NOMA-based energy efficiency optimization of UAV Communications using metaheuristic techniques

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Candidate of **Master of Science in Electrical Engineering (MSEE)** at the National University of Modern Languages do hereby declare that the thesis **NOMA-based energy efficiency optimization of UAV communications using metaheuristic techniques** submitted by me in partial fulfillment of MSEE degree, is my original work, and has not been submitted or published earlier. I also solemnly declare that it shall not, in the future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be canceled, and the degree revoked.

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ABSTRACT

Unmanned Aerial Vehicles (UAVs) have become critical communication platforms in diverse applications, including telemetry, agriculture, disaster response, and military operations, particularly in remote and challenging environments. Often deployed as aerial base stations, UAV communication systems require optimization of key performance metrics like sum rate, coverage area, transmission power, network capacity, and energy efficiency. While prior research has focused on optimizing altitude and power allocation for energy efficiency, it has largely overlooked the potential of user-pairing. This thesis addresses this research gap by proposing a joint optimization framework to optimize user pairing and altitude optimization in NOMA-based UAV communication systems. By leveraging metaheuristic optimization techniques, this study compares the efficacy of the proposed metaheuristic approaches with the conventional OMA and the NOMA benchmark schemes such as worst and random pairing to maximize the energy efficiency of NOMA-based UAV communication systems. The effectiveness of the proposed schemes has been evaluated under various scenarios, which include varying the coverage region from 100 meters to 500 meters, the SNR from 0 dB to 30 dB, the number of users from 10 to 100, as well as suburban, urban, and dense urban environments. The PSO-based NOMA outperforms and achieves an overall performance improvement of 51% as compared to OMA, 28% to worst pairing, 23% to random pairing, and 7% to GA-based NOMA.

Keywords: *UAV (Unmanned Aerial Vehicle), wireless communication, aerial base station, optimization, energy efficiency, NOMA (Non-Orthogonal Multiple Access), metaheuristic techniques, coverage area, transmission power, user-pairing.*

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LIST OF ABBREVIATIONS:

A2G	Air to Ground
AHA	Artificial Humming Bird
AS	Ant System
BS	Base Station
CR	Cognitive Radio
CSI	Channel State Information
D2D	Device-to-Device
DL	Downlink
DR	Demand Response
EE	Energy Efficiency
GA	Genetic Algorithm

HAP	High Altitude Platform
IoT	Internet of Things
LAP	Low Altitude Platforms
LOS	Line of Sight
MANETs	Mobile Ad-Hoc Networks
MBPS	Mega Bit Per Second
MIMO	Multiple Input Multiple Output
M2M	Machine to Machine
MS-ABC	Multi-Swarm Artificial Bee Colony
NLOS	Non-Line of Sight
NOMA	Non-Orthogonal Multiple Access
OFDMA	Orthogonal Frequency Division Multiple Access
OMA	Orthogonal Multiple Access
PA	Power Allocation
PSO	Particle Swarm Optimization
QOS	Quality of Service
ROI	Region of Interest
SCA	Successive Convex Approximation
SDG	Sustainable Development Goals
SIC	Successive Interference Calculation
SNR	Signal-to-Noise Ratio
UAV	Unmanned Aerial Vehicle

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I would like to begin by expressing my deepest gratitude to Allah Almighty for granting me the strength and guidance to complete this research endeavor. My heartfelt appreciation extends to my parents, whose unwavering support has been a constant source of strength throughout my academic journey. Their love, encouragement, and unwavering belief in my abilities have been instrumental in my achievements.

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DEDICATION

This thesis is dedicated to my parents, whose unwavering support and encouragement have been the foundation of my achievements. To my father, whose inspiration and guidance sparked the determination to pursue my goals with courage; this work stands as a testament to his enduring faith in me.

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CHAPTER 1

INTRODUCTION

This chapter introduces the UAVs for communication purposes, particularly focusing on optimizing energy efficiency in NOMA-based UAV communication systems using metaheuristic techniques. This study will explore the advantages of UAVs in communication networks, the existing challenges, and the potential of NOMA technology for improving energy efficiency.

1.2 UAV Systems

UAVs, or drones, are unmanned aircraft controlled remotely or programmed for autonomous operation. Initially used for military reconnaissance and surveillance, UAV applications have proliferated across civilian sectors, including agriculture, environmental monitoring, infrastructure inspection, and search and rescue missions [1]. Recently, the integration of UAVs into wireless communication systems has emerged as a significant area of research. Their unique mobility allows access to remote or geographically challenging areas, making them valuable assets for extending communication network coverage, particularly in rural or disaster-stricken regions. Additionally, UAVs equipped with communication payloads can function as aerial base stations or relays, bolstering connectivity in infrastructure-limited areas or during emergencies [2]. This convergence of UAV technology and wireless communication presents a promising avenue for improving network coverage, enhancing communication resilience, and facilitating data transmission in diverse scenarios [3].

1.2.1 UAV Applications

UAVs, with their adaptability in altitude and design, are transforming how we communicate [4]. Low-altitude platforms excel in short -range tasks like crop monitoring and search-and-rescue due to their proximity to the target area [5]. Rotary-wing UAVs, recognizable by their hovering ability, can serve as communication base stations, relays, or even integral parts of mobile networks [5] [6]. This technology extends beyond communication, revolutionizing industries like agriculture with "precision farming" through aerial crop assessments [7]. Similarly, UAVs offer cost-effective and efficient solutions for infrastructure inspections, traffic monitoring, and parcel delivery [8, 9] Mapping has also been transformed by UAVs, enabling the acquisition of high-resolution aerial imagery at a lower cost, with applications in agriculture, urban planning, and more [8]. Finally, the agility and reach of UAVs make them invaluable assets in search-and-rescue operations, navigating complex environments to locate people in disaster zones [8]. This ability to operate as aerial base stations opens doors for innovative network architectures and communication strategies, particularly in remote or disaster-stricken areas.

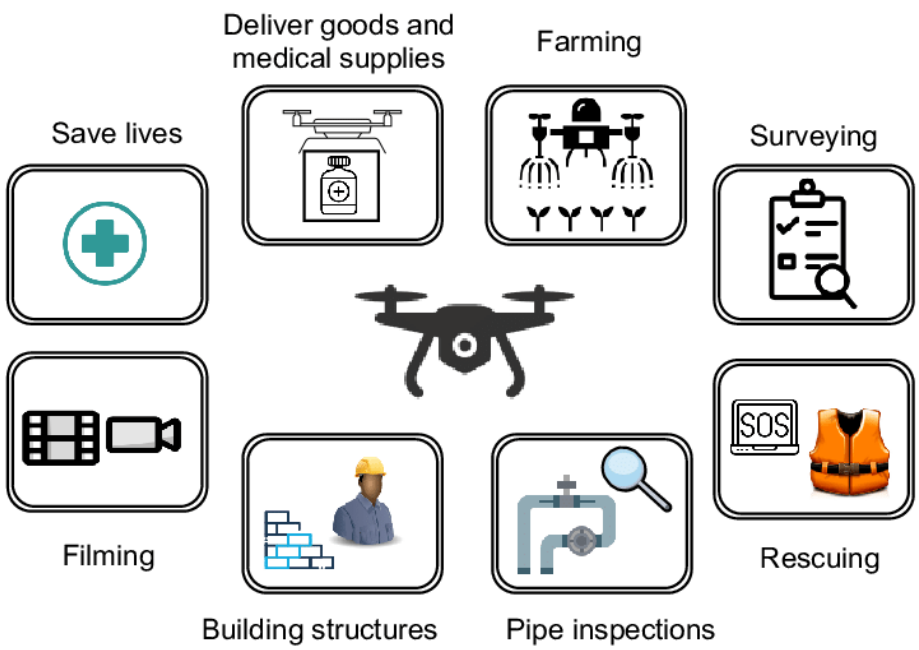

Figure 1.1 UAV Applications [10]

1.2.2 UAV Communication

UAVs' most transformative application lies in the realm of wireless communication. Their ability to reach significant altitudes, coupled with advanced communication technologies, positions them as unparalleled contributors to communication networks [11]. This technology empowers UAVs to serve as aerial base stations, data relays, and critical components of mobile ad-hoc networks (MANETs), expanding cellular service to remote and disaster-stricken areas. Rotary-wing UAVs enable rapid deployment of temporary communication networks in emergencies and underserved areas, bridging connectivity gaps and enhancing the resilience and effectiveness of wireless communication infrastructure [12]. This research focuses on the potential of UAVs as aerial base stations, paving the way for a future where these flying platforms seamlessly integrate into communication networks, extending internet access to remote locations, and transforming information access.

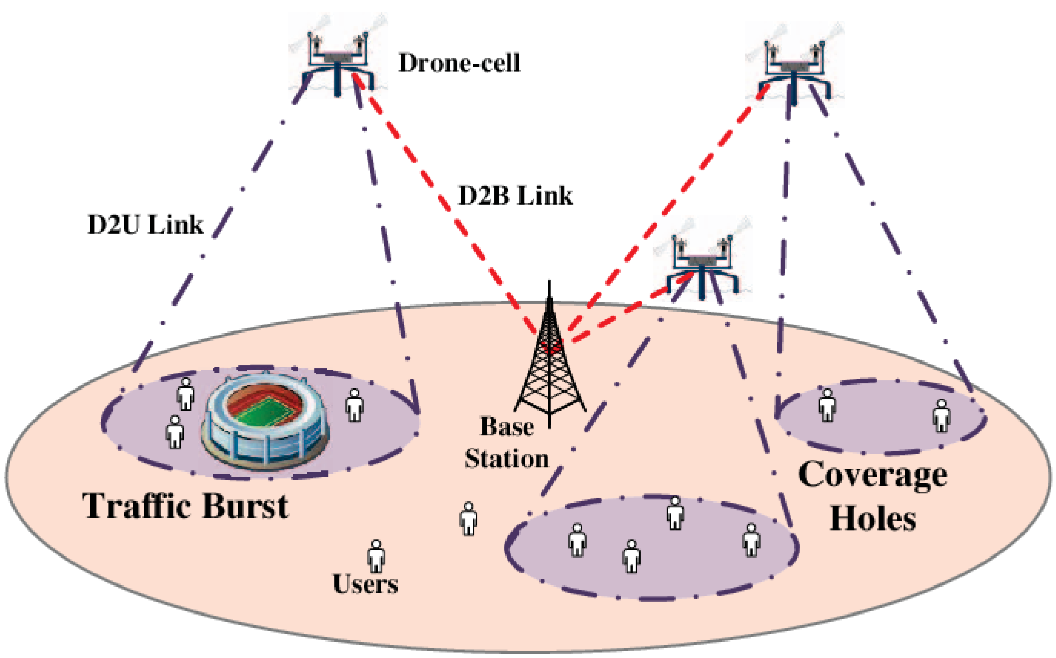

Figure 1.2 UAV as Base Station

1.3 Problems in UAV communication

While UAV communication systems offer significant advantages, they face challenges related to spectral and energy efficiency. Spectral efficiency refers to the system's ability to transmit data effectively within a limited bandwidth. Traditional communication techniques often underutilize the available spectrum in UAV networks, hindering data transmission capabilities. Furthermore, limited battery life is a major constraint for UAVs. Optimizing energy consumption is crucial for extending their operational time and maximizing network performance. Addressing these challenges is essential for unlocking the full potential of UAV communication systems.

1.4 Energy Efficiency

In UAV communication systems, energy efficiency, measured in bits per second per joule (bits/sec/joule), is paramount. It reflects the amount of data transmitted per unit of energy consumed. Optimizing this metric requires balancing several factors: sum rate, which influences the number of users a UAV can support [13-15]; coverage area, defining the reach of the UAV's communication [16]; transmission power, where lower power translates to lower energy consumption [17]; and network capacity, which reflects the maximum data transmission rate [18]. By carefully considering these parameters, researchers can develop UAV communication systems that achieve optimal energy efficiency, maximizing data throughput while minimizing battery usage.

1.5 Non-Orthogonal Multiple Access (NOMA)

NOMA technology presents a promising solution for improving energy efficiency in UAV communication systems. NOMA allows multiple users to share the same time-frequency resources by assigning different power levels to each user [19]. This approach significantly improves spectral and energy efficiency compared to existing multiple-access approaches. NOMA's capabilities can benefit both ground and UAV communication systems within UAV networks [24]. Research is ongoing to explore NOMA's potential for enhancing energy efficiency in aerial systems by optimizing user power distribution and altitude [20, 21]. In this setting, improving efficiency is a significant priority. Previous analyses focused largely on Orthogonal multiple-access (OMA), which was measured by the ratio of the feasible sum rate to the total power consumption. This highlights the need to increase energy efficiency in this situation [3, 22, 23].

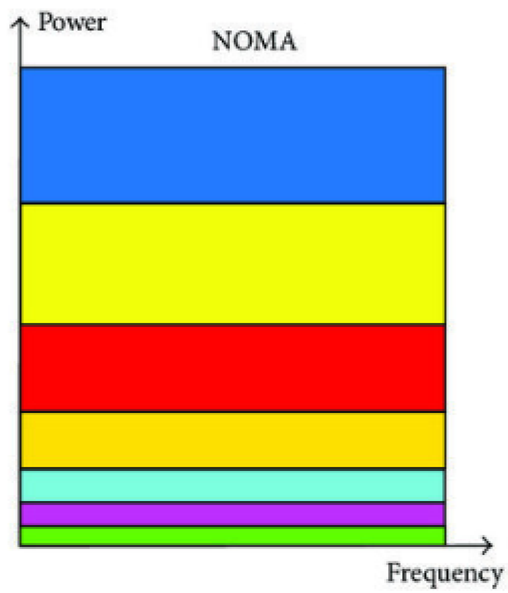

Figure 1.3 Working principle of power-domain NOMA [24]

1.5.1 NOMA UAV Communication

The integration of NOMA technology into UAV communication systems presents a promising solution for achieving significant advancements in energy efficiency. By leveraging NOMA's capabilities, UAVs can serve ground users as aerial base stations at various altitudes. This strategic deployment broadens the user coverage area served by the UAV, consequently enhancing energy efficiency by distributing the user load more effectively. Furthermore, optimizing NOMA parameters in conjunction with UAV operational parameters holds the potential to further improve the overall energy efficiency of the UAV system. This optimization ensures optimal resource utilization and translates to improved system performance in terms of energy consumption [25, 26].

1.6 Research Gap and Motivation

Despite significant advancements in UAV communication systems, achieving optimal energy efficiency remains a critical challenge. Existing research has primarily focused on isolated aspects of the system, neglecting the intricate interplay between various design elements that can significantly impact energy consumption [21]. This limited perspective hinders the development of truly efficient UAV communication networks. A holistic approach that considers the complex relationships between these elements is essential. After all, energy efficiency fundamentally revolves around striking a balance between maximizing network performance metrics, such as data rate, and minimizing overall power usage [27-29]. This research aims to address this critical gap by proposing a novel optimization framework specifically designed for NOMA-based UAV communication systems. By focusing on energy efficiency, this work has the potential to significantly improve network performance, extend operational times for UAVs, and ultimately pave the way for a more sustainable future for UAV-enabled communication applications. The potential future of wireless communications, particularly in overcoming challenges associated with delivering service to remote and difficult terrains, could be significantly shaped by this research on energy-efficient UAV communication systems [30, 31].

1.7 Problem Statement

In NOMA-based UAV systems, power allocation, altitude optimization, and user pairing are important performance parameters that can impact the overall energy efficiency of the system. However, most of the existing literature has mainly focused on jointly optimizing altitude and power allocation while assuming fixed user pairing. To fully optimize the energy efficiency, it is important to investigate the joint optimization of all three parameters [32].

1.8 AIM AND OBJECTIVES

The research aims to optimize NOMA-based UAV communication energy efficiency by jointly adjusting UAV-BS altitude, user pairing, and NOMA power allocation. It also involves comparing metaheuristic methods to identify the most effective approach for enhancing energy efficiency.

- To jointly optimize NOMA UAV-BS altitude, user-pairing, and NOMA power allocation to maximize the energy efficiency of the NOMA UAV system.
- To compare the performance of various Metaheuristics methods for improved energy efficiency.

1.9 Research Scope

This research investigates optimizing energy efficiency in NOMA-based UAV communication systems. It employs a systematic optimization approach for downlink communication using a single-antenna rotary-wing UAV at low altitudes. The goal is to maximize energy efficiency by jointly optimizing the parameters involved. The research focuses on a single-cell scenario to isolate the impact of NOMA energy efficiency across diverse deployment contexts (rural, urban, and dense urban). A well-established Air-to-Ground channel model considers the dynamic channel gains between the UAV and users based on altitude and location [33, 34]. Similarly, a recognized energy consumption model accounts for the influence of altitude on energy usage [35, 36]. Furthermore, the research formulates optimization problems that consider the multiple Quality-of-Service (QoS) requirements of NOMA users, ensuring a fair comparison with traditional Orthogonal Multiple Access (OMA) systems [37-39]. By achieving joint optimization of these critical aspects and comparing various metaheuristic approaches, this research aims to identify the most effective strategy for enhancing system-wide energy efficiency in NOMA-based UAV communication systems, ultimately leading to more sustainable and effective network performance.

1.10 Sustainable Development Goals and Social Impact

This research contributes significantly to advancing multiple SDGs by leveraging innovative technology to address complex challenges and promote sustainable development. Primarily, the optimization framework for NOMA-based UAV communication systems contributes to SDG 9 (Industry, Innovation, and Infrastructure) by enhancing the efficiency and effectiveness of communication technologies, which are essential for infrastructure development and innovation. Moreover, by focusing on energy efficiency, the research directly supports SDG 7 (Affordable and Clean Energy) by promoting sustainable energy practices in UAV deployments, thereby reducing environmental impact and fostering cost-effective solutions.

Figure 1.4 Sustainable Development Goals (SDGs)

1.11 Resource Requirement

This research relies on computational tools to achieve its goals. MATLAB 2019b serves as the primary software environment for simulations, while Visual Studio is used for figures.

EndNote manages references, and all tasks are executed on an MS Office laptop with a 10th-generation Intel Core i7 processor. Within MATLAB, complex matrix operations are performed for NOMA simulations, various metaheuristic algorithms are implemented for energy efficiency optimization, and data plots are generated. A thorough literature review explores research papers and articles on NOMA and heuristic optimization techniques. Visual Studio is employed to create high-quality figures and diagrams for clear visualization related to this research. By strategically utilizing these resources, the research is conducted efficiently, data is analyzed effectively, and the findings are presented in a clear and comprehensible manner.

1.12 Organizational Structure of Report

This thesis explores the challenge of optimizing energy efficiency in NOMA-based UAV communication systems. Chapter 1 introduces the problem, outlines the project's scope and potential applications, and details the study's requirements. Chapter 2 reviews existing research in the field. Chapter 3 dives into the technical details, explaining the mathematical model and software tools used. This includes algorithms, mathematical formulations, and implementation specifics. Chapter 4 validates the simulations and presents the key scientific achievements through results, figures, and graphs. Finally, Chapter 5 concludes the research by summarizing the findings, discussing limitations, and proposing areas for future improvement.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews energy efficiency optimization in NOMA-based UAV communication systems. NOMA offers spectral efficiency gains, but UAV mobility presents unique energy challenges. Existing research focuses on terrestrial NOMA, neglecting the interplay between energy, power allocation, user pairing, and altitude optimization in UAV-based systems. By synthesizing prior research, this chapter lays the groundwork for a novel metaheuristic framework to address these energy efficiency challenges.

2.1 Introduction

UAVs are increasingly integrated across diverse sectors due to their versatility and maneuverability. They play a vital role in data collection, surveillance, and disaster response. However, limited bandwidth and power constraints hinder effective communication between UAVs and ground stations. Non-Orthogonal Multiple Access (NOMA) emerges as a promising solution. NOMA facilitates efficient resource allocation by enabling multiple users to share the same frequency band, potentially improving spectral efficiency and network performance in UAV networks [2]. While UAVs offer vast application potential, challenges like limited range, signal blockage, and power constraints hinder communication effectiveness. Research confirms NOMA's potential to address these limitations [2, 40-43].

Rotary wings UAVs deployed as base stations open new avenues for improved wireless communication and network expansion [44]. Contemporary research explores deploying UAVs as aerial base stations to improve critical performance metrics like data rates, coverage area, and energy efficiency for various UAV communication systems. However, traditional Orthogonal

Multiple Access (OMA) techniques struggle with limited bandwidth and power constraints. NOMA offers a compelling alternative by enabling efficient resource allocation, potentially leading to significant improvements in spectral efficiency and network performance [45-48]. Furthermore, the integration of NOMA, a key technology for future wireless communication systems beyond 5G, into aerial platforms opens doors to even greater possibilities for UAV communication systems [49]. This review delves into research on NOMA-based UAV communication systems, emphasizing optimization techniques, energy efficiency considerations, and overall network performance advancements.

2.2 Challenges and Opportunities in UAV Communication

Energy efficiency (ηEE) is a critical performance metric for UAV communication systems, driving significant research efforts. This review explores NOMA as a promising technology for improving energy efficiency by enabling efficient resource allocation and potentially reducing power consumption for UAVs [50]. A key challenge in UAV communication systems is Air-to-Ground (A2G) channel modeling, which is crucial for system effectiveness [51]. UAV altitude is another critical factor influencing communication efficiency [52]. Fortunately, NOMA offers a promising approach to address these limitations. This review explores how NOMA, combined with metaheuristic techniques, can be leveraged to optimize various performance metrics in UAV communication systems. Metaheuristic methods are powerful optimization tools well-suited for tackling the challenges associated with joint optimization in NOMA-UAV systems [53]. This review underscores the potential of NOMA combined with metaheuristic techniques to optimize energy efficiency in UAV communication systems. This approach holds significant promise for achieving more sustainable and effective UAV deployments.

2.3 UAV Classification

Understanding the classification of UAVs is critical when considering their impact on wireless network performance. The UAV's operation altitude, which has a considerable impact on its wireless network capabilities, is one of the distinguishing characteristics in this categorization [54]. The Quality of Service, or QoS, needs within the chosen service region are a major determinant of this important metric [55]. Additionally, it is crucial to abide by legal requirements governing the maximum and lowest operational altitudes. In particular, the Federal Aviation Authorities (FAA) of the USA has mandated a maximum flying height for UAVs of 400 feet [56]. This rule emphasizes the necessity for UAVs to be operated within certain height restrictions to maintain the integrity of the airspace and ensure safety. A UAV's structural layout also has a significant impact on how it is classified. The UAV's capability to do vertical landings and takeoffs without needing to use a runway [57], its maneuverability in flying, and its capability to efficiently carry payloads are all factors to be taken into account. The planned uses and operating capabilities of the UAV are directly impacted by these design characteristics.

In essence, categorizing UAVs involves a variety of variables, including altitude, legal requirements, and structural design. Each feature influences how the UAV fits into the larger picture of aerial technology, eventually determining how well-suited it is to certain jobs and applications. An exploration of the diverse functionalities of UAVs within the contemporary technological landscape furthers our understanding of their categorization. According to the operational altitude and construction type, UAVs may generally be divided into the following categories [29, 58]:

1. Altitude

(a) High Altitude Platform (HAP)

(b) Low Altitude Platform (LAP)

2. Structure

(a) Fixed-wing UAVs

(b) Rotary-wing UAVs

2.3.1 High Altitude Platform (HAP)

UAVs of the High Altitude Platforms (HAP) category fly beyond the Earth's surface, especially in the stratosphere, at altitudes of 17 km and above. These stratospheric UAVs differ from their lower-altitude versions in that they have special qualities. In the field of aviation technology, it is essential to comprehend the function and potential of HAPs [59]. HAPs are frequently distinguished by their very limited maneuvering speed and high deployment costs. Because of this, they are less ideal for circumstances that call for quick action, such as sudden emergencies or real-time applications. HAPs provide a standout compromise between space and terrestrial wireless networks, nevertheless [60]. HAPs have more latency compared to ground wireless networks because of their higher altitude. Despite this flaw, they have a significant benefit: they are less expensive than satellites and make payload maintenance and upgrades simple. For lengthy missions that might last for many months, HAPs are a desirable alternative because of their low maintenance and update costs [61]. Haps’ durability is one of its main advantages. The capacity of these stratospheric platforms to continue operating for lengthy periods of time is a desirable trait in situations needing continuous wireless communication across a large geographic region. Although their latency may make them unsuitable for certain applications, their capacity to provide connectivity for a long time might compensate for this drawback [62]. Moreover, HAPs play a crucial role in the growing UAV scene by providing special benefits that address certain mission needs. Even if it results in decreased latency, their implementation is especially helpful when long-term, cost-effective aerial connectivity is required.

2.3.2 Low Altitude Platform (LAP)

UAVs that fly low to the ground, usually within a few kilometers of the Earth's surface, are referred to as low altitude platforms (LAPs). These low-flying UAVs have a number of benefits and uses that make them an important tool in the field of aerial technology [63]. LAPs are characterized by their capacity to offer quick and affordable solutions for meeting the transient connection requirements of terrestrial customers. They can create the best communication linkages possible with numerous nodes on the ground thanks to their nearness to the Earth's surface. Due to this distinctive feature, LAP-based UAVs are ideally suited for a variety of applications [64]. LAPs have a lot of potential in the Age of IoT, for example. UAVs can be crucial in the IoT environment by effectively gathering data from sensors placed in various areas. These sensors frequently have limited power resources, therefore by using LAPs, UAVs may reduce the transmission power consumption of the sensors, hence increasing their operating lives. This interaction among LAPs and IoT shows how they may work together to improve data collecting efficiency and guarantee smooth communication in unpredictable circumstances [65]. Additionally, the adaptability of LAPs goes beyond IoT. These low-altitude vehicles can be used for a variety of operations, such as search and rescue operations, surveillance, and disaster management. In situations when speedy data gathering and transmission are essential, their capacity to quickly orient themselves and create the best communication links makes them significant assets [66]. LAPs are a desirable option for applications that call for frequent, brief UAV operations due to their cost-effectiveness. These missions can entail checking on agricultural fields, evaluating the condition of the infrastructure, or helping with disaster response. LAPs provide a practical answer in any situation by fusing cost and agility.

Furthermore, As LAPS are incorporated in wireless communications and networks, they are extremely successful at satisfying critical connection and data collecting requirements. Their low-altitude capabilities, cost-efficiency, and outstanding versatility make them great for reacting quickly to important communication and data collection requirements in a variety of wireless network applications [67]. In today's environment, wireless network applications range from residential Wi-Fi to cellular networks, industrial detectors, healthcare surveillance, and retail solutions. One interesting application is the use of LAP UAVs to be communication and network base stations [68].

2.3.3 Fixed-wing UAVs

Fixed-wing UAVs, shown as Figure 2.1, fall under a separate classification of UAVs [69]. These UAV platforms stand out from other UAV categories due to their distinctive characteristics, which present both benefits and drawbacks. One of the main advantages of fixed-wing UAVs is their ability to travel at incredible speeds and carry heavy payloads. Due to this characteristic, they are especially well suited for applications that call for the movement of bulky machinery, data-gathering devices, or specialized sensors across large geographic distances. Fixed-wing UAVs thrive in situations where fast coverage is necessary because they make it possible to complete tasks quickly over vast terrains [70]. But it's important to recognize the fixed-wing UAVs' inherent limitations. Fixed-wing UAVs continuously move forward throughout flight, in contrast to rotary-wing UAVs, which can hover stationary. Since sustaining their flight depends on this constant forward propulsion, they are unsuitable for situations requiring immobile deployment or prolonged hovering over certain areas [71].

The UAV's dependency on a circular flying trajectory to cover prescribed regions is one prominent effect of this trait. They can sustain flight due to this circular path, but establishing reliable communication links becomes more difficult. Dynamic changes in connectivity brought on by the UAV's mobility cause sporadic connections to ground-based communication nodes. Applications that cannot tolerate delays or need uniform, uninterrupted network connections may find their performance constrained by this intermittent connectivity pattern [72]. Fundamentally, fixed-wing UAVs provide an appealing option for uses that value speed, long-range coverage, and the movement of large payloads [73]. They are essential resources in situations like extensive data collecting, surveillance flights, and remote cargo transfer because to their special mix of qualities [74, 75]. They are less suited for applications that need fixed, delay-intolerant network setups, nonetheless, due to their inability for hovering and the difficulties they have in establishing stable communication links [76].

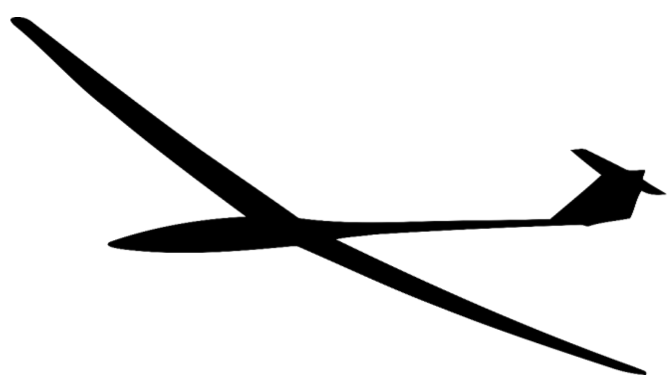

Figure 2.1 Fixed-Wing UAV

2.3.4 Rotary-wing UAVs

UAVs fall into a key group that is represented by rotary-wing UAVs in Figure 2.2 [77]. These adaptable aerial platforms have unique qualities that set them apart and provide a range of benefits that appeal to a variety of applications both within and beyond the wireless communication industry. The capacity of rotary-wing UAVs to hover and retain a nearly motionless condition while in flight is one of its key advantages. This skill helps to minimize latency while increasing network connection and performance. Rotor-wing UAVs, as opposed to their fixed-wing equivalents, may quickly and cheaply meet on-demand communication demands. Their ability to hover still enables quick responses to shifting communication needs within the coverage area, maximizing the value of the whole network [78]. Additionally, rotary-wing UAVs fly at lower altitudes, which has a number of advantages. Because of their greater closeness to the Earth's surface, communication nodes may more easily establish Line-of-Sight (LOS) links. These LOS connections considerably increase the performance of the wireless system, resulting in better signal quality and fewer interference. In situations when dependable, high-quality connections are essential, this trait is especially beneficial [79]. Positioning network elements closer to communication devices is a strategic move that is essential to the development of 5G networks. Rotor-wing UAVs play a key role in improving network capacity as well as coverage by utilizing their adaptability in low altitude missions, which helps to promote the effective deployment of cutting-edge wireless technology[80]. Rotor-wing UAVs' inherent advantages perfectly match the changing requirements of upcoming wireless networks. This is the rationale for the selection of the rotary-wing UAVs model as the main point of focus for the design and assessment for the NOMA UAV-BS within this thesis. This decision was motivated by the knowledge that rotary-wing UAVs have the qualities required to meet the demanding requirements of contemporary wireless communication systems [81]. The following sections delve into the intricacies of rotary-wing UAVs, examining their capabilities, uses, and contributions for the larger field of aerial technology. We'll also travel through the critical area of A2G channels models, which is a crucial link in the signal's transmission process. Since these models serve as the foundation for the design, analysis, and optimization of the wireless communications network under consideration, their correctness is crucial [78].

Rotary-wing UAVs serve as an example of innovation and flexibility in the UAV technology industry. They serve as vital resources across a range of applications thanks to their special mix of hovering skills, low altitude operation, and adaptability, which ultimately shapes the next generation of wireless communications. This study will discover the numerous roles and contributions made by rotary-wing UAVs in tackling a wide range of technical issues and breakthroughs as work our way through the complexities of this UAV classification.

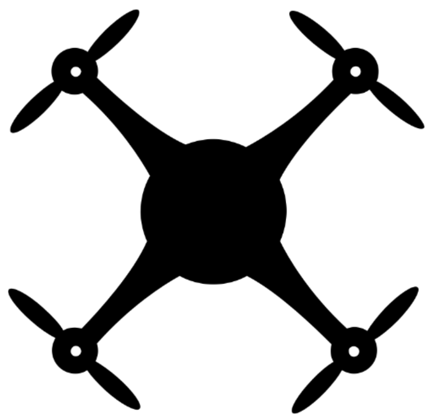

Figure 2.2 Rotary-Wing UAV

2.4 Overview of Air-to-Ground Channel Model

This section explores the unique characteristics of the communication channel between a UAV and a ground user in the context of LAPs. Unlike high-altitude platforms that primarily benefit from line-of-sight (LoS) connections, LAPs encounter a more balanced mix of LoS and non-line-of-sight (NLoS) links. The probability of establishing a LoS connection is directly linked to the UAV's altitude. The higher the UAV flies, the greater the chance of an unobstructed path for the signal to reach the user on the ground. This probability is influenced by environmental factors like urban density. The A2G channel also experiences distinct phases based on the level of signal scattering during its journey. Initially, near the UAV, there's minimal scattering, resulting in minimal signal loss. However, as the signal travels towards the ground and encounters buildings and other structures, it experiences significant additional losses due to scattering. This two-phase nature of the A2G channel highlights the importance of considering both types of environments when calculating signal loss. The total path loss is influenced by factors like distance and the specific type of link (LoS or NLoS). Since the type of link (LoS or NLoS) depends on the terrain, a more comprehensive approach considers the overall channel condition based on the average path loss. This approach takes into account the probabilistic nature of link establishment and the varying scattering environments, providing a robust framework for analyzing A2G communication systems [32, 82].

2.5 NOMA

The NOMA protocol has become a key participant in the constantly changing wireless communication environment. The number of linked devices has increased worldwide in an unheard-of way during the last several years. As a result of our networked lifestyles and digital ecosystems, there is an exponential increase in the insatiable desire for mobile data. It is anticipated that by the year 2022, there will be an astounding 77 Exabyte of monthly mobile data traffic [111]. Our communication networks' basic structure is changing as a result of the data flood, forcing us to reconsider how to manage connection, capacity, and effectiveness. Tech industry visionaries are focusing on the fifth generation of cellular networks, often known as 5G, as a solution to this data deluge. The leap into the next generation is anticipated to be nothing less than transformational. It's a revolutionary increase in our wireless infrastructure's capabilities, not just a small step. Imagine this: With ten times less energy use than our present 4G technology, 1000 times greater bits per second might be transmitted across the radio [112]. It represents a significant change in the way that design and construct wireless networks. The urgent requirement to support an unimaginably huge amount of connected devices is at the core of this revolutionary journey. This study discusses a wireless environment where billions of smartphones, Internet of Things (IoT) gadgets, driverless cars, and smart appliances coexist. A surge of innovation in wireless technology has been sparked by the high density of users competing for a piece of the finite physical radio resources. With its suite of enabling technologies, 5G excels in this area.

Massive MIMO technology or Multiple Input, Multiple Output turns base stations into highly intelligent systems that can support a large number of users at once. By using hitherto unutilized high-frequency bands, millimeter-wave (mmWave) communication has the potential to deliver lightning-fast data speeds. Device-to-device (D2D) communication allows for direct communication between devices, which lowers latency and boosts productivity. By bringing base stations nearer to users, ultra-densification creates an extensive network fabric that improves coverage and capacity. Simultaneous transmission and receiving are made possible by full-duplex communication, substantially enhancing spectral efficiency [9]. However, in the middle of this technological upheaval, NOMA stands out as a paradigm-shifting idea. A fundamental shift in how to distribute and use resources in communication networks is represented by NOMA. Imagine a situation in which numerous users share a single channel resource block, but not in the conventional, orthogonal fashion, but rather by making use of superposition. The idea of two-user NOMA communication is depicted in Fig. 2.4 [12], which is consistent with the proposed scheme for Long Term Evolution-Advanced (LTE-A) under the Third Generation Partnership Project (3GPP), which would pair users in the same channel resource block by choosing the two NOMA users within each group [114].

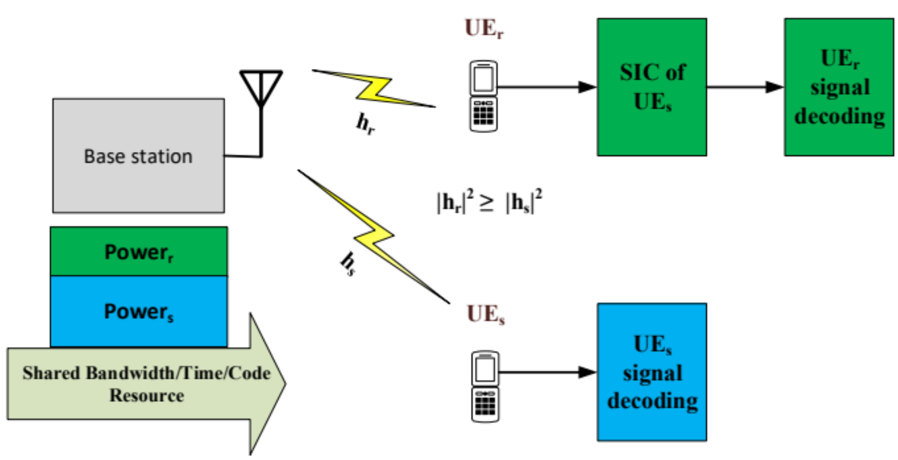

Figure 2.3 Two-user NOMA Communications system

The fundamental principle of NOMA is to first overlay an increased data-rate signal for a user (r) with improved channel conditions ($|h_r|^2$) over a signal for the user (s) with weaker channel conditions ($|h_s|^2$) using the idea of power domains superposition code [115]. This is how it goes, all users share the same channel resource, and the signal that is transferred is created as a superposition of linear of each user's data. Each user receives a percentage of the total power that is made accessible, and this amount is proportional to the inverse of each user's channel gains. SIC works its magic at the receiver's end. Users who have been given more authority and stronger channels get to decipher their communications first. Once their messages have been properly decoded, they are removed from the signal that has been received, allowing a clearer field for users on weak channels to decode their messages. It's comparable to a symphony, when several instruments play in unison, alternately, and produce lovely music without stomping on one another's toes [116]. NOMA represents a paradigm shift in resource allocation for wireless communication systems. It contradicts the conventional idea of orthogonal access, according to which each user has a unique time or frequency slot. Instead, it welcomes non-orthogonal communication, where users share the same channel resources block while using the variations within their channel conditions to increase spectral efficiency along with capacity.

2.5.1 NOMA user-pairing and power allocation

NOMA is a transformational force in the field of wireless communication, especially in the dynamic area of aerial systems [25]. NOMA's primary goal is to maximize the use of shared channels. NOMA adopts a novel strategy in contrast to conventional OMA, in which every user has exclusive access to a channel. It makes it possible for numerous users to effectively use a single-channel resource block, achieving multiplexing benefits by pairing users to use a single channel simultaneously and establishing NOMA's superior performance over OMA. However, this successful multiplexing creates a basic problem: how to efficiently divide and distribute power to users who share the same channel resource. Power allocation becomes a crucial design consideration for NOMA systems with the addition of SIC allowing user signals separation [25]. Because of this, complex power allocation strategies that can adjust to changing channel conditions including QoS requirements are required. Fixed allocation of power has traditionally been a common strategy in NOMA systems. It entails assigning customers predetermined amounts of power following long-term QoS objectives. For users with poor channel gains, when the established QoS criteria may not be properly maintained, this fixed allocation system lacks the flexibility to react to changing channel circumstances [122, 123]. To overcome this difficulty, NOMA researchers investigated the user's power split strategy that was modeled after cognitive radio technology (CR) [38]. This plan ensures that consumers with poorer channels will receive the minimal data rates they need. The weaker user is designated as the Primery User (PU), and when the QoS criteria for the PU have been met, the Secondary User (SU) is served opportunistically.

It has been extensively studied how user pairing techniques affect system performance, taking into account either fixed or CR-inspired power distribution algorithms. According to thorough evaluations, matching users having the best versus worst channel circumstances can optimize performance for fixed power allocation. In contrast, it has been demonstrated that matching the best to second-best users in the sense of channel condition produces better outcomes for CR power allocation. The secondary user may experience lesser system capacity and a higher likelihood of an outage as a result of the CR-based power allocation, albeit [38]. Dynamic NOMA was established in response to the requirement for a more flexible and equitable power allocation mechanism [40]. This system offers several fairness-throughput trade-offs while ensuring that all users reach their data-rate criteria. Similar to a comparable OMA approach, it enables the system to rigorously satisfy the data-rate threshold established for all users while giving flexibility in realizing various fairness-throughput trade-offs. With the low-complexity user-pairing technique that takes into account different channel conditions amongst paired users to increase system rate, this solution also includes dynamic user clustering as well as power allocation. A joint allocation of resources challenge was put forth in the search to maximize system sum rate, notably in the setting of full-duplex in NOMA base station (BS) [11]. The goal of this issue is to concurrently optimize power distribution and sub-carrier assignment under the assumption of a full-duplex NOMA BS. The complexity of this joint optimization issue prompted the development of a suboptimal iterative approach that uses the successive convex approximation. This method enables a comparison with traditional half-duplex systems and offers insightful information on the operation of full-duplex NOMA systems.

In NOMA systems, power allocation is optimized by taking into account factors like fairness maximization, weighted sum-rate maximization with QoS restrictions, and system energy efficiency [124]. Multi-carrier NOMA systems for communication have also been demonstrated to function better when users are paired with diverse channel characteristics [125]. The research cited above offers important information about changing user power allocation, however, they mostly focus on terrestrial NOMA systems. Given the NOMA-based UAV communication systems' flexible altitude and fundamentally differing A2G channel characteristics, this research might not be immediately relevant to them. The successful implementation of NOMA in UAV communication systems is therefore considered to need both a changing power allocation method that considers the height of the UAV-BS and suitable user-pairing algorithms [47, 50]. NOMA has demonstrated creativity and flexibility throughout its user-pairing as well as power allocation processes. Researchers are laying the groundwork for more effective and adaptable wireless communications, whether on the ground as well as in the air, using techniques like fixed power allocation, CR-inspired systems, and dynamic NOMA.

2.6 Energy efficiency

UAV communication systems hold immense potential, but a critical challenge stands in the way: maximizing energy efficiency. Limited battery capacity restricts UAV operational times and data transmission capabilities. Research focused on improving energy efficiency is crucial to unlocking their full potential [21, 83-86]. This work explores strategies to achieve this within UAV communication systems. By strategically positioning multiple UAVs and adjusting their coverage zones, the overall power required for seamless coverage can be significantly reduced [20]. Further enhancement comes from dynamic optimization techniques that consider real-time user distribution and adjust UAV flight paths and altitudes, leading to up to 20 times improvement in power efficiency [20,21].

This research proposes a mathematical framework to estimate optimal UAV altitude and transmission power, maximizing data delivery per unit of energy consumed while maintaining desired communication quality and coverage [8]. To further optimize energy efficiency, the study investigates Particle Swarm Optimization (PSO) for user pairing, prioritizing minimizing downlink power consumption while ensuring Quality of Service (QoS) for all users [22]. Building upon this foundation, Deep Reinforcement Learning (DRL) is explored to address complex 3D UAV scheduling and overcome limitations in energy and coverage. DRL offers a powerful approach for maximizing energy efficiency by optimizing power allocation and strategically deploying UAVs at minimal altitudes while dynamically providing services and opportunistically charging [23]. Another approach involves a comprehensive algorithmic approach that iteratively optimizes various system parameters, encompassing UAV trajectory, power allocation, and communication scheduling. This technique leverages advanced algorithms to achieve significant gains in overall energy efficiency compared to alternative approaches, with a strong emphasis on altitude optimization [7].

A critical challenge is achieving maximum coverage while minimizing energy consumption. The proposed approach meticulously determines optimal UAV placements that maximize fair coverage and minimize energy usage, taking into account UAV altitudes and backhaul limitations [24]. This research also investigates a model for predicting the energy requirements of UAVs. This model is crucial for maximizing energy efficiency by iteratively adjusting UAV trajectories, optimizing power allocation, and selecting optimal altitudes [25]. A unique transmission strategy is proposed to minimize energy consumption while guaranteeing required transmission rates. This approach skillfully addresses user pairing and power allocation complexities, achieving significant improvement in overall energy efficiency [26].

This research investigates a range of techniques to significantly improve the energy efficiency of UAV communication systems. These techniques pave the way for a future where UAVs can operate at higher altitudes, expanding their reach and enhancing communication capabilities, all while consuming less energy. This translates to longer mission times, broader coverage areas, and a more sustainable UAV communication ecosystem [21].

2.7 Fundamental challenges for UAV communication systems

A number of attractive characteristics and a complex set of design issues coexist in the world of rotary-wing LAPs, and these issues are crucial for the successful integration of these types of platforms in the environment of 5G as well as B5G wireless networks. Rotating-wing UAVs have a lot of promise for wireless provisioning, but how well they do it depends on where the aerial nodes are placed [87]. This location, which is crucial for achieving the expected advantages of UAVs over wireless communication, closely depends on the deployment's unique goal [88, 89]. The goal-oriented function guiding the location for rotary-wing LAPs is a vital component of optimizing their deployment. The strategic placement of these flying nodes in the network to satisfy the needs of the coverage region depends critically on this goal function. Rotor-wing UAVs' versatility and flexibility are demonstrated by their capacity to fly horizontally, bringing the network's nodes near regions of high demand. In addition, by carefully adjusting the UAV's altitude, the footprint for the aerial cell may be brought into line with the goals of the deployment [90].

The ability of UAV communications systems to provide on-demand coverage through quick and dynamic movement is its defining characteristic. For example, optimizing UAV altitude to increase coverage while staying within permitted QoS, standards. This strategy offers seamless connection across a wide area while guaranteeing that consumers' minimal QoS requirements are satisfied [91-94]. Similar to this, UAV communication systems' 3-D location may be dynamically changed to accommodate the greatest number of users possible within the demand region, hence maximizing revenue creation [95-97]. There are situations, nevertheless, in which a single UAV might not completely achieve the Region of Interest, or ROI, while maintaining the established QoS standards. Adjusting coverage is necessary in these circumstances. This calls for reducing multi-UAV density to prevent aerial cells from overlapping, optimizing resource allocation, and raising network effectiveness [98-101]. The power of IoT gadgets that send data to the aircraft network may be maintained by strategically positioning UAVs to reduce the distance between connecting nodes. By doing this, these sensors' operating lifetimes are increased, which is important for applications that depend on long-term data collecting and monitoring [81]. Further boosting the efficiency of the wireless communications system is the positioning of UAVs that will minimize transmission delays and maximize network data rates [102-106].

2.7.1 The problem of UAV-BS altitude and NOMA user power allocation

Optimizing UAV base station altitude and NOMA users power allocation are complex problems in wireless communication [30]. The complexity of NOMA technology with the unpredictability of aerial communication circumstances are the causes of these difficulties. Notably, current A2G channels models have shown that the likelihood of establishing Line of Sight or LOS communications linkages with terrestrial users increases as the UAV-BS ascends. But this rise in altitude also causes an increase in route loss between the nodes of communication [107].

Whereas Orthogonal multiple-access OMA strategies have typically improved channel dynamics of cell-edge users, this deviates from NOMA's core principles and calls for more research into the ideal altitude to NOMA systems. The envisioned advantages of NOMA transmission could be hampered by this difference [108]. Furthermore, unlike OMA-based aerial nodes, the performance of NOMA is closely linked to the asymmetrical channel circumstances that NOMA users encounter. Successive Interference Cancellations (SIC) as well as NOMA user power allocation are essential for striking a balance among system capacity and equitable access [109].

In order to fully use NOMA's potential in UAV communication systems, user power distribution must be dynamically adjusted in reaction to changes in UAV-BS height rather than following predetermined power allocation algorithms [110]. Although dynamic NOMA allocation of power techniques have been investigated in terrestrial wireless networks, using them in aerial NOMA communication systems poses special difficulties. In order to overcome this, our research goes into an original altitude displacement approach that is closely related to dynamic power allocation [111, 112].

This study describes the creation of a NOMA-based UAV communication system that performs better than analogous OMA schemes [21]. This also compares the results to grounded NOMA systems that use set altitudes and power distribution plans. This project seeks to understand the complexities of optimizing UAV-BS altitudes as well as NOMA users power allocation. It mainly focuses on the changing environment of aerial communication. Through creative altitude displacement techniques and dynamic power allocation strategies, The is aim to maximize the energy efficiency of NOMA technology for communications [113].

2.7.2 The problem of NOMA user-pairing

Optimizing user-pairing for Non-Orthogonal Multiple Access (NOMA) in UAV communication systems presents a complex challenge, demanding a comprehensive analysis of its various facets. This thesis delves into the viability and efficiency of NOMA within UAV communication networks [114]. Achieving optimal user experience within a UAV's coverage zone necessitates careful consideration of the complexities involved in managing a large number of users. Identifying the most effective user-pairing strategy for these UAV base stations (BS) remains a crucial research challenge. As expand our evaluation to scenarios with even greater user density, the challenges associated with user-pairing become even more pronounced [115], which is usual in actual deployments, this subject assumes paramount significance.

While NOMA user-pairing presents a complex challenge, it's not entirely uncharted territory. Extensive research on terrestrial networks has yielded valuable insights into how user-pairing strategies impact various network performance metrics [116-118]. Unlike terrestrial networks with relatively stable channel conditions, UAV-based communication systems face significant complexities due to dynamic Air-to-Ground (A2G) channels. These channels fluctuate significantly as the UAV adjusts its altitude, impacting the user experience for all connected devices within its range. This dynamic environment presents a multifaceted challenge: designing user-pairing systems that can not only account for these fluctuations but also leverage them to improve overall system performance. While existing research on terrestrial NOMA user-pairing provides a valuable foundation, it does not offer a definitive roadmap for NOMA deployments in UAV networks. Further research efforts are crucial to identify optimal user-pairing strategies specifically tailored to the dynamic channel conditions of NOMA-based aerial deployments [119]. To fully harness the potential of NOMA in dynamic UAV communication environments, future research should explore the intricate interplay between user-pairing strategies and altitude adjustments. Optimizing both aspects simultaneously is crucial for maximizing system performance. Furthermore, energy efficiency remains paramount in UAV communication systems, as extending mission duration and maximizing resource utilization are critical priorities [120]. To address these challenges, a user-pairing mechanism based on Particle Swarm Optimization (PSO) has been proposed. This approach aims to minimize the transmission power required in UAV NOMA communication systems [121]. While intriguing, the PSO-based user-pairing strategy exhibits certain limitations. Notably, it simplifies the problem by assuming a fixed altitude for the UAV base station (BS). This assumption, while practical, overlooks the intricate interplay between user-pairing, power allocation, and altitude optimization. To fully harness the potential of NOMA in UAV communication systems, this study further explores the complex relationships between these critical elements. This necessitates a holistic optimization strategy that simultaneously considers NOMA user-pairing, power allocation, and UAV BS altitude [82]. Considering these factors as interconnected elements within a comprehensive optimization architecture can achieve a significant reduction in transmission power for UAV NOMA systems. This, in turn, will lead to enhanced performance, sustainability, and energy efficiency in UAV communication networks [113].

Furthermore, this research delves into the techniques of NOMA user-pairing within UAV communication systems, specifically addressing the dynamic challenges posed by altitude adjustments. This investigation aims to unlock the full potential of NOMA technology in UAV networks, prioritizing system performance, energy efficiency, and practical implementation [86].

2.7.3 The problem of NOMA UAV-BS energy efficiency

Optimizing energy efficiency in NOMA-based UAV communication systems is a significant challenge. A large portion of a UAV's onboard energy is consumed by flight, making energy efficiency critical [3]. Prior research focused on minimizing energy consumption and maximizing spectral energy efficiency (SEE) in fixed-wing UAV-BS systems with constant altitude (e.g., [23]). However, these studies mainly considered Orthogonal Multiple Access (OMA) and may not directly apply to NOMA-based UAV-BS with dynamic altitude.

In NOMA-based wireless networks, energy efficiency is measured as the ratio of achievable data rate to total power consumption [122-126]. Studies like [122, 123] explored user scheduling and power allocation for NOMA under ideal and imperfect channel conditions. However, these works assumed fixed base stations, unlike UAVs with variable altitudes. A key distinction between terrestrial and UAV-based NOMA systems lies in energy consumption. For rotary-wing UAVs, total power consumption includes both signal transmission and hovering power, which increases linearly with altitude [35, 36].

Optimizing energy efficiency in UAV-BS systems is further complicated by dynamic channel conditions due to varying altitudes. Unlike terrestrial systems with static channels, UAV altitude dynamically affects the signal strength for all users. Furthermore, finding the optimal balance between maximizing data rate (sum rate), minimizing transmission power, and efficient UAV flight is challenging. Lower altitudes reduce hover energy but may require higher transmission power, while higher altitudes may require less transmission power but increase hover energy. This complex interplay necessitates a new approach to optimize energy efficiency in NOMA-based UAV-BS systems, distinct from existing methods for terrestrial NOMA [26].

2.8 State of the art: NOMA aerial communication systems

In the field of wireless communication, NOMA, particularly in the context of aerial systems, has become a key participant. This study explores the most recent innovations of NOMA-based UAV communication systems and finds a landscape brimming with innovation and opportunity. Researchers are working to fully use NOMA's potential in their quest for high-performance, energy-efficient communication in the air. Its promise includes not only effective spectrum use but also different aspects of aerial communication optimization. A two-user NOMA system within a fixed-wing oriented base station (BS) releasing assistance system was the subject of significant research [126]. This study set the door for further investigation into the special advantages NOMA offers aerial communication. Additionally, [127] dabbled with NOMA-based UAV computing cloudlets. The complex problem of overall energy reduction, which included communication, flying operations, and computation energies, was addressed by this inquiry. The findings were enlightening and demonstrated NOMA's superiority in energy conservation for mobile users as compared to identical OMA systems. An in-depth study of rate optimization on a single-antenna NOMA-based Ariel system was conducted by Nasir et al. [128]. Critical parameters such as antenna beamwidth, power, and bandwidth, as well as UAV flight height, were jointly optimized as part of their effort. The objective function significantly improved as a result of this all-encompassing strategy, demonstrating the value of concurrently optimizing all these factors. With an emphasis on throughput maximization, power allocation methods for quasi-static NOMA UAV-BS installations were investigated in [129] and [130]. These studies didn't examine the subtleties of user-pairing methods since they operated on the oversimplifying premise of fixed altitude. Similar to [131], but restricting the situation to a fixed height and power allotment, developed a NOMA user schedule strategy for a cyclical BS. Rupasinghe et al.'s [132] exploration of multi-beam arrays of antennas for NOMA broke free from the limitations of conventional methods. Through the use of directed beamforming, this cutting-edge device allowed several users to share a single beam. It's important to note, though, that the study addressed the vertical beam width constraints of antenna arrays, leading to the recommendation of a beam-based scanning strategy to increase the system's outage sum rate. While this was going on, [133] looked at an efficient NOMA UAV-assisted relay system that served a solitary cell-edge user. The study effectively attained throughput maximization by jointly optimizing transmit signal duration and power allocation. In [134], a NOMA paradigm UAV-BSs was suggested, focusing on cooperating NOMA over the uplink. Stochastic geometry was included in this study. This scenario broadened the potential uses of NOMA by examining how terrestrial users and UAVs may share a spectrum. A strategy that jointly optimized transmission power distribution and trajectories for NOMA UAV-BS deployment was presented by machine learning enthusiasts in [47]. The study emphasized the need for more research to identify the ideal pairing method for such deployments by highlighting alternative user-pairing techniques for NOMA aerial deployment. A channel allocation mechanism based on Particle Swarm Optimization (PSO) was devised to reduce transmission power for multiple NOMA systems [50]. This method provided information on how NOMA performed in terrestrial disaster relief networks and UAV BS deployments. However, there was still a need for further research into the complementary contributions of jointly optimized altitude and gearbox power. It becomes clear that the potential is enormous and mostly unrealized when examining the state of the art of NOMA-based UAV communication systems. These groundbreaking investigations pave the path for an efficient, intelligent, adaptable, and energy-conscious UAV communication system in the future.

To sum up, NOMA technology demonstrates significant potential to revolutionize wireless communication, particularly for UAV-based systems. This research has explored the application of NOMA to optimize energy efficiency in UAV communication, contributing to the ongoing pursuit of improved efficiency and resource management in our increasingly interconnected world. As research in this field progresses, NOMA will continue to be a guiding principle, paving the way for a future filled with more effective and intelligent aerial communication systems. These scientific efforts hold immense value, pushing the boundaries of what's achievable in aerial communication. While challenges remain, the potential rewards are vast. The journey of NOMA in UAV communication has just begun, and the ultimate destination is a future characterized by interconnected, efficient, and sustainable aerial communication networks.

The comprehensive literature review has identified a wealth of valuable research directly relevant to this study. The key findings and insights are summarized in a table below, providing a concise reference point that highlights the most important prior works and contributions that inform this research. The latest literature more related to this research is summarized in the following table 2.1

Table 2.1 Literature Review Summary

Year	**Ref.**	**Objectives**	**Multiple Access**	**Optimization Parameters**		
				User Pairing	**Power Allocation**	**Altitude Opt.**
2018	[127]	Energy Efficiency	NOMA	×	✓	✓
2019	[127]	Transmission power optimization.	NOMA	✓	✓	×

2020	[52]	Energy efficiency	OMA	×	✓	×
2020	[128]	Energy Efficiency/Coverage	OMA	×	✓	✓
2021	[129]	UAV Future Communication System	OMA	×	✓	×
2022	[20]	Energy efficiency	OMA	×	✓	×
2022	[130]	Energy Efficiency	OMA	×	×	✓
2022	[131]	Energy Efficiency	OMA	×	✓	✓
2022	[25]	Transmissions power optimization	NOMA	✓	✓	×
2022	[132]	Energy efficiency	OMA	✓	✓	×

2.9 Literature Review Observations

UAVs are becoming popular for communication purposes, including IoT and cellular networks. The success of a NOMA aerial system depends on finding the right balance between the altitude of the system, the distribution of power among users, and the pairing of users. Develop an algorithm to dynamically adjust U AV altitude, User pairing, and power allocation for optimal performance and energy efficiency based on network conditions. Furthermore, there are challenges and opportunities in implementing UAVs in communication systems, and future work should focus on improving energy efficiency, user pairing, and network performance However, in literature did not evaluate three parameters to fully optimize the energy efficiency, therefore it is important to investigate the joint optimization of all three parameters.

2.10 Metaheuristic Techniques

In the realm of optimization, where complex problems often lack straightforward solutions, metaheuristic techniques have emerged as powerful tools for finding near-optimal solutions in a reasonable amount of time. Metaheuristic techniques represent a class of algorithms that iteratively explore the solution space, leveraging heuristics and stochastic processes to guide the search toward promising regions. These techniques are particularly well-suited for tackling optimization problems characterized by nonlinearity, multimodality, and high dimensionality, where traditional optimization methods may struggle to provide satisfactory results [133].

2.10.1 Characteristics of Metaheuristic Techniques

Metaheuristic techniques encompass a diverse set of algorithms inspired by natural phenomena, social behavior, physical processes, and mathematical principles. Unlike conventional optimization approaches, which often rely on explicit problem-specific knowledge, metaheuristic algorithms operate more abstractly, making minimal assumptions about the problem structure. This abstraction enables metaheuristics to be applied across a wide range of problem domains, from engineering design and logistics to finance and bioinformatics. Key characteristics of metaheuristic techniques includes [134]:

Metaheuristic algorithms exemplify iterative improvement by iteratively refining candidate solutions across successive iterations, thereby steadily converging toward optimal solutions. These algorithms embody a delicate balance between exploration and exploitation, strategically navigating the solution space by diversifying the search to uncover new regions while capitalizing on promising solutions to refine them further. Stochasticity plays a pivotal role in metaheuristic algorithms, introducing randomness into the search process to prevent entrapment in local optima and foster exploration of the solution landscape. Moreover, the inherent flexibility of metaheuristic techniques allows for tailoring approaches to accommodate diverse problem characteristics and constraints, making them invaluable tools for tackling a wide array of optimization challenges [135]. Moreover, metaheuristic techniques embody a unique set of characteristics that underpin their efficacy in tackling complex optimization problems. From their diverse inspirations to their iterative refinement process, balance between exploration and exploitation, stochastic nature, and flexibility, these characteristics collectively contribute to the versatility and effectiveness of metaheuristic algorithms across various domains. Such as in the domain of UAVs energy efficiency metaheuristic algorithms can dynamically allocate resources such as battery power, processing capacity, and communication bandwidth based on real-time demand and environmental conditions. This adaptability ensures optimal utilization of energy resources, prolonging UAV mission endurance and maximizing operational efficiency [136].

2.10.2 Classification of Metaheuristic Techniques

Metaheuristic techniques can be classified into several categories based on their underlying principles and operation. Some common classifications include:

Evolutionary Algorithms: Inspired by the principles of natural selection and genetics, evolutionary algorithms (e.g., genetic algorithms, evolutionary strategies, and genetic programming) maintain a population of candidate solutions that evolve over generations through mechanisms such as selection, crossover, and mutation [137].

Swarm Intelligence: Swarm intelligence algorithms draw inspiration from the collective behavior of social organisms, such as ant colonies and bird flocks. Examples include particle swarm optimization (PSO), ant colony optimization (ACO), and artificial bee colony (ABC) algorithms [138].

Simulated Annealing: Simulated annealing mimics the annealing process in metallurgy, where a material is slowly cooled to minimize its energy. In optimization, simulated annealing iteratively explores the solution space, allowing occasional uphill moves to escape local optima [139].

Tabu Search: Tabu search maintains a short-term memory, storing previously visited solutions and forbidden moves (tabu list) to avoid revisiting the same regions of the solution space. This helps to diversify the search and escape local optima [140].

Local Search: Local search algorithms focus on improving a single solution iteratively by exploring its neighborhood. Examples include hill climbing, simulated annealing, and genetic algorithms with local search operators [141].

Hybrid and Memetic Algorithms: Hybrid metaheuristic algorithms combine elements of multiple techniques to leverage their respective strengths. Memetic algorithms, in particular, integrate local search procedures into evolutionary algorithms to enhance their performance [142].

2.10.3 Advanced Metaheuristic Techniques

Evolutionary Algorithms (EAs) Enhancements: While traditional genetic algorithms (GAs) form the cornerstone of evolutionary computation, recent advancements have led to the development of enhanced evolutionary algorithms. These include multi-objective evolutionary algorithms (MOEAs), which optimize multiple conflicting objectives simultaneously, and surrogate-assisted evolutionary algorithms, which use surrogate models to approximate expensive fitness evaluations and accelerate convergence. In the context of UAV communications, MOEAs can be particularly valuable for optimizing multiple conflicting objectives such as energy efficiency, latency, and reliability [143].

Swarm Intelligence Variants: The field of swarm intelligence continues to expand with the development of novel algorithms inspired by diverse natural phenomena. For instance, bacterial foraging optimization (BFO) mimics the foraging behavior of bacteria to solve optimization problems, while firefly algorithms (FA) emulate the flashing patterns of fireflies to guide the search process. These variants offer alternative optimization strategies that may exhibit superior performance in specific problem domains, including UAV communication network optimization[144].

Hybrid and Ensemble Approaches: Hybrid metaheuristic algorithms combine elements of different optimization techniques to harness their complementary strengths. For example, hybridizing genetic algorithms with local search operators can improve exploration-exploitation balance and enhance convergence speed. Similarly, ensemble approaches integrate multiple metaheuristic algorithms to leverage their collective intelligence and enhance solution quality. In the context of UAV communications, hybrid and ensemble metaheuristic approaches can tailor optimization strategies to the specific requirements and constraints of the communication network [145].

Adaptive and Self-Adaptive Algorithms: Adaptation mechanisms play a crucial role in enhancing the robustness and scalability of metaheuristic algorithms. Adaptive metaheuristics dynamically adjust their parameters or strategies based on the evolving characteristics of the optimization landscape, while self-adaptive algorithms autonomously adapt their search operators or control parameters during runtime. These adaptive mechanisms enable metaheuristic algorithms to effectively navigate complex and dynamic UAV communication environments characterized by varying terrain, weather conditions, and network dynamics [146].

2.10.4 Application in UAV Communications

Metaheuristic techniques find widespread application in various domains, including UAVs, where they play a pivotal role in optimizing operations and enhancing efficiency. In the realm of wireless communication and networks, UAVs serve as versatile platforms for delivering connectivity to remote or inaccessible areas. Metaheuristic algorithms are instrumental in optimizing UAV trajectories, resource allocation, and interference mitigation strategies to maximize coverage, minimize energy consumption, and ensure seamless connectivity [147, 148]. Specifically, in the context of UAVs acting as base stations in wireless communication networks, metaheuristic techniques offer tailored solutions to optimize trajectory planning, resource allocation, interference management, and deployment strategies [141, 149]. By leveraging these algorithms, UAVs can efficiently serve as base stations, extending network coverage, improving connectivity, and enabling a wide range of applications, from disaster response and rural connectivity to aerial surveillance and beyond [150].

2.10.5 Optimization Strategies in UAV Communications

Dynamic Resource Allocation: Efficient utilization of resources, such as bandwidth, power, and computational capacity, is essential for optimizing UAV communication performance. Metaheuristic optimization techniques can dynamically allocate resources based on real-time demand, network conditions, and user requirements. By continuously adapting resource allocation strategies, UAV communication networks can achieve optimal resource utilization, minimize interference, and maximize throughput and reliability [148].

Trajectory Planning and Path Optimization: Optimal trajectory planning is critical for maximizing coverage, minimizing energy consumption, and ensuring seamless connectivity in UAV communication networks. Metaheuristic optimization methods, such as PSO and GA, can be employed to optimize UAV trajectories considering various constraints, including airspace regulations, terrain features, and mission objectives. By iteratively refining trajectory plans, metaheuristic algorithms can guide UAVs to traverse optimal paths that balance energy efficiency, communication quality, and mission requirements [148].

Energy-Efficient Communication Protocols: Energy efficiency is a paramount concern in UAV communications, where limited onboard power constrains mission endurance and operational capabilities. Metaheuristic optimization techniques offer avenues for designing energy-efficient communication protocols that minimize energy consumption while maintaining reliable and robust communication links. By optimizing transmission power levels, modulation schemes, and routing protocols, metaheuristic algorithms can tailor communication strategies to prolong UAV flight duration, extend communication range, and enhance network resilience [151].

Interference Mitigation and Spectrum Management: Interference mitigation and spectrum management are critical challenges in UAV communication networks, particularly in crowded or congested airspace. Metaheuristic optimization methods can optimize spectrum allocation, channel assignment, and interference mitigation strategies to mitigate co-channel interference, maximize spectral efficiency, and ensure reliable communication links. By dynamically adapting transmission frequencies and avoiding frequency bands prone to interference, UAV communication networks can operate more efficiently and achieve better performance in challenging environments [152].

Distributed and Cooperative Communication Strategies: Cooperative communication among multiple UAVs or between UAVs and ground stations can enhance network coverage, capacity, and reliability. Metaheuristic optimization techniques enable the design of distributed communication strategies that coordinate UAVs' actions to achieve collective optimization objectives. By leveraging swarm intelligence principles, such as decentralized decision-making and information sharing, metaheuristic algorithms can orchestrate collaborative communication behaviors that adapt to changing network conditions and mission requirements [153].

2.10.6 Challenges for Optimization

While metaheuristic techniques hold tremendous promise for optimizing UAV communications, several challenges and opportunities warrant further exploration:

Scalability and Complexity: As UAV communication networks scale up to accommodate a growing number of UAVs and connected devices, scalability becomes a paramount concern. Metaheuristic algorithms must evolve to handle large-scale optimization problems efficiently while maintaining acceptable convergence speed and solution quality [153].

Real-time Adaptation and Dynamic Optimization: UAV communication environments are inherently dynamic, characterized by evolving network conditions, mission requirements, and environmental factors. Metaheuristic techniques need to incorporate real-time adaptation mechanisms to dynamically adjust optimization strategies and respond to changing circumstances [153].

Robustness and Resilience: UAV communication networks operate in challenging and often unpredictable environments, where disruptions, failures, and adversarial attacks are common. Metaheuristic optimization strategies must prioritize robustness and resilience, ensuring that communication networks can withstand unforeseen events and maintain essential functionalities under adverse conditions [148].

Metaheuristic techniques offer versatile and powerful tools for optimizing UAV communication networks, enabling efficient resource allocation, trajectory planning, energy management, and interference mitigation. By harnessing the adaptive and exploratory nature of metaheuristic algorithms, researchers can address the unique challenges posed by UAV communications and pave the way for more resilient, efficient, and intelligent communication systems in the skies.

2.10.7 Optimization Methods in Metaheuristics

While the core principles of metaheuristic algorithms remain consistent across different techniques, the specific optimization methods employed may vary depending on the algorithm and problem domain. Some common optimization methods used in metaheuristics include:

Objective Function Evaluation: Metaheuristic algorithms evaluate the objective function (or fitness function) to assess the quality of candidate solutions. Efficient methods for evaluating the objective function can significantly impact the algorithm's performance, especially for computationally expensive problems [154].

Parameter Tuning: Many metaheuristic algorithms include parameters that influence their behavior and performance. Parameter tuning techniques, such as grid search, random search, and metaheuristic-based optimization of parameters, aim to find optimal or near-optimal parameter configurations for a given problem [141].

Initialization Strategies: The initial population or solution plays a crucial role in the convergence behavior of metaheuristic algorithms. Initialization strategies, such as random initialization, Latin hypercube sampling, and adaptive initialization, aim to generate diverse and promising initial solutions [155].

Exploration and Exploitation Strategies: Balancing exploration and exploitation is essential for the effectiveness of metaheuristic algorithms. Various strategies, such as adaptive mutation rates, dynamic neighborhood structures, and multi-operator search, aim to adaptively adjust the search process to explore new regions while exploiting promising solutions [156].

Convergence Criteria: Metaheuristic algorithms typically terminate when certain termination criteria are met, such as reaching a maximum number of iterations, achieving a satisfactory solution quality, or stagnating the search progress. Choosing appropriate convergence criteria is crucial for balancing computational resources and solution quality [153].

Parallelization and Distributed Computing: To handle large-scale optimization problems efficiently, parallelization and distributed computing techniques can be employed to harness the computational power of multiple processing units or distributed computing resources. Parallel metaheuristic algorithms and distributed optimization frameworks facilitate the exploration of the solution space in parallel, accelerating the search process [157].

2.10.8 Metaheuristic Optimization for UAV Communication Energy Efficiency

Optimizing energy efficiency in UAV communication systems presents unique challenges. Researchers are exploring various metaheuristic optimization methods, inspired by natural processes, to address these challenges effectively. One prominent example is Particle Swarm Optimization (PSO). Inspired by the social behavior of swarms in nature, PSO offers adaptability and flexibility. Researchers are investigating ways to refine PSO's implementation specifically for energy-efficient UAV communication scenarios, aiming to develop a robust theoretical framework for its application [158]. Similarly, the Ant System (AS) algorithm, inspired by ant colony behavior, presents a promising approach. This algorithm excels at tackling stochastic combinatorial optimization problems, making it well-suited for addressing optimization challenges in UAV communications. Its efficient search capabilities and the cooperative interactions among its "agents" contribute to its effectiveness [159].

Beyond these specific examples, a vast array of bio-inspired metaheuristic techniques exist, such as the Bat Algorithm [160], Glowworm Swarm Optimization [161], Zebra swarm optimization and Fruit Fly Optimization Algorithm[160, 162]. Each offers unique local and global search strategies, broadening the toolbox available to researchers for optimizing energy efficiency in complex UAV communication systems. By leveraging these diverse approaches inspired by nature's problem-solving strategies, researchers can effectively tackle a wide range of energy efficiency challenges in this evolving field.

CHAPTER 3

METHODOLOGY

The proposed research methodology involves different techniques to achieve an Energy-efficient placement of a UAV communication system. This is accomplished by conducting a literature review, utilizing UAVs, and employing NOMA as a multiple-access technology. The study focuses on specific parameters such as user pairing, power allocation, and altitude optimization. To evaluate the performance of the proposed system, various optimization techniques such as Genetic Algorithm and Particle Swarm Optimization are utilized. The simulation results analyzed to determine the energy efficiency of the proposed system. Overall, the study aims to improve the energy efficiency of the UAV communication system by optimizing its placement. The results of the study will contribute to the development of more efficient communication systems for UAVs.

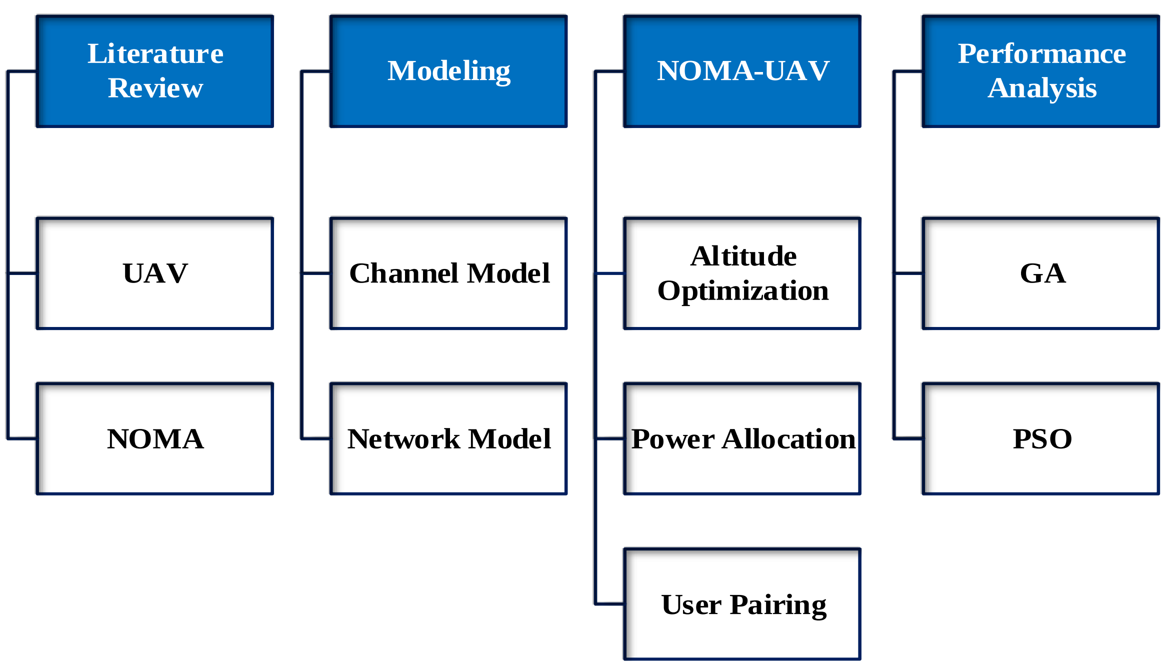

Figure 3.1 Methodology of proposed work

The methodology of the thesis includes modeling several aspects of the system as well as the NOMA transmitting scheme. Following that, it comprises defining the problem and proposing solutions that are consistent with the thesis goals. Finally, the findings are examined and compared against the OMA baseline framework.

3.1 System Model

The precise mathematical modeling of the system and its characteristics is required for an accurate analysis of the suggested NOMA-based UAV wireless communications systems. The UAV-BS, users, as well as the A2G wireless channel, are the three key components of this wireless communication system. Through geographical modeling, channel modeling, and energy modeling, their integrated contribution to the system are clarified.

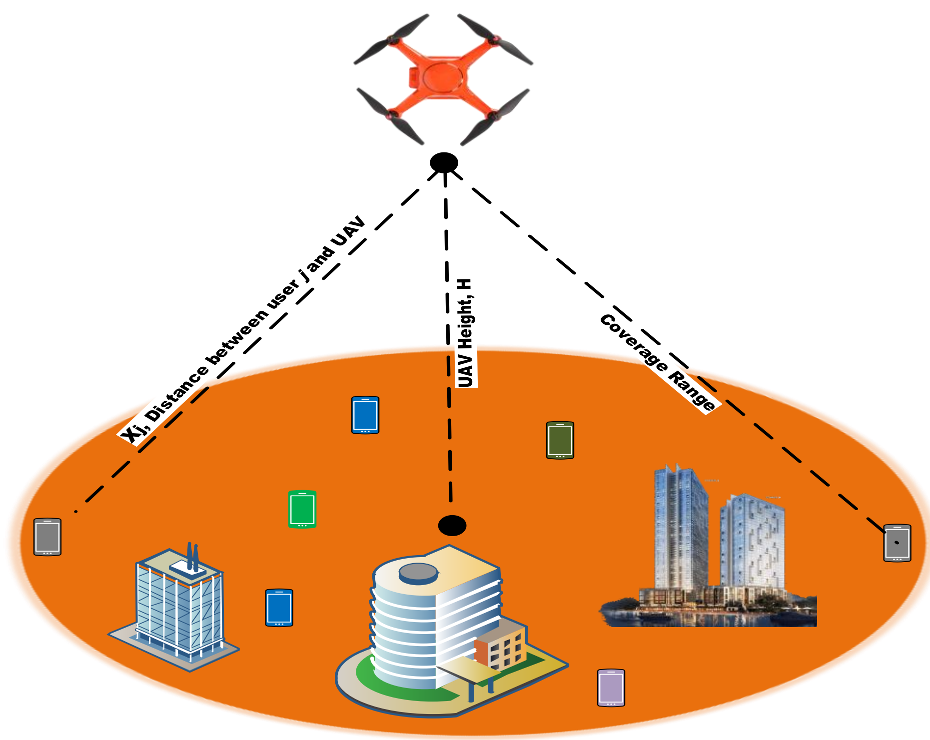

Figure 3.2 System Model, serving as flaying base station.

3.2 Spatial Model

The analysis begins with a collection of single-antenna ground users (NU) strategically arranged inside shaped like discs Region of Interest (ROI) defined by the given covering radius (Rc) in meters. This study proposes to NOMA Downlink (DL) communications system with a competent single-antenna rotary-wing UAV-BS providing wireless access to ground users. The picture Fig. 3.3 depicts a general architecture for a multiple-user UAV communications system based on NOMA. The UAV-BS's 3-D position is denoted as (x0, y0, H), indicating the center point of contact for user locations scattered throughout the Region of Interests (ROI). As a result, the computation of a horizontal distance D_j among each user located at (xj, yj, 0), wherein j ranges from 1 to N, with the vertical projection for the UAV-BS is as follows:

$$D_j = \sqrt{(x_j - x_0)^2 + (y_j - y_0)^2} \tag{3.1}$$

The distance among the UAV-BS as well as each user may be calculated as follows:

$$X_j = \sqrt{D_j^2 + H^2} \tag{3.2}$$

The elevation angle for the UAV-BS about each user is specified as:

$$\theta_j = \arctan\left(\frac{H}{D_j}\right) \tag{3.3}$$

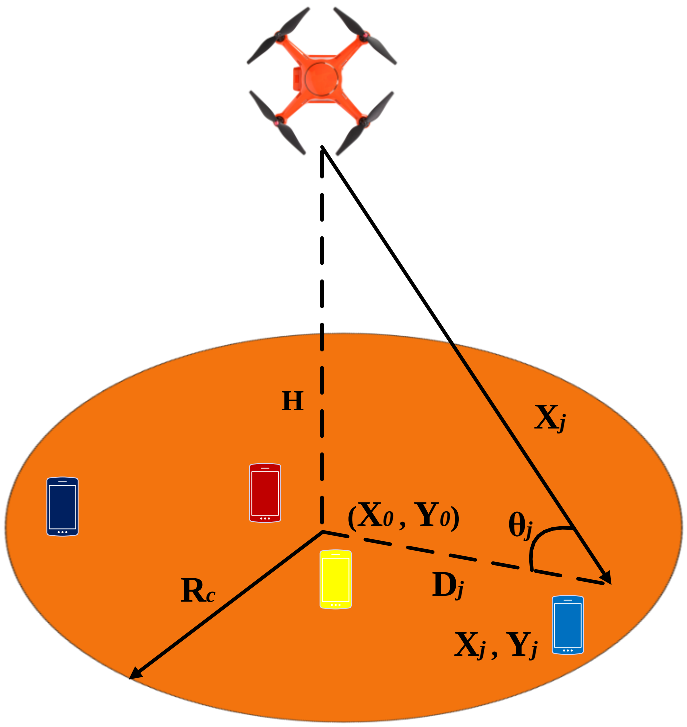

Figure 3.3 A general spatial model of a UAV communication system

3.3 Channel Model

As shown in Figure. 3.4, the link between the UAV with ground users may be divided into two separate situations. The first situation involves modest scatter and reflections near the UAV, but the second situation has strong scattering produced by man-made buildings near ground users. These scattering environment changes have a significant influence on overall path loss, which refers to the sum of free space path loss along with excessive loss. It's vital to know that ground users are classified into two categories, those who have a direct line of sight (LOS) link to the UAV-BS versus those who have an excellent non-line of sight (NLOS) link. Because of significant signal reflection along with shadowing induced by barriers in the coverage region, NLOS connections incur a more pronounced excessive loss.

To clarify, [2, 63] explains the likelihood of a user possessing a LOS link with the UAV-BS:

$$Pr_j(LOS) = \frac{1}{1+\alpha \exp(-\beta[\theta_j - \alpha])} \tag{3.4}$$

The probability of LOS and NLOS linkages are defined by scaling factors where α and β are the scaling factors, which are impacted by the coverage region's particular environmental circumstances, which include rural, suburban, and dense metropolitan regions.

The likelihood of a user seeing NLOS links is estimated as follows:

$$Pr_j(NLOS) = 1 - Pr_j(LOS) \tag{3.5}$$

The chance of each connection type contributing to overall channel status is determined by environmental circumstances and the angle of elevation (j) involving a specific user (j^{th}) with the UAV-BS. The elevation angle is defined by the relative locations of the UAV-BS along with the ground users inside the coverage region. When the UAV's altitude rises, the odds of establishing an unimpeded Line-of-Sight (LOS) link between the UAV-BS and ground users improve. As a result, the route loss for the UAV-BS to the j^{th} terrestrial user is estimated as follows [62]: The path loss coefficient is represented by the symbol. Furthermore, the terms LOS and NLOS are utilized to identify excessive route losses for LOS along with NLOS connections, respectively. Both of these variables have a normal distribution, with the elevation angle as well as environment-specific constant values influencing their mean and variance [32]. In the absence of terrain data, knowledge of both UAV and user locations is insufficient to definitively classify the links (LOS/NLOS) between them. To overcome the unpredictability associated with LOS and NLOS connections, an estimation of the central tendency is achieved by calculating the mean route loss by taking both propagated link types and the associated probabilities into account, rather than depending on random instantaneous behavior [23, 32, 62]. As a result, [2, 146] the overall path loss within the UAV-BS as well as its j^{th} user is expressed as follows:

$$L_j\left(D_j\ H\right) = Pr_j(LOS)L_j\ (LOS) + Pr_j(NLOS)L_j(NLOS) \tag{3.7}$$

Thus, the received power at the j^{th}jth user in the downlink (DL) is expressed as [63]:

$$P_{Rj}(dB) = P_T(dB) - L_j^{-}\ (D_j\ H) \tag{3.8}$$

where P_T represents the transmitted power by the UAV-BS.

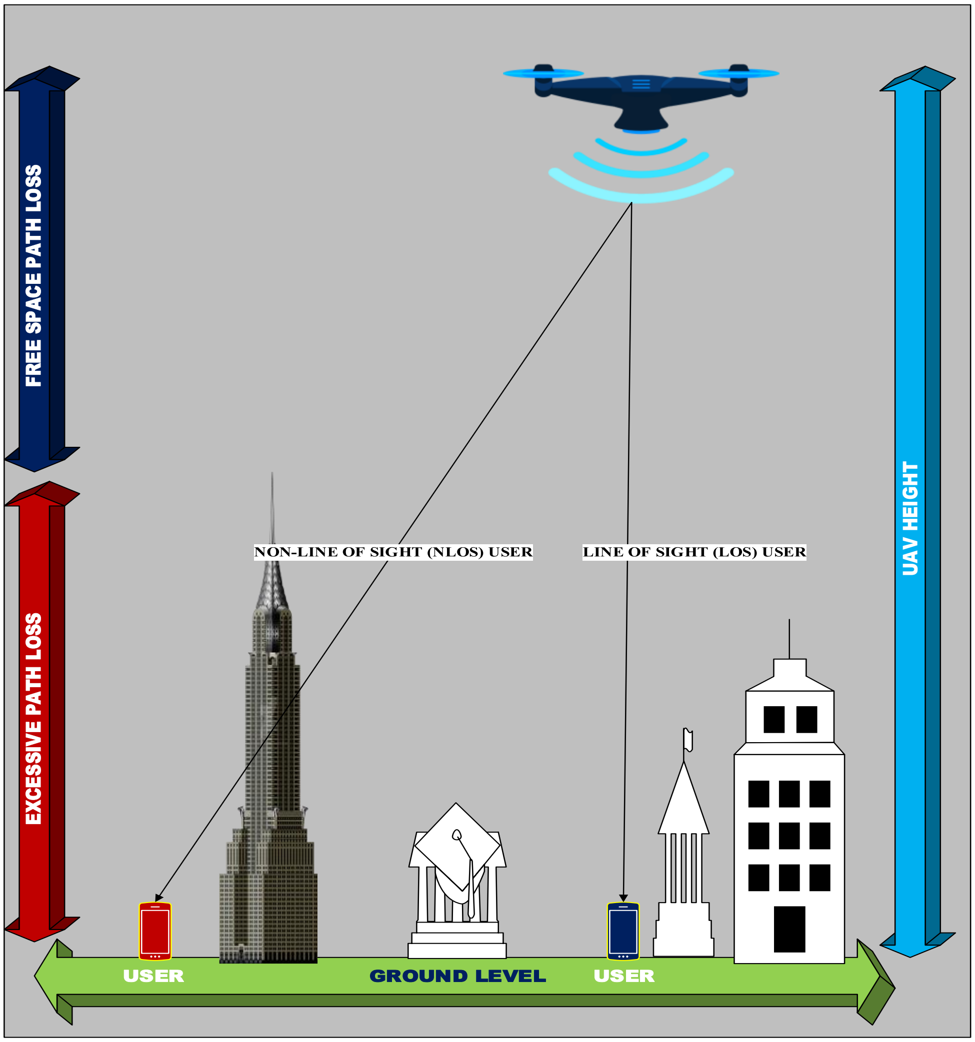

Figure 3.4 Air-to-Ground Channel Model

3.4 Energy Model

Researchers showed a strong link between rotary-wing UAV energy consumption and altitude and weight [147]. According to their suggested model, a UAV's energy consumption may be expressed as E = mgH, whereby mg is calculated by the UAV's weight (m) where the acceleration for gravity (g), and H is the height of the UAV. Although this model offers an overview of the connection between UAV altitude and consumption of energy, it is simplistic and does not account for a variety of factors that can influence overall energy consumption, such as velocity, flight maneuvers, motor efficiency, as well blade profiles. Other research, such as [59, 69, 108], have conducted experiments and gathered real-world data to address these constraints. This research looked at various UAV postures, including sitting on the ground, rising and falling from particular elevations, hovering, and hovering in a straight line. Their findings reveal that as the UAV reaches greater altitudes, its energy consumption climbs considerably. Furthermore, they discovered that hovering consumes less energy than other aircraft maneuvers, with hovering height having a major impact on energy efficiency. The following equation [59] is used to calculate the total energy use of a UAV while hovering for a second at a chosen height H from its starting ground position:

$$E = E_{climb} + E_{hover} = P_{climb}t_{climb} + P_{hover}t_{hover} \tag{3.9}$$

P_{climb} and P_{hover} represent the power needed by the UAV to ascent and hover, respectively. Furthermore, t_{climb} denotes the time required to achieve the target height. To give more insights, the model described in equation (3.9) is developed based on the authors' study in [60]. According to their findings, rotary-wing UAVs can fly at greater altitudes to provide better coverage, although this occurs at the expense of more energy being used. As a result, the consumption of energy model in equation (3.9) might be changed as follows [60]:

$$E = P_{climb}\left(\frac{H_O}{\gamma_{climb}}\right) + \left(\frac{\Psi + \Gamma H}{P_{hover}}\right) t_{hover} \tag{3.10}$$

The first portion of the equation denotes the energy spent to elevate the UAV to a certain height H utilizing a constant velocity climb and the motor's maximum power capability, represented as P_{climb}. The second half of the equation depicts the energy usage during the hover phase, with "Γ" being the minimum power required to hover just above the ground and representing the speed of the motor multiplier where "ψ" represents the minimum power needed to hover just over the ground. Given that, P_{climb}, t_{hover}, and climb are constants, the energy consumption of the UAV during its hovering phase may be calculated as a function that is linear of altitude (E_{hover} / H). This is true if the UAV has identical design specs and velocity in both NOMA along OMA situations. As a result, lowering the UAV's operational height leads to greater energy efficiency. This assumption is correct since air density as well as pressure decrease with height, resulting in less upward push for the UAV, which requires more power to continue hovering at higher altitudes than at lower altitudes [107].

Let "H_O" indicates the UAV's altitude in the OMA arrangement, as discussed in Section 2.6.1. The energy expenditure EO, assuming OMA, may thus be stated as:

$$E_O = P_{climb} \left(\frac{H_O}{\gamma_{climb}}\right) + (\psi + \Gamma \mathrm{H}_O) t_{hover} \tag{3.11}$$

Likewise, EN denotes the operational energy consumption of the UAV with HN as the altitude.

$$E_N = P_{climb} \left(\frac{H_N}{\gamma_{climb}}\right) + (\psi + \Gamma \mathrm{H}_N) t_{hover} \tag{3.12}$$

Thus, the subsequent difference equation can be utilized to compare the energy consumption of OMA and NOMA schemes:

$$E_O - E_N = \Delta \mathrm{E} = (\Gamma t_{hover} + \left(\frac{P_{climb}}{\gamma_{climb}}\right) \Delta \mathrm{h} \tag{3.13}$$

In this case, where Δh = HO – HN, a positive Δh indicates that NOMA achieves improved energy savings by requiring a lower altitude HN.

3.5 NOMA Transmission Schemes for the UAV-BS

The preceding section laid the groundwork for determining how spatial distribution along with environmental variables influence both channel conditions plus the energy usage of the UAV communications system. The following phase entails detailing the NOMA transmission technique as well as the signal processing performed by every user in the planned UAV communications system. The given capacity equations, which are dependent on the allocation of power, are essential to the approaches discussed in the following sections. Figure 3.5 serves as a reference for a generic UAV NOMA deployment scenario.

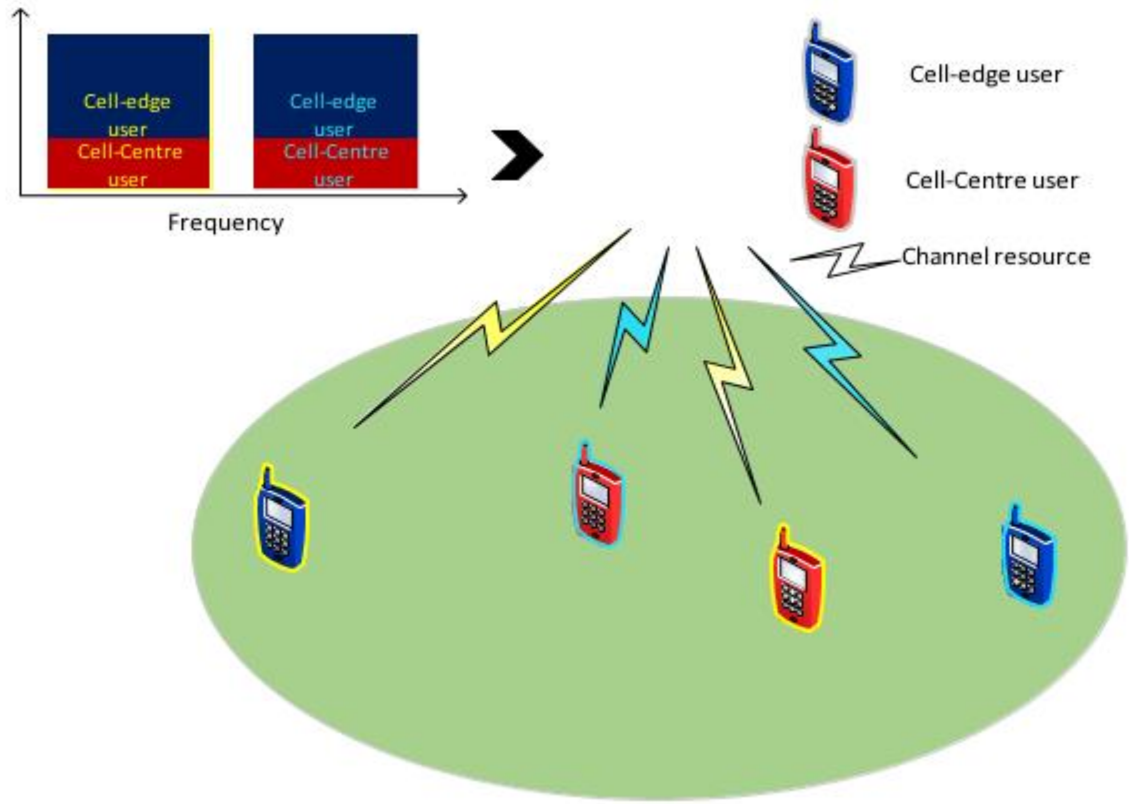

Figure 3.5 NOMA Transmission Model

Applying the NOMA principles indicated by Figure 3.5, a resource block assigned to every user-pair, Where $1, \leq m \leq M = \frac{N}{2}$ is accessible concurrently by both component users $\{r, s\}_m$ through an overlaid message written as:

$$x_u = \sqrt{P_r}\, x_r + \sqrt{P_s} x_s, \forall\, 1 \leq m \leq M \tag{3.14}$$

P{r, s} denotes the assigned power, and x_u denotes the signal at the user u = {r, s} of the user-pair m. The signals that are received by users can be characterized as follows:

$$y_r = h_r \left(\sqrt{P_r}\, x_r + \sqrt{P_s} x_s \right) + n_r \tag{3.15a}$$

$$y_s = h_s \left(\sqrt{P_r}\, x_r + \sqrt{P_s} x_s \right) + n_s \tag{3.15b}$$

In this setting, the communication channel between the UAV-BS with the user is represented by h_u. Furthermore, n_u represents additive white Gaussian noise having a power of *Pn* at the receiver. It is vital to notice that the relation $|hs|^2$ $|hr|^2$ always holds for user-pair m, which consists of two users {r, s}. This condition is required for effective Successive Interference Cancellation (SIC) efficiency since it allows the s^{th} user's message to be removed from the signal received by the r^{th} user [148]. As a result, the r^{th} user, who has a better channel gain, uses SIC for decoding the message that was intended for the s^{th} user first. The decoded message is then removed from the original received signal, yielding an interference-free, noise-limited capability for the r^{th} user. Simultaneously, the signal obtained at the s^{th} user is immediately decoded. Assuming that the power allotted for each user-pair *m* is indicated by $P_m = P_r + P_s$, the possible separate rates for the r^{th}as well as s^{th}users of user-pair *m* are determined as follows:

$$\Upsilon_s^N = \log_2(1 + \frac{\omega_s |h_s|^2}{\omega_r |h_s|^2 + {}^1/_\Gamma}) \tag{3.16}$$

$$\Upsilon_r^N = \log_2(1 + \omega_r\ \Upsilon |h_r|^2), \tag{3.17}$$

Where $\Gamma = \frac{P_{(m)}}{P_n}$ is the ration of signal power to noise power, ω_r and ω_s are the power allocation coefficients and can be obtained using the following equation [163].

$$\omega_s = \frac{\chi_1}{\sqrt{1+p|h_r|^2}+1} + \frac{\chi_2}{\sqrt{1+p|h_s|^2}+1} \tag{3.18}$$

$$\omega_r = 1 - \omega_s \tag{3.19}$$

Where χ_1 *and* χ_2 are the constants and χ_1+$\chi_2 = 1$.

3.6 Problem Formulation

Here, the power allocation vector for all paired users in the coverage area is denoted by $\bar{P}_T = \{ \{P_r, P_S\}_1, \{P_r, P_S\}_2 \dots, \{P_r, P_S\}_M\}$ Where, $\{P_r, P_S\}_M$ represents the power allocated to the S^{th} and the r^{th} user belonging to the x^{th} user. Therefore, the expression for η_{EE} can be formulated as:

$$\eta_{EE} = \frac{R(\bar{P}_T, H_N)}{|\bar{P}_T|_1 + P_F(H_N)} \tag{3.2}$$

The sumrate of all users is represented by $R(\bar{P}_T, H_N, u) = \sum_{m=1}^{M} \left(\Upsilon_r^N \left(P_r, H_{N,u}\right) + \Upsilon_S^N (P_S, H_{N,u}) \right)$ where H_N is the altitude of the UAV-BS, and M is the number of user pairs. The power consumption of the UAV-BS during hover operation at altitude H_N is given by $P_F\ (H_N)$ where $|.|_1$ denotes the $(\ell - 1)$-norm. The problem of maximizing η_{EE} can be presented in the following form:

$$(P1) : \max_{H_N, \bar{P}_T, u} \eta_{EE} \tag{3.2.1}$$

Subject to:

$$C1 : \ \Upsilon_r^N (P_r\ , H_N, u)\ \geq \Upsilon_r^O ,$$

$$C2 : \ \Upsilon_s^N (P_s\ , H_N, u)\ \geq \Upsilon_s^O \ ,$$

$$C3 : \ P_r + \ P_s \ \leq \ P^{max}\ \forall\ 1\ \leq m\ \leq M\ ,$$

$$C4 : \ \sum_{n=1}^{M} u_m^n \ = 2\ , \forall\ 1\ \leq m\ \leq M\ ,$$

$$C5 : \ \sum_{m=1}^{u} u_m^n = 1\ \forall\ 1\ \leq\ n\ \leq N\ ,$$

$$C6 : \ H^{min}\ \leq\ H_N\ \leq\ H^{max}.$$

The collection of constraints (C1 - C6) imposed in the current optimization framework issue formulation ensures that the NOMA-based UAV communications system operates effectively. NOMA users, represented by the letters R and S, are the subject of C1 and C2. Due to these constraints, the lowest rates these users may achieve under NOMA must match or exceed the rates they could achieve under OMA. This means that NOMA is required to offer maximum or at least the same quality of service as OMA. The user-pairing power allocation is linked to C3. The maximum available power sets a limit that must be adhered to by the combined power allotted to users "r" and "s" in every pair (m). This guarantees effective power management for the presented system. C4 addresses user pairing where "u" used as paring metrics, permitting a maximum of two users to get linked inside each group (m). This pairing constraint improves system organization and streamlines communication procedures. C5 indicates user pairing to be exclusive, meaning that the same user cannot belong to more than one group. This rule reduces redundancy and optimizes user-group allocations. C6 relates to the UAV's operational altitude and specifies a range that is acceptable for flying or hovering, from H^{min} to H^{max}. To preserve security and efficiency. This constraint is essential. Collectively, these constraints establish the framework for the NOMA-based UAV communication system, ensuring its reliable and efficient operation while accommodating operational conditions and user preferences.

3.7 Methodology

This research investigates optimizing energy efficiency in NOMA-based UAV communication systems. An optimization function, detailed in Equation (6), is developed to maximize the sum rate (total data rate) experienced by NOMA users while incorporating relevant constraints. Heuristic algorithms, guided by the general optimization flowchart in Figures 3.3 and 3.4, are employed iteratively to improve this function. The focus is on optimizing the user pairing matrix, which significantly impacts the overall system performance.

Solving the optimization problem defined by Equation (6) presents a challenge due to its non-convex combinatorial nature. This means finding the absolute best solution is difficult due to the vast number of potential user pairs and the complex interactions between them. To address this challenge, the study utilizes metaheuristic techniques. These techniques, while not guaranteeing the absolute optimal solution, offer efficient approaches for tackling complex optimization problems within a reasonable timeframe. Common metaheuristic techniques include.

- Genetic Algorithms (GA)
- Zebra Swarm Optimization (ZSO)
- Ant Colony Optimization (ACO)
- Cat Swarm Optimization (CSO)
- Artificial Hummingbird Algorithm (AHA)
- Particle Swarm Optimization (PSO)
- Hybrid GA-PSO

Each technique employs a unique problem-solving approach, ultimately contributing to the overall efficiency of the NOMA-based UAV communication system. This research investigates the following metaheuristic techniques for optimization:

- Genetic Algorithms (GA)
- Particle Swarm Optimization (PSO)

3.8 Genetic Algorithms (GAs):

Genetic Algorithms (GAs) are powerful tools in the realm of heuristic optimization, drawing inspiration from the principles of natural selection and evolution. They excel at tackling problems with vast search spaces and numerous potential solutions. The core concept of GAs lies in iteratively refining a population of potential solutions, termed individuals. Each individual represents a candidate solution encoded by a set of parameters. The optimization process unfolds in a series of well-defined steps[164]:

1. **Initialization:** An initial population is generated, either randomly or using a predetermined strategy.

2. **Evaluation:** Each individual's fitness is assessed based on an objective function that quantifies the optimization goal.

3. **Selection:** Individuals with higher fitness values are preferentially chosen for reproduction, ensuring promising traits are passed on to the next generation.

4. **Reproduction:** The selected individuals undergo genetic operators like crossover and mutation. Crossover combines genetic material from parents to create offspring, while mutation introduces slight variations, fostering exploration of the search space.

5. **Replacement:** The current population is updated by replacing some individuals with newly generated offspring, following a specific strategy.

6. **Termination:** The process iterates through these steps until a termination criterion is met. This criterion could be reaching a maximum number of iterations or attaining a satisfactory solution.

Through this iterative process, GAs navigate the search space, progressively favoring individuals with higher fitness. This leads to a gradual improvement in the overall population's quality. The effectiveness of GAs lies in their inherent advantages such as parallelism, robustness, and the ability to handle complex optimization problems. A visual representation of the GA flowchart can be found in Figure 3.6.

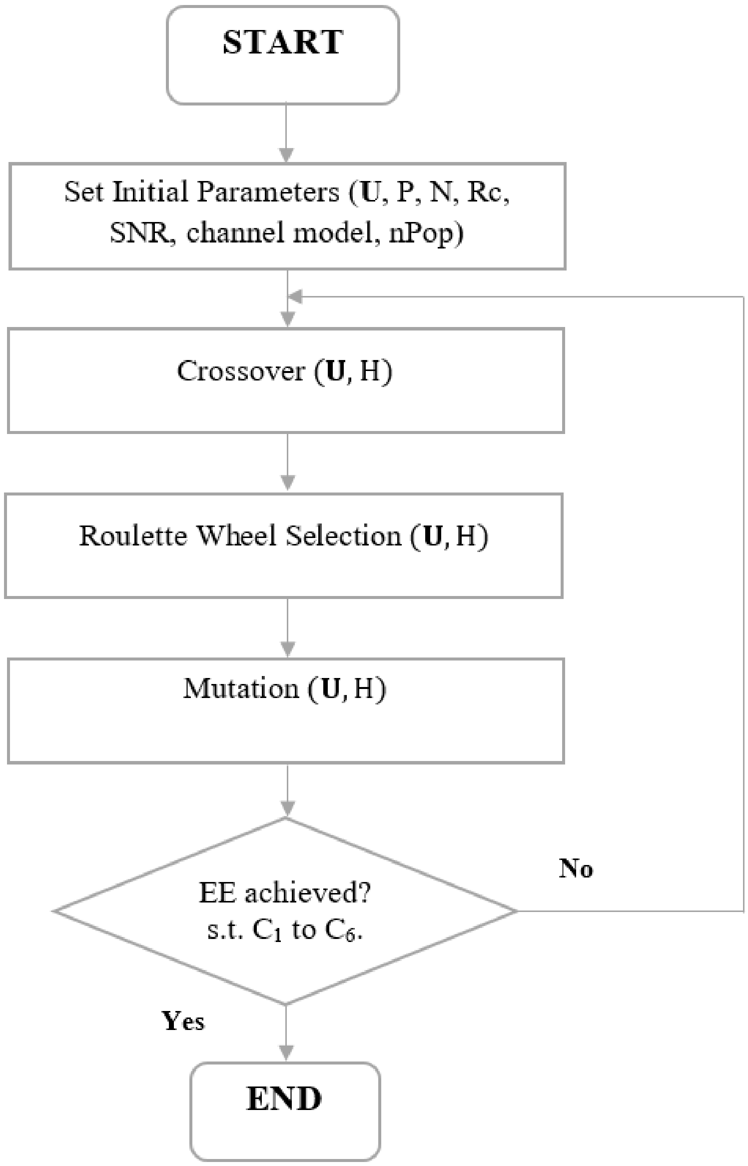

Figure 3.6 Flow chart for GA Algorithm

3.9 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) represents another powerful metaheuristic technique drawing inspiration from the fascinating collective behavior observed in swarms of birds or schools of fish. In PSO, a population of candidate solutions, termed particles, collaboratively navigates a multidimensional search space in search of an optimal solution. Each particle embodies a potential solution encoded by its position within the search space, and its velocity guides its movement[165]. The optimization process in PSO figure 3.7, unfolds through a series of well-defined steps:

1. **Initialization:** An initial swarm of particles is created, randomly distributed within the defined search space.

2. **Evaluation:** Each particle's fitness is assessed based on an objective function, quantifying the optimization goal.

3. **Velocity and Position Update:** The core of PSO lies in iteratively updating the velocity and position of each particle. This update considers two key factors:

   - **Cognitive Component:** The particle's memory of its personal best position (pbest) encountered so far, promoting exploration of promising regions it has discovered.

   - **Social Component:** The influence of the swarm's best-known position (gbest), guiding particles towards areas identified as favorable by the entire swarm.

4. **Local and Global Best Update:** Following the velocity and position update, the pbest of each particle and the gbest of the entire swarm are potentially updated based on the newly evaluated fitness values.

5. **Termination:** The process iterates through these steps until a termination criterion is met, similar to Genetic Algorithms (GAs). This criterion could be reaching a maximum number of iterations or attaining a satisfactory solution.

Through this iterative process, PSO particles collaborate and learn from each other's experiences. Particles with superior performance not only improve their own search trajectories but also influence the movement of others, collectively converging towards promising regions of the search space. PSO offers advantages such as simplicity, fast convergence, and the ability to handle complex problems with continuous search spaces.

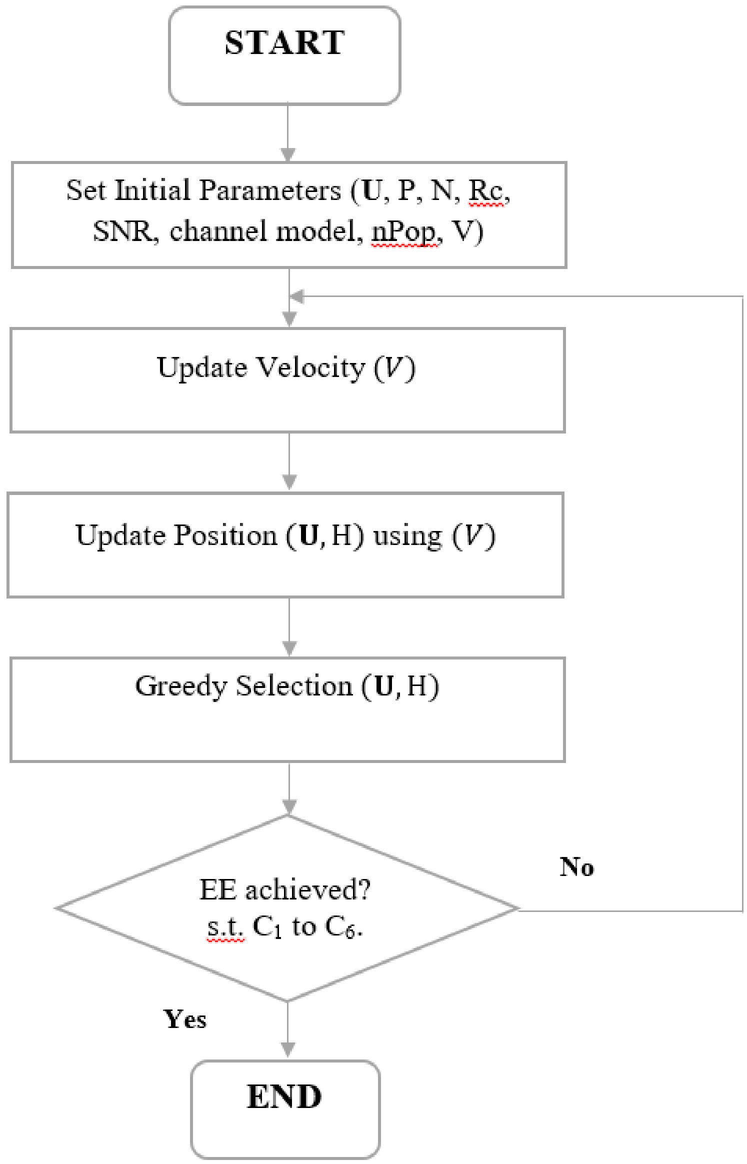

Figure 3.7 Flow chart for PSO Algorithm

CHAPTER 04

SIMULATION RESULTS AND DISCUSSION

This research delves into optimizing energy efficiency within NOMA-based UAV communication systems by leveraging metaheuristic techniques. To ensure the simulations closely resemble real-world conditions, the selection of parameters prioritizes maximizing energy efficiency while upholding optimal system performance. The simulation setup consists of 10 to 100 users grouped in pairs, operating within a 100 to 500 meters' coverage radius. A SNR of 0 to 30 dB is established, with a path loss exponent of 2.5 to model signal attenuation. The optimization process iterates for a maximum of 100 cycles, with simulations conducted across various environments, including suburban areas. The overall objective is to optimize energy efficiency while adhering to constraints. The study then performs a comparative analysis to evaluate the effectiveness of various metaheuristic techniques, such as GA, to identify the most efficient user-pairing scheme and optimization technique that maximizes energy efficiency in NOMA-based UAV communication systems. Table 4.1 outlines the crucial simulation parameters employed in the study, providing a comprehensive overview of the experimental setup and methodology.

4.1 Analysis of Paring Schemes

This section explores various user-pairing techniques for NOMA-based UAV communication systems, contrasting their effectiveness with the traditional OMA approach. Four distinct pairing strategies are evaluated: worst pairing, which prioritizes users closest together; random pairing, which selects users arbitrarily; GA pairing, a sophisticated technique that leverages a genetic algorithm to find optimal pairings; and finally, PSO pairing, which utilizes the PSO for user pairing. Through a comprehensive analysis of these methods alongside OMA, the study aims to gain valuable insights into their relative strengths and weaknesses. This in-depth analysis will ultimately guide researchers towards the optimal user pairing strategies that maximize performance within NOMA-based UAV communication systems.

Table 4.1 Simulation Parameters used to validate the proposed system.

Simulation Parameters	**Values**
No. of users	10 to 100
Coverage radius (Rc)	100m to 500m
Pairing	2 Users per pair
SNR	0 to 30 dB
Path loss exponent (α)	2.5
Candidate solutions (J)	40
Max iterations	100
Power allocation constant: χ_2	0.1
Environment	Suburban, Urban and Dense urban
Max users in a pair	2
Transmission power of a cluster (p)	1W
GA Parameters	
Crossover	Multipoint point
Mutation	Adaptive
PSO Parameters	
Inertia Weight ω_{IW}	0.7
Constants c_1 and c_2	1.7

4.1 User Deployment

In the deployment scenario described, a 3D environment is envisioned, characterized by a user distribution spanning a vast area of 100 by 100 square meters and extending to a height of 80 meters. Within this spatial domain, UAVs are positioned at an altitude of 80 meters, suggesting a three-dimensional operational framework. This configuration implies a comprehensive coverage scheme, wherein the UAVs act as aerial nodes servicing the users distributed across the spatial extent. Utilizing 100 by 100 square meter user distribution highlights the scale and potential complexity of the communication network.

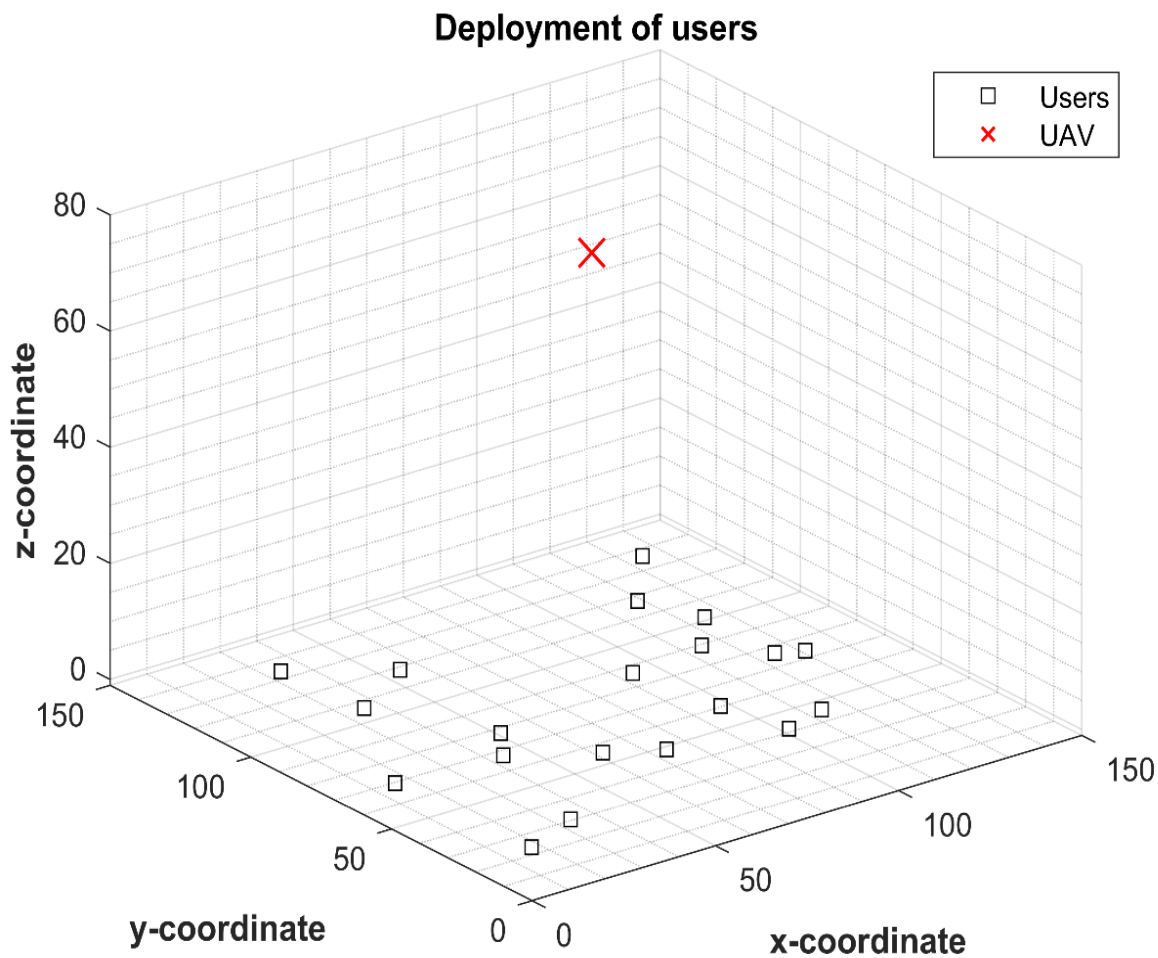

Figure 4.1 User Deployment (3D environment)

4.2 Impact of Varying Coverage Region

Table 4.2 Altitudes achieved for various coverage regions

CR	OMA-Altitude	GA-NOMA Altitude	PSO-NOMA Altitude
100m	45m	43m	43m
200m	88m	106m	96m
300m	132m	147m	147m
400m	174m	179m	169m
500m	200m	253m	171m

The examination of energy efficiency across different coverage regions, with an SNR of 20dB and 20 users, provides valuable insights into network performance Figure 4.2. In the case of worst pairing and random pairing schemes, there was a consistent decline in energy efficiency with the increasing coverage area. As the coverage region expands from 100m to 500m, both GA and PSO for NOMA exhibit a decreasing trend in energy efficiency. In the case of GA NOMA, the energy efficiency decreases from 1.1264 bps/Joules at 100m to 0.2719 bps/Joules at 500m, while for PSO NOMA, it declines from 1.1288 bps/Joules to 0.3502 bps/Joules over the same range. This decrease is notably more pronounced in the PSO NOMA scheme. Conversely, the OMA approach also experiences a decrease in energy efficiency with increasing coverage region, from 0.555 bps/Joules at 100m to 0.1292 bps/Joules at 500m. Despite the decline in efficiency, both NOMA GA and NOMA PSO consistently outperform OMA across all coverage regions, with NOMA PSO demonstrating the highest energy efficiency overall. Therefore, NOMA PSO exhibits better performance in optimizing energy efficiency across varying coverage regions compared to NOMA GA and OMA.

NOMA PSO shows higher percentage improvements over OMA and achieves an average improvement of 55% whereas NOMA GA, with an average improvement of 51% across the coverage regions, indicates its effectiveness in optimizing energy efficiency in urban environments. Overall, NOMA PSO emerges as the optimal choice for enhancing energy efficiency in wireless networks across diverse coverage regions.

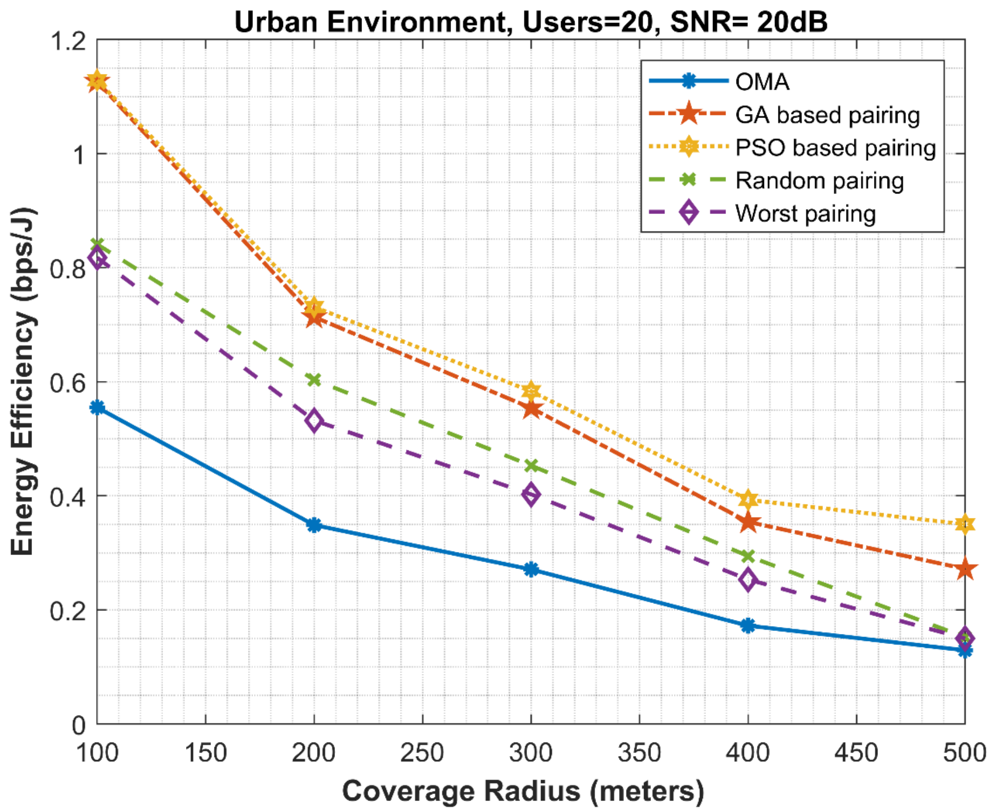

Figure 4.2 Impact of Varying Coverage Region.

4.3 Impact of varied SNRs

The impact of varying SNR on energy efficiency in urban environments, with a coverage radius of 100m and 20 users, is evident from Figure 4.3. For the OMA approach, as the SNR increases from 0dB to 30 dB, the energy efficiency gradually rises. Similarly, both the GA and PSO for NOMA exhibit an upward trend in energy efficiency with increasing SNR. However, GA consistently shows slightly lower energy efficiency compared to PSO across all SNR levels. For instance, at SNR 20dB, GA achieves an energy efficiency of 2.0917 bps/Joules, whereas PSO achieves 2.2639 bps/Joules. Despite these differences, both GA and PSO demonstrate considerable improvements in energy efficiency compared to OMA across all SNR levels. Overall, while GA performs slightly lower than PSO, both techniques significantly enhance energy efficiency in urban environments with varying SNR levels. In the case of pairings of users, a noticeable trend emerges for worst pairing and random pairing schemes. These pairing schemes demonstrate increasing energy efficiency as SNR levels rise, similar to GA and PSO for NOMA. However, both pairings exhibit slightly lower efficiency compared to GA and PSO across all SNR levels.

The analysis reveals significant improvements in energy efficiency achieved by both NOMA GA and NOMA PSO over the OMA approach across all SNR levels. On average, NOMA GA demonstrates an average improvement of 46% over OMA, while NOMA PSO shows an average improvement of 51% over OMA. When comparing NOMA GA and NOMA PSO, NOMA PSO exhibits an average improvement of 10% over NOMA GA. These results indicate that both NOMA GA and NOMA PSO offer substantial enhancements in energy efficiency compared to OMA, with NOMA PSO slightly edging out NOMA GA on average.

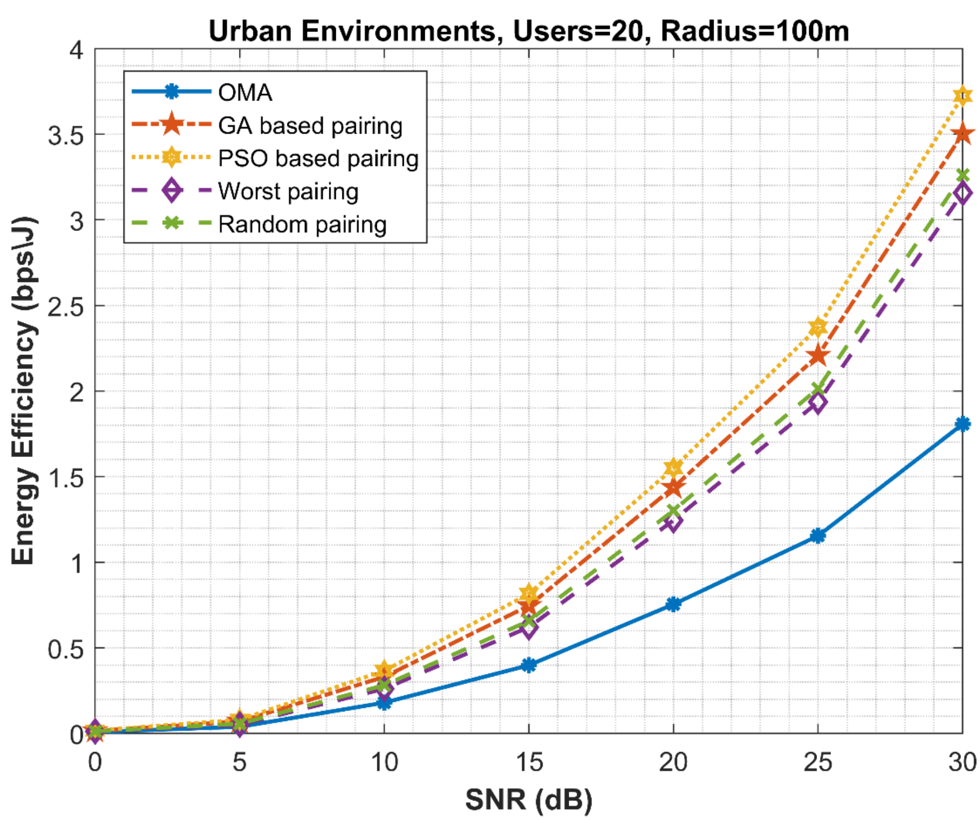

Figure 4.3 Impact of varied SNR.

4.4 Impact of Varied Users

The examination of how varying user counts affect energy efficiency in urban settings, with a coverage radius of 500m and SNR of 20dB, provides valuable insights into the efficacy of different pairing schemes within the NOMA framework Figure 4.4. Contrasted with the OMA approach, NOMA showcases substantial enhancements in energy efficiency across diverse user counts. Both NOMA GA and NOMA PSO, employing random pairing and worst pairing schemes, demonstrate improved energy efficiency with increasing user numbers. However, NOMA PSO consistently surpasses NOMA GA in energy efficiency, indicating its superior performance in urban contexts. For instance, at 100 users, NOMA PSO achieves an energy efficiency of 0.2781 bps/Joules, while NOMA GA reaches 0.2506 bps/Joules. These findings underscore the effectiveness of PSO-based pairing schemes in optimizing energy efficiency in NOMA systems, particularly when compared to GA-based approaches. Overall, NOMA PSO, leveraging both random and worst pairings, showcases superior energy efficiency improvements over NOMA GA, highlighting the importance of efficient pairing strategies in enhancing energy efficiency in urban wireless networks.

The average percentage improvement of NOMA PSO over NOMA GA is 10%. These results indicate significant enhancements in energy efficiency for both NOMA GA and NOMA PSO compared to OMA. Moreover, NOMA PSO exhibits a greater average percentage improvement over NOMA GA, suggesting its superior performance in enhancing energy efficiency.

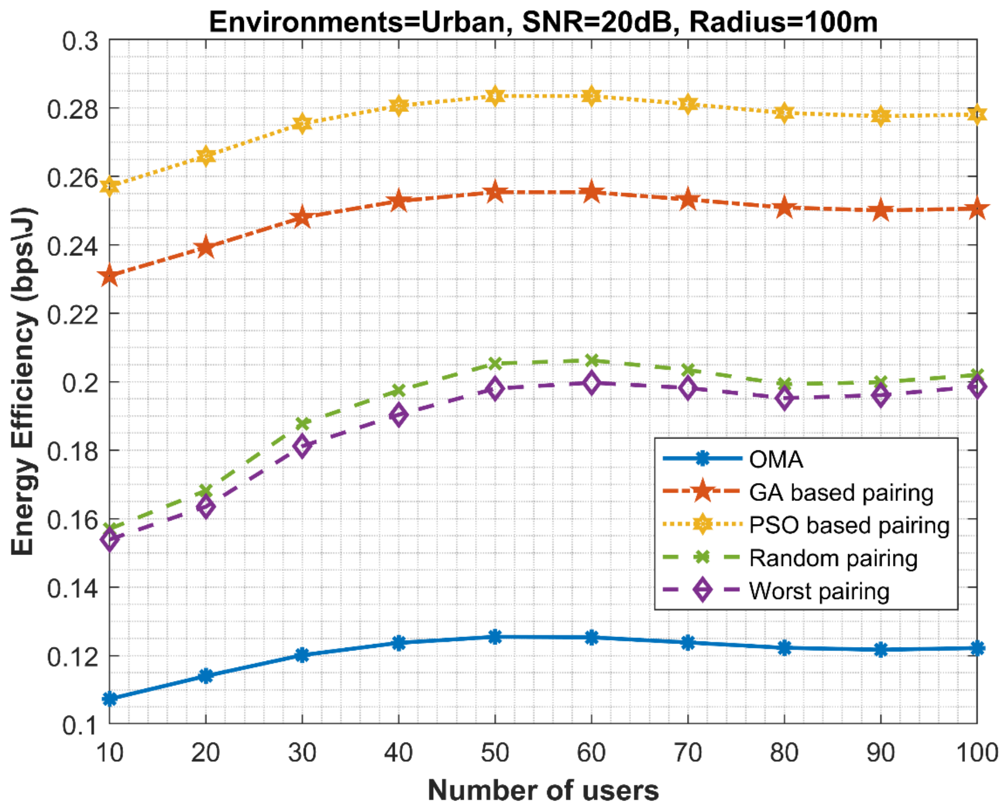

Figure 4.4 Impact of Varied Users

4.5 Impact of Varying Environments

The examination of how different environments impact energy efficiency, considering a coverage radius of 100m, SNR of 20dB, and 20 users, reveals distinct trends in Figure 4.5. In Suburban settings, both GA and PSO within the NOMA framework exhibit notably higher energy efficiency than the traditional OMA approach. PSO NOMA achieves the highest efficiency at 1.1287 bps/Joules, followed closely by GA NOMA at 1.0717 bps/Joules, while OMA trails at 0.5334 bps/Joules. Similarly, in Urban areas, NOMA techniques outperform OMA, with PSO NOMA leading at 0.8354 bps/Joules, followed by GA NOMA at 0.7913 bps/Joules, and OMA at 0.3693 bps/Joules. However, in Dense Urban settings, though NOMA still surpasses OMA, the margin is narrower. PSO NOMA maintains the highest efficiency at 0.7749 bps/Joules, followed by GA NOMA at 0.7434 bps/Joules, while OMA records an efficiency of 0.3693 bps/Joules.

Overall, NOMA, particularly PSO NOMA, demonstrates superior energy efficiency across diverse environments compared to OMA, showcasing its adaptability and effectiveness in optimizing energy efficiency in urban settings.

NOMA techniques, including GA and PSO, significantly outperform OMA in terms of energy efficiency across various environments. PSO consistently outperforms GA by and achieves 5% improvement on average. Overall, NOMA PSO exhibits the highest enhancement in energy efficiency compared to OMA and NOMA GA, making it the optimal choice for urban wireless networks.

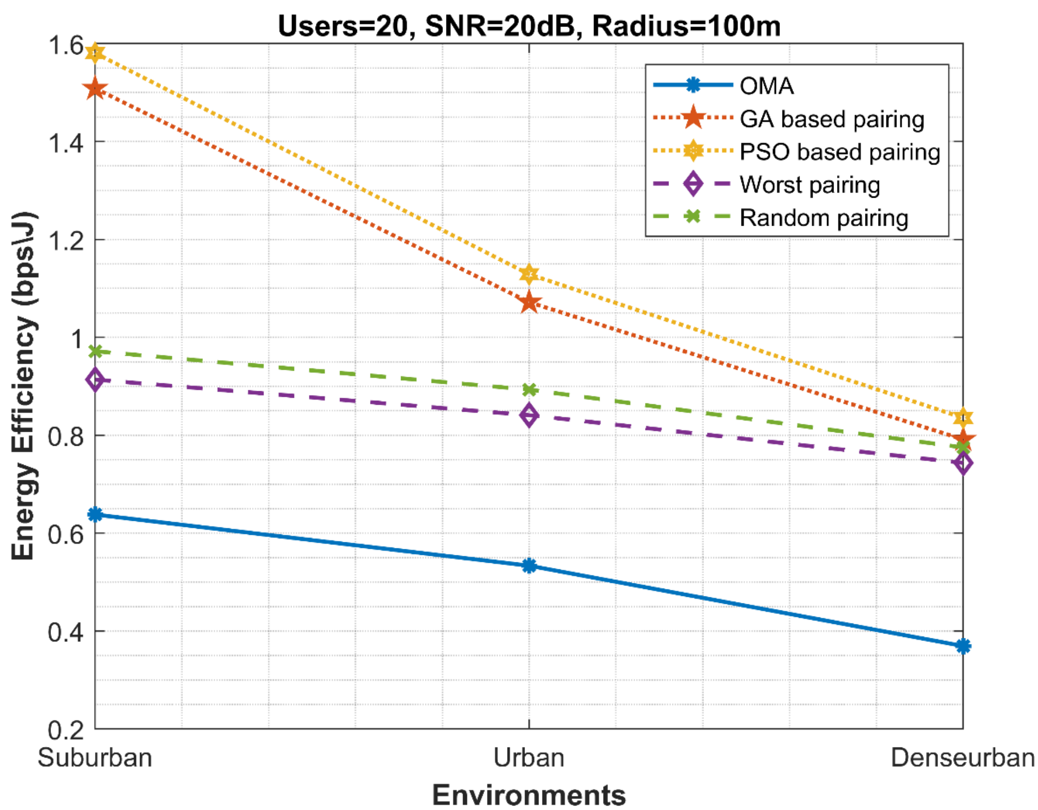

Figure 4.5 Impact of Varying Environments.

CHAPTER 05

CONCLUSION AND FUTURE WORK

This study achieves a significant breakthrough in the field of UAV communication systems by focusing on optimizing energy efficiency through the application of Non-Orthogonal Multiple Access (NOMA) technology. It carefully investigates all the parameters involved in obtaining energy efficiency. Each of these factors/parameters significantly influences energy consumption within NOMA-based UAV communication systems. To address this challenge, an optimization framework is used. This framework leverages metaheuristic techniques, and advanced algorithms inspired by natural phenomena. The framework strategically balances these crucial parameters, demonstrably achieving substantial improvements in energy efficiency while upholding desired system performance.

5.1 Conclusion

In conclusion, the growing demand for communication networks, particularly in Internet-of-Things (IoT) and cellular applications, necessitates the development of more efficient and sustainable solutions. UAVs offer a promising approach, but energy consumption remains a critical challenge. This research has explored the potential of NOMA technology to revolutionize energy efficiency in NOMA-based UAV communication systems. Previous research has primarily focused on optimizing altitude and power allocation for NOMA-based UAV systems. However, this research addresses this gap by investigating the joint optimization of three key parameters – NOMA UAV-BS altitude, user pairing, and NOMA power allocation – to maximize the overall energy efficiency of the system. By leveraging metaheuristic techniques, this research proposes an optimization framework that demonstrably achieves substantial improvements in energy efficiency while upholding desired system performance. This work makes the way for the development of more sustainable and efficient UAV communication solutions, ultimately contributing to the advancement of the evolving wireless communication landscape.

5.2 Contribution and Significance

The proposed study on energy-efficient placement for UAV communication systems is significant because it aims to optimize three important performance parameters, namely power allocation, altitude optimization, and user pairing in NOMA-based systems. Previous literature has not optimized all the parameters. Therefore, this study's contribution is to investigate the joint optimization of all three parameters using various metaheuristic methods, which can significantly improve energy efficiency and performance. This research will provide insights into balancing these parameters to optimize energy efficiency and performance in NOMA-based aerial systems. The results will contribute to the development of more efficient and sustainable communication solutions for UAVs. By developing such solutions, this study can help in promoting a more sustainable and energy-efficient approach to aerial communication systems. which is crucial for the technological advancement and growth of such systems. Overall, this study's contribution and significance lie in optimizing energy efficiency and performance, which can lead to the development of sustainable and efficient communication solutions for UAVs.

5.3 Future Work

This research on using NOMA and Metaheuristic algorithms to optimize energy use in UAV communication systems paves the way for future developments. One key area is designing algorithms to position multiple UAVs instead of a single one. Additionally, future research can explore how machine learning can be used to constantly adjust communication settings based on real-time situations, like how strong the signal is or how much data needs to be sent. Furthermore, the shift, from quasi-static to mobile evaluations, will enable a more comprehensive understanding of system adaptability and development of efficient and reliable solutions for diverse real-world applications. By tackling these areas, researchers can create highly efficient UAV communication networks for future applications.

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