates a specific combination of UEs and UAV-BSs. In the first set of trials, where the number of UAV-BSs is held constant, different quantities of UEs are employed to evaluate their impact on the performance metrics. Conversely, in the second set of trials, the number of UEs remains fixed while the number of UAV-BSs is varied to discern their influence on the aforementioned metrics.

5.3 Results and Discussions

This section discusses the simulation results obtained from the characterization of the proposed optimization problem and the algorithm including, the movement and communication powers, packet loss ratio, latency, throughput, and the number of connected UEs to each UAV-BS.

- *Optimal location of UAV-BSs in different scenarios:* The presented optimization model aims to determine the UAV-BSs optimal positions for a comprehensive experimental design encompassing 50, 75, and 150 UEs, paired with varying numbers of UAV-BSs set at 2, 3, 5, and 10 units. These calculations span across diverse input data configurations spanning 10 time steps. Figure 5.3 showcases the optimal positions of UAV-BSs across 12 experiments and their associations with UEs during the initial time step for each scenario. According to Figure 5.3 each UAV-BS is denoted by a differently colored square. UEs are represented by their IDs as small dots colored corresponding to their connected UAV-BS. Disconnected UEs are depicted in gray. Notably, Figure 5.3 demonstrates that when the number of UAV-BSs is set to ten, achieving 100% coverage probability ensues, effectively covering all UEs. While the positions of UAV-BSs and UEs across 10-time steps are displayed for each experiment, due to space limitations, only the positions at time 0 are provided in this presentation. Table 5.1 shows the number of connected and disconnected UEs for different scenarios at time 0.

Table 5.1 – The number of connected and disconnected UEs to each UAV-BS in each scenario at time 0.

Experiment	Number of UEs	Number of UAV-BSs	Number of Connected	Number of Disconnected
1	50	2	31	19
2		3	38	12
3		5	46	4
4		10	50	0
5	75	2	47	28
6		3	61	14
7		5	65	10
8		10	75	0
9	150	2	80	70
10		3	112	38
11		5	147	3
12		10	150	0

For further insights and additional results across multiple time steps for each experiment, interested readers can find the complete dataset in the Git repository made available by this research group. Complete dataset repository available at: [1] link.

[1] <https://github.com/Faezeh1989/final_PhD_UAV_Placement/tree/main>

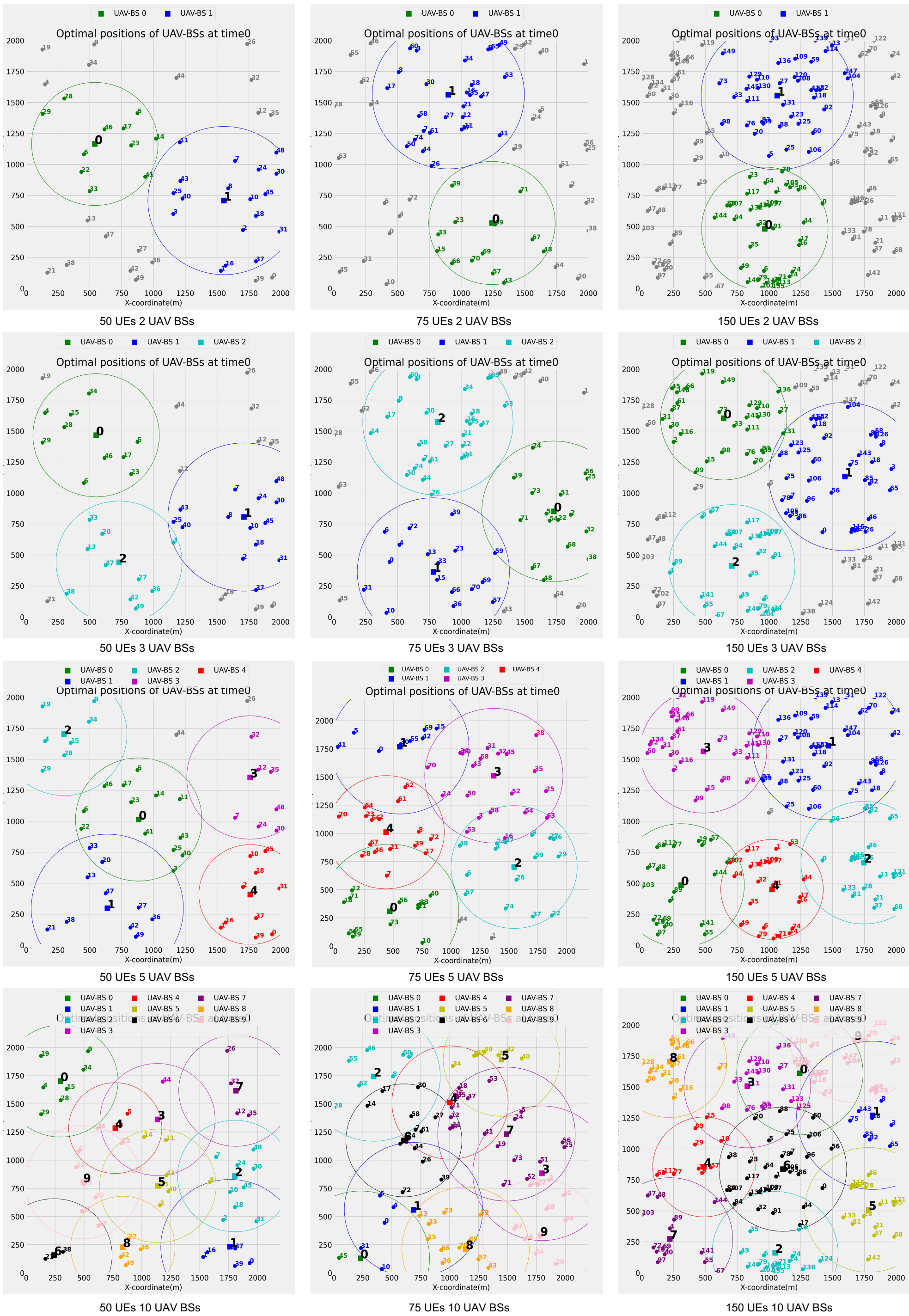


Figure 5.3 – Optimal positions of UAV-BSs while serving different numbers of UEs.

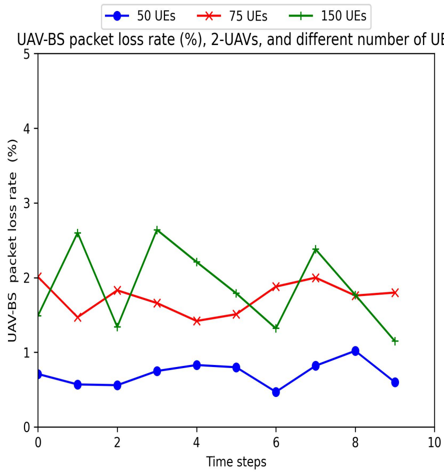
- *Packet loss rate:* In wireless communication systems, especially in scenarios involving UAV-based communication, ensuring minimal packet loss is crucial for optimizing network performance. As UAV-BS start to move from their original locations, multiple UEs establish connections with these UAV-BS units. The time it takes for a UAV-BS to reach the vicinity of a UE becomes a critical factor in accurately measuring packet loss. Estimating the packet loss rate involves a complex interplay of variables governed by a linear relationship that encompasses several influential factors. These factors include but are not limited to:

- Number of Connected UEs: The total count of UEs establishing connections with the UAV-BS significantly impacts the network's packet loss rate. Higher UE density might lead to increased contention for network resources, potentially elevating packet loss.
- Data Rate of UEs: The transmission speeds or data rates at which UEs communicate with the UAV-BS influence packet loss. Higher data rates might strain the network, potentially resulting in a higher probability of packet loss, especially if network resources are limited.
- Proximity of UEs to UAV-BS: The distance between UEs and the UAV-BS plays a crucial role. UEs closer to the UAV-BS typically experience better signal strength and lower interference, thereby potentially experiencing lower packet loss compared to UEs farther away.
- Movement of UAV-BS: The dynamic nature of UAV-BS relocation introduces variability in the network topology. This movement affects the connectivity and signal quality experienced by UEs, thereby impacting the packet loss rate.

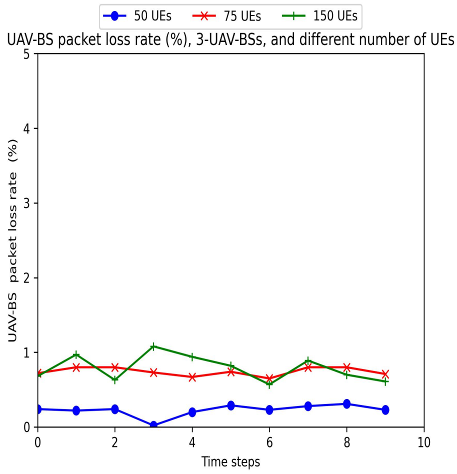
Accurately estimating and managing packet loss rate under these dynamic conditions necessitates continuous monitoring, predictive modeling, and adaptive algorithms. Strategies involving proactive handover mechanisms, resource allocation algorithms, and predictive path planning for UAV-BS can be employed to mitigate packet loss and enhance overall network performance in such scenarios. In Figure 5.4, the packet loss rates for 2, 3, 5, and 10 UAV-BSs are depicted over time across different experiments, each involving varying numbers of UEs (50, 75, and 150). Observing Figure 5.4 plots a, b, and c, it is apparent that the average packet loss for UAV-BSs 2, 3, and 5 tends to be higher when accommodating 150 UEs compared to scenarios with 75 and 50 UEs respectively. However, when employing 10 UAV-BSs to cover these sets of UEs, the packet loss values converge to nearly the same levels due to the enhanced coverage. With 10 UAV-BSs deployed, complete coverage is achieved for each subset of 50, 75, and 150 UEs. Notably, the variance observed in the plots regarding packet loss is attributable to the stochastic nature of data demands from UEs at different time instances.

- *Latency:* The latency of UEs and UAV-BSs is of paramount importance in numerous modern applications, particularly in the realms of remote sensing, surveillance, and communication. Low latency is critical for real-time decision-making and control, as it directly impacts the responsiveness of UAV-BSs to UE commands and the timely delivery of data or services. Reduced latency enhances the effectiveness of UAV-BSs in tasks such as disaster response, where quick decision-making and communication can save lives, or in autonomous UAV-BS delivery services, where prompt navigation and obstacle avoidance are essential. In summary, minimizing latency between UEs and UAV-BSs is vital for ensuring the efficiency, safety, and reliability of UAV-BS operations across a wide range of industries and applications. Figure 5.5 displays bar charts illustrating the varied latency of UAV-BSs in an experiment involving 75 UEs. As depicted in the figure, an increase in the number of available UAV-BSs serving UEs potentially reduces the distance between a UE and the nearest UAV-BS. This proximity results in shorter communication paths, thus contributing to lower latency. It is important to note that the low latency values observed are due to the direct single-hop communication between UEs and the UAV-BSs.

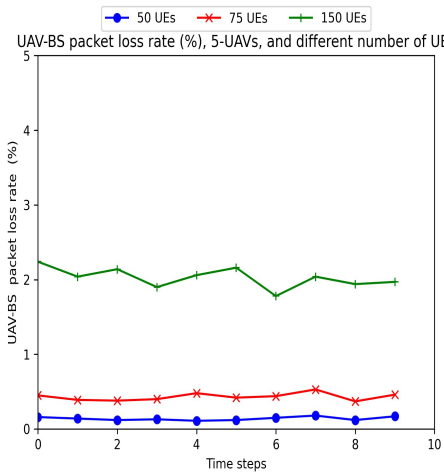
  Additionally, Table 5.2 shows the comparison of the average latency of the proposed optimization model for a full factorial design. As indicated by Table 5.2, the average latency in for each set of UEs and their respective UAV-BSs remains approximately 1 ms. Latency within this context is notably influenced by the spatial separation between UEs and UAV-BSs. A direct correlation exists where increased distance between UEs and UAV-BSs results in higher observed latency. The proposed optimization model strategically minimizes the distance between UEs and UAV-BSs, thereby inherently reducing the latency. The reduction in spatial separation inherently leads to a considerable decrease in latency, exemplifying the efficacy of the proposed model in achieving lower communication delay. This optimization approach plays a significant role in enhancing the efficiency and responsiveness of the communication system by mitigating latency concerns through minimized distances between UEs



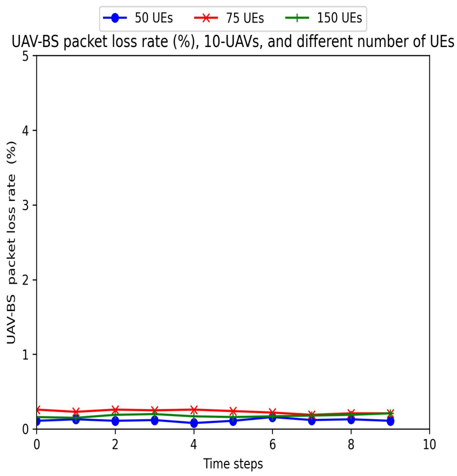
(a) UAV-BSs packet loss, 2 UAV-BSs, varying UEs



(b) UAV-BSs packet loss, 3 UAV-BSs, varying UEs

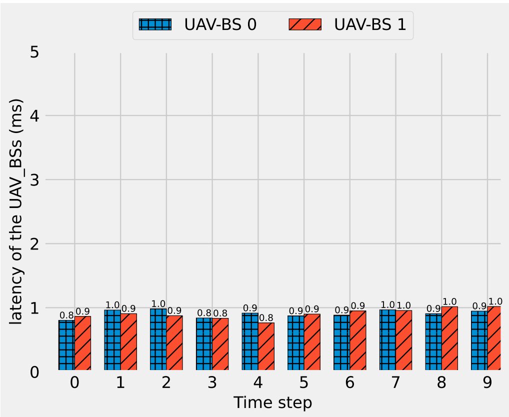


(c) UAV-BSs packet loss, 5 UAV-BSs, varying UEs

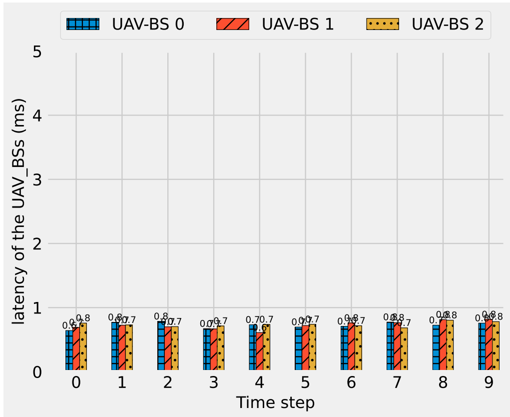


(d) UAV-BSs packet loss, 10 UAV-BSs, varying UEs

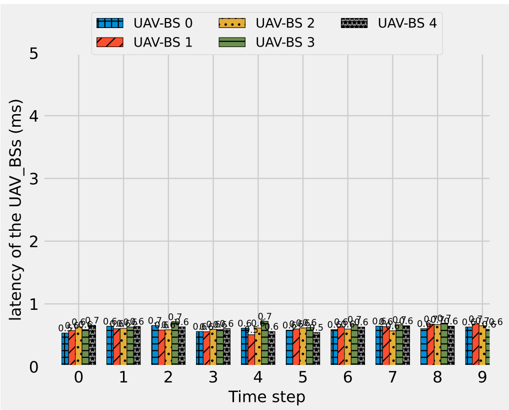
Figure 5.4 – The packet loss rate of each UAV-BS over time in different experiments with varying number of UEs



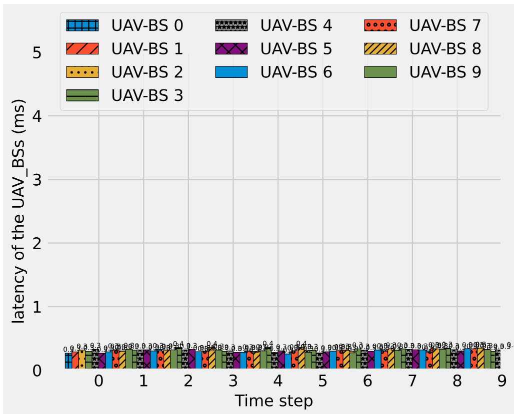
(a) Latency of UAV-BSs, the experiment with 75 UEs and 2 UAV-BSs



(b) Latency of UAV-BSs, the experiment with 75 UEs and 3 UAV-BSs



(c) Latency of UAV-BSs, the experiment with 75 UEs and 5 UAV-BSs



(d) Latency of UAV-BSs, the experiment with 75 UEs and 10 UAV-BSs

Figure 5.5 – Latency of UAV-BSs, the experiment with the fixed number of 75 UEs and varying number of UAV-BSs

Table 5.2 – Average latency of each UAV-BS in each scenario over time.

Experiment	Number of UEs	Number of UAV-BSs	Average Latency (ms)
1	50	2	0.60
2		3	0.40
3		5	0.24
4		10	0.20
5	75	2	0.90
6		3	0.72
7		5	0.61
8		10	0.37
9	150	2	1.82
10		3	1.22
11		5	1.66
12		10	0.67

and UAV-BSs.

It is worth mentioning that, the low values observed in both parameters, Latency and Packet Loss, stem from the direct single-hop communication between UEs and the UAV-BSs. The assumption of single or multiple hops between UAV-BS and users significantly impacts packet loss and latency in communication systems. In a single-hop configuration, where UAV-BSs directly communicate with users, packet loss and latency tend to be lower due to the simplified transmission path, minimizing potential points of failure and interference. Conversely, in a multiple-hop setup, where data is relayed between UAV-BSs before reaching users, packet loss and latency may increase as each additional hop introduces transmission delays, potential points of failure, and the risk of interference or signal degradation at relay points. While multiple hops can offer broader coverage, the trade-off often involves higher packet loss and latency, emphasizing the importance of carefully considering network topology and application requirements to optimize communication efficiency and reliability. However, based on the presented model, factors influencing packet loss and latency also include the distance between the UE and the UAV-BS, the number of concurrent connections to the UAV-BS, and the data requirements of the UEs.

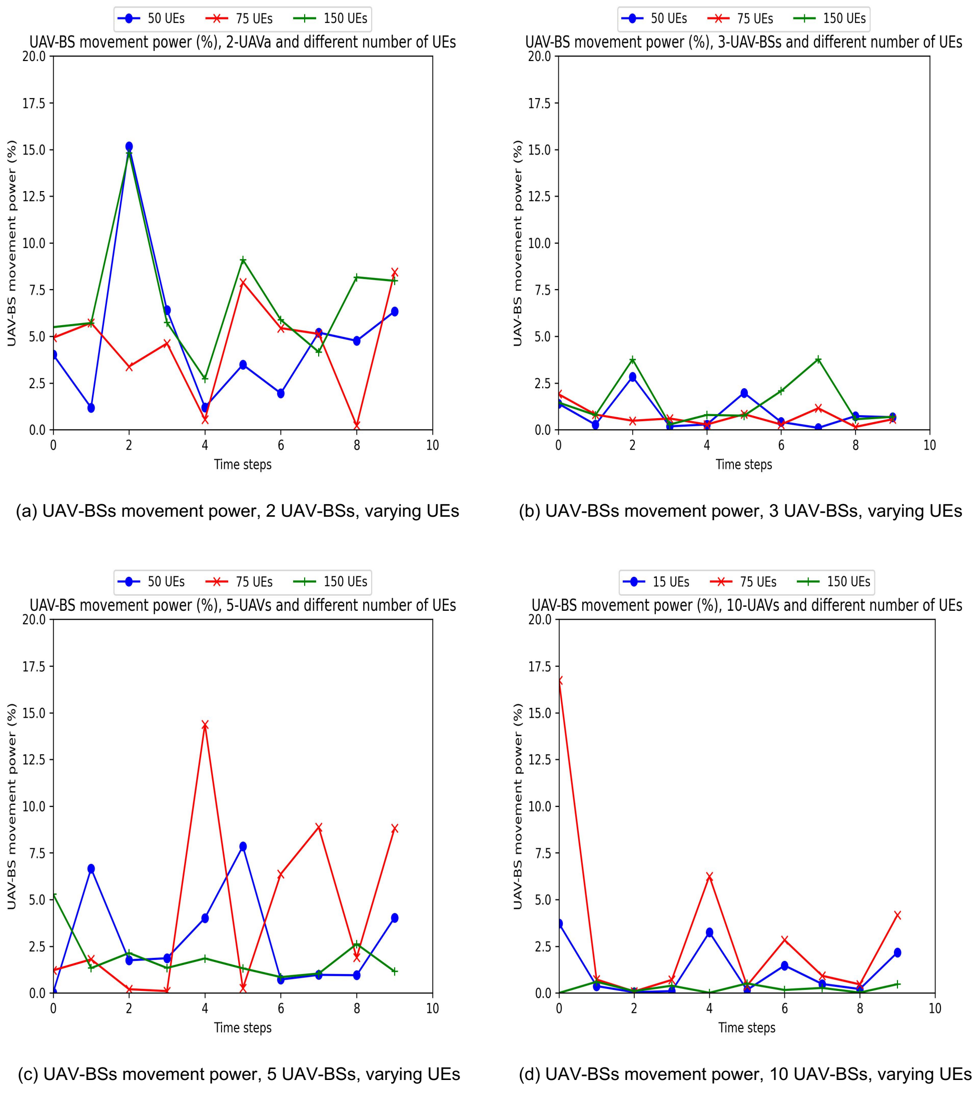
- *Power consumed by UAV-BSs :* The power consumption of UAV-BS is a multifaceted aspect influenced by several key factors, primarily impacted by their mobility and communication operations. While the movement of UAV-BSs significantly affects their power usage, it is crucial to emphasize that the energy expended during data transmission and reception processes is equally significant, albeit often overshadowed when compared to movement-related power consumption. Movement-related power consumption encompasses a spectrum of activities inherent in UAV-BS mobility. This includes horizontal and vertical motion, landing, take-off, and hovering. Each of these activities contributes to the overall energy expenditure of the UAV-BSs. Optimizing these movements is crucial to effectively managing power consumption. However, beyond movement, communication processes—such as transmitting and receiving data—also demand substantial power resources. This aspect is pivotal and should not be underestimated in the overall power consumption profile. Efforts aimed at reducing movement-related power consumption should be aligned with strategic optimization of UAV-BS placement to maximize coverage for UEs. By strategically placing UAV-BSs, coverage can be enhanced while unnecessary movements are minimized, thereby reducing overall power consumption. In summary, while movement plays a significant role in the power consumption of UAV-BSs, it's essential to acknowledge and address the energy demands associated with communication processes. Strategic placement and operational optimization are key to balancing both movement-related and communication-related power consumption while ensuring optimal coverage for UE. Figure 5.6, and 5.7 illustrate the comparison of movement power, and communication power consumption of UAV-BSs in different scenarios and experiments, respectively. According to Figure 5.6, movement power consumption is the most significant portion of power consumption compared to communication power. As determined by the proposed model, movement power is a function of UAV-BS movement, rotor specifications, UE positions, UAV-BS positions, wind speed, wind direction, and UAV speed. According to Figure 5.6 where the lines representing average movement power remain small when UAV-BS movement is limited.

As it is possible to observe in Figure 5.6, there are instances where movement power increases during certain time steps. This occurs when UAV-BSs need to reposition themselves more extensively to attain optimal locations for comprehensive UE coverage. In Figure 5.6, specifically in plot (a), there exist peak values at time step 2 for the experiments with 50, and 150 UEs, which can be attributed to the UAVs covering a distance of nearly 100 units between time steps 1 and 4. This distance is crucial as it aligns with the data requirements of the UEs and is influenced by various factors such as UAV mobility patterns, movement dynamics, positional changes, UAV capacity, and coverage range. Moreover, the simulation considers randomly selected wind conditions, ranging from 1 to 21 km/h in speed and 0 to 360 degrees in orientation. Notably, at time step 2, the specific values of wind speed (V_t^{Wind}) registering at 17.23 km/h and wind orientation (θ_t^{Wind}) at 251.06 degrees indicate a strong wind opposing the direction of the UAV's movement. Consequently, this opposition leads to increased power consumption by the UAV-BS due to the adverse effect of wind resistance. Similar adjustments might be observed in other plots concerning their respective peak values, which could also be influenced by these diverse environmental and mobility factors.

Figure 5.7 indicates the communication power consumed by each UAV-BS over time in different experiments with varying number of UEs. One crucial factor affecting this communication power is the number of UEs being covered by each UAV-BS. Generally, when a UAV-BS covers more UEs, it tends to consume more power for communication, as it needs to manage data transmission and reception for a larger UE base. Conversely, when fewer UEs are connected, communication power is lower. This relationship is consistent across the depicted graphs.

Figure 5.8 depicts the connectivity percentage in an experiment where the number of UEs was fixed at 50 while the number of UAV-BSs varied (2, 3, 5, and 10) over time. As observed from Figure 5.8, there is a noticeable upward trend correlating an increased number of UAV-BSs with enhanced connectivity. With a higher count of UAV-BSs, the connectivity of UEs demonstrates a consistent increase. Notably, when employing 10 UAV-BSs, a 100% coverage probability was achieved. Similar experiments were conducted for different sets of UEs (75, 150) alongside varying numbers of UAV-BSs.

Additionally, Table 5.3 offers valuable insights into the average percentage of connected and disconnected UEs over the duration of each UAV-BS interaction, directly influencing the observed trends in communication power displayed in the communication-related power chart. An analysis of the table



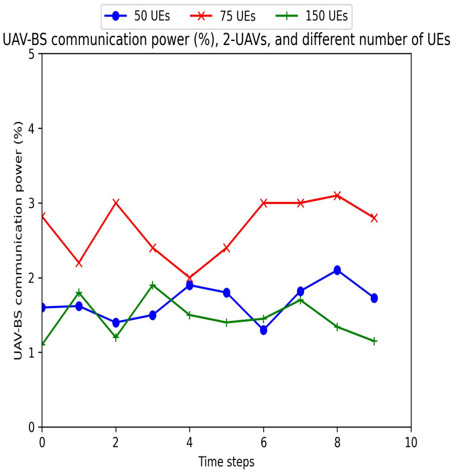
(a) UAV-BSs movement power, 2 UAV-BSs, varying UEs

(b) UAV-BSs movement power, 3 UAV-BSs, varying UEs

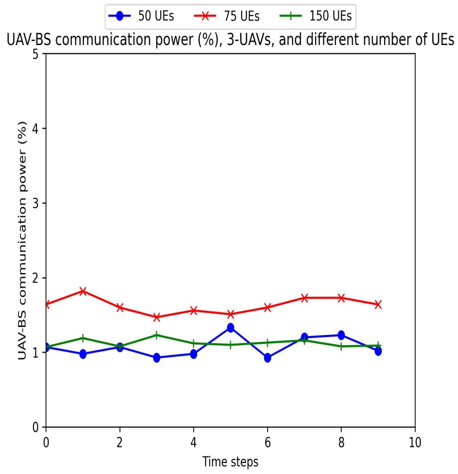
(c) UAV-BSs movement power, 5 UAV-BSs, varying UEs

(d) UAV-BSs movement power, 10 UAV-BSs, varying UEs

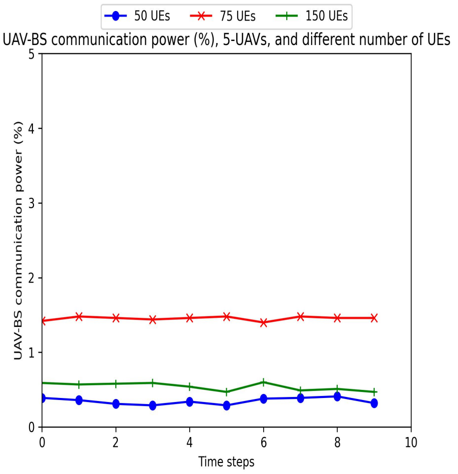
Figure 5.6 – The movement power consumed by each UAV-BS over time in different experiments with varying number of UEs



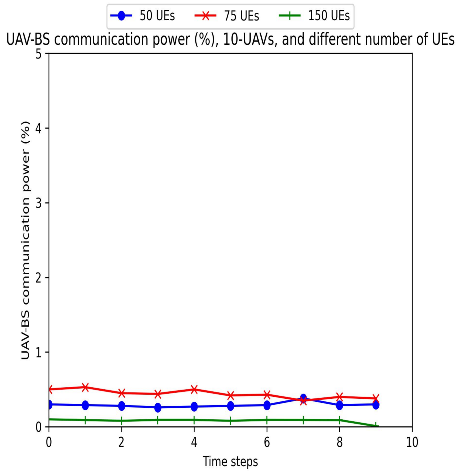
(a) UAV-BSs communication power, 2 UAV-BSs, varying UEs



(b) UAV-BSs communication power, 3 UAV-BSs, varying UEs



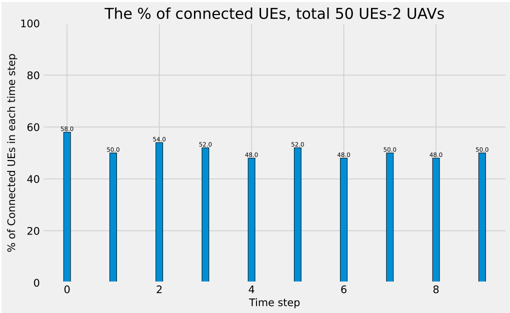
(c) UAV-BSs communication power, 5 UAV-BSs, varying UEs



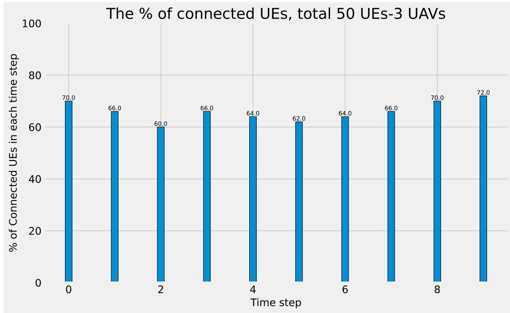
(d) UAV-BSs communication power, 10 UAV-BSs, varying UEs

Figure 5.7 – The communication power consumed by each UAV-BS over time in different experiments with varying number of UEs

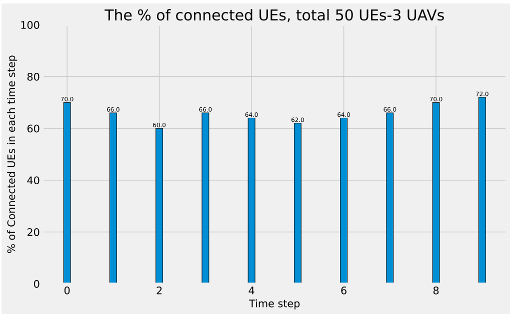
indicates a clear trend: as the number of UAV-BSs increases, there is a rise in the percentage of connectivity observed among the UEs. Moreover, it is noteworthy that in each experiment, a 100% coverage rate was achieved using 10 UAV-BSs, emphasizing the correlation between the quantity of UAV-BSs and the enhanced connectivity observed across the interactions with UEs.



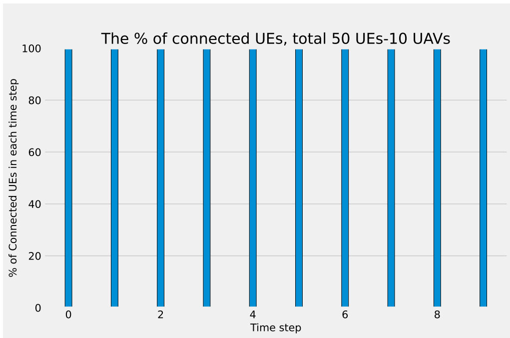
(a) The % of UEs connectivity for experiment with 50 UEs, 2 UAV-BSs



(b) The % of UEs connectivity for experiment with 50 UEs, 3 UAV-BSs



(c) The % of UEs connectivity for experiment with 50 UEs, 5 UAV-BSs



(d) The % of UEs connectivity for experiment with 50 UEs, 10 UAV-BSs

Figure 5.8 – The percentage of UEs connectivity for experiments with fixed number of 50 UEs, and varied number of UAV-BSs

- *UAV-BSs Throughput:*

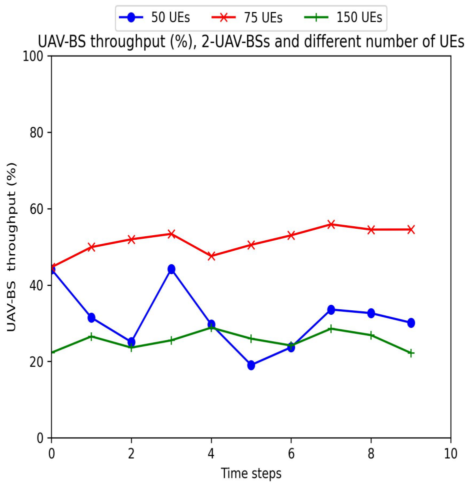
  The graphical representation in Figure 5.9 showcases the dynamic nature of throughput measured in milliseconds, reflecting the data transfer speed achieved by UAV-BSs across a period of time. The fluctuations in throughput are influenced by various interrelated factors, each contributing significantly to the observed variations.

  – Number of Connected UEs: The primary determinant affecting throughput is the quantity of UEs simultaneously linked to each UAV-BS. Higher throughput is typically experienced when a UAV-BS serves a larger number of UEs concurrently. This situation leads to increased data transmission and reception, thereby elevating the throughput. Conversely, a lower number of connected UEs results in reduced data exchange demands and subsequently lower throughput.

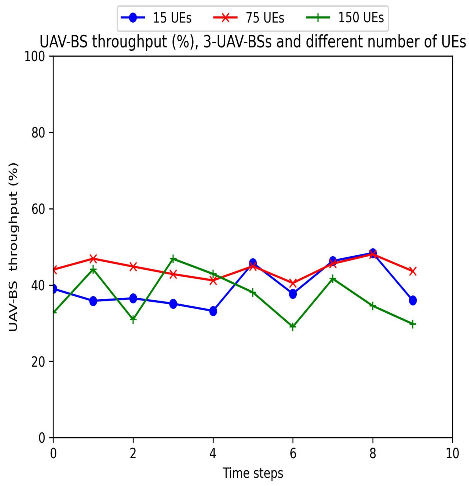
- Quality of Wireless Link: The strength and stability of the wireless connection between the UAV-BSs and UEs significantly impact throughput. Strong, stable connections enhance data transfer rates, while weaker or unstable links can cause fluctuations and lower throughput.
- Network Congestion: Congestion within the network infrastructure can hinder data flow and subsequently reduce throughput. High network traffic or bottlenecks in the communication pathways can restrict the efficient transfer of data, resulting in decreased throughput.
- Efficiency of Data Transmission Protocols: The effectiveness of the protocols governing data transmission plays a crucial role in determining throughput. Efficient protocols facilitate rapid and reliable data exchange, thereby positively impacting throughput. Conversely, inefficient protocols may lead to slower data transfer rates and reduced throughput.
- Packet Loss: Throughput can be affected by the occurrence of packet loss during data transmission. Higher packet loss rates can result in retransmissions and slower overall throughput.
- UAV-BS Capacity: The randomly generated capacity of UAV-BSs, typically falling within the range of 400-500 meters, contributes to throughput variations. Depending on the capacity available, the UAV-BSs may handle differing quantities of UEs and data traffic, thereby impacting throughput.
- UEs' Data Rate: The randomly generated data rates of UEs directly influence throughput. Higher data rates lead to faster data transmission, increasing throughput, while lower data rates can cause imbalances and fluctuations in throughput plots.

5.4 Comparative Analysis

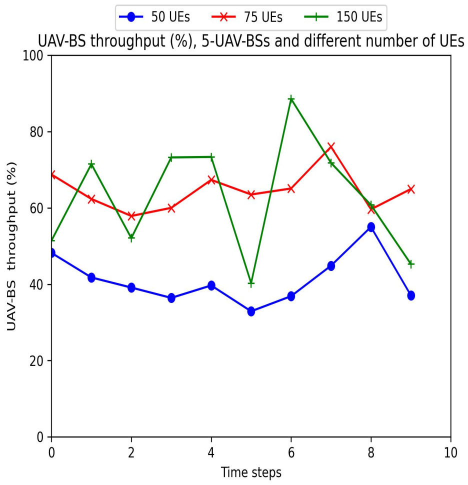
To validate the efficacy of the optimization model proposed in this dissertation, algorithms found in the literature, including (PASANDIDEH et al., 2023a)



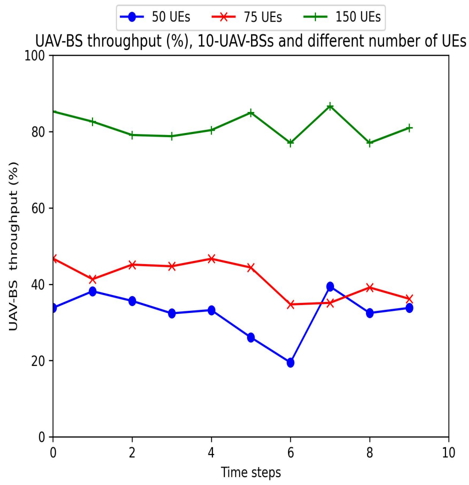
(a) UAV-BSs throughput, 2 UAV-BSs, varying UEs



(b) UAV-BSs throughput, 3 UAV-BSs, varying UEs



(c) UAV-BSs throughput, 5 UAV-BSs, varying UEs



(d) UAV-BSs throughput, 10 UAV-BSs, varying UEs

Figure 5.9 – UAV-BSs Throughput of each UAV-BS over time in different experiments with varying number of UEs.

Table 5.3 – The average of connected and disconnected UEs to each UAV-BS in each scenario over time.

Experiment	Number of UEs	Number of UAV-BSs	Average % Connected	Average % Disconnected
1	50	2	51	49
2		3	66	34
3		5	91.80	8.2
4		10	100	0
5	75	2	51.99	48.01
6		3	60.94	39.06
7		5	78.93	21.07
8		10	100	0
9	150	2	39.07	60.93
10		3	62	38
11		5	88.81	11.19
12		10	100	0

and (MANZOOR; KIM; HONG, 2019), have been chosen for comparative analysis.

In (PASANDIDEH et al., 2023a), it was observed that specific UEs experienced a significantly high packet loss rate. This issue predominantly stemmed from the distant positioning of these UEs beyond the coverage area of the corresponding UAV-BSs, causing data packets from these UEs to fail to reach the UAV-BSs. However, an evident improvement is apparent when considering the comprehensive factorial experiments depicted in Figure 5.4, showcasing the packet loss rates of UAV-BSs. According to Figure 5.10, the overall packet loss rate achieved through the proposed method is lower than the average packet loss rate outlined in (PASANDIDEH et al., 2023a). This enhancement can be attributed to the increased precision of the current model in determining optimal UAV-BS positions. Consequently, UEs are efficiently allocated to closer UAV-BSs, resulting in a reduction in packet loss rates.

According to Figure 5.11, (PASANDIDEH et al., 2023a) the average latency recorded for each set of UEs and their corresponding UAV-BSs is approximately 15 ms. This latency value stands notably higher when compared to the latency rates achieved in the proposed method, as presented in Table 5.2, where the average latency is approximately 1 ms. Latency is intricately tied to the distance between UEs and UAV-BSs, indicating that greater physical distance between these entities tends to result in higher latency. The proposed method focuses on minimizing the distance between UEs and UAV-BSs, consequently leading to a reduction in latency when

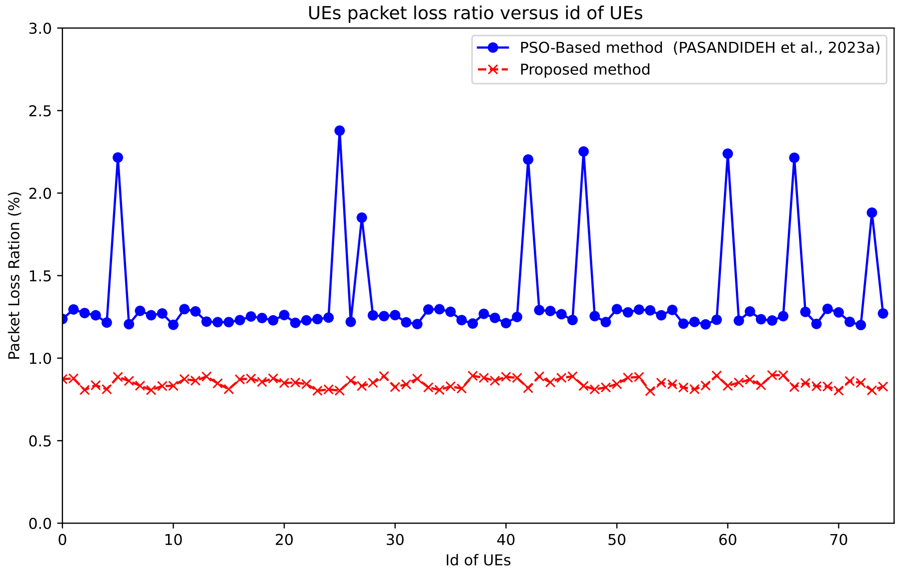


Figure 5.10 – The comparison of UEs packet loss rate between proposed method, and (PASANDIDEH et al., 2023a)

compared to the latency reported in (PASANDIDEH et al., 2023a). Furthermore, a direct correlation exists between packet loss and latency. The proposed method has notably decreased packet loss in contrast to the prior work. When packets are lost during transit through the network, additional time is required for the sender to detect and recover these lost packets. Therefore, the reduced packet loss in the proposed method directly contributes to the lower latency observed.

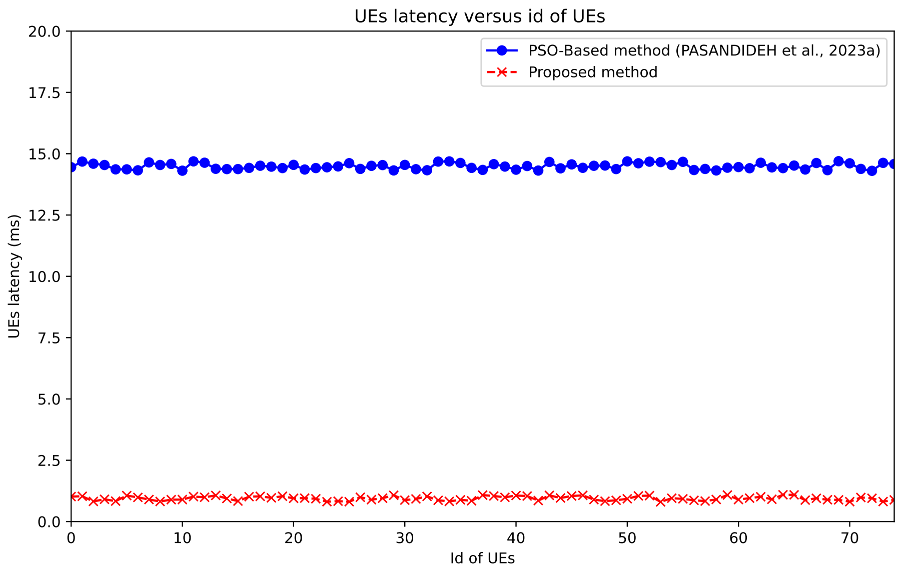


Figure 5.11 – The comparison of UEs latency between proposed method, and (PASANDIDEH et al., 2023a)

Table 5.4 shows the performance comparison of PSO and JAYA for UAV-BS placement problem. Convergence speed reflects how quickly the algorithm converges to a solution. According to Table 5.4, JAYA outperforms PSO, demonstrating a faster convergence. Solution quality shows the quality of the solutions produced by the algorithms, which are assessed based on the objective function values. The accuracy of optimal UAV positions achieved by the JAYA algorithm surpasses that of the PSO algorithm. This assessment is based on the deviation from the true optimal positions and the achieved coverage rate. As depicted in Table 5.4, JAYA exhibits superior performance with lower UAV-BS latency and reduced packet loss rates, signifying accelerated communication compared to PSO.

Table 5.4 – Performance of PSO and Jaya for UAV-BS Placement

Algorithms	**Convergence Speed**	**Solution Quality**	**UAV Positions Accuracy**	**Packet Loss**	**Latency**
PSO	Moderate	Good	Moderate	Moderate	High
Jaya	Fast	Excellent	High	Low	Low

The power consumption comparison depicted in Figure 5.12 highlights an ascending trend in the red line, representing the power consumption according to the methodology outlined in (MANZOOR; KIM; HONG, 2019). This trend implies a direct correlation between the increasing number of UEs and elevated power usage. However, the proposed model, represented by the blue line, recognizes that power consumption is not solely dependent on the quantity of users served. In the proposed model, various additional factors contribute significantly to power consumption. Elements such as wind speed and direction, the velocity of UEs, their data rate requirements, UAV-BS capacity, and other contributing factors are integral components within the proposed power consumption model. These factors collectively shape and influence the dynamics of power consumption. This broader perspective results in a more intricate and nuanced power consumption pattern. For instance, an escalation in wind speed and opposing direction can exert a notable impact on power utilization, even in scenarios with a consistent number of UEs. By integrating these diverse factors, the proposed model provides a comprehensive understanding of power consumption dynamics, moving beyond a singular focus on the quantity of UEs served to capture the complex interplay of multiple variables influencing power usage.

The choice of the (MANZOOR; KIM; HONG, 2019) as one of the baselines for comparison stems from several key factors. Firstly, the (MANZOOR; KIM; HONG, 2019) provides a solid foundation for understanding power consumption dynamics in UAV-BS systems. Additionally, the formulation of power consumption in the proposed method is derived from the baseline, indicating a logical starting point for comparison. The third reason is the similarities in parameters such as UAV-BS rotor specifications and experimental setup, the proposed model expands upon the baseline by incorporating additional factors that significantly impact power consumption, such as wind speed and direction, UE velocity, data rate requirements, and UAV-BS capacity. By integrating these diverse factors, the proposed model offers a more comprehensive understanding of power consumption dynamics, moving beyond a simplistic focus on the quantity of UEs served. Thus, the (MANZOOR; KIM; HONG, 2019) serves as a relevant reference point for evaluating the improvements and nuances introduced by the proposed model in capturing the complex interplay of multiple variables influencing power usage in UAV-BS systems.

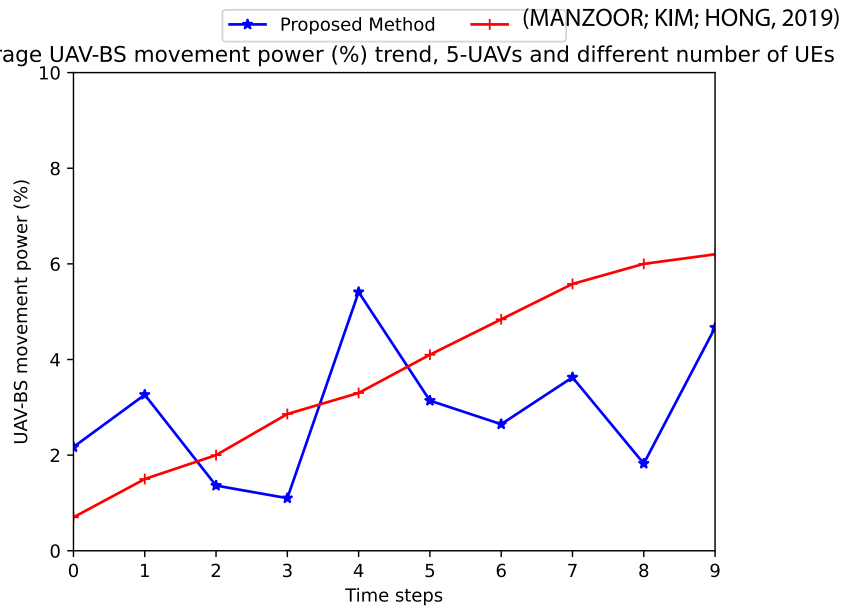


Figure 5.12 – The comparison of power consumption between proposed method, and (MANZOOR; KIM; HONG, 2019)

5.5 Discussion

This section, delves into an extensive examination of how the proposed methods establish and uphold the integrity and accuracy of the models. It thoroughly explores the techniques meticulously employed to ascertain not only the precision of the models but also the correctness of their implementations. Furthermore, this section extensively addresses the myriad challenges entailed in the practical application and integration of this research into real-world scenarios. Additionally, it furnishes a comprehensive elucidation of the inherent limitations inherent in the work, thereby offering a nuanced perspective on its scope and applicability.

5.5.1 Techniques and validation procedures

To ensure the correctness and validity of the proposed energy-efficient UAV-BS positioning mechanism, several techniques are employed. Firstly, the model formulation is rigorously validated by comparing it against established theoretical principles in wireless communication and optimization. This formulation was based on a thorough literature review and consultation with domain experts to ensure that the model accurately represented the complexities of UAV-BS positioning. The model assumptions and equations are cross-referenced with existing literature to ensure accuracy and consistency.

Secondly, the implementation of the model is thoroughly verified by extensively testing it against known scenarios and benchmarks. This includes code review, unit testing, and validation against test cases to identify and correct any errors or inconsistencies. Additionally, sensitivity analyses are conducted to assess the impact of parameter variations on the results, ensuring robustness across different scenarios. Finally, the achieved results with JAYA are compared with those obtained using a PSO-based method, enabling us to validate the effectiveness and efficiency of the proposed approach against established techniques. By employing these techniques, correctness and validity is guaranteed in the models, implementations, and experiments, enhancing the reliability and trustworthiness of the research outcomes.

5.5.2 The challenges to utilizing this work in the real world

Utilizing research findings in real-world applications presents several challenges and limitations. One significant challenge lies in scaling the proposed energy-efficient UAV-BS positioning mechanism to accommodate large-scale deployment scenarios. While the performed experiments demonstrate promising results, they may not fully capture the complexities and dynamics of real-world environments. Additionally, practical implementation faces hurdles such as regulatory constraints, technological limitations, and cost considerations. Integrating UAV-BS into existing communication infrastructure requires collaboration with various stakeholders, including regulatory bodies, telecommunications providers, and urban planners. Furthermore, ensuring seamless operation and compatibility with existing systems poses challenges that need to be addressed. Despite these limitations, proposed work provides valuable insights and serves as a foundation for further research and development in the field of UAV-assisted communication networks. It is essential to acknowledge these challenges and work towards overcoming them to realize the full potential of the provided research in real-world applications.

6 CONCLUSION

This study at hand extends the scope of prior research by introducing a cutting-edge MINLP model, specifically tailored to optimize energy efficiency by strategically situating UAVs as BSs. This novel approach aims to significantly enhance wireless connectivity across diverse scenarios. To tackle this optimization challenge, the paper proposes an algorithm that ingeniously merges the JAYA optimization algorithm with the K-means clustering technique. The fusion of these methodologies presents a robust solution for addressing the optimization model's complexities.

This study aims to address two primary research questions. In response to the initial research question concerning techniques, optimized algorithms, and data structures for mitigating wasted power consumption in achieving optimal UAV-BS placement, various strategies can be adopted. Here are several approaches to consider:

- Efficient Data Structures: Utilizing data structures such as spatial indexes or graph-based representations can significantly improve the efficiency of accessing and processing spatial information. This optimization aids in route planning, navigation, and communication tasks, ultimately reducing UAV-BS energy expenditure. Techniques such as quadtrees, R-trees, or graph data structures can be leveraged.

- Machine Learning-Based Predictive Models: Implementing predictive models based on machine learning enables proactive decision-making regarding UAV-BS movement and resource allocation. These models can learn from historical data and environmental factors to predict optimal placement and operational strategies, thereby contributing to energy-efficient deployment.

- Dynamic Resource Allocation: Dynamically allocating resources based on real-time demand and environmental conditions can help optimize energy consumption. Adaptive algorithms that adjust UAV-BS placement and task assignments in response to changing requirements and energy levels can mitigate power wastage.

- Topology Control: Controlling the network topology to minimize redundant coverage and optimize communication paths can also reduce energy consumption. Techniques such as clustering or relay node placement can be employed to ensure efficient data transmission while conserving UAV-BS energy.

In response to the second question, to improve the adaptive algorithms and optimization techniques for UAV-BS placement and energy consumption while maintaining network quality, several strategies can be considered:

- Enhanced Learning Capabilities: Increasing the complexity and diversity of the environmental datasets used for training reinforcement learning models can improve their adaptability and decision-making capabilities. This can involve incorporating more real-world scenarios, including a wider range of weather conditions, terrain variations, and user demands.

- Refinement of Metaheuristic Algorithms:

  Metaheuristic algorithms like genetic algorithms and particle swarm optimization can be enhanced by improving their convergence speed. This can be achieved through the development of more efficient search strategies or by parallelizing computations to handle larger problem sizes more effectively.

- Multi-Objective Optimization:

  Integrating multi-objective optimization strategies can help balance conflicting objectives, such as optimizing energy consumption while ensuring network quality. Techniques like Pareto optimization can be employed to find a set of solutions that represent trade-offs between different objectives, providing decision-makers with a range of options to choose from based on their priorities.

- Real-Time Data Integration:

  Continuous integration of real-time environmental data, such as weather conditions and user demands, into the optimization algorithms can improve their responsiveness and adaptability. This may involve developing efficient data collection and processing mechanisms to ensure timely updates for decision-making.

- Hybrid Approaches:

  Combining different optimization techniques, such as dynamic programming, reinforcement learning, and metaheuristic algorithms, into hybrid frameworks can leverage the strengths of each approach while mitigating their individual limitations. Hybrid approaches can provide more robust and flexible solutions that are better suited to dynamic and uncertain environments.

- Simulation and Testing:

  Conducting extensive simulations and real-world testing can help validate and fine-tune the performance of adaptive algorithms and optimization techniques. This iterative process allows researchers and practitioners to identify potential weaknesses and areas for improvement, leading to more effective solutions in practice.

To tackle large-scale scenarios involving thousands of UEs more efficiently, future work will focus on developing algorithms tailored to such contexts. Specifically, we aim to explore algorithms that can handle the increased computational demands and ensure optimal UAV-BS placement while mitigating runtime challenges. Algorithms such as advanced optimization techniques, machine learning algorithms, or hybrid approaches combining different methodologies could be promising avenues for investigation. These algorithms will be designed to efficiently manage the complexities of large-scale scenarios, facilitating the seamless integration of UAV-BSs into diverse communication environments.

A comprehensive factorial experiment is conducted within communication networks, varying UE and UAV quantities (ranging from 50 to 150 UEs and 2 to 10 UAVs). The implementation of the proposed optimization model realized through Python, facilitates a meticulous evaluation of critical performance metrics. These metrics encompass packet loss, throughput, latency, UAV movement, and the power dynamics in UAV-BS communications.

Simulation results underscore the efficacy of the JAYA-based algorithm, showcasing its adeptness in minimizing packet loss, latency, and power consumption. Notably, the observed variations in metrics are attributed to the dynamic nature of UE data demands over time. Moreover, the proposed model ensures an average connectivity rate surpassing 50%, validating its practical viability within real-world scenarios.

Nevertheless, this study conscientiously acknowledges a limitation concerning optimization algorithms, specifically the challenge of attaining the absolute global optimum within intricate parameter spaces. The inherent tendency of optimization algorithms to converge towards local optima poses a significant constraint, restricting exploration beyond initial starting points.

To fortify the proposed approach, the study suggests potential enhancements. Strategies such as diverse initializations or the integration of multiple optimization algorithms could expand the solution space, thereby potentially yielding superior solutions. Introducing methodologies like simulated annealing, genetic algorithms, or PSO is recommended to navigate the complexities of the landscape more effectively.

Future endeavors are urged to concentrate on alternative methodologies that could delve into and converge upon the global optimum solution. Investigating advanced optimization techniques, pioneering algorithms, or hybrid approaches holds promise in circumventing limitations associated with reaching the global optimum within intricate parameter spaces. Such initiatives are envisioned to bolster the efficacy of UAV-BS deployment, driving cost-effectiveness, sustainability, and performance improvements in wireless communication networks.

REFERENCES

Garaffa, L. et al. Reinforcement learning for mobile robotics exploration: A survey. *IEEE transaction on neural networks and learning systems*, v. 8, p. 1–15, 2021.

ABDOLI, M.; AL. et. A dynamic programming framework for energy-efficient uav navigation in changing environments. **IEEE Transactions on Vehicular Technology**, 2020.

ABU-BAKER, A. et al. Efficient Data Collection in UAV-Assisted Cluster-Based Wireless Sensor Networks for 3D Environment: Optimization Study. **Journal of Sensors**, v. 2023, 2023. ISSN 16877268.

ABUBAKAR, A. I. et al. Coverage and throughput analysis of an energy efficient uav base station positioning scheme. **Computer Networks**, v. 232, p. 109854, 2023. ISSN 1389-1286. Available from Internet: <https://www.sciencedirect.com/science/article/pii/S1389128623002992>.

Akram, T. et al. Multicriteria uav base stations placement for disaster management. **IEEE Systems Journal**, v. 14, n. 3, p. 3475–3482, 2020.

AKYILDIZ, I. F.; WANG, X.; WANG, W. Wireless mesh networks: a survey. **Computer Networks**, v. 47, n. 4, p. 445–487, 2005.

AL-HOURANI, A.; KANDEEPAN, S.; JAMALIPOUR, A. Optimal 3d uav base station placement for maximum coverage and minimal interference. **IEEE Communications Letters**, 2014.

AL-HOURANI, A.; KANDEEPAN, S.; JAMALIPOUR, A. Optimal lap altitude for maximum coverage. **IEEE Wireless Communications Letters**, v. 3, n. 6, p. 569–572, 2014.

ALFAIA, R. D. et al. Resource management in 5g networks assisted by uav base stations: Machine learning for overloaded macrocell prediction based on usersrsquo; temporal and spatial flow. **Drones**, v. 6, n. 6, 2022. ISSN 2504-446X. Available from Internet: <https://www.mdpi.com/2504-446X/6/6/145>.

ALOQAILY, M. et al. An adaptive UAV positioning model for sustainable smart transportation. **Sustainable Cities and Society**, Elsevier Ltd, v. 78, mar 2022. ISSN 22106707.

ALZENAD, M. et al. 3-d placement of an unmanned aerial vehicle base station (uav-bs) for energy-efficient maximal coverage. **IEEE Wireless Communications Letters**, v. 6, n. 4, p. 434–437, 2017.

BABU, N.; PAPADIAS, C. B.; POPOVSKI, P. Energy-efficient 3-d deployment of aerial access points in a uav communication system. **IEEE Communications Letters**, v. 24, n. 12, p. 2883–2887, 2020.

BAJRACHARYA, R. et al. 6G NR-U Based Wireless Infrastructure UAV: Standardization, Opportunities, Challenges and Future Scopes. **IEEE Access**, IEEE, v. 10, p. 30536–30555, 2022. ISSN 21693536.

BISWAS, S.; TATCHIKOU, R.; DION, F. Vehicle-to-vehicle wireless communication protocols for enhancing highway traffic safety. **IEEE Communications Magazine**, v. 44, n. 1, p. 74–82, 2006.

BOUCHER, P.; SILVA, C. W. de. Unmanned aerial vehicles: A historical perspective. In: **Springer Handbook of Robotics**. [S.l.]: Springer, 2018. p. 1909–1936.

BOUVRY, P.; THOMAS, L. **Mobility models in wireless ad hoc networks: A survey**. [S.l.], 2005.

Bozkaya, E.; Canberk, B. Sdn-enabled deployment and path planning of aerial base stations. **Computer Networks**, v. 171, 2020.

BROWN, M.; WILLIAMS, S. Path loss modeling for uav communication systems in urban environments. In: **International Conference on Communications (ICC)**. [S.l.: s.n.], 2019.

Chaalal, E.; Reynaud, L.; Senouci, S. M. A social spider optimisation algorithm for 3d unmanned aerial base stations placement. In: **2020 IFIP Networking Conference (Networking)**. [S.l.: s.n.], 2020. p. 544–548.

CHEN, C. et al. Cloud-based uav monitoring and management framework. In: **2018 3rd International Conference on Control, Robotics and Cybernetics (CRC)**. [S.l.: s.n.], 2018. p. 61–66.

CHERIF, N. et al. **On the Optimal 3D Placement of a UAV Base Station for Maximal Coverage of UAV Users**. 2020.

Cicek, C. T. et al. Backhaul-aware optimization of uav base station location and bandwidth allocation for profit maximization. **IEEE Access**, v. 8, 2020.

DAI, Z. et al. A multi-agent collaborative environment learning method for uav deployment and resource allocation. **IEEE Transactions on Signal and Information Processing over Networks**, v. 8, p. 120–130, 2022.

DING, Z. et al. Energy-efficient deployment of uavs for data collection in wireless sensor networks using graph-based modeling. **IEEE Internet of Things Journal**, 2020.

DONG, N. et al. An opposition-based chaotic ga/pso hybrid algorithm and its application in circle detection. **Computers Mathematics with Applications**, v. 64, n. 6, p. 1886 – 1902, 2012. ISSN 0898-1221. Available from Internet: <http://www.sciencedirect.com/science/article/pii/S0898122112002453>.

Fahim, A.; Gadallah, Y. Optimized 3d drone placement and resource allocation for lte-based m2m communications. In: **2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)**. [S.l.: s.n.], 2020. p. 1–5.

GAPEYENKO, M. et al. Line-of-sight probability for mmwave-based uav communications in 3d urban grid deployments. **IEEE Transactions on Wireless Communications**, v. 20, n. 10, p. 6566–6579, 2021.

GARG, H. A hybrid pso-ga algorithm for constrained optimization problems. **Applied Mathematics and Computation**, v. 274, p. 292 – 305, 2016. ISSN 0096-3003.

GONG, H. et al. Modelling power consumptions for multi-rotor uavs. **IEEE Transactions on Aerospace and Electronic Systems**, p. 1–14, 2023.

GUO, H. et al. 3d location optimization for uav-aided uplink/downlink transmissions. **IEEE Transactions on Vehicular Technology**, v. 71, n. 4, p. 4477–4482, 2022.

Guo, J. et al. 3d aerial vehicle base station (uav-bs) position planning based on deep q-learning for capacity enhancement of users with different qos requirements. In: **2019 15th International Wireless Communications Mobile Computing Conference (IWCMC)**. [S.l.: s.n.], 2019. p. 1508–1512.

IKUNO, J. C.; BARROS, J. A survey of 5g networks for the internet of things: Communication technologies and challenges. **IEEE Communications Surveys & Tutorials**, v. 18, n. 4, p. 2347–2376, 2016.

IQBAL, Y.; AHMAD, A.; KALEEM, Z. Power-efficient uav placement in relay assisted heterogeneous public safety networks. In: ______. **Intelligent Unmanned Air Vehicles Communications for Public Safety Networks**. Singapore: Springer Nature Singapore, 2022. p. 91–103. ISBN 978-981-19-1292-4. Available from Internet: <https://doi.org/10.1007/978-981-19-1292-4_4>.

ISLAM, M. M. et al. Dynamic positioning of UAVs to improve network coverage in VANETs. **Vehicular Communications**, Elsevier Inc., v. 36, aug 2022. ISSN 22142096.

ISLAM, N. et al. A review of applications and communication technologies for internet of things (iot) and unmanned aerial vehicle (uav) based sustainable smart farming. **Sustainability**, v. 13, n. 4, 2021. ISSN 2071-1050.

JAYATILAKA, R. V. Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems. **International Journal of Industrial Engineering Computations**, v. 7, n. 1, p. 19–34, 2016.

KRISHNA, K.; MURTY, M. N. Genetic k-means algorithm. **IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)**, v. 29, n. 3, p. 433–439, 1999.

K.S., S. R.; MURUGAN, S. Memory based hybrid dragonfly algorithm for numerical optimization problems. **Expert Systems with Applications**, v. 83, p. 63 – 78, 2017. ISSN 0957-4174. Available from Internet: <http://www.sciencedirect.com/science/article/pii/S0957417417302762>.

LAI, C.-C.; CHEN, C.-T.; WANG, L.-C. On-demand density-aware uav base station 3d placement for arbitrarily distributed users with guaranteed data rates. **IEEE Wireless Communications Letters**, v. 8, n. 3, p. 913–916, 2019.

LEE, D.; GARCIA, J. Performance analysis of air-to-ground channel models for uav communications. **IEEE Wireless Communications Letters**, 2018.

LI, Z. et al. Energy efficient resource allocation for uav-assisted space-air-ground internet of remote things networks. **IEEE Access**, v. 7, p. 145348–145362, 2019.

LIAO, Y.; FRIDERIKOS, V. Optimal Deployment and Operation of Robotic Aerial 6G Small Cells with Grasping End Effectors. **IEEE International Conference on Communications**, v. 2022-May, p. 1–6, 2022. ISSN 15503607.

LIU, C. H. et al. Energy-efficient uav control for effective and fair communication coverage: A deep reinforcement learning approach. **IEEE Journal on Selected Areas in Communications**, v. 36, n. 9, p. 2059–2070, 2018.

LIU, J.; ZHANG, L.; ZHOU, Y. A survey on 5g communication for uav-assisted networks: Recent advances, key technologies, and open challenges. **IEEE Access**, IEEE, v. 9, p. 25202–25221, 2021.

LIU, Y. et al. Fair and energy-efficient coverage optimization for uav placement problem in the cellular network. **IEEE Transactions on Communications**, v. 70, n. 6, p. 4222–4235, 2022.

LYU, H. et al. Energy-efficient deployment of unmanned aerial vehicles for cellular-connected iot systems. **IEEE Transactions on Wireless Communications**, 2020.

MANDLOI, D.; ARYA, R. FRAT: a fuzzy rule based adaptive technique for intelligent placement of UAV-mounted base station. **Wireless Networks**, Springer US, v. 29, n. 5, p. 2061–2077, 2023. ISSN 15728196. Available from Internet: <https://doi.org/10.1007/s11276-023-03273-0>.

MANZOOR, A.; KIM, D. H.; HONG, C. S. Energy efficient resource allocation in uav-based heterogeneous networks. In: **2019 20th Asia-Pacific Network Operations and Management Symposium (APNOMS)**. [S.l.: s.n.], 2019. p. 1–4.

MARANI, M. R.; MIRREZAEI, S. M.; MIRZAVAND, R. Joint throughput and coverage maximization for moving users by optimum uav positioning in the presence of underlaid d2d communications. **AEU - International Journal of Electronics and Communications**, v. 161, p. 154541, 2023. ISSN 1434-8411. Available from Internet: <https://www.sciencedirect.com/science/article/pii/S1434841123000158>.

MERZ, S. (Ed.). **Drones and the Future of Air Transportation: Proceedings of the International Conference on Unmanned Aerial Systems**. [S.l.]: Springer, 2020.

MOUSTAFA, R.; ALYAHFOUFI, M.; ABBAS, N. Energy efficient uav-based relay system for iot networks in hazardous industrial areas. In: **2022 4th IEEE Middle East and North Africa COMMunications Conference (MENACOMM)**. [S.l.: s.n.], 2022. p. 223–228.

MOZAFFARI, M.; AL. et. Drone small cells in the clouds: Design, deployment, and performance analysis. **IEEE Journal on Selected Areas in Communications**, v. 34, n. 5, p. 256–273, 2016.

MOZAFFARI, M.; AL. et. Efficient deployment of multiple uavs for optimal wireless coverage. **IEEE Transactions on Wireless Communications**, v. 16, n. 3, p. 758–769, 2017.

MOZAFFARI, M. et al. A tutorial on uavs for wireless networks: Applications, challenges, and open problems. **IEEE Communications Surveys Tutorials**, 2019.

MOZAFFARI, M. et al. A tutorial on uavs for wireless networks: Applications, challenges, and open problems. **IEEE Communications Surveys & Tutorials**, v. 21, n. 3, p. 2334–2360, 2019.

MUTHANNA, M. S. A. et al. Towards optimal positioning and energy-efficient uav path scheduling in iot applications. **Computer Communications**, v. 191, p. 145–160, 2022. ISSN 0140-3664. Available from Internet: <https://www.sciencedirect.com/science/article/pii/S0140366422001414>.

NAWROCKI, P.; AL. et. Particle swarm optimization for real-time adaptive uav placement considering environmental factors. **IEEE Transactions on Intelligent Transportation Systems**, 2021.

NOH, S.-C.; JEON, H.-B.; CHAE, C.-B. Energy-efficient deployment of multiple uavs using ellipse clustering to establish base stations. **IEEE Wireless Communications Letters**, v. 9, n. 8, p. 1155–1159, 2020.

OMONIWA, B.; GALKIN, B.; DUSPARIC, I. Energy-aware optimization of uav base stations placement via decentralized multi-agent q-learning. In: **2022 IEEE 19th Annual Consumer Communications Networking Conference (CCNC)**. [S.l.: s.n.], 2022. p. 216–222.

OUAMRI, M. A. et al. Coverage Analysis and Efficient Placement of Drone-BSs in 5G Networks †. **Engineering Proceedings**, v. 14, n. 1, 2022. ISSN 26734591.

Pan, C. et al. Joint 3d uav placement and resource allocation in software-defined cellular networks with wireless backhaul. **IEEE Access**, v. 7, p. 104279–104293, 2019.

Pan, C. et al. 3d uav placement and resource allocation in software defined cellular networks. In: **2018 IEEE/CIC International Conference on Communications in China (ICCC Workshops)**. [S.l.: s.n.], 2018. p. 136–141.

PARVARESH, N.; KANTARCI, B. A Continuous Actor-Critic Deep Q-Learning-Enabled Deployment of UAV Base Stations: Toward 6G Small Cells in the Skies of Smart Cities. **IEEE Open Journal of the Communications Society**, IEEE, v. 4, n. March, p. 700–712, 2023. ISSN 2644125X.

PASANDIDEH, F. et al. An improved particle swarm optimization algorithm for uav base station placement. **Wireless Personal Communications**, v. 130, n. 2, p. 1343–1370, May 2023. ISSN 1572-834X. Available from Internet: <https://doi.org/10.1007/s11277-023-10334-2>.

PASANDIDEH, F. et al. A systematic literature review of flying ad hoc networks: State-of-the-art, challenges, and perspectives. **Journal of Field Robotics**, v. 40, n. 4, p. 955–979, 2023.

PASANDIDEH, F. et al. A review of flying ad hoc networks: Key characteristics, applications, and wireless technologies. **Remote Sensing**, v. 14, n. 18, 2022. ISSN 2072-4292. Available from Internet: <https://www.mdpi.com/2072-4292/14/18/4459>.

PASANDIDEH, F. et al. Topology management for flying ad hoc networks based on particle swarm optimization and software-defined networking. **Wireless Networks**, Nov 2021. ISSN 1572-8196.

PASANDIDEH, F. et al. Topology management for flying ad hoc networks based on particle swarm optimization and software-defined networking. **Wireless Networks**, v. 28, n. 1, p. 257–272, Jan 2022. ISSN 1572-8196. Available from Internet: <https://doi.org/10.1007/s11276-021-02835-4>.

Paul, S.; De, S.; Dey, S. A novel approach of data clustering using an improved particle swarm optimization based k–means clustering algorithm. In: **2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT)**. [S.l.: s.n.], 2020. p. 1–6.

PEREIRA, P. H. M. et al. Design and deployment of an efficient communication service for multi-uav systems. In: **2023 International Conference on Unmanned Aircraft Systems (ICUAS)**. [S.l.: s.n.], 2023. p. 753–760.

PSOSCALF: A new hybrid PSO based on Sine Cosine Algorithm and Levy flight for solving optimization problems. **Applied Soft Computing**, v. 73, p. 697 – 726, 2018. ISSN 1568-4946.

QI, W. et al. Energy-efficient resource allocation for uav-assisted vehicular networks with spectrum sharing. **IEEE Transactions on Vehicular Technology**, v. 71, n. 7, p. 7691–7702, 2022.

Qiu, C. et al. Multiple uav-mounted base station placement and user association with joint fronthaul and backhaul optimization. **IEEE Transactions on Communications**, v. 68, n. 9, p. 5864–5877, 2020.

RABBATH, C. A.; KIRUBARAJAN, T. Unmanned vehicle systems. In: **Signal Processing and Networking for Big Data Applications**. [S.l.]: CRC Press, 2017. p. 257–294.

REN, H. et al. Energy minimization in ris-assisted uav-enabled wireless power transfer systems. **IEEE Internet of Things Journal**, v. 10, n. 7, p. 5794–5809, 2023.

RODRIGUES, M. et al. Authentication methods for uav communication. In: **2019 IEEE Symposium on Computers and Communications (ISCC)**. [S.l.: s.n.], 2019. p. 1210–1215.

SHAKHATREH, H. et al. Efficient Placement of an Aerial Relay Drone for Throughput Maximization. **Wireless Communications and Mobile Computing**, Hindawi Limited, v. 2021, 2021. ISSN 15308677.

SHAKOOR, S. et al. Joint optimization of uav 3-d placement and path-loss factor for energy-efficient maximal coverage. **IEEE Internet of Things Journal**, v. 8, n. 12, p. 9776–9786, 2021.

SILVA, T. Dapper e et al. Stfanet: Sdn-based topology management for flying ad hoc network. **IEEE Access**, v. 7, p. 173499–173514, 2019.

SINGH, P.; CHAUDHARY, H. A modified jaya algorithm for mixed-variable optimization problems. **Journal of Intelligent Systems**, v. 29, n. 1, p. 1007–1027, 2020. Available from Internet: <https://doi.org/10.1515/jisys-2018-0273>.

SINGH, S. N.; SINHA, R. P. (Ed.). **Recent Advances in Unmanned Aerial Vehicle (UAV) Technologies**. [S.l.]: CRC Press, 2019.

SMITH, J.; JOHNSON, E. A survey of uav communication models for air-to-ground communication. **IEEE Transactions on Wireless Communications**, 2020.

SULTAN, L. et al. Communication among heterogeneous unmanned aerial vehicles (uavs): Classification, trends, and analysis. **IEEE Access**, v. 9, p. 118815–118836, 2021.

SUN, R. et al. Uav-net+: Effective and energy-efficient uav network deployment for extending cell tower coverage with dynamic demands. **IEEE Transactions on Vehicular Technology**, v. 72, n. 1, p. 973–985, 2023.

TAREKEGN, G. B. et al. Deep-reinforcement-learning-based drone base station deployment for wireless communication services. **IEEE Internet of Things Journal**, v. 9, n. 21, p. 21899–21915, 2022.

THIBBOTUWAWA, A. et al. Energy consumption in unmanned aerial vehicles: A review of energy consumption models and their relation to the uav routing. In: ŚWIĄTEK, J.; BORZEMSKI, L.; WILIMOWSKA, Z. (Ed.). **Information Systems Architecture and Technology: Proceedings of 39th International Conference on Information Systems Architecture and Technology – ISAT 2018**. Cham: Springer International Publishing, 2019. p. 173–184. ISBN 978-3-319-99996-8.

Vashisht, S.; Jain, S.; Mann, R. S. Software defined uav-based location aware deployment scheme for optimal wireless coverage. In: **2019 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)**. [S.l.: s.n.], 2019. p. 907–912.

WANG, L.; HU, B.; CHEN, S. Energy efficient placement of a drone base station for minimum required transmit power. **IEEE Wireless Communications Letters**, v. 9, n. 12, p. 2010–2014, 2020.

WANG, L. et al. Deployment and association of multiple uavs in uav-assisted cellular networks with the knowledge of statistical user position. **IEEE Transactions on Wireless Communications**, v. 21, n. 8, p. 6553–6567, 2022.

WU, F.; ZENG, Y.; ZHANG, R. Energy-efficient deployment of uav-mounted mobile base stations for optimizing wireless coverage. **IEEE Transactions on Vehicular Technology**, 2018.

WU, H. et al. Energy-efficient and secure air-to-ground communication with jittering uav. **IEEE Transactions on Vehicular Technology**, v. 69, n. 4, p. 3954–3967, 2020.

WU, S. et al. Distributed federated deep reinforcement learning based trajectory optimization for air-ground cooperative emergency networks. **IEEE Transactions on Vehicular Technology**, v. 71, n. 8, p. 9107–9112, 2022.

XIANG, T.; LIAO, X.; WONG, K. wo. An improved particle swarm optimization algorithm combined with piecewise linear chaotic map. **Applied Mathematics and Computation**, v. 190, n. 2, p. 1637 – 1645, 2007. ISSN 0096-3003. Available from Internet: <http://www.sciencedirect.com/science/article/pii/S0096300307002081>.

YAN, H.; VUCETIC, B.; HANLY, S. Quality-of-service-constrained placement of uav base stations for wireless coverage enhancement. **IEEE Transactions on Wireless Communications**, 2019.

YOU, J. et al. Energy-efficient 3-d placement of an unmanned aerial vehicle base station with antenna tilting. **IEEE Communications Letters**, v. 24, n. 6, p. 1323–1327, 2020.

YU, L. et al. Backhaul-aware drone base station placement and resource management for fso-based drone-assisted mobile networks. **IEEE Transactions on Network Science and Engineering**, p. 1–10, 2022.

ZAHEDI, M. H. et al. Fuzzy based efficient drone base stations (dbss) placement in the 5g cellular network. **Iranian Journal of Fuzzy Systems**, University of Sistan and Baluchestan, v. 17, n. 2, p. 29–38, 2020. ISSN 1735-0654.

ZENG, Y.; WU, Q.; ZHANG, R. Optimal deployment of uav base stations for maximum coverage and energy efficiency. **IEEE Journal on Selected Areas in Communications**, 2016.

ZENG, Y.; XU, J.; ZHANG, R. Energy minimization for wireless communication with rotary-wing uav. **IEEE Transactions on Wireless Communications**, v. 18, n. 4, p. 2329–2345, 2019.

ZENG, Y.; ZHANG, R.; LIM, T. Wireless communications with unmanned aerial vehicles: Opportunities and challenges. **IEEE Communications Magazine**, v. 54, n. 5, p. 36–42, 2019.

Zhang, S.; Ansari, N. 3d drone base station placement and resource allocation with fso-based backhaul in hotspots. **IEEE Transactions on Vehicular Technology**, v. 69, n. 3, p. 3322–3329, 2020.

ZHANG, Y.; AL. et. Uav base station placement in disaster scenarios: Joint optimization of communication and control. **IEEE Transactions on Wireless Communications**, v. 20, n. 4, p. 2463–2477, 2021.

ZHAO, J.; AL. et. Deep reinforcement learning for adaptive uav trajectory planning in dynamic environments. **IEEE Access**, 2021.

ZHONG, W. et al. Energy-efficient trajectory design for uav-enabled wireless communication systems. **IEEE Transactions on Wireless Communications**, 2021.

Zhong, X. et al. Qos-compliant 3-d deployment optimization strategy for uav base stations. **IEEE Systems Journal**, p. 1–9, 2020.

ZITAR, R. A. et al. An intensive and comprehensive overview of jaya algorithm, its versions and applications. **Archives of Computational Methods in Engineering**, v. 29, n. 2, p. 763–792, Mar 2022. ISSN 1886-1784. Available from Internet: <https://doi.org/10.1007/s11831-021-09585-8>.

APPENDIX A — EXTENDED ABSTRACT IN PORTUGUESE (RESUMO ESTENDIDO EM PORTUGUÊS)

Este apêndice apresenta brevemente esta tese de doutorado, que é intitulada "Posicionamento energeticamente eficiente de Estações-Base Montadas em VANTs para melhoria de conectividade em redes sem fio".

A.1 Introdução

Este estudo discute o campo em crescimento dos Veículos Aéreos Não Tripulados (VANTs), comumente conhecidos como drones, concentrando-se em seus sistemas colaborativos, especialmente no contexto das Redes Ad Hoc Aéreas (FANETs). Destaca o aumento do investimento no mercado global de VANTs comerciais e o papel em evolução dos drones em diversas aplicações, citando o crescimento de 1,1 bilhão de dólares em 2020 para uma expectativa de 58,4 bilhões de dólares até 2026. A integração de IA e robótica impactou significativamente o desenvolvimento das FANETs. Essas redes de VANTs operam de forma colaborativa, sem intervenção humana, e apresentam diversos desafios como mobilidade, dinâmica de rede e questões de segurança. O avanço da IA, particularmente em aprendizado de máquina (ML), oferece soluções promissoras para enfrentar esses desafios nas FANETs (Fahim; Gadallah, 2020), (ZAHEDI et al., 2020).

Este estudo enfatiza a importância da otimização do posicionamento das Estações Base montadas em VANTs (UAV-BSs) para aprimorar as redes de comunicação sem fio. Aponta os objetivos associados ao posicionamento de UAV-BSs, incluindo maximização da cobertura, minimização da interferência de sinal, otimização da capacidade de rede, melhoria das métricas de Qualidade de Serviço (QoS) e redução do consumo de energia (Akram et al., 2020), (SHAKOOR et al., 2021), (CHERIF et al., 2020), (Chaalal; Reynaud; Senouci, 2020), (TAREKEGN et al., 2022), (WANG et al., 2022), (DAI et al., 2022), (WU et al., 2022), ground nodes (Fahim; Gadallah, 2020) (ZAHEDI et al., 2020) (Akram et al., 2020) (SHAKOOR et al., 2021) (CHERIF et al., 2020) (Chaalal; Reynaud; Senouci, 2020), (TAREKEGN et al., 2022), (WANG et al., 2022), (DAI et al., 2022), (WU et al., 2022),(SHAKOOR et al., 2021), (Zhang; Ansari, 2020) (Zhong et al., 2020), (Vashisht; Jain; Mann, 2019), (Cicek et al., 2020), (Guo et al., 2019), e (YOU et al., 2020).

Além disso, este estudo introduz questões de pesquisa específicas: a primeira aborda técnicas para mitigar o consumo de energia desperdiçada na obtenção do posicionamento ideal de VANTs e a segunda se concentra em algoritmos adaptativos ou técnicas de otimização que consideram fatores ambientais em tempo real para otimizar o posicionamento e o consumo de energia de VANTs, mantendo a qualidade da rede (Fahim; Gadallah, 2020)-(YOU et al., 2020).

A.1.1 Proposta de Pesquisa e Contribuições

Este estudo de pesquisa apresenta duas contribuições fundamentais no âmbito da otimização de implantação de Veículos Aéreos Não Tripulados (VANTs). O foco principal gira em torno de abordar as restrições de consumo de energia nos modelos de posicionamento de VANTs. A primeira contribuição reside na formulação de um modelo ótimo de posicionamento de VANTs que incorpora problemas de otimização não lineares. Este modelo leva em consideração as complexidades do consumo de energia, colocando estrategicamente os VANTs respeitando as restrições energéticas.

A segunda contribuição adentra em um estudo abrangente voltado para a solução do modelo matemático mencionado. Ao empregar técnicas matemáticas avançadas e algoritmos, esta pesquisa explora metodologias eficazes para resolver de forma eficiente o complexo problema de otimização não linear associado ao posicionamento de VANTs. Estas contribuições oferecem coletivamente uma abordagem inovadora para otimizar a implantação de VANTs, considerando as restrições de consumo de energia e propondo soluções viáveis para o modelo matemático resultante, enriquecendo assim o panorama das estratégias de implantação de VANTs.

As contribuições podem ser elucidadas da seguinte maneira:

- Formulação de uma representação robusta do problema de posicionamento de VANTs como um Programa Não Linear de Inteiros Mistos (MINLP), permitindo a integração simultânea de diversos objetivos e restrições.

- Integração de restrições relacionadas às especificações do rotor do VANT, alcance de comunicação, velocidade de voo, fatores ambientais (como velocidade e direção do vento), especificações de Equipamentos de Usuário (EU) e outras limitações pertinentes no modelo formulado.

- Otimização do modelo proposto de posicionamento de VANTs enquanto considera várias métricas de desempenho, como cobertura, capacidade, consumo de energia e requisitos de Qualidade de Serviço (QoS).

- Introdução de um algoritmo meta-heurístico, nomeadamente PSO e JAYA, projetado para determinar as localizações ótimas de VANTs.

- Validação do modelo analítico derivado por meio de análises numéricas inspiradas em simulações de Monte Carlo, reforçando sua aplicabilidade e confiabilidade.

A.2 Modelo de sistema e abordagem proposta

A.2.1 Modelo de sistema

Na situação descrita na Figura 3.1, em que a BS terrestre (BSk) pode ficar inoperante devido a danos no equipamento ou problemas de energia, UAV-BSi, que está localizada em $(x_{i,t}^{UAV-BS}, y_{i,t}^{UAV-BS}, h_{i,t}^{UAV-BS})$ no momento t torna-se crucial para o restabelecimento rápido e eficaz da comunicação, por exemplo, para o UEj que está localizado em $(x_{j,t}^{UE}, y_{j,t}^{UE})$, em uma área de raio R_t^{UAV-BS} no momento t.

O problema de determinar as posições ideais continua sendo um desafio constante. Os UAV-BSs são comumente chamados de problema de posicionamento, que este estudo investiga.

çãoModelo de rede O modelo de rede é composto por vários UAVs de baixa altitude e um grupo de UEs móveis em um ambiente projetado para simular uma rede ad-hoc dinâmica e voadora. O padrão de mobilidade dos UEs é regido pelo modelo de mobilidade Random Walk, caracterizado por uma faixa de velocidade variável de [5-100 km/h], refletindo os padrões de movimento imprevisíveis semelhantes aos cenários do mundo real. Abaixo estão as suposições refinadas descritas no trabalho proposto:

- O ambiente operacional dos UAV-BSs abrange uma área de 2 quilômetros quadrados.

- Os UAV-BSs possuem intervalos de comunicação variados (R_t^{UAV-BS}) e capacidades. taxa de exigência de dados para UEs varia a cada etapa de tempo, determinada aleatoriamente para cada UE.

nó (compreendendo UAV-BSs e UEs) recebe um identificador exclusivo para distinção da rede.

- Todas as UEs manobram com base em um modelo de mobilidade Random Walk, com velocidades que variam de 5 a 100 km/h.

- A configuração de comunicação pressupõe comunicação direta de salto único entre UEs e UAV-BSs. õe-se que a velocidade vertical dos UAV-BSs não seja afetada pela velocidade e direção do vento.

- As estações base terrestres (GBS) e os links de backhaul entre UAV-BSs e BSs não são considerados nesse contexto.

A tabela 3.1 mostra a lista de notações usadas neste trabalho e a formulação de otimização do problema.

A.3 Formulação do problema de posicionamento

O modelo de otimização proposto foi projetado para atingir simultaneamente dois objetivos principais: minimizar o consumo de energia de movimento e comunicação ($P_{i,t}^{Total}$) utilizada pelos UAV-BSs; a primeira função objetiva é fornecida em (3.26), minimizando o número de UEs descobertas ($I_{i,j,t}^{UE}$); a segunda função objetiva é fornecida em (3.27). Esses objetivos são integrados na função objetiva composta f mostrada em (3.28). As restrições são categorizadas em restrições de mobilidade, restrições de consumo de energia, perda de caminho e restrições de taxa de dados, além de restrições operacionais.

A.3.1 Método proposto

Para permitir que o modelo seja executado em aplicativos assistidos por UAV, foi fornecido um algoritmo meta-heurístico chamado JAYA. Esse algoritmo é caracterizado por sua velocidade, simplicidade e eficiência em termos de tempo de computação e uso de memória, superando outros algoritmos meta-heurísticos. O JAYA exibe a capacidade de convergir rapidamente para soluções globais ou quase ideais. O algoritmo JAYA tem menos parâmetros algorítmicos em comparação com algumas outras técnicas de otimização e tem um comportamento determinístico, portanto, produz resultados consistentes para o mesmo problema e entrada (ZITAR et al., 2022; SINGH; CHAUDHARY, 2020).

Depois de inicializar os parâmetros do problema de otimização e do algoritmo JAYA, os primeiros locais em potencial para UAV-BSs são encontrados no tempo 0 ($x_{i,t}^{UAV-BS,initial}$, $y_{i,t}^{UAV-BS,initial}$, $h_{i,t}^{UAV-BS,initial}$), usando o agrupamento k-means. Depois de formular o problema de posicionamento de acordo com o fluxograma fornecido na Figura 4.1, parâmetros como o tamanho da população, o número de iterações, as variáveis e os critérios de encerramento precisam ser definidos. Em seguida, as soluções, denotadas como coordenadas para UAVs, dentro da população são classificadas, distinguindo as melhores e as piores soluções. O refinamento de novas soluções envolve a utilização de equações 4.1, 4.2 e 4.3 que representam atualizações iterativas para otimizar as coordenadas ($X_{i,t,New}^{UAV-BS}$, $Y_{i,t,New}^{UAV-BS}$ e $H_{i,t,New}^{UAV-BS}$) de posicionamentos de UAV-BS no processo de otimização proposto. Cada conjunto de equações delineia como as novas coordenadas (denotadas como New) são recalculadas com base nas coordenadas atuais ($Current$), nas melhores coordenadas ($Best$) e nas piores coordenadas ($Worst$).

O processo envolve o ajuste iterativo das coordenadas do UAV-BS até que a convergência ou um critério específico seja alcançado. O parâmetro r atua como um fator de escala ou etapa nesse processo de atualização. Se uma solução aprimorada for encontrada, ela substituirá a solução anterior; caso contrário, o algoritmo reverterá para a solução anterior. Depois que todas as soluções da população tiverem sido avaliadas e se a contagem de iterações atingir N, ocorrerá uma verificação da condição de término. Se for atendida, as soluções melhores ou ótimas (coordenadas do UAV) são retornadas; caso contrário, o processo continua com uma nova iteração.

A complexidade de tempo do programa fornecido é dominada pela inicialização da população e avaliação da função que têm uma complexidade de tempo de $O(I \times J)$ ou $O(n^2)$. Quanto à intensidade computacional do código, ela depende dos valores específicos de I e J. Se esses valores forem relativamente pequenos, o código deverá ser computacionalmente viável para ser executado em UAV-BSs. Entretanto, se os valores forem grandes, o código poderá se tornar computacionalmente intensivo e exigir recursos computacionais mais potentes para ser executado em um tempo razoável. para ser executado em um período de tempo razoável.

A.4 Conclusões

O estudo em questão amplia o escopo de pesquisas anteriores ao introduzir um avançado modelo de Programação Não Linear de Inteiros Mínimos (MINLP), especificamente elaborado para otimizar a eficiência energética ao situar estrategicamente Veículos Aéreos Não Tripulados (VANTs) como Estações Base (BSs). Esta abordagem inovadora visa aprimorar significativamente a conectividade sem fio em diversos cenários. Para lidar com esse desafio de otimização, o estudo propõe um algoritmo que mescla de forma engenhosa o algoritmo de otimização JAYA com a técnica de agrupamento K-means. A fusão dessas metodologias apresenta uma solução robusta para lidar com as complexidades do modelo de otimização.

Um experimento fatorial abrangente é conduzido em redes de comunicação, variando as quantidades de Equipamentos de Usuário (EU) e VANTs (variando de 50 a 150 EUs e de 2 a 10 VANTs). A implementação do modelo de otimização proposto, realizada por meio de Python, facilita uma avaliação meticulosa de métricas de desempenho críticas. Essas métricas englobam perda de pacotes, throughput, latência, movimento de VANTs e dinâmica de energia nas comunicações entre VANTs e BSs.

Os resultados da simulação destacam a eficácia do algoritmo baseado em JAYA, demonstrando sua habilidade em minimizar a perda de pacotes, latência e consumo de energia. Notavelmente, as variações observadas nas métricas são atribuídas à natureza dinâmica das demandas de dados dos EUs ao longo do tempo. Além disso, o modelo proposto garante uma taxa média de conectividade superior a 50

No entanto, este estudo reconhece conscientemente uma limitação relacionada aos algoritmos de otimização, especificamente o desafio em alcançar o ótimo global absoluto dentro de espaços de parâmetros intricados. A tendência inerente dos algoritmos de otimização em convergir para ótimos locais apresenta uma restrição significativa, restringindo a exploração além dos pontos iniciais.

Para fortalecer a abordagem proposta, o estudo sugere aprimoramentos potenciais. Estratégias como inicializações diversas ou a integração de múltiplos algoritmos de otimização poderiam expandir o espaço de solução, potencialmente gerando soluções superiores. A introdução de metodologias como recozimento simulado, algoritmos genéticos ou Otimização por Enxame de Partículas (PSO) é recomendada para navegar de forma mais eficaz nas complexidades do cenário.

Futuros esforços são instados a concentrar-se em metodologias alternativas que possam explorar e convergir para a solução do ótimo global. Investigar técnicas avançadas de otimização, algoritmos pioneiros ou abordagens híbridas têm potencial para contornar limitações associadas à busca do ótimo global em espaços de parâmetros intricados. Tais iniciativas são imaginadas para fortalecer a eficácia do implante de VANTs como BSs, impulsionando a economia de custos, a sustentabilidade e melhorias de desempenho em redes de comunicação sem fio.

A.5 Publications

The outcomes and collaborations resulting from this research are documented in the following publications.

a) The research conducted while developing this PhD thesis laid the groundwork for the papers listed below:

1. (PASANDIDEH et al., 2023b) *A systematic literature review of flying ad hoc networks: State-of-the-art, challenges, and perspectives*,**F Pasandideh**, JPJ Costa, R Kunst, W Hardjawana, EP de Freitas **Journal of Field Robotics** 40 (4), 955-979, 2023.

   Abstract: Unmanned aerial vehicles (UAVs), also known as drones, communicate, collaborate, and form flying ad hoc networks (FANETs) to perform many different missions, ranging from delivery tasks to agriculture applications. Recently, FANETs have been integrated with different technologies, such as artificial intelligence (AI), virtual reality, and the Internet of Things. Such new avenues for the use of UAVs directly impact the research on FANETs and cause some major challenges, such as security and physical layer issues, resource management, and UAV-BS positioning issues that need to be addressed. Several researchers have been working for the last few years to propose AI and machine learning (ML)-based solutions for different use cases in UAV-based networks. They present the limitations of the existing research work and highlight some possible future works on FANETs. However, exhibiting the trends in the UAV research papers quantitatively is still required to motivate researchers to rethink the research on FANETs. Therefore, this study covers more than

170 scientific publications extracted from five trusted academic databases published from 2013 to 2021 to provide a thorough overview of the main research and development statistics in the area of FANETs, the open challenges existing in this area and the ML-based solutions to solve these challenges. In addition, the investigation of emerging technologies integrated with FANETs, as well as the simulation tools employed for evaluating FANETs' performance are discussed. Moreover, the future research directions in the area of FANETs are considered within a prospective vision discussion.

2. (PASANDIDEH et al., 2021) *An Improved Particle Swarm Optimization Algorithm for UAV Base Station Placement*,**F. Pasandideh**, F E. Rodriguez Cesen, P. Henrique Morgan Pereira, C. Esteve Rothenberg, E. Pignaton de Freitas, **Wireless Personal Communications** 130 (2), 1343-1370, 2023. ***Abstract:*** In cellular networks, a set of Base Stations (BSs) might be out of service and failed in the aftermath of natural disasters. One of the promising solutions to fix this situation is to send low-altitude drones equipped with a small cellular BS (DBSs) to the target locations. This can provide cellular networks with vital communication links and make available temporary coverage for the users in unexpected circumstances. However, finding the minimum number of DBSs and their optimal locations are highly challenging issues. In this work, a Mixed-Integer Non-Linear Programming formulation is provided, in which the DBSs' location and the proper number of DBSs are jointly determined. An improved PSO-based algorithm is proposed to jointly optimize DBSs' locations and find the minimum number of DBSs. As in the original PSO algorithm, the particles are randomly distributed in the initialization phase and a K-means-based clustering method is employed to generate the positions of the first-generation particles (DBSs). In addition, a custom communication protocol is presented for data exchange between the users' equipment (UE) and the network controller. The proposed approach is evaluated through four simulation experiments implemented using Mininet-Wifi integrated with CopelliaSim. The acquired results show that the proposed solution based on the integration of PSO and K-means algorithms provides a low packet loss and latency. Moreover, it indicates that most of the users in the considered scenarios are covered by the DBSs.

3. (PASANDIDEH et al., 2022) *A review of flying ad hoc networks: Key characteristics, applications, and wireless technologies*,**F Pasandideh**, JPJ da Costa, R Kunst, N Islam, W Hardjawana, **Remote Sensing** 14 (18), 4459, 2022.

   Abstract: Recent advances in unmanned aerial vehicles (UAVs), or drones, have made them able to communicate and collaborate, forming flying ad hoc networks (FANETs). FANETs are becoming popular in many application domains, including precision agriculture, goods delivery, construction, environment and climate monitoring, and military surveillance. These interesting new avenues for the use of UAV-BSs are motivating researchers to rethink the existing research on FANETs. Therefore, this paper provides a comprehensive and thorough review of the different types of UAVs used in FANETs, their mobility models, main characteristics, and applications, as well as the routing protocols used in this type of network. Other important contributions of this paper include the investigation of emerging technologies integrated with FANETs.

4. *Providing an energy efficient UAV BS positioning mechanism to improve wireless connectivity* ,**F Pasandideh**, A. Najafzadeh, JP. Javidi da Costa, E. Pignaton de Freitas, **Wireless Networks, under-submission**, 2023.

   Abstract: In the era of ubiquitous wireless communication, the demand for improved wireless connectivity has surged dramatically. This paper addresses the challenge of enhancing wireless connectivity by introducing an innovative energy-efficient mechanism for positioning Unmanned Aerial Vehicles (UAVs) as base stations (BS) called UAV-BSs. In this study, a Mixed-Integer Non-Linear Programming (MINLP) energy-efficient optimization model is provided to adaptively position UAV-BSs based on real-time demand and network conditions. Traditional optimization methods often face challenges in handling the complex and dynamic nature of UAV-BSs deployment. To overcome this limitation, a novel algorithm is presented that combines the strengths of the optimization algorithm and the K-means clustering technique. Through extensive experimentation and comparative analysis, the performance of the optimization model and the improved JAYA-based algorithm against existing techniques is evaluated. The results demonstrate that this approach outperforms other methods in terms of UAV-BS placement accuracy, lower power

consumed by UAV-BSs, packet loss rate, and latency. Furthermore, the algorithm exhibits adaptability to varying network conditions, making it a valuable tool for optimizing UAV-BS locations in dynamic environments.

b) Additional papers have been published as follows:

1. (PASANDIDEH et al., 2021) *Topology management for flying ad hoc networks based on particle swarm optimization and software-defined networking*, **F Pasandideh**, TDE Silva, AAS Silva, E Pignaton de Freitas **Wireless Networks**, 1-16, 2022.

Abstract: Flying Ad Hoc Networks (FANETs) are composed of a set of high mobility flying nodes, such as unmanned aerial vehicles (UAVs), connected in an ad-hoc manner and collaborating to perform specific tasks or to achieve specific goals, such as providing connection to other nodes on the ground. The high mobility degree of UAVs, and the possible connected users on the ground, might cause fast and frequent changes in the network topology. Hence, the topology management adaptation to the UAVs' movements is required to reduce UAVs' mobility negative effects on the communication and to improve the overall network performance. Observing these needs, this paper proposes Software-defined networking (SDN) based manageable topology formation to construct a more resilient and manageable UAV formation. This novel proposal considers a set of graph theory concepts for network evaluation to guarantee user connectivity, alternative transmission paths, and a lower possible amount of nodes being points of failure, as a consequence. Also, the spring virtual force method is applied by using attractive-repulsive forces among nodes to accomplish the following objectives: to impose safety distance gaps for collision avoidance; to provide sufficient communication link distance for proper link quality; and to maximize area coverage for enabling end-user mobility. Finally, the Particle Swarm Optimization (PSO) algorithm's particle selection procedure is proposed to maximize the number of interconnected nodes. Simulation results show that the proposed solution can correct routing policies and reestablish connections in every occurrence of failure. The results also indicate that the considered packet loss was significantly lower compared to the state-of-the-art, achieving results from 10% to 80% lower in the performed experiments, as a higher number of packets were delivered within the required delay limit.

2. (PEREIRA et al., 2023)*Design and Deployment of an Efficient Communication Service for Multi-UAV Systems*,**PHM Pereira, F Pasandideh, M Basso, JP da Costa, E Pignaton de Freitas 2023 International Conference on Unmanned Aircraft Systems (ICUAS), Warsaw, Poland, 2023**.

Abstract: Recent advances in the areas of microelectronics, information technology, and communication protocols have made possible the development of smaller devices, with increasing processing capacity and low energy consumption. This context contributed to the growth of applications based on the use of one or multiple Unmanned Aerial Vehicles (UAVs). Networks composed of multiple UAVs are being used as a matter of improving the effectiveness, accuracy, and minoring the time of missions. However, these applications demand a high rate of data exchange, such as the localization information of each UAV, which can be a challenge, due to the limited transmission power of certain drone platforms. This article proposes a communication service for multi-UAV systems based on dividing the UAV-fleet into groups using the communication protocol IEEE 802.11 ac. Each group has its local network, whose participants can be chosen based on the UAV's localization or task assignment. UAVs/Drones within the same group constantly communicate, exchanging pose information and specific mission-related data. On the other hand, communication between different groups is only established by messenger drones in pre-set times. The communication service from its detailed implementation to its simulated and field validation experiments is presented in this work. The results of three different network topologies provide evidence that the proposed communication service for multi-UAVs is efficient and can be used for drone cooperative missions.

3. (ISLAM et al., 2021)*A review of applications and communication technologies for internet of things (Iot) and unmanned aerial vehicle (uav) based sustainable smart farming*,N. Islam, Md Mamunur Rashid, F. Pasandideh|, B, Ray, S. Moore, R. Kadel, **Sustainability**, 2021.

Abstract: To reach the goal of sustainable agriculture, smart farming is taking advantage of the Unmanned Aerial Vehicles (UAVs) and Internet of Things (IoT) paradigm. These smart farms are designed to be run by interconnected

devices and vehicles. Some enormous potential can be achieved by the integration of different IoT technologies to achieve automated operations with minimum supervision. This paper outlines some major applications of IoT and UAV in smart farming and explores the communication technologies, network functionalities, and connectivity requirements for Smart farming. The connectivity limitations of smart agriculture and its solutions are analyzed with two case studies. In case study 1, we propose and evaluate meshed Long Range Wide Area Network (LoRaWAN) gateways to address the connectivity limitations of Smart Farming. While in case study 2, we explore satellite communication systems to provide connectivity to smart farms in remote areas of Australia. Finally, we conclude the paper by identifying future research challenges on this topic and outlining directions to address those challenges.

4. (ISLAM et al., 2021)*IoT Based Smart Farming: Are the LPWAN Technologies Suitable for Remote Communication?* ,N. Islam, F. Pasandideh, B. Ray, **IEEE international conference on smart internet of things (SmartIoT)**, 2021

   Abstract: The Internet of Things (IoT) has changed the definition of smart farming and enhanced it's capabilities to monitor and assess crop and soil quality; to plan planting locations to optimize resources and land area. The Low-Power Wide-Area Network (LPWAN) technologies have enhanced these capabilities by increasing the wireless communication range, by eliminating the dependency of Backhaul networks and by reducing power consumption. In this study, we have presented an experimental analysis of LPWAN literature with the support of simulation and actual implementation of a Long Range Wide Area Network (LoRaWAN) based IoT network for smart farming. Based on our evaluation and experiment of the existing work and the practical implementation of IoT based smart sprinkler using LoRaWAN communication protocol, this paper has presented a comparison and evaluation of different LPWAN technologies for remote smart farming. The empirical equation of wireless communication range of LoRaWAN gateways and power consumption model of LoRaWAN end devices helped us to determine that, the LoRaWAN communication system enables an IoT network to be deployed over 10 kilometers wirelessly in remote settings without being dependent on a Long Term Evolution (LTE-4G/5G) or other backhaul network and the end devices consume as low energy as only 15.36mAh per day.