ARTIFICIAL INTELLIGENCE-BASED APPROACH FOR DEPLOYMENT AND POWER OPTIMIZATION OF UNMANNED AERIAL VEHICLE-ASSISTED FUTURE WIRELESS COMMUNICATION NETWORK

Thesis Submitted for the Award of the Degree of

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DECLARATION

I declare that the thesis entitled "**ARTIFICIAL INTELLIGENCE-BASED APPROACH FOR DEPLOYMENT AND POWER OPTIMIZATION OF UNMANNED AERIAL VEHICLE-ASSISTED FUTURE WIRELESS COMMUNICATION NETWORK"** has been prepared by me under the guidance of **Dr. Shakti Raj Chopra** Professor, School of **Electronics and Electrical Engineering and Co-Supervised by Dr. Akhil Gupta,** Associate Professor, School of **Electronics and Electrical Engineering**. No part of this thesis has been included in or has formed the basis for the award of any Degree or Diploma or Fellowship of any institution or university anywhere previously.

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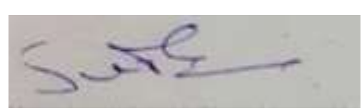

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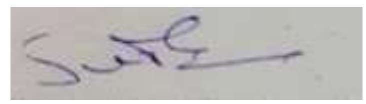

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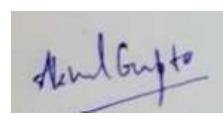

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ABSTRACT

Utilizing unmanned aerial vehicles (UAVs) offers a revolutionary way to improve network performance as wireless communication networks develop to satisfy the increasing need for dependable, fast connectivity. In order to support future wireless networks, this study suggests a framework for UAV-assisted communication that tackles important issues like latency, capacity, and coverage. UAVs' adaptability allows for quick deployment in underdeveloped areas, dynamic reconfiguration according to user density, and an affordable option for remote and rural connectivity. Additionally, when terrestrial infrastructure is compromised, UAVs can quickly restore networks, which might be crucial for disaster recovery. The suggested network structure provides scalable, adaptive coverage with low latency by utilizing UAVs in combination with cutting-edge technologies such as large multiple-input multiple-output (MIMO) systems and millimeter-wave (mmWave) communications. Results from simulations show that in a variety of operating scenarios, a UAV-assisted architecture can greatly increase connection, decrease outages, and improve quality of service (QoS). This study addresses present and future connectivity issues by highlighting UAV-assisted networks as a possible option for the next generation of wireless communications.

In the first phase of the thesis, presents an optimization framework for power management in unmanned aerial vehicle (UAV)-assisted wireless communication networks using advanced beamforming techniques. As UAVs become integral to enhancing network coverage and capacity, efficient power allocation is essential to extend battery life, maintain reliable connectivity, and support high data rates. This study focuses on optimizing the power control of UAV-mounted base stations to dynamically adapt to varying network conditions and user demands. By incorporating beamforming, the framework enables precise directional signal transmission, which minimizes interference, maximizes signal-to-noise ratio (SNR), and improves network spectral efficiency. A multi-objective optimization algorithm is proposed to allocate power resources adaptively, balancing energy efficiency and user quality of service (QoS). Simulation results demonstrate that the beamforming-based power optimization significantly reduces energy consumption, extends UAV operational time, and enhances network throughput, compared to conventional omnidirectional power allocation methods. This research

highlights the effectiveness of integrating beamforming in UAV-assisted networks as a promising solution for scalable, energy-efficient next-generation wireless communications.

The second phase of the thesis to address the challenges of managing a high volume of users affected by disasters and the difficulties of scaling centralized algorithms for quick restoration of emergency communication services, this work proposes a distributed, intent-based optimization framework utilizing multi-agent reinforcement learning (MARL). This approach seeks to minimize service inconsistencies and accommodate dynamic user needs. In the network feature layer, a distributed K-sums clustering algorithm adapts to user service variations by allowing each UAV base station to autonomously adjust its local network structure based on user demands. These base stations select features from cluster centers as input states for the MARL neural network. In the trajectory regulation layer, a multi-agent soft actor-critic (MASAC) algorithm is introduced, enabling each UAV base station, acting as an intelligent node, to optimize its flight trajectory through a "distributed training – distributed execution" paradigm. Techniques such as integrated learning and curriculum learning are incorporated to improve training stability and accelerate convergence. Simulation results confirm that the distributed K-sums clustering algorithm outperforms traditional K-means in load efficiency and cluster balance. Moreover, the MASAC-based UAV trajectory control algorithm significantly reduces communication interruptions, enhances network spectral efficiency, and outperforms conventional reinforcement learning approaches.

In the third and last phase of the thesis, presents a new method for establishing and optimizing power consumption in wireless communication networks aided by unmanned aerial vehicles (UAVs). Though careful resource and energy management is necessary to optimize efficiency, the integration of UAVs in these networks offers notable gains in coverage, capacity, and overall network performance. The two main contributions of this work are an optimized power distribution model to increase UAV longevity and energy efficiency, and a strategic deployment of UAVs to improve network coverage and user happiness. To optimize performance, the suggested framework dynamically modifies its tactics in response to real-time data, such as network topology, user demand patterns, and environmental factors. According to experimental findings, this strategy can greatly increase network speed and solve issues like resource constraints, user mobility, and interference mitigation. The model presents a viable answer for the future of UAV-assisted wireless networks because of its versatility, which also makes it well-suited to dynamic and changing communication settings.

This thesis may provide a significant impact on future research in terms of power optimization and deployment of UAV assisted future wireless commination network.

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High achievement always takes place in the framework of high expectation. The expectation was there and I begin with determined resolve and put in sustained hard work. It has been rightly said that every successful individual knows that his or her achievement depends on a community of persons working together but the satisfaction that accompanies the successful completion of any task would be incomplete without the mention of the people who made it possible.

This is to acknowledge with gratitude the guidance and ameliorating suggestion from my supervisor, Dr. Shakti Raj Chopra and my co-supervisor, Dr. Akhil Gupta for his support and motivation throughout the thesis work.

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RAHUL SHARMA

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ABBREVIATION

3D	Three-dimensional
4G	4th generation
5G	5th generation
6G	6th generation
AI	Artificial intelligence
AoD	Angles of Departure
AoI	age of information
B5G	Beyond 5th generation
BER	Bit Error Rate
BS	BS
CR	Cognitive radio
CSI	Channel State Information
D2D	Device to device
DDPG	Deep deterministic policy gradient
DPC	Dirty paper precoding
DRL	Deep reinforcement learning
eMBB	Enhanced mobile broadband
FANET	Flying Ad Hoc Networks
FD-MIMO	Full-dimensional MIMO
FSO	Free-space optical communication
FSPL	Free Space Path loss
HAP	High altitude platforms
HetNets	Heterogeneous networks
IoT	Internet of Things
LAP	Low altitude platforms
LoS	Line of sight
MADDPG	Multi-agent deep deterministic policy gradient
MASAC	Multi-agent Soft Actor-Critic
MEC	Mobile edge computing

MIMO	Multiple-input multiple-output
ML	Machine learning
mMTC	Massive machine-type communications
MRT	Maximum Ratio Transmission Precoding Technique
MZF	ZF precoding matrix
NOMA	Non-orthogonal multiple access
OABF	On-Off analogue beamforming
PPO	Proximal policy optimization
PSO	Particle Swarm Optimization
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
RADAR	Radio Detection And Ranging
RAN	Radio Access Network
RF	Radio Frequency
RIS	Reconfigurable intelligent surfaces
RZF	Regularized Zero Forcing
SDN	Software-Defined Networking
SINR	Signal-to-interference-plus-noise ratio
SNR	Signal-to-Noise Ratio
SONAR	Sound Navigation and Ranging
TDD	Time Division Duplex
UAV	Unmanned Aerial Vehicle
UE	User Equipment
URLLC	Ultra-reliable low-latency communication
UWB	Ultra-wideband
VANET	Vehicular Ad-Hoc Network
Wi-Fi	Wireless Fidelity
WPT	Wireless power transfer
ZF	Zero forcing

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CHAPTER 1

INTRODUCTION

1.1 Overview

Fifth-generation radio access networks are built to provide seamless and ubiquitous connection while fulfilling much greater performance standards, which is different from current fourth-generation networks. This includes providing support for 100 billion wireless devices, allowing for a 1000-fold increase in data throughput, and meeting a range of requirements for reliability, low latency, and long battery life. The rapid adoption of the Internet of Things has increased the rise of mobile data traffic, which has created significant issues for wireless networks that use 5G and beyond 5G technology. Recent studies [1] predict that global mobile traffic will reach 1 zettabyte per month by 2028. This will put a tremendous strain on current infrastructure and create financial difficulties for telecom operators because of the increased operational and capital investments that would be required. To address these growing demands, initial efforts have focused on heterogeneous networks, which involve deploying small cells [2]. However, in unpredictable scenarios such as disaster recovery or emergency responses, terrestrial infrastructure deployment becomes economically impractical due to high costs and challenging environmental conditions. To overcome these limitations, the incorporation of UAVs, into intelligent heterogeneous architectures has emerged as auspicious solution. UAVs enable key usage scenarios for future wireless networks, including huge machine-type communications, ultra-reliable low-latency communication, and improved mobile broadband for bandwidth-intensive applications [3]. In a number of applications, including improving public safety networks, resuming network services in areas impacted by disasters, and facilitating communication during emergencies that call for URLLC, UAVs are essential. Additionally, UAV assisted Enhanced Mobile Broadband is seen as a valuable enhancement to 5G cellular networks [4]. In wireless communication, UAVs serve as aerial communication platforms, functioning as flying base stations to improve connectivity in areas with high traffic demand. This capability, referred to as UAV-assisted communications, is extensively utilized in scenarios such as low-altitude surveillance, disaster recovery, and logistics applications [5]–[9].Furthermore, UAVs can form Flying Ad Hoc Networks [12], [13], enabling broadband wireless communication across large geographical areas by establishing links with ground nodes. Field experiments and theoretical studies have validated FANETs as a viable alternative or complement to terrestrial networks. With their high mobility and versatility, UAVs demonstrate significant potential for diverse applications beyond communication assistance, including cargo delivery and post-disaster rescue operations. As a result, UAVs are increasingly recognized as a critical component of 5G and B5G wireless technologies, combining advanced connectivity capabilities with flexibility to meet various demands [10], [11].UAV communications offer distinct advantages, such as adaptability, mobility, and scalability, making them a desirable candidate to supplement or replace terrestrial cellular networks [14].

- **Line-of-Sight Links:** UAVs, flying autonomously, excel at establishing line-of-sight connections with ground users, ensuring reliable long-distance communication. Their ability to dynamically adjust hovering positions further optimizes link quality, making them highly effective for stable transmissions.
- **Dynamic Deployment Capability:** Unlike fixed ground-based infrastructures, UAVs offer dynamic deployment capabilities, adapting swiftly to real-time demands and environmental changes. Acting as aerial base stations, UAVs eliminate the need for traditional infrastructure components like site rentals, towers, and cables, resulting in substantial cost savings. This flexibility and cost efficiency make UAVs ideal for modern communication networks.
- **UAV-Based Swarm Networks**: Scalable multi-UAV networks can be created by a swarm of UAVs, giving ground users omnipresent connectivity. Multi-UAV networks provide a workable way to swiftly restore and increase communication coverage because to their great flexibility and speedy deployment rates. However, UAVs are subject to stringent constraints related to size, weight, and power, which directly influence their operational altitude, communication range, coverage area, computational capacity, and endurance. For example, low-altitude platforms are limited by lower power, payload capacity, and autonomy, whereas

high-altitude platforms provide extended coverage and longer endurance. As UAV altitude increases, the likelihood of establishing a line-of-sight link for air-to-ground communication improves, due to fewer obstructions. However, this comes at the cost of more severe path loss resulting from the increased distance between UAVs and ground users. Consequently, optimizing UAV altitude involves balancing these opposing factors to maximize cell coverage effectively. Next-generation 5G and beyond 5G wireless networks are expected to feature significant heterogeneity in communication infrastructure and resource allocation to support diverse devices and services. Researchers are exploring designs for heterogeneous infrastructures, such as densely deployed small cells, and integrating communication networks across space, air, and ground domains [17]. Additionally, advanced 5G communication technologies, such as massive multiple-input multiple-output, millimeter-wave, non-orthogonal multiple access, device-to-device communication, and cognitive radio, are being employed to enhance spectrum and energy efficiency [18]. In UAV-assisted cellular networks, operational costs, especially endurance, are critical considerations. To address this, energy harvesting emerges as a vital enabling technology. Furthermore, UAVs can function as edge network controllers to optimize resource allocation for computing and storage. Specifically, UAVs can act as edge computing platforms to offload IoT devices' computational tasks or serve as caching nodes for popular content, alleviating backhaul network congestion [19].

1.2 Unmanned Aerial Vehicles: An Overview

Unmanned Aerial Vehicles (UAVs), commonly known as drones, are aircraft that operate without an onboard pilot. They are increasingly used across various domains such as military operations, disaster management, surveillance, entertainment, and telecommunications due to their versatility, mobility, and cost-effectiveness. In wireless communication, UAVs can serve as aerial communication platforms—for example, as flying base stations (BSs) or mobile relays—by carrying communication transceivers. This setup enhances or restores connectivity in areas of high demand or infrastructure failure. UAV deployment is also economically beneficial in regions where constructing ground cellular networks is expensive.

1.2.1 UAV Classification

UAVs are broadly classified into fixed-wing and rotary-wing types, each with unique advantages and limitations.

- Fixed-wing UAVs fly faster and can carry heavier payloads but cannot hover, making them unsuitable for close inspections.
- Rotary-wing UAVs (like quadcopters) can hover, move in any direction, and provide stable coverage, though they have limited endurance and payload capacity.

  Recently, hybrid UAVs have emerged, combining the endurance of fixed-wing models with the vertical takeoff ability of rotary types.

In addition to UAVs, High-Altitude Platforms (HAPs) such as balloons operate in the stratosphere, offering wider coverage and longer endurance than Low-Altitude Platforms (LAPs). HAPs are preferred for large-area, long-term communication coverage.

1.2.2 UAV Characteristics and Features

1.2.2.1 Payload

The payload represents the maximum weight a UAV can carry, ranging from a few grams to several kilograms. Common payloads include cameras, sensors, or communication modules such as base stations (BSs) or remote radio heads (RRHs). However, higher payloads reduce flight time and increase energy consumption.

1.2.2.2 Flying Mechanism

UAVs achieve flight through different mechanisms:

- Multi-rotor UAVs: Provide vertical takeoff, hovering, and precise control but consume high power.
- Fixed-wing UAVs: Offer higher speeds and endurance but need runways and cannot hover.
- Hybrid UAVs: Combine both features for better flexibility and efficiency.

1.2.2.3 Range and Altitude

The range indicates how far a UAV can be controlled, while altitude represents the maximum height it can reach.

- Low-Altitude Platforms (LAPs) are quick to deploy and ideal for local coverage.
- High-Altitude Platforms (HAPs) offer extended coverage and endurance but involve complex deployment and potential interference issues.

1.2.2.4 Speed and Flight Time

Small drones usually fly below 15 m/s, while larger ones can exceed 100 m/s. Flight time depends on power and payload, typically ranging from 20–30 minutes for small drones to several hours for larger models. New hybrid-electric drones can fly for over 4 hours, improving operational reliability.

1.2.2.5 Power Source

Most UAVs are powered by rechargeable batteries, while larger ones may use fuel-based or solar systems for longer endurance. The onboard energy must power both flight mechanisms and communication modules such as antennas and amplifiers.

1.2.2.6 Security

Security is vital in UAV-assisted communication systems due to their remote and wireless operation. UAVs are vulnerable to hacking, jamming, or hijacking, which could disrupt communication or cause crashes. Therefore, ensuring cyber-physical security is critical for safe UAV-based cellular operations.

1.3 UAV in Wireless Communication Networks

With their strong line-of-sight communication capabilities, high mobility, and quick and affordable deployment, UAVs are becoming an essential part of 5G and beyond networks. Because of these characteristics, UAVs can improve the effectiveness and capacity of current communication systems. This section explores UAV wireless networks' distinct channel properties, how they integrate with 5G infrastructures, and a number of real-world uses. By examining these aspects, it highlights how UAVs can address the challenges of modern communication demands, providing flexible, scalable, and efficient solutions for diverse scenarios such as emergency response, remote connectivity, and capacity expansion in dense urban environments.

1.3.1 Channel Characteristics Because strong line-of-sight links have a significant impact on UAV wireless networks, one of the main differences between aerial and ground-based UAV stations is their distinct channel characteristics. These links enable robust communication but also make network performance highly susceptible to channel variations caused by UAV mobility. Understanding these dynamic channel characteristics is essential for optimizing UAV deployments to meet the Quality of Service requirements across diverse applications. UAV wireless networks typically involve two primary types of communication channels: UAV-to-ground node and UAV-to-UAV channels. Both play critical roles in determining network efficiency, reliability, and scalability in scenarios ranging from disaster recovery to enhanced 5G network capacity.

1.3.2. UAV-to-Ground Channel A UAV-to-ground channel typically includes a robust line-of-sight link; however, this may be obstructed by shadowing from obstacles like buildings and trees. Additionally, UAV mobility can cause dynamic shadowing during flight. Therefore, accurately modeling an UAV-to-ground channel is critical for evaluating the performance of UAV wireless networks. Reference [20] introduces the LoS probability as:

$$P_{LoS}(\theta) = \frac{1}{1+a exp(-b[\theta-a])} \qquad 1.1$$

Channel modeling for UAV communication incorporates a dominant LoS component influenced by environmental parameters a and$b$, representing scenarios like suburban, urban, dense urban, and high-rise urban areas. The Line of Sight probability depends on the elevation angle θ between the UAV and the ground node, directly impacting signal reliability and performance.The evaluation angle θ is defined as $\theta = \arctan\left(\frac{h}{r}\right)$, where r is the horizontal distance between UAV and ground node and h is the UAV altitude. Note that $P_{LoS}(\theta)$ increases as the elevation angle becomes large. The non-Line of Sight probability is $P_{NLoS}(\theta) = 1 - P_{LoS}(\theta)$. The pathloss PL_{LoS} for LoS link and P_{NLoS} for non-LoS link and $PL_{NLoS}$for non-LoS link can be expressed in the dB scale as [14]

$$L_{LoS} = 20\log(d) + 20\log(f) + 20\log\frac{4\pi}{c} + \eta LoS \qquad 1.2$$

$$PL_{NLoS} = 20\log(d) + 20\log(f) + 20\log\frac{4\pi}{c} + \eta NLoS \qquad 1.3$$

Respectively, Where FSPL$\left(20\log(d) + 20\log(f) + 20\log\frac{4\pi}{c}\right)$ represents the free space pathloss, d is the distance between ground node and UAV.C is the speed of light,f is the system frequency,$\eta NLoS$ are the excessive pathloss and non-LoS links, repectively. The resulting average pathloss

$$PL = P_{LoS}(\theta) \times PL_{LoS} + P_{NLoS}(\theta) \times PL_{NLoS} \qquad 1.4$$

and the UAV-to-ground channel gain G can be defined as

$$G = \frac{G_0}{PL}$$

Based on the probabilistic channel model, the UAV-to-ground channel has been developed to better depict its link characteristics. Reference [21] discusses how building shadows affect non-LoS linkages and LoS likelihood. A two-ray ground reflection model in Reference [22] provides a framework for UAV-ground station data transfer while optimizing radio resource allocation. In [23], a link budget study determines the best frequency band, propagation loss, antenna gain, and other variables for UAV-ground communication. [24] models height-dependent small-scale fading and path loss exponent. The Rician model in this model accounts for LoS and multipath scattering. In addition, [25] proposes a statistical propagation model to anticipate air-to-ground route loss between UAVs and terrestrial terminals, and [26] introduces a UWB-specific propagation channel model. The air-to-ground channel model is affected by ambient circumstances and system characteristics, therefore detailed measurements and evaluations are needed to meet the numerous UAV deployment situations.

1.3.3. UAV-to-UAV Channel UAV-to-UAV channels are most affected by line-of-sight, which reduces multipath fading. By neglecting small-scale fading, a path loss-based large-scale fading model with LoS probability is sufficient for successful modeling. This makes 5G's mmWave protocol ideal for UAV-to-UAV wireless communication, delivering increased capacity and smooth 5G integration [27]. Despite these benefits, UAV-to-UAV channel models and communication protocols must be refined and optimized for specific channel conditions to ensure reliable and efficient performance in diverse UAV network scenarios and advance their potential in modern communication systems.

1.4 UAV Implementation Challenges

UAVs are becoming an important part of next-generation wireless networks (5G and beyond), which is leading to considerable growth and research in the industry. UAVs provide many benefits for wireless communication, but there are a number of obstacles that need to be overcome in order to guarantee their effective use and implementation as shown in figure 1.1.

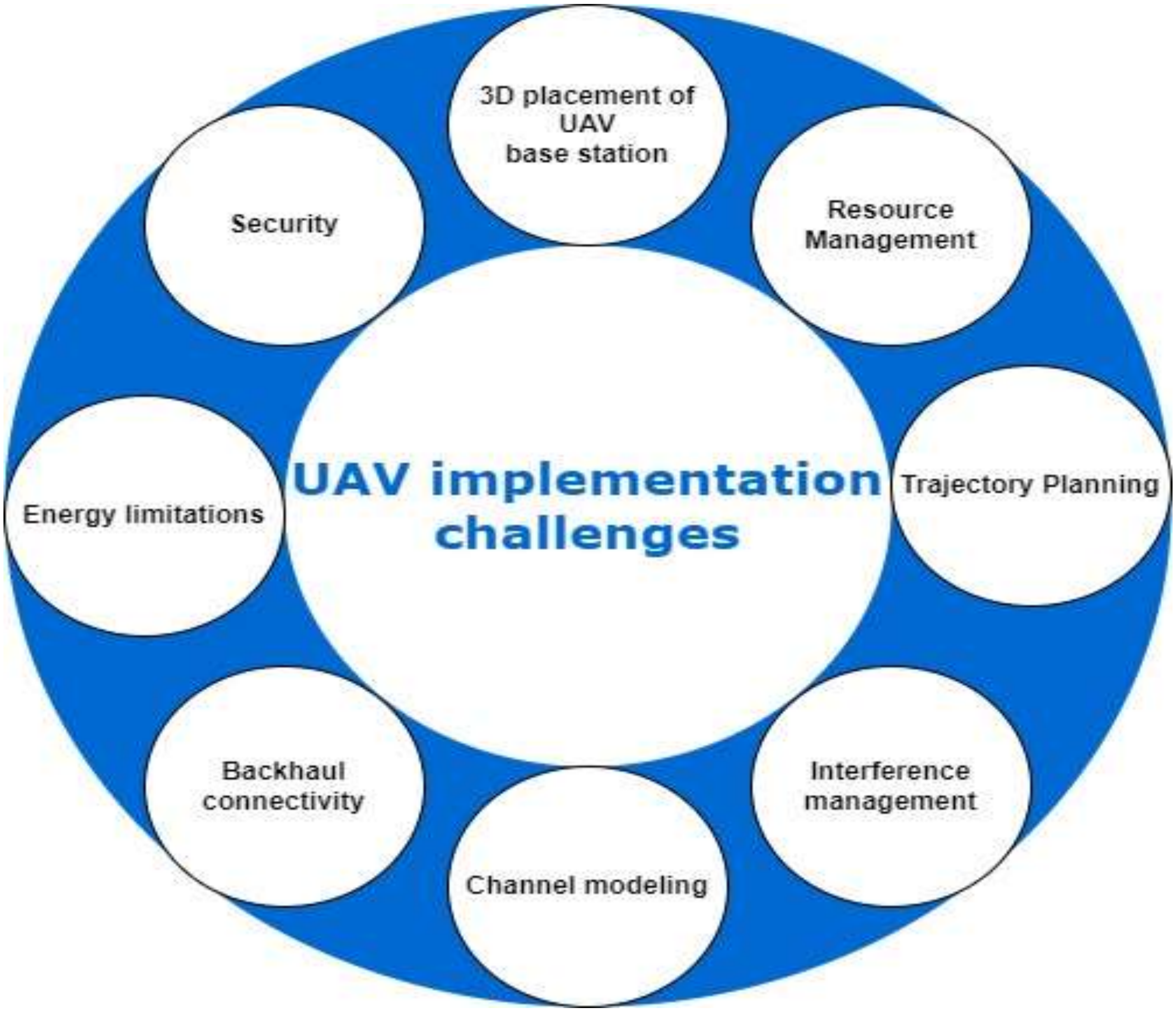

Figure 1.1 UAV implementation Challenges

1.4.1 3D Placement of UAV Base Stations

A major challenge in UAV-assisted communication lies in the three-dimensional placement of UAV base stations. Unlike terrestrial communication, where BS placement occurs on a two-dimensional plane, UAV placement must incorporate altitude as a critical factor. Optimal placement depends on multiple parameters, including user locations, air-to-ground channel characteristics, geographical constraints, and UAV limitations such as energy, battery capacity, and flight time. In scenarios involving multiple UAVs, the challenge intensifies as placement must also mitigate interference among UAVs to maintain optimal network performance. Addressing these factors is crucial for achieving efficient and reliable UAV-based communication systems that meet diverse operational requirements [28][29].

1.4.2 Resource Management

Resource management in UAV-assisted wireless communication is a critical and complex task. Resources must be efficiently shared between UAVs and existing terrestrial networks, considering UAV-specific constraints such as limited energy, path planning requirements, and mobility. Additional challenges include interference in air-to-ground and air-to-air links, as well as maneuverability. Developing optimized resource-sharing schemes is essential for enhancing network efficiency and achieving seamless communication.

1.4.3 Trajectory Planning

Planning optimal UAV trajectories is another significant challenge, as it involves numerous considerations such as energy constraints, flight duration, collision avoidance, and user demands. Trajectory planning is inherently complex due to the need to optimize a large number of variables, such as UAV positions, in real time. This complexity necessitates advanced algorithms to determine efficient and safe flight paths [30][31]

1.4.4 Interference Management

In multi-UAV deployments, managing interference is crucial to ensuring network efficiency. UAVs must be strategically positioned to maximize coverage footprints while minimizing interference between them. Effective interference mitigation strategies are necessary to enhance throughput and maintain reliable communication.

1.4.5 Channel Modeling

Channel modeling is fundamental in communication systems, as the characteristics of the communication channel between the transmitter and receiver significantly impact quality. In UAV-assisted communication, air-to-ground channels differ greatly from terrestrial systems due to UAV mobility. Factors such as UAV location, altitude, elevation angle, and channel characteristics dynamically influence communication quality, adding complexity to channel modeling and system design.

1.4.6 Backhaul Connectivity

Providing wireless backhaul connectivity is a key challenge in UAV-assisted communication, as the flying nature of UAVs precludes wired connections. Potential solutions for wireless backhauling include satellite links, Wi-Fi, mmWave, and free-space optical communication. Satellite links offer higher capacity, while Wi-Fi remains a cost-effective option with low latency. mmWave and FSO technologies leverage UAVs' line-of-sight capabilities to enable high-speed and wide-coverage backhauling [32][33][34]

1.4.7 Energy Limitations

Energy limitations pose significant constraints on UAV performance, as battery-powered UAVs have finite operational times. These limitations affect flight duration, communication range, and data processing capabilities. Energy consumption is influenced by payload weight, altitude, and communication protocols. Addressing these challenges requires energy-efficient strategies, such as energy harvesting, trajectory optimization, and advanced power management. Innovations in battery technology, such as wireless charging, are also being explored to extend UAV operational time [35].

1.4.8 Security

Security is a critical concern in UAV-assisted communication. As UAVs rely on broadcast communication without human intervention, they are susceptible to various cyber threats, such as eavesdropping and man-in-the-middle attacks. The multi-layered topology of integrated UAV networks further complicates security, as dissimilar nodes are vulnerable to malicious activities. Protecting software-defined network (SDN) controllers in such systems is particularly important. Recent research has proposed artificial intelligence-based solutions and physical layer security techniques to address these vulnerabilities [36][37].

1.5 Motivation

Future wireless networks are evolving in response to the growing need for dependable, high-quality, and pervasive wireless communication. Communication networks are anticipated to provide enormous data speeds, ultra-low latency, and vast connection in the 5G and beyond period. Because they may function as mobile base stations or relays, UAVs provide a viable way to improve these networks' capacity, flexibility, and coverage. However, because wireless surroundings are dynamic and complicated, improving the deployment and power consumption of UAV-assisted networks poses considerable issues.

Conventional methods of UAV deployment and power optimization are frequently ineffective because they rely on preset guidelines or models that are unable to effectively adjust to changes in network circumstances in real time. These restrictions make UAV-assisted networks less scalable and perform worse, particularly as user density and network needs change. This highlights the need for creative solutions that may reduce energy use and enhance service quality while intelligently adapting to changing circumstances.

For tackling these issues, artificial intelligence, and in particular machine learning algorithms, provide a potent tool. Because AI-based methods can dynamically optimize UAV placement, flight routes, and power management tactics, they may improve the decision-making process. AI has the potential to greatly enhance the performance, scalability, and energy efficiency of UAV-assisted wireless networks through ongoing learning and real-time modifications.

The goal of this thesis is to provide an AI-based framework for future wireless communication networks that will optimize UAV deployment and power. The suggested architecture will allow UAVs to automatically adjust to shifting network needs, improve network performance, and use less power by utilizing AI approaches. The results of this study will address important issues in current and future networks and make a significant contribution to the creation of intelligent, scalable, and energy-efficient UAV-enabled wireless communication systems.

1.6 Research Gap

UAVs have drawn more attention as a potential way to improve capacity, network coverage, and flexibility in the rapidly changing wireless communication market. Nevertheless, a number of crucial sectors are still lacking in development, even with the increased interest in UAV-assisted networks. Particularly from the standpoint of 5G and beyond, these research gaps provide chances for innovation and advancement in the deployment and optimization of UAVs. The following research gaps point to important topics that need more investigation:

i. Lack of UAV architectures focused on power optimization

There is currently no architecture created especially for UAVs that prioritizes power consumption optimization. Given that power efficiency is a major obstacle in UAV operation, this creates a crucial gap.

ii. Inadequate Integration of UAVs and antennas

Despite the fact that UAVs are considering many antennas, not much study has been done on how to best integrate and perform these antennas in practical situations.

iii. Limited Investigation into the Use of UAVs in 5G networks

There is still a lack of study on the best way to deploy UAVs in 5G network design. Optimizing network performance and efficiency requires effective UAV deployment and mobility methods.

iv. Unrealized Beamforming Potential in UAVs

There is a lot of space for improvement in this area since beamforming, a technology that may greatly increase power efficiency and signal quality, has not been thoroughly investigated in the context of UAVs.

v. Untested AI-Powered 5G UAV network optimization

Even though AI has a lot of promise to improve UAV deployment and network management in 5G systems, this field is still in its infancy and needs further study.

vi. Risks of eavesdropping and data security

There are also significant potential for improving the security of data transfers between users and UAVs, especially to guard against eavesdropping. This problem in UAV-assisted networks cannot currently be adequately addressed by current security methods.

Future efforts to overcome the operational, technological and security difficulties of integrating UAVs into contemporary wireless communication networks will be built upon these research gaps.

1.7 Objectives of Proposed Research

Based on the literature review of the research articles, following objectives have been formulated:

I. Proposing an unmanned aerial vehicle (UAV) assisted future wireless communication network.

II. Optimization of the power in the unmanned aerial vehicle (UAV) assisted future wireless communication network using the beamforming technique.

III. Artificial intelligence-based approach for deployment of unmanned aerial vehicle (UAV) assisted future wireless communication network.

The primary objective of this research is to enhance power optimization in UAV-assisted future wireless communication networks. Initially, a novel UAV-assisted network architecture will be proposed and compared with existing wireless communication systems. Following this, the proposed architecture will undergo optimization with a focus on minimizing power consumption. This will involve key factors such as efficient UAV deployment, advanced beamforming techniques for UAVs in next-generation communication environments. Lastly, artificial intelligence will be utilized to further optimize the network, supporting the efficient deployment and management of UAVs in future wireless communication systems.

1.8 Organization of Thesis

The rest of the report is prepared as follows:

Chapter 2 presents a comprehensive literature review, analyzing existing studies on key advancements and challenges in the field of wireless communication and UAV-assisted networks. The chapter identifies critical research gaps and trends, focusing on areas such as power optimization, machine learning applications, and hybrid beamforming techniques. By evaluating methodologies, algorithms, and technological developments, the review provides a foundation for understanding current limitations and potential innovations. The insights gained from this study guide the development of novel approaches discussed in subsequent chapters, ensuring alignment with the latest research and industry needs for future wireless communication systems.study of literature was performed.

Chapter 3 focuses on using hybrid beamforming techniques to optimize the power of future wireless communication systems helped by UAVs. The chapter examines how UAVs' dynamic and adaptable coverage can improve wireless communication. One important method for lowering power consumption without sacrificing communication quality is hybrid beamforming, which blends analog and digital beamforming. The chapter introduces a number of optimization models and methods designed to reduce power consumption while maintaining effective coverage and data transfer. One approach for future sustainable wireless communication systems is the use of hybrid beamforming in UAV-assisted networks.

In C**hapter 4 t**he use of Multi-Agent Reinforcement Learning (MARL) approaches for Unmanned Aerial Vehicle (UAV) deployment is examined. The chapter highlights the benefits of MARL in allowing UAVs to function independently and cooperatively in challenging circumstances. It describes how learning-based techniques might help UAVs optimize their positions and jobs, including coverage, resource allocation, and energy efficiency. Because MARL is decentralized, UAVs can minimize communication costs and adjust to changing network circumstances. The chapter illustrates how MARL might improve UAV deployment for improved performance in wireless communication networks and associated applications by modeling real-world scenarios.

In chapter 5 introduces a hybrid strategy that combines Random Forest (RF) and Support Vector Machine (SVM) methodologies. The chapter demonstrates how SVM's classification accuracy and RF's strong feature selection combine to provide a complementary paradigm for problems including resource allocation, signal prediction, and interference mitigation. The hybrid approach enhances system accuracy, scalability, and adaptability to changing settings by combining various techniques. Simulations and case studies show how effective the approach is at maximizing wireless network performance. This combination of machine learning methods is positioned as a viable remedy for the problems associated with wireless communication in the next generation.

Chapter 6 presents the conclusion of the study, summarizing key findings and insights. It also outlines potential directions for future research, highlighting areas where further exploration and improvements can enhance the system's performance and applicability in real-world scenarios.

CHAPTER 2
LITERATURE SURVEY

As 5G and future wireless communication progresses, UAVs can improve network coverage, capacity, and connectivity. Their mobility makes them excellent for communication in regions with little ground infrastructure. UAV integration into these networks is difficult, especially in deployment optimization and power management. By optimizing UAV deployment and power usage in dynamic environments in real time, AI, especially machine learning, can solve these problems. This literature assessment will identify gaps and possibilities for an AI-based framework for UAV-assisted wireless communication networks by reviewing UAV deployment tactics, power optimization, and AI applications in wireless networks.

2.1 UAV-Assisted Wireless Network

Wu, Zeng, and Zhang [37] optimize multi-UAV wireless networks using UAV trajectory design and communication scheduling. Maximum communication throughput and stable ground user connections are the study's principal goals. The sequential optimization approach breaks the problem into UAV trajectory optimization and communication scheduling. The framework optimizes UAV flight paths to boost network coverage and efficiency. The study shows how UAV mobility improves wireless network performance and how joint trajectory and communication design can be used in UAV-enabled networks.

Zhang et al. [38] review 5G mmWave communications in UAV-assisted wireless networks. This article discusses mmWave's high data speeds and capacity, as well as its route loss and signal blockage issues. The authors explore how adaptive beamforming and robust handover techniques can address these issues. The survey also suggests using mmWave communications in UAV networks for disaster recovery and high-capacity mobile hotspots. The findings show that 5G mmWave technology improves UAV-assisted network capabilities and scalability.

Hosseinalipour, Rahmati, and Dai [39] optimize position planning to reduce interference in UAV-assisted wireless communication networks. Optimizing UAV locations and communication resource distribution reduces UAV-ground user disturbance, according to the study. This optimization framework works well in congested metropolitan situations with high interference. The authors show that strategically deploying UAVs improves network capacity and quality of service, making this technique essential for effective UAV-assisted networks.

Zhao et al. [40] examine disaster-related UAV-assisted networks in 2019. UAVs are crucial to communication networks when terrestrial infrastructure is disrupted. They recommend UAV deployment tactics for different crisis scenarios to maximize coverage and energy efficiency. This article presents a temporary communication network design using UAV swarms to connect rescue efforts and affected communities. The findings show that UAV-assisted networks can strengthen emergency communication systems, aiding disaster recovery.

Liu et al. [41] present a machine learning-based trajectory design and power control optimization method for multi-UAV aided wireless networks. UAV energy efficiency and ground user communication are the study's goals. Machine learning is used to create an adaptive algorithm that adjusts UAV trajectories and transmission power based on real-time network conditions. Machine learning can improve energy usage and coverage in UAV-assisted wireless networks, as shown by the results.

Wireless-powered UAV-assisted communication systems in Nakagami-m fading channels are examined by Perera et al. [42]. The study proposes a wireless power transfer (WPT) technology to power UAVs during missions to improve communication in fading settings. The authors study how fading channels affect system performance and propose optimization methods to increase communication system dependability and efficiency. They found that WPT in UAV-assisted networks improves communication reliability, especially in harsh conditions with extreme fading.

UAV placement and trajectory optimization in UAV-assisted wireless networks is studied by Lakew, Masood, and Cho [43]. A new optimization methodology considers UAV location and trajectory design to enhance network coverage and reduce interference. The study stresses the necessity of 3D considerations in UAV deployment for more flexible and efficient network setups. We found that the suggested optimization strategies can increase UAV-assisted network coverage, capacity, and energy efficiency, making them a promising alternative for future deployments.

Ji et al. [44] optimize multi-UAV assisted wireless networks' cache placement, flight trajectory, and transmission power. This article presents an integrated approach to maximize network performance that incorporates these aspects' interdependencies. The authors show how to improve the network's data delivery efficiency by strategically putting data caches aboard UAVs and optimizing their flight trajectories and transmission power. When UAVs must modify their operations in real time to meet changing consumer demand, the proposed optimization approach works well. The findings show that combined optimization methodologies can improve UAV-assisted wireless network efficiency and scalability.

Zhang et al. [45] discuss IoT UAV-MEC integration problems. The study optimises computation offloading and communication scheduling to improve UAV-assisted MEC networks. A framework that dynamically distributes computational resources and optimizes UAV-ground user communication is proposed. Their method reduces latency and energy usage, making it ideal for real-time IoT applications. The study shows that UAV-assisted MEC networks can improve efficiency and reliability by improving computation and communication, which is crucial for IoT application deployment.

Shahzadi et al. [46] present a complete UAV survey for 5G and beyond wireless networks. This work includes deployment tactics, communication technologies, and applications of UAV-assisted networks. UAV integration into 5G networks can improve coverage, capacity, and reliability, but it also presents problems and opportunities. They also note that UAVs can support IoT, smart cities, and emergency response. The survey stresses the need for improved technology and optimization to maximize UAV-assisted 5G networks.

Masroor, Naeem, and Ejaz [47] optimize UAV-assisted wireless network resource management. Optimization methods for UAV network bandwidth, power, and computing capacity are examined. Multiple optimization approaches are proposed to solve resource allocation in dynamic and diverse network contexts. They found that UAV-assisted networks operate best with good resource management, especially in low-resource, high-demand settings. The study sheds light on UAV-assisted wireless network resource management optimization methodologies.

Jiang et al. [48] study UAV-assisted air-ground network clandestine communication. The study examines UAV-ground user communication methods that are secure and untraceable. The authors present a framework that uses modern cryptography and signal processing to secure and anonymize UAV communication. The results suggest that the proposed solutions can prevent eavesdropping and unauthorized access, making them crucial for military and intelligence activities. UAV-assisted networks need secure communication protocols, especially in sensitive and mission-critical situations, according to the study.

Deep reinforcement learning resource allocation in cooperative UAV-assisted wireless networks is studied by Luong et al. [49]. A DRL-based system that learns from the network environment optimizes resource allocation in real time is proposed. The study shows that DRL can adapt to dynamic network conditions, enhancing resource allocation efficiency and performance. The proposed system surpasses standard resource allocation approaches in network capacity, energy efficiency, and latency. The study shows that DRL can manage complex and dynamic UAV-assisted networks, laying the groundwork for future research.

Matracia, Kishk, and Alouini [50] study post-disaster UAV-assisted wireless communication network topology. In areas with damaged or destroyed infrastructure, the study examines communication network establishment and maintenance. The authors present a topological framework to optimize UAV deployment and movement for reliable and efficient communication. They show that the suggested structure may greatly enhance network resilience and recovery time after a disaster. The study illuminates UAV-assisted network design and deployment in tough and uncertain conditions.

Xiong et al. [51] optimize UAV-assisted network wireless energy and data transfer. The study provides a DRL-based architecture that dynamically adjusts UAV energy and data transfer techniques to real-time network conditions. Results show that DRL can greatly increase energy and data transfer efficiency, reducing latency and energy usage. DRL can improve UAV-assisted networks, especially in energy and data transmission applications, according to the study.

Elnabty, Fahmy, and Kafafy [52] examine UAV placement optimization in 5G and beyond UAV-assisted communication networks. This article examines UAV placement optimization methods to increase network coverage and minimize disturbance. The authors explore real-time flexibility and improved communication technology integration for UAV placement in 5G networks. Optimizing UAV placement improves 5G and beyond network speed and scalability, according to the report.

Atif et al. [53] investigate UAV wireless localization for search and rescue. The study suggests using UAVs to locate people in disaster-stricken areas more accurately and efficiently. The authors explore localization issues in dynamic and unpredictable contexts and provide optimization methods to increase localization performance. The results suggest that the proposed framework can improve search and rescue operations, aiding catastrophe response.

Basharat et al. [54] systematically survey UAV-assisted wireless network resource optimization. The study examines UAV network bandwidth, power, and computational capacity optimization methods. Resource optimization in dynamic and diverse networks presents difficulties and opportunities. Effective resource management is crucial to the performance and efficiency of UAV-assisted networks, and the survey provides useful insights into resource management optimization methodologies.

Fu et al. [55] investigate how AI may improve UAV-assisted wireless network energy efficiency. The study provides an AI-based system that dynamically adjusts UAV trajectories and communication mechanisms to maximize energy consumption. The authors show that AI may considerably cut energy consumption while maintaining reliable communication links. The study shows that AI can manage UAV-assisted network energy efficiency, laying the groundwork for future research.

Pogaku et al. [56] explore reconfigurable intelligent surfaces (RIS) in UAV-assisted wireless communications. This article examines RIS-UAV network optimization methods to improve communication. The authors explore real-time flexibility and improved communication technology integration as RIS problems and potential in UAV networks. The survey shows how RIS might improve UAV-assisted network performance and scalability, revealing wireless communication technology's future.

Lakew et al. [57] investigate aerial energy orchestration in heterogeneous UAV-assisted wireless communications. The article presents a paradigm for UAV energy management in dynamic and heterogeneous networks. UAV network energy management problems include real-time adaptation and renewable energy integration. The article shows how aerial energy orchestration can improve energy efficiency and sustainability in UAV-assisted networks, guiding energy management strategy creation.

UAV-assisted wireless communication system by Jeganathan et al. [58] uses age of information (AoI) as a performance parameter. The study examines UAV information collecting and dissemination in dynamic networks. The authors present energy-efficient optimization methods that prioritize information freshness. Results show that the suggested system may increase UAV-assisted networks' information freshness and energy efficiency, making it useful for real-time information dissemination applications.

Liu et al. [59] discuss multi-UAV aided wireless network access control and deployment design. The study presents a methodology to improve UAV deployment and access control resource allocation for network performance. The authors explore access control difficulties in dynamic and heterogeneous network contexts and provide optimization methods to increase system efficiency. Results reveal that the proposed architecture can greatly improve multi-UAV network performance, providing insights into access control strategy creation.

To achieve long-term communication coverage, Liu et al. [60] investigate distributed deployment in UAV-assisted networks. The study suggests a paradigm for managing UAV deployment in dynamic and heterogeneous networks to maximize coverage duration.

The current accomplishments and future prospects in UAV-assisted wireless communications are reviewed by Gu and Zhang [61]. The article discusses UAV-assisted network deployment, communication, and applications. Real-time flexibility and sophisticated communication technologies are UAV-assisted network challenges and potential. The survey emphasizes the need for sophisticated technology and optimization to maximize UAV-assisted wireless network potential.

Table 2.1 UAV Assisted Wireless Network

Author/Year	**Focus**	**Features and Key performance parameter**	**Advantages**	**Limitations**
Wu, Qingqing, Yong Zeng, and Rui Zhang (2018)	Joint trajectory and communication design for multi-UAV enabled wireless networks	Proposes a joint optimization framework for UAV trajectories and communication scheduling to maximize throughput. Altitude: 200–500 m; Throughput gain: +25%; Energy efficiency (EE): +30%	Enhanced network performance by optimizing UAV paths and communication resources,	High computational complexity due to joint optimization problem
Zhang, Long, et al. (2019)	5G mmWave communications for UAV-assisted wireless networks	Survey on 5G millimeter-wave (mmWave) communications for UAV-assisted networks, covering channel characteristics, UAV deployments, and protocols. Frequency: 28–60 GHz; Data rate: up to 10 Gbps; Coverage: 1–2 km	Comprehensive overview of 5G mmWave, highlighting potential for high-speed, low-latency communication	Limited focus on real-world implementation challenges and interference issues
Hosseinalipour, Seyyedali, et al. (2019)	Interference avoidance in UAV-assisted communication	Introduces interference-aware position planning for UAVs to avoid signal interference in wireless networks. SIR improvement: +20 dB; Coverage: +15%	Helps mitigate signal interference, improving communication quality	Lack of real-time adaptive techniques for dynamic environments
Zhao, Nan, et al. (2019)	UAV-assisted emergency networks in disasters	Proposes UAV-assisted wireless networks for emergency communication during	Provides an efficient and resilient solution for maintaining communications in emergency	Limited energy resources of UAVs restrict long-term

Author/Year	Focus	Features and Key performance parameter	Advantages	Limitations
		disasters. Deployment time: <15 min; Coverage radius: 2–3 km; Delay: <20 ms	scenarios	operations
Liu, Xiao, et al. (2019)	Trajectory design and power control for multi-UAV networks using machine learning	Uses machine learning to optimize UAV trajectories and power control in wireless networks. Deployment time: <15 min; Coverage radius: 2–3 km; Delay: <20 ms	Machine learning approach enables dynamic adaptability and improved efficiency	Requires significant data and processing power for machine learning models
Perera, Tharindu D. Ponnimbaduge, et al. (2020)	Wireless-powered UAV communication in Nakagami-m fading channels	Proposes a wireless-powered UAV communication system operating in Nakagami-m fading environments. Path loss exponent: 2–3; Energy harvesting gain: +22%	Efficient energy management through wireless power transfer	Performance degrades in highly dynamic or complex fading environments
Lakew, Demeke Shumeye, et al. (2020)	3D UAV placement and trajectory optimization in UAV-assisted networks	Proposes a method for optimizing 3D placement and trajectory of UAVs to improve network performance. Throughput: +40%; Altitude: 100–400 m; SNR: +18 dB	Enhanced communication efficiency through optimized placement and trajectories	Computational overhead increases with the number of UAVs and network size
Ji, Jiequ, et al. (2020)	Joint cache placement, flight trajectory, and transmission power optimization	Proposes a joint optimization of cache placement, UAV flight trajectory, and transmission power.	Improves data delivery and reduces latency in UAV-assisted networks	High computational complexity in solving the joint optimization problem
Zhang, Tiankui,	Joint	Proposes a framework	Enhances	Limited by

Author/Year	Focus	Features and Key performance parameter	Advantages	Limitations
et al. (2019)	computation and communication for UAV-assisted mobile edge computing in IoT	combining computation offloading and communication optimization for UAV-assisted IoT systems. Cache hit ratio: +50%; Delay: -30%; Energy: -15%	computational efficiency and reduces latency for IoT applications	UAV energy and computing capabilities
Shahzadi, Rizwana, et al. (2021)	UAV-assisted 5G and beyond wireless networks: A survey	A comprehensive survey on the integration of UAVs in 5G and beyond wireless networks. Data rate: up to 20 Gbps; Latency: <1 ms; Coverage: 5 km²	Broad coverage of UAV use cases and future trends for UAV-assisted networks	Lacks practical insights into implementation challenges in real-world environments
Masroor, Rooha, et al. (2021)	Resource management in UAV-assisted wireless networks	Explores optimization techniques for resource management in UAV-assisted networks. Spectrum utilization: +28%; Energy saving: +18%	Enhances resource efficiency, balancing energy consumption and throughput	High complexity and real-time management challenges
Jiang, Xu, et al. (2021)	Covert communication in UAV-assisted air-ground networks	Investigates covert communication techniques to ensure security in UAV-assisted air-ground networks. Secrecy rate: 2.5–5 bps/Hz; Detection probability: <10%	Enhances communication security and privacy through covert techniques	Limited by UAV energy capacity and environmental interference
Luong, Phuong, et al. (2021)	Deep reinforcement learning for resource allocation in UAV-assisted	Proposes a deep reinforcement learning approach to optimize resource allocation in cooperative UAV-	Dynamic adaptability with improved resource allocation	Requires significant training time and data for the learning

Author/Year	Focus	Features and Key performance parameter	Advantages	Limitations
	networks	assisted networks. Throughput: +45%; Latency: <5 ms; EE: +25%	efficiency	model
Matracia, Maurilio, et al. (2021)	Topological aspects of UAV-assisted post-disaster wireless communication	Investigates the topological design of post-disaster UAV-assisted networks to ensure communication resilience	Provides efficient network topology for post-disaster scenarios	Limited focus on energy and mobility management of UAVs in extended disaster recovery operations
Xiong, Zehui, et al. (2020)	UAV-assisted wireless energy and data transfer using deep reinforcement learning	Combines wireless energy transfer and data transfer in UAV-assisted networks using deep reinforcement learning	Improved energy efficiency and dynamic resource management	High computational complexity and data requirements for reinforcement learning
Elnabty, Israa A., et al. (2022)	UAV placement optimization in 5G and beyond networks	Survey on UAV placement optimization in 5G and future networks, focusing on efficient resource allocation	Comprehensive coverage of UAV placement strategies to improve communication quality	Lack of focus on real-time placement strategies in highly dynamic environments
Atif, Muhammad, et al. (2021)	UAV-assisted wireless localization for search and rescue	Proposes UAV-assisted wireless localization techniques for search and rescue operations	Enhances localization accuracy in critical scenarios like disaster management	Limited by UAV battery life and environmental factors like weather conditions
Basharat, Mehak, et al. (2022)	Resource optimization in UAV-assisted wireless networks	Provides a comprehensive survey on resource optimization techniques in UAV-assisted wireless	Comprehensive overview of optimization techniques, improving network	Lack of focus on real-time optimization and scalability issues

Author/Year	Focus	Features and Key performance parameter	Advantages	Limitations
		networks	performance	
Fu, Shu, et al. (2022)	Energy-efficient UAV-assisted wireless networks using AI	Proposes AI-based techniques to optimize energy efficiency in UAV-assisted wireless networks	Reduces energy consumption while maintaining communication quality	AI techniques require significant computational power and training data
Pogaku, Arjun Chakravarthi, et al. (2022)	UAV-assisted RIS for future wireless communications	Explores the use of reconfigurable intelligent surfaces (RIS) in UAV-assisted networks to optimize performance	RIS enhances signal quality and reduces energy consumption	Implementation challenges due to complex RIS deployment and management
Lakew, Demeke Shumeye, et al. (2021)	Aerial energy orchestration in heterogeneous UAV-assisted networks	Proposes a method for orchestrating energy usage across heterogeneous UAVs in wireless networks	Improves energy efficiency and network lifetime	Complex energy management techniques may not scale well in large networks
Jeganathan, Anandpushparaj, et al. (2022)	UAV-assisted wireless communication with age of information (AoI) optimization	Introduces an age-of-information (AoI) driven UAV-assisted communication system to ensure timely information delivery	Ensures timely information delivery for mission-critical applications	UAV mobility and energy constraints limit long-term operations
Liu, Yaqun, et al. (2022)	Access control and deployment design for multi-UAV networks	Focuses on access control and deployment strategies for multi-UAV wireless networks	Enhances network access control, improving resource allocation and communication efficiency	Limited adaptability in dynamic environments with varying network demands
Liu, Xiaojie, et al. (2021)	Distributed deployment for long-lasting communication coverage in	Proposes a distributed deployment strategy for UAV-assisted networks to ensure long-term	Improves network coverage and reliability	UAV energy constraints limit long-duration

Author/Year	Focus	Features and Key performance parameter	Advantages	Limitations
	UAV-assisted networks	communication coverage		deployment
Gu, Xiaohui, and Guoan Zhang (2023)	Survey on UAV-assisted wireless communications	Provides a comprehensive survey on the advancements and future trends of UAV-assisted wireless communications	Extensive coverage of recent advancements and future trends in UAV-assisted networks	Lacks focus on practical deployment challenges and real-world testing

2.2 AI-based UAV-Assisted Wireless Network

[62] Sonny et al. This article offers a modified PSO method for UAV path planning in wireless communication networks. The authors stress the need of optimizing UAV location to improve network coverage and reduce interference. The PSO approach lets UAVs adaptively relocate based on real-time data in changing network conditions. The approach has energy efficiency issues, especially in long-term UAV operations. For trustworthy real-world application, the algorithm's performance in highly dynamic contexts like urban areas with variable consumer demand must be validated.

[63] Wang et al. Deep reinforcement learning is used to deploy UAVs autonomously on demand in this article. The proposed methodology optimizes resource allocation by dynamically positioning UAVs based on user demand and energy restrictions. The method boosts network responsiveness, according to the data. The approach's scalability is still an issue, especially in heavily populated areas with simultaneous demand spikes. Further research is needed to maintain energy economy and performance in such situations.

[64] Zhang et al. Data-driven machine learning is used to estimate consumer demand and optimize UAV positioning in this work. The results show network efficiency improvements, especially in variable demand locations. The model's heavy use of computational resources and data sets limits its real-time deployment in fast-changing

contexts. Future research could build lightweight algorithms that retain performance and reduce resource use.

[65] Klaine et al. This study proposes a reinforcement learning framework for emergency cellular network drone base station placement. The distributed learning technology lets UAVs adapt to changing user needs in real time. The results show that the model can boost network capacity during emergencies. However, computational complexity, especially in bigger installations, is a concern. Addressing these problems is essential for real-world deployment of this method.

[66] Wang et al. The authors offer an adaptive UAV-assisted communication deployment architecture that adapts UAV placements to user movement and network needs. This adaptability improves coverage and energy efficiency, they found. The technique has computational overhead limits, especially in large-scale environments with many UAVs and users. Future research may investigate optimization methods that lower computing needs without losing performance.

[67] Yao et al. This article discusses how artificial intelligence might optimize resource allocation and decision-making in UAV-assisted 5G radio access networks. AI improves network efficiency but also challenges real-time decision-making in quickly changing settings. Research is needed to develop robust AI algorithms that can handle real-time activities in high-mobility environments.

[68] Wang et al. Communication solutions for intelligent drone cruisers must be reliable and smooth in dynamic conditions, according to the study. The suggested system improves UAV real-time decision-making and operational efficiency. Energy consumption and processing requirements are major issues, especially during long missions. Solving these issues will help UAVs reach their full potential in vital applications.

[69] Dai et al. In this research, the authors optimize UAV-mounted base stations with caching to improve wireless data delivery. The multi-objective optimization methodology they offer boosts coverage and energy efficiency. Despite encouraging results, the model's computing demands are difficult in big networks. Future work should improve optimization algorithms to balance performance and computational efficiency.

[70] Alsamhi et al. UAV-focused AI-based robotic communication systems are examined in this survey. The authors examine AI-powered path planning and resource management systems that can automate difficult operations. However, computational and energy constraints in real-world systems provide substantial hurdles. To overcome these constraints, future research should investigate hybrid AI-traditional models.

[71] Yang et al. The essay explores AI in intelligent 6G networks for UAV-assisted wireless communication. AI improves resource allocation and predictive analysis, improving network performance, say the authors. However, real-time AI deployment in high-mobility contexts remains difficult. These issues must be addressed for future wireless networks to use AI efficiently.

[72] Bithas et al. This survey extensively reviews UAV-based communications machine learning methods. The authors examine positioning, path planning, and resource allocation methods. The review underlines the potential benefits of these strategies but questions their real-time application due to high processing needs. Future research could produce efficient algorithms that balance performance and practicality.

[73] Liu et al. This study proposes a machine learning-based UAV trajectory and power control optimization method for wireless networks. Their model improves energy efficiency and network coverage significantly. However, large-scale deployments increase solution complexity, raising practicality and real-time applicability difficulties. Future research should streamline algorithms to improve scalability and usability in varied situations.

[74] Al-Ahmed et al. The research proposes a 3D UAV base station placement technique that accounts for user demand and coverage gaps. Real-time UAV location optimization improves network performance. However, computing efficiency and scalability issues in densely populated metropolitan areas persist. More research is needed to create more efficient algorithms that adjust to user density and network circumstances.

[75] Ullah et al. Joint optimization difficulties in UAV-based 5G communication are addressed using machine learning to improve network performance. The technique tackles important issues including coverage and energy efficiency. Real-time

implementations' computational complexity limits scalability. Future work could reduce algorithms while preserving performance.

[76] Wang et al. address AI-enabled wireless networking advances for 5G and beyond UAVs. The authors recommend researching real-time decision-making in high-density situations and integrating AI to improve network adaptability and efficiency. These difficulties must be addressed to maximize AI benefits in future wireless networks.

[77] Ali et al. Machine learning in 6G wireless communication networks for UAV applications is discussed in this article. AI can manage complicated network environments and boost operational efficiency. Scalability and real-time performance issues in dynamic scenarios persist. Such algorithms should be developed in future study to improve AI's responsiveness and flexibility.

[78] Zhang et al. This work proposes an artificial bee colony technique to optimize UAV-mounted base station deployment. Their findings show significant coverage and energy efficiency gains. The model's real-time adaptation in highly dynamic contexts remains a difficulty, suggesting the method needs more refining to improve its practical usefulness.

[79] Lin et al. UAV-assisted networks are the focus of this survey on AI-driven wireless resource management. The authors demonstrate how AI improves resource allocation and network optimization. However, computational load management and real-time decision-making remain practical issues, requiring further research.

[80] Liu et al. The research emphasizes trajectory optimization and resource management using AI in next-generation UAV-based wireless networks. AI-driven techniques can improve network performance, but real-time operations demand a lot of computer power. Future research should examine ways to offset these needs while preserving performance.

[81] Shehzad et al. UAV placement for fronthaul connectivity in wireless networks is optimized using backhaul-aware algorithms in this study. The method works but has real-time scalability and energy efficiency issues. More study is needed to improve UAV adaptability in varied network contexts.

[82] Shafik et al. A quick machine learning approach for three-dimensional UAV base station location in mobile networks is proposed in this article. The approach could

improve deployment efficiency, but its computational intensity makes it unsuitable for big networks. To enable real-time applications, the method should be streamlined.

[83] Ben Aissa et al. This survey examines UAV communications machine learning issues and applications. AI's potential to improve network efficiency and autonomy is highlighted, but energy limits and scalability remain. To expand AI use in UAV networks, further research should overcome these issues.

[84] Mandloi et al. Using machine programming, 5G-enabled UAVs establish continuous connectivity. The suggested method improves UAV network performance in dynamic situations but struggles with energy and computational demands in big deployments. Future research should integrate performance and energy efficiency.

[85] Khan et al. This article discusses 5G networks' use of UAVs and millimeter-wave (mmWave) technologies, including recent advances and ongoing issues in integrating UAVs for coverage and capacity. The authors stress the need for energy efficiency and real-time adaptation research in highly populated areas.

[86] Elnabty et al. UAVs' effects on 5G wireless communications are examined in this article. UAV operations need a lot of energy, however the authors suggest ways to improve coverage and latency. Future research could optimize performance and energy use with hybrid systems.

[87] Gwak et al. The study examines UAV integration in 5G networks and how communication protocols affect UAV performance. Specific protocols can improve UAV communication efficiency, although network scalability and energy consumption remain issues. These protocols need more research to function better in varied network situations.

[88] Zhang et al. This study covers intelligent algorithms for urban UAV path planning, emphasizing route optimization for communication efficiency. The offered techniques are promising, but real-time flexibility and computing complexity must be addressed. Better urban dynamics-coping algorithms should be developed in the future.

[89] Xie et al. The authors propose a hybrid UAV-assisted communication system using aerial and ground networks. They found significant network performance improvements,

particularly in coverage and latency. However, integrating these networks and regulating energy use require further study.

[90] Chen et al. This essay considers data-driven UAV deployment optimization in 5G networks. Predictive analytics improves network efficiency, according to the authors. However, the model's high processing needs make real-time implementations difficult, requiring more efficient techniques.

[91] Salhab et al. UAV communication difficulties and solutions in 5G networks are examined in this survey. Energy efficiency, real-time processing, and scalable algorithms are important study areas. These difficulties must be addressed to maximize UAV potential in next-generation wireless networks.

[92] Liu et al. This study discusses coordination and resource allocation issues in multi-UAV wireless communication systems. The authors suggest a cooperative communication technique to boost network performance. Computational demands and real-time adaptability remain challenges, requiring additional refining for practical deployment.

[93] Song et al. The study proposes a machine learning framework for smart city UAV operational optimization. The authors suggest improving routing and scheduling algorithms to improve service delivery. Despite encouraging results, scalability and real-time processing issues must be solved for wider applicability.

[94] Guo et al. UAVs improve emergency response communication, highlighting the need for reliable connectivity in crises. A dynamic deployment technique improves network resilience, say the authors. However, quick adaptation and energy efficiency in high-demand settings require further study.

[95] Zhang et al. UAV trajectory and power control are optimized using machine learning to improve rural wireless coverage. Their strategy improves network coverage but has computational complexity that limits scalability. Simplifying algorithms for large-scale use should be the focus of future study.

[96] Ahmad et al. Intelligent beamforming for UAV-assisted wireless networks is examined in this article. The proposed strategies improve communication, especially in

high-mobility contexts. For real-world applications to be feasible and scalable, real-time processing needs and energy efficiency must be addressed.

[97] Ren et al. This article optimizes smart city UAV deployment using reinforcement learning. The authors demonstrate how dynamic placement boosts communication efficiency. However, computational load and real-time decision-making issues remain, requiring algorithmic efficiency development.

[98] Liu et al. The authors propose decentralized algorithms for UAV-assisted communications to improve network resilience and adaptability. While promising, these algorithms' scalability in big networks is difficult, indicating the need for more robust models to ensure performance across various conditions.

[99] Chen et al. Edge computing is used to improve UAV-based communication systems in this study. The authors show gains in latency and processing efficiency, but energy consumption and real-time adaptation remain issues, requiring further study.

[100] Xu et al. This research investigates intelligent beamforming approaches for UAV-assisted wireless networks to improve communication in high-mobility conditions. Their methods work, but real-time computational needs and energy efficiency are still issues that need further study.

Table 2.2 AI-Based UAV Assisted Wireless Network

Author/Year	Focus	Features/Findings	Advantages	Limitations
Sonny, Amala, Yeduri, Reddy (2023) [62]	Autonomous UAV path planning	Utilizes modified PSO algorithm for UAV-assisted wireless networks	Enhances path planning efficiency and reduces computation time	Limited scalability in large network scenarios
Wang et al. (2023) [63]	Autonomous on-demand deployment	Proposes autonomous UAV deployment algorithm for on-demand networks	Improves coverage and connectivity in dynamic environments	High energy consumption for continuous operation

Author/Year	Focus	Features/Findings	Advantages	Limitations
Zhang et al. (2018) [64]	Machine learning for UAV deployment	Machine learning techniques for predictive deployment	Reduces response time and enhances deployment accuracy	High computational complexity
Klaine et al. (2018) [65]	Distributed drone base station positioning	Uses reinforcement learning for positioning in emergency networks	Provides decentralized decision-making and robustness	Requires extensive data for model training
Wang et al. (2019) [66]	Adaptive deployment for UAV networks	Proposes adaptive deployment mechanism for UAV-aided communication	Increases system throughput and flexibility	Limited in highly dynamic network conditions
Yao et al. (2019) [67]	AI-defined 5G RAN	Discusses the integration of AI in 5G RAN	Improves efficiency in network management	High dependency on AI accuracy and reliability
Wang et al. (2019) [68]	Drone communication technologies	Explores communication technologies for intelligent drone cruisers	Enhances connectivity for UAVs in 5G environments	High power consumption in extended use cases
Dai et al. (2019) [69]	UAV-mounted base station deployment	Multi-objective optimization for cache-enabled UAV base stations	Improves resource allocation and system efficiency	Limited real-time performance in large-scale networks
Alsamhi et al. (2019) [70]	AI in robotic communication	Surveys AI-based techniques in robotic communications	Enhances decision-making and autonomous operations	Limited by current AI algorithms' scalability
Yang et al. (2020) [71]	AI-enabled 6G networks	Discusses AI's role in enabling intelligent 6G networks	Boosts automation and efficiency in network management	High data requirements for training models

Author/Year	Focus	Features/Findings	Advantages	Limitations
Bithas et al. (2019) [72]	ML techniques in UAV-based communications	Survey on machine learning techniques for UAV communication	Facilitates efficient data processing and decision making	High energy consumption for complex algorithms
Liu et al. (2019) [73]	Trajectory design for UAV networks	Proposes ML-based trajectory design and power control	Optimizes power usage and network coverage	Limited by the computational resources of UAVs
Al-Ahmed et al. (2020) [74]	3D UAV base station placement	Considers coverage holes, backhaul, and user demand in UAV placement	Improves service quality and coverage efficiency	Requires significant processing power
Ullah et al. (2020) [75]	Joint optimization for 5G and beyond	Proposes joint optimization methods with ML for UAVs in 5G networks	Enhances network performance and efficiency	Computational complexity in large networks
Wang et al. (2020) [76]	AI in 5G wireless networking	Highlights recent advances and challenges in AI for 5G	Promises intelligent and adaptive network management	Requires extensive data and advanced hardware
Ali et al. (2020) [77]	6G white paper on ML	Discusses machine learning in 6G wireless communication networks	Provides guidelines for integrating AI in next-gen networks	High complexity in real-time deployment
Zhang et al. (2020) [78]	Artificial bee colony algorithm for UAVs	Uses ABC algorithm for UAV-mounted base station deployment	Increases coverage and reduces deployment cost	Limited effectiveness in dynamic scenarios
Lin & Zhao (2020) [79]	AI-empowered resource management	Surveys AI techniques for future wireless communications	Enhances resource management and network efficiency	Limited by AI model training and deployment costs

Author/Year	Focus	Features/Findings	Advantages	Limitations
Liu et al. (2020) [80]	AI-aided UAV networks	Discusses AI techniques for next-gen UAV networks	Increases flexibility and automation in network management	High reliance on AI for critical decision-making
Shehzad et al. (2021) [81]	Backhaul-aware UAV positioning	Intelligent positioning of UAVs considering backhaul and fronthaul connectivity	Optimizes network performance and reduces latency	Requires advanced computational models
Shafik et al. (2020) [82]	3D ML for UAV base stations	Fast machine learning algorithm for 3D UAV base station placement	Enhances speed and accuracy in UAV deployment	Limited scalability for larger network sizes
Aissa & Letaifa (2022) [83]	UAV communication with ML	Discusses challenges and applications of ML in UAV communications	Improves decision-making and adaptability	Limited by the need for extensive real-time data processing
Mandloi & Arya (2022) [84]	Seamless connectivity with UAVs in 5G	Uses machine programming to ensure seamless connectivity with UAV base stations	Enhances connectivity in complex environments	Limited by resource constraints in UAVs
Khan et al. (2021) [85]	UAVs and mmWave in 5G	Reviews the role of UAVs and mmWave technology in 5G networks	Increases data transmission rates and coverage	High energy consumption in mmWave technologies
Elnabty et al. (2022) [86]	UAV placement in 5G	Surveys optimization techniques for UAV placement in 5G networks	Optimizes coverage and reduces deployment costs	Complex optimization models for real-time deployment
Lim et al. (2021) [87]	Federated learning in UAV networks	Explores the use of UAVs in federated learning	Reduces data transmission and enhances privacy	High dependency on network stability

Author/Year	Focus	Features/Findings	Advantages	Limitations
Lahmeri et al. (2021) [88]	AI for UAV-enabled networks	Surveys AI-based approaches for UAV-assisted wireless networks	Enhances network automation and resource allocation	High data and computation requirements for AI models
Fatemidokht et al. (2021) [89]	AI-based secure routing for VANETs	Uses AI algorithms for secure routing in vehicular ad hoc networks	Enhances security and routing efficiency	Limited by the complexity of integrating AI in real-time scenarios
Lins et al. (2021) [90]	AI for mobility in UAV missions	Discusses AI for enhanced mobility and connectivity in UAV-based missions	Improves mission success rates and reduces downtime	Requires advanced hardware and AI models
Hu et al. (2021) [91]	UAV-assisted vehicular edge computing	Explores the use of UAVs in vehicular edge computing for 6G	Reduces latency and enhances processing power	High energy consumption in UAV operations
Yang et al. (2021) [92]	UAVs in 5G/6G networks	Joint scheduling and resource allocation using asynchronous RL	Enhances network flexibility and resource use	High computational complexity in large networks
Parvaresh et al. (2022) [93]	AI-powered 3D deployment of UAV base stations	Tutorial on AI-powered 3D deployment techniques for UAV base stations	Provides state-of-the-art deployment strategies for emergency and dense urban environments	Requires large datasets for AI model training, high computational complexity
Rolly et al. (2022) [94]	UAV applications and challenges as aerial base stations	Survey of UAVs as aerial base stations with a focus on applications, techniques, and challenges	Identifies potential applications in disaster recovery, smart cities, and defense	Challenges include energy constraints and limited flight time of UAVs

Author/Year	Focus	Features/Findings	Advantages	Limitations
Baig & Shahzad (2022) [95]	ML and AI for UAV communication	Explores machine learning and AI approaches to enhance UAV communication and networking	Improves network efficiency and UAV autonomy	Limited by processing power and battery life of UAVs
Wang et al. (2022) [96]	UAV-based physical-layer intelligent technologies	Survey on UAV-based physical-layer technologies for 5G IoT applications	Enhances network performance and energy efficiency in IoT environments	Requires advanced algorithms and higher computational resources
Khan et al. (2022) [97]	Swarm of UAVs for network management in 6G	Technical review of swarm UAVs for network management in 6G	Enhances scalability, coverage, and reliability using swarm intelligence	Limited by communication delays and synchronization challenges among UAVs
Dastranj et al. (2022) [98]	Energy-efficient airborne base station selection	Proposes deep-predictive algorithms for UAV base station selection and power allocation	Improves energy efficiency and reduces operational costs	High computational complexity and potential delays in real-time scenarios
Fu et al. (2022) [99]	AI for energy-efficient UAV-assisted networks	AI-based techniques for improving energy efficiency in UAV-assisted wireless networks	Reduces energy consumption and enhances operational efficiency	Limited by the complexity of AI models in dynamic environments
Rezwan & Choi (2022) [101]	AI for UAV navigation	Reviews recent advances in AI approaches for UAV navigation	Improves precision and adaptability in autonomous UAV navigation	Requires high computational power and energy for real-time AI processing

Author/Year	Focus	Features/Findings	Advantages	Limitations
Chen et al. (2022) [102]	Deep learning for energy optimization in UAV-aided communications	Proposes a deep learning-based energy optimization model for edge devices in UAV-assisted networks	Reduces energy consumption while maintaining high communication quality	High dependency on the accuracy of deep learning models
Pasandideh et al. (2023) [103]	Particle Swarm Optimization (PSO) for UAV base station placement	Improves UAV base station placement using an enhanced PSO algorithm	Increases network coverage and reduces deployment cost	High computational cost in larger networks
Yazici et al. (2023) [104]	AI and ML in future mobile networks	Surveys applications of AI and ML in mobile networks-enabled systems	Improves network efficiency and scalability for future networks	Requires extensive training data and high computational capacity
Zuo et al. (2023) [105]	Block chain and AI for 6G wireless communications	Survey of block chain and AI integration in 6G networks	Enhances security, transparency, and decentralized control	Complexity in combining AI and block-chain technologies
Sarkar & Gul (2023) [106]	Autonomous UAV networks using AI	Survey on AI-based approaches for autonomous UAV networks	Enhances UAV network autonomy and adaptability in dynamic environments	Limited by energy consumption and real-time processing requirements
Gu & Zhang (2023) [107]	UAV-assisted wireless communications	Reviews advances and future trends in UAV-assisted wireless communication	Expands on new applications such as IoT, smart cities, and disaster recovery	Challenges include energy efficiency and UAV deployment complexity

Author/Year	Focus	Features/Findings	Advantages	Limitations
Dai et al. (2022) [108]	UAV-assisted wireless networks	Discusses advancements, challenges, and solutions in UAV-assisted wireless networks	Proposes solutions for improved coverage, energy efficiency, and resource allocation	High computational demands for real-time data processing
Cheng et al. (2023) [109]	AI for UAV-assisted IoT applications	Comprehensive review on AI techniques for UAV-assisted IoT networks	Enhances IoT network performance and scalability using UAVs	Limited by energy constraints and AI model training complexity

CHAPTER 3

POWER OPTIMIZATION OF UAV-ASSISTED FUTURE WIRELESS COMMUNICATION USING HYBRID BEAMFORMING TECHNIQUE

3.1 Introduction

The rise of sophisticated applications like as autonomous driving, remote sensing, smart cities, and the Internet of Things has led to a large increase in the need for wireless communication systems that have a high capacity and low latency. In order to solve these problems, future wireless networks, including 5G and beyond, will require innovative technologies that can guarantee reliable connectivity in challenging environments. UAVs have emerged as a useful tool for enhancing wireless networks. They serve as flexible, mobile communication platforms that may be used to expand network coverage, provide connection in rural or disaster-stricken areas, and enable efficient data transmission. However, UAVs have a number of unique issues, especially when it comes to power consumption, which is critical for the sustainability and effectiveness of networks that include UAVs.

Given the limitations of on-board battery capacity and the high energy requirements of communication equipment, power efficiency is a critical issue in communication with UAVs. Traditional methods of beamforming, which enable focused communication linkages, usually demand a substantial amount of power, especially in dynamic environments where UAVs must regularly change their locations and beam orientations. In this context, hybrid beamforming has emerged as a promising method for enhancing power efficiency. Hybrid beamforming combines both analog and digital processing, whereas purely digital beamforming requires a large number of RF chains and uses a lot of power. This method significantly reduces the number of RF chains needed while still providing narrow beams that can help reduce route loss. This approach is particularly useful in high-frequency mmWave bands, where power consumption is a critical limiting factor.

This research investigates the use of hybrid beamforming to improve power efficiency in wireless networks that are supported by UAVs. We have developed a framework that aims to reduce power consumption while guaranteeing that high-quality communication links are maintained. This framework makes use of the flexibility of UAVs and the efficacy of hybrid beamforming. This inquiry looks at a variety of optimization strategies to change the location, altitude, and beam direction of a UAV in an adaptive manner. The objective is to reduce power consumption and increase the amount of time the UAV can operate.

3.2 System Model

The system model of power optimization of an UAV in future wireless communication employing a hybrid beamforming technique integrates UAVs as aerial base stations or relays to improve wireless connectivity and communication performance. The primary objective is to optimize the power allocation and beamforming strategy of the UAV's communication system in order to maximize spectral efficiency, prolong the UAV's battery life, and enhance overall system performance. The UAV's communication system uses a hybrid beamforming technique that incorporates analog and digital beamforming techniques. Digital beamforming is performed at the baseband using digital signal processing techniques to fine-tune the beam direction and shape. Analog beamforming is used at the RF (Radio Frequency) front end to redirect beams in different directions. To adapt its beamforming strategy, the UAV's communication system acquires accurate and timely CSI. This information is obtained via a variety of means, including pilot signals transmitted by ground users and channel estimation techniques. The primary objective of power optimization is to allocate transmit power among the UAV's antennas in an efficient manner. By optimizing power allocation, the UAV is able to increase link reliability, decrease interference, and reduce overall power consumption. This is essential for extending the UAV's flight duration and maintaining its communication capabilities. The system model of power optimization of UAV in future wireless communication employs a hybrid beamforming approach that combines UAVs as aerial base stations or relays in order to increase wireless connection and communication performance. The main goal is to improve the power allocation and beamforming strategy of the UAV's communication system. This will increase spectral efficiency, extend the UAV's battery life, and improve the overall performance of the system. The communication system of the UAV employs a hybrid beamforming methodology that combines both analog and digital beamforming methods. Digital beamforming is done at the baseband using digital signal processing techniques to adjust the direction and shape of the beam. At the radio frequency front end, analog beamforming is utilized to redirect beams in various directions. CSI. The communication system of the UAV obtains precise and timely CSI in order to adjust its beamforming approach. There are a number of different ways to collect this information, including the use of pilot signals that are sent by ground users and channel estimate algorithms. The main goal of power optimization is to distribute transmit power across the UAV's antennas in a way that is as efficient as possible. The UAV can improve network reliability, minimize interference, and lower total power consumption by optimizing power allocation. This is crucial for increasing the amount of time the UAV can stay in the air and for keeping its communication skills intact. The proposed method is expected to provide substantial benefits in scenarios where unmanned aerial vehicles are used as temporary base stations or relays, especially in settings such as emergency response or improving connectivity in rural regions life figure 3.1.

3.2.1 Beamforming

Beamforming is the method of directing a radiation pattern at a specific user. This method produces constructive interference at the angles that are wanted and destructive interference at the angles that are not wanted. Channel estimation is often used in the process of beamforming. In order to create a beam that is directed at a specific user, the antenna's weighting is adjusted in real time. This is different from beam steering, which includes selecting an orientation from a set of preset alternatives. Radio waves will be focused in a small angular area, which will greatly increase spectral efficiency. The more antennas there are, the narrower the beam will be. Unlike traditional array and full-dimensional MIMO (FD-MIMO), every antenna element in massive MIMO may be controlled.

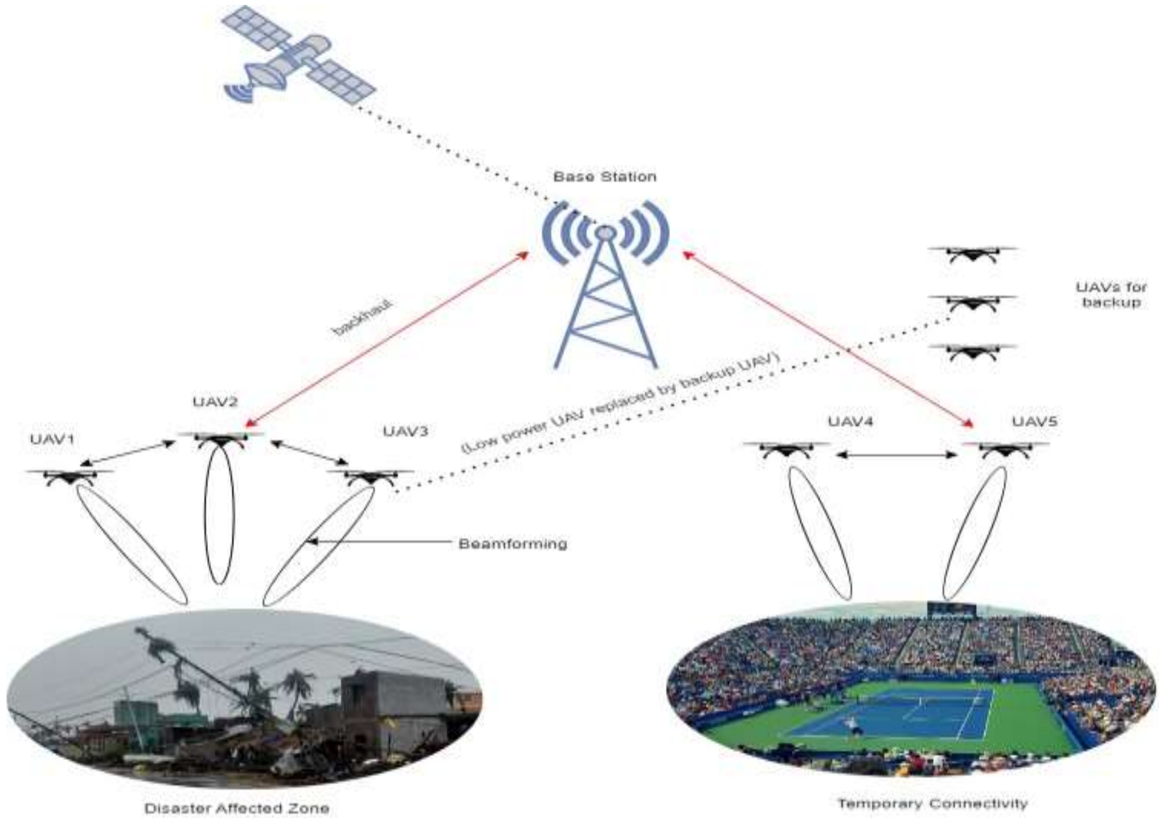

Figure 3.1. UAV-assisted emergancy wireless communication network

This customizable feature will allow for beamforming, which is the core of 5G and future wireless communication technologies. Karl B. Braun, a scientist from Germany, was the first person to effectively demonstrate it in 1905 by designing a phased array that was made up of three antenna components. The more antennas that are involved in beamforming, the more directionality there will be, and the more power the user equipment will get. For beamforming to be executed in a practical way, the base station must have at least 10 times as many transmitters as there are single-antenna User Equipment (UE) devices in the cluster.

The utilization of base station antennas in a huge MIMO system has an impact on the length of time it takes to complete channel training, which is also known as channel estimation. The number of pilots that antennas can pick up is determined by the number of pieces of User Equipment (UEs) that are present. Base stations are trained while simultaneously monitoring signals from multiple UEs, so the total number of pilots they can pick up is proportional to the number of UEs that are present. When the coherence time of a cell grows, it may support more user terminals, which results in a higher overall number of users. When using Time Division Duplex (TDD) systems, it is advisable to utilize a suitable precoding matrix for channel training. In addition, the Channel State Information (CSI) parameter is utilized to describe how good the channel is. In a TDD system, the uplink channel is examined by using broadcast pilots from users, and the CSI of the downlink channel is calculated by using the concept of channel reciprocity.

Beamforming is widely recognized in a variety of fields, including SONAR, RADAR, acoustics, seismology, biomedical applications, and wireless communication. It does this by using the interference rescission concept and effective beamforming methods at the same time. As a result, the communication system's functionality is improved. Beamforming allows for the amplitude and phase of signals to be changed, which is useful for power deviation and beam direction in a positive way. This is achieved by changing the phase of the signal. As a result, the security provided by beamforming is improved because the signal will only be received by the chosen receiver. Beamforming's structural makeup is made up of three categories: analog, digital, and hybrid structures. Before we go on to hybrid beamforming, let's take a moment to briefly look at analog and digital beamforming.

i. Analog Beamforming

The most straightforward approach is known as analog beamforming, and it involves making only a single-phase adjustment in the analog domain. The output of a single RF transceiver is split up into a number of different routes using analog beamforming. These routes correspond to the array's antennas. Before reaching the antenna element, each signal goes through a phase shifter first. This ensures that it will be received correctly. Each transmitting component contains a phase and amplitude controller that regulates the transmitted signals' phase and amplitude, respectively. Active beamforming antennas provide the capacity to integrate a power amplifier in the transmitting element, hence allowing for signal amplification and increased system performance. Passive beamforming antennas, on the other hand, only make use of a single high-power amplifier in the RF chain, which may result in a degradation of the signal as well as a reduction in the efficiency of the system.

$$y_n(t) = x(t)e^{i\varphi_n} \quad (3.1)$$

Where x(t) represents the single input data stream and Y(t) gives the output of the circuit with n count of phase shifters and antenna elements as shown in figure 3.2. The difference in phase that exists between the radio transmissions that are sent to each transmitter is what determines the path that the emitted beam will take. An analog beam former can only produce one beam at a time since it has only one RF chain. This beam forming technology is the most straightforward, affordable, and energy-efficient method that is currently accessible. It is efficient since it has modest hardware and software requirements, and it uses less power due to the phase shifters and attenuators. That so, its performance is slightly restricted because of the decreased antenna gain.

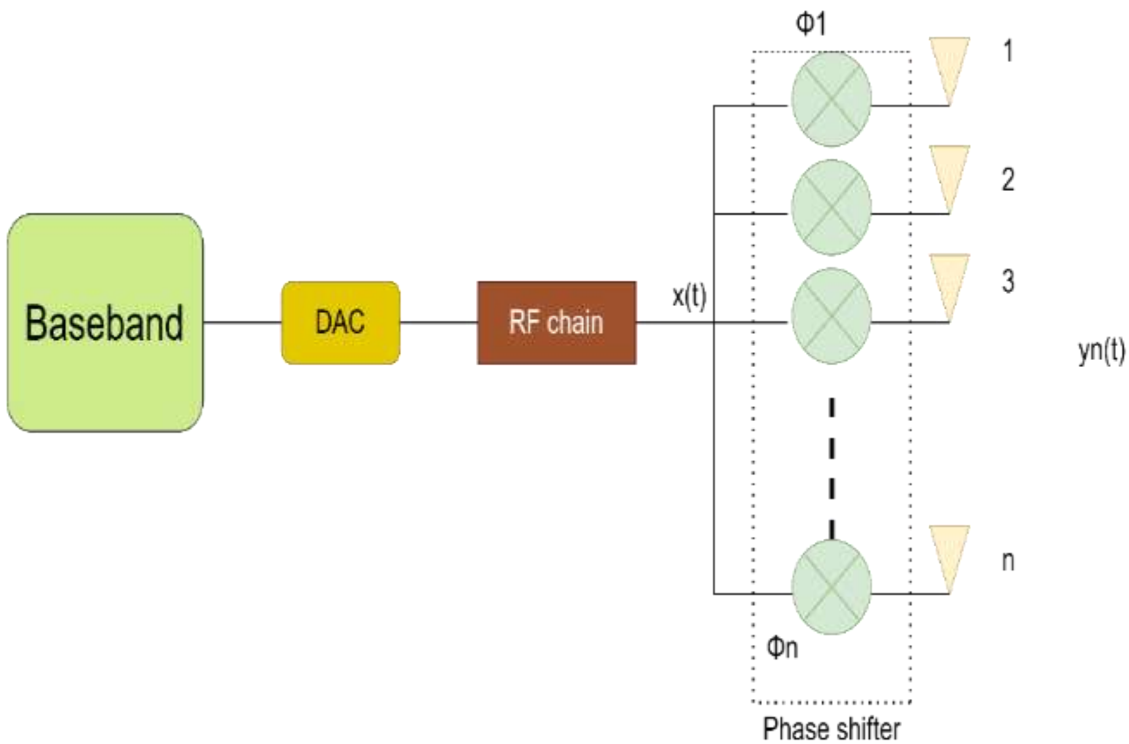

Figure 3.2 Analog beamforming architecture.

In analog beamforming, each antenna is used for transmission; additionally, in order to modify the period of the signal while it is still in the analog domain, each element is attached to a phase shifter. This procedure makes it possible to concentrate the signal in the desired direction by creating constructive interference, while at the same time suppressing interference coming from other directions. Adjustments are made to the phase shifters in order to produce the best possible analog beamforming solution. Because this approach is simple, it is a good option for real-time use in large MIMO systems. As a result, methods like phase-aligned analog beamforming and RF variable gain amplifiers are employed in order to achieve amplitude control. The downside of this analog beamforming is that it becomes a problem when it is used at wide-bandwidth and high frequencies since the analog phase shifters are quite costly and take up a lot of space. A different approach, called antenna selection, was created to compensate for this loss. This approach involves selecting a single antenna that is connected to an RF chain in order to broadcast the signal. It is feasible to attain both complete diversity gain and extremely low array gain at the same time. A block representation of AOBF is shown in Figure 3.3. The concept that resulted in the creation of OABF was selecting a group of antennas that had suitable operating conditions and phase matchings.

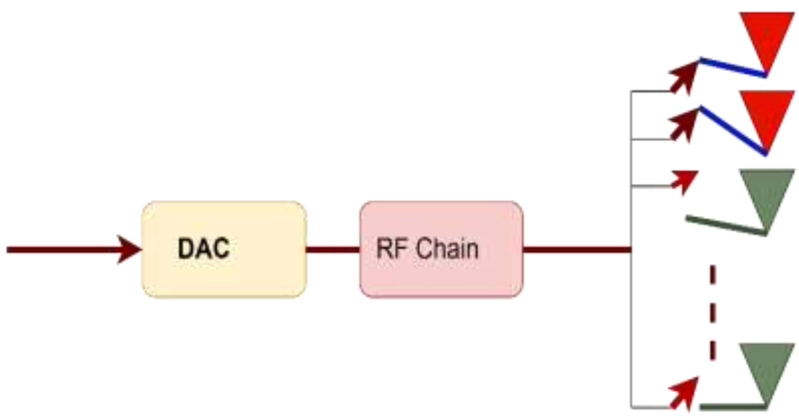

Figure 3.3. AOBF architecture.

The received baseband signal (S) will be given by the equation,

$$S = \sum_{h_i \epsilon m} \sqrt{p_i} h_i x + n \tag{3.2}$$

ii. Digital Beamforming

Digital beamforming has several advantages over analog beamforming. The most significant of these are its ability to support spatial multiplexing, which allows for the use of a variety of frequency subcarriers with different levels of directivity, and its ability to identify and eliminate interference by changing the period and magnitude of the input data. Both of these benefits are major advancements. Every single data operation is performed in the baseband. A digital baseband precoder is a device that adjusts the amplitude and phase of the broadcast signals for each antenna element separately. Digital beamforming may be further classified into two subcategories: linear digital precoding and non-linear digital precoding. In linear precoding, users at the transmitter are allocated different precoding matrices. The transmit signal for each antenna is created separately in the digital baseband, which allows for complete freedom in signal creation as a consequence. For instance, MRT, ZF, and RZF are all types of linear precoding. Linear precoding is an efficient method of completing the task since it transmits data in a linear manner. On the other hand, non-linear precoding methods, such as Tomlinson-Harashima, dirty paper precoding (DPC), and vector perturbation, are more challenging to implement than linear systems, but they have more potential. Filthy paper precoding is one of the approaches that may be used. These tactics can improve performance, but they do require more sophisticated equipment. Because of the high amount of antennas, it consumes a lot of energy, and therefore becomes intolerable in the event of massive MIMO. The necessity that each antenna have its own RF chain creates an excessive amount of complexity.

The Linear Precoding techniques are mentioned bellow:

a) Maximum Ratio Transmission Precoding Technique (MRT):

The MRT technique utilizes a precoding matrix, denoted as W_{MRT}, which is amounting to the Hermitinadjoint of the channel matrix H,

$$(W_{MRT} = H^H) \tag{3.3}$$

MRT beamforming method is employed in wireless communication networks. To maximize signal power and raise the ratio of signal-to-noise at the receiver, it entails modifying the phases and amplitudes of transmissions delivered from various antennas. Massive MIMO systems employ MRT to boost overall system efficiency as well as signal quality.

b) Zero forcing(ZF):

The ZF technique, which is utilized in spatial signal processing, employs multiple transmitting antennas to mitigate multi-user interference signals. Its linear precoding strategy, aided by a precoding matrix, minimizes interference among all user streams, making it the optimal choice for large MIMO systems. The ZF technique performs exceptionally well in channels devoid of noise. The base station employs the ZF precoding matrix (MZF), which is provided as:

$$M_{ZF} = {H^H}/{HH^H} \tag{3.4}$$

c) Regularized Zero Forcing (RZF):

In MIMO (Multiple Input Multiple Output) systems utilized for wireless communication, Regularized Zero-Forcing (RZF) serves as a linear precoding technique designed to improve system efficiency by reducing interference levels. The linear precoder in question is recognized as the most advanced for MIMO wireless communication systems, as it effectively integrates the advantages of both MRT and ZF precoders. The primary objective of RZF is to reduce the Mean Square Error between sent and received messages. The precoding matrix utilized in RZF is expressed as follows:

$$W_{RZF} = \beta(HH^H + \alpha I_k)^{-1} H^H \tag{3.5}$$

Where the power normalization parameter is given by ß and the regularization factor α $=k/p_d$. p_d represents downlink transmit power for particular receiver. The achievable sum rate of the RZF is superior the moment compared to the MRT and ZF at higher SNR values.

3.2.2 Massive-MIMO with Beamforming

The exponential growth of wireless data traffic across networks places strain on the current communication system. The MU-MIMO technology has been superseded by the enormous MIMO technology, which is currently in development. Massive MIMO was developed in response to the bandwidth constraint in the wireless communication industry. Massive MIMO provides power efficiency, a wide spectrum, and extremely simple processing by employing a large number of antennas on both the receiver and transmitter. The vast MIMO network employs synchronous TDD technology. To achieve channel hardening, base stations with a large number of antennas (€>>1) are deployed and will communicate simultaneously with single-antenna users on each time/frequency sample. The ratio of base station antennas to user apparatus is always greater than one (€/σ >>1). Each base station operates independently utilizing distinct precoding methods [110].

Massive MIMO technology Figure 3.4 has substantially improved spectral efficiency, and MIMO technology with multiple antennas at both the base station and consumer equipment is a viable solution for enhancing spectral efficiency. The latter satisfies the requirement for high-quality mobile communication services by providing superior coverage while minimizing power consumption, resulting in decreased bandwidth and transmission power [111]. When using such short wavelengths, extremely small antennas are required. This reduction in antenna size satisfies the requirements of massive MIMO and contributes to the viability of large-scale antenna array technology [112] and can provide sufficient antenna gain due to which signal attenuations caused by mm waves will be compensated using beamforming capability.

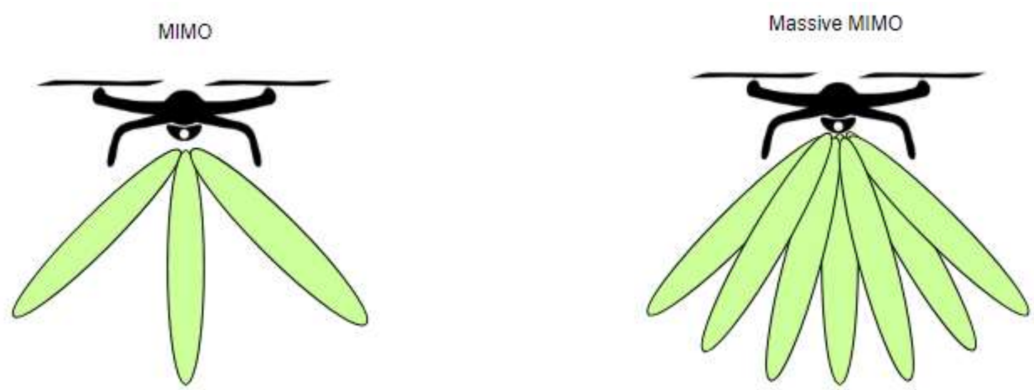

Figure 3.4. MIMO and massive MIMO representation

3.2.3 Performance

MIMO systems are assessed according to many key performance parameters, such as Bit Error Rate (BER), Signal-to-Noise Ratio (SNR), Achievable Sum Rate, and Energy Efficiency. These matrices are important indications for determining how well these systems work and how effective they are.

a) Bit Error Rate (BER): BER measures the amount of flaws that occur during transmission across a communication channel. When bits are changed while they are being sent, this is known as bit error rate (BER). This usually happens because of interference, noise, distortion, or problems with synchronization. Another way to view it is as the ratio of the number of incorrect bits received to the total number of bits sent during a specific period of time. In a downlink single-cell big MIMO communication system, the transmission modulation scheme that is used has a substantial impact on the BER. In a large MIMO system utilizing ZF precoding and gray-coded square QAM modulation, the BER for the kth subscriber is determined as follows:

$$p_e(\gamma_q) = \left\{ \frac{c_N}{2d_N} \frac{\frac{\Gamma(\tau+\frac{1}{2})}{\Gamma(\tau+1)}}{(\gamma_q {d_N}^2+1)^{\tau+\frac{1}{2}}\sqrt{\pi\gamma_q}} \right\} \tag{3.6}$$

where τ = € − K is the level of freedom and k is the number of users, the transmission SNR of the user is given by the formula

$\gamma_k = P_T/K\sigma^2$ where P_T is the total transmission power at the BS distributed evenly among all use

$$p_e(\gamma_q) \approx (\gamma_q d_N + 1)^{-(\tau+\frac{1}{2})}\gamma_q^{-\frac{1}{2}} \tag{3.7}$$

This is approximation of the average bit error rate when $\frac{\Gamma(\tau+\frac{1}{2})}{\Gamma(\tau+1)}$ is omitted because of its negligible effect. The above equation describes the effect on BER on increasing the transmit antennas at base station.

i. Achievable sum rate:

In the world of massive MIMO systems, the attainable rate serves as a critical statistic to analyze system performance. This rate represents the greatest feasible data rate that can be produced while operating below the channel capacity, hence it is an important indicator of how well the system is performing. Understanding this parameter is critical for engineers in order to optimize system design and operation, which will ultimately result in enhanced data transmission and reception.

$$ASR = B\sum_{\kappa=1}^{\kappa} \log_2(1 + SINR_\kappa) \tag{3.8}$$

ii. Power consumption in massive MIMO

The evaluation of power utilization efficiency in massive MIMO systems needs the combination of two critical parameters: the power that is transmitted and the power that is consumed by the hardware. Power consumption efficiency is a basic problem in massive MIMO systems. In order to optimize system execution and improve energy efficiency, it is vital to have an accurate calculation of the entire power consumption. This will ultimately lead to improved system design and operation, which may be seen as the following:

$$ŋ \sum_{k=1}^{k} p_k + €p_n + p_f \tag{3.9}$$

The symbol for the inverse of the power efficiency of the base station is ŋ. The term "downlink transmitter power," abbreviated as "P_k," refers to the allotment of resources that are made available to each user, whereas "P_n" refers to the amount of continuous circuit energy that is consumed by each antenna. In addition, P_f is a symbol for the total amount of power that is consumed by the base station, and this amount of power is constant regardless of the number of dispatch antennas.

iii. Efficient Use of Energy

Energy efficiency is an important metric that determines how successfully a massive MIMO network utilizes power to achieve a particular data rate. Because it is defined as the ratio of the feasible sum rate to the total amount of power that is being consumed, it is a helpful tool that can be used to optimize the design and operation of a system. Monitoring and enhancing this parameter will allow us to improve energy efficiency, limit power consumption, and increase data transfer speeds, which will eventually lead to greater system performance.

$$EE = \frac{B \sum_{k=1}^{k} \log_2(1+SINR_k)}{ŋ \sum_{k=1}^{k} p_k + €p_c + p_f} \tag{3.10}$$

Massive MIMO is a mode of operation that uses hundreds of individually programmable antenna components (for example, 256 antennas [113], often on the base station end of the wireless communication connection, in order to adaptively change the elevations and azimuth angles at which the signal is propagated [114]. In addition, massive MIMO improves system performance by boosting the signal-to-interference-plus-noise ratio (SINR). SINR is an essential statistic that assesses the quality of the received signal in relation to the background clatter and other obstacles. enormous MIMO helps to improve SINR. The following are some of the possible advantages of utilizing this method:

The use of spatial multiplexing, interference reduction, improved channel conditions, and higher spectral efficiency are some of the ways that massive MIMO's capacity and connection dependability may be improved. Spatial multiplexing is a method that may be used by base stations to send several data streams to different users at the same time. Massive MIMO makes it possible for base stations to adopt this method. Massive MIMO is able to expand the number of accessible spatial dimensions since it makes use of a huge number of antennas that are each adjustable on their own. This ultimately leads to an increase in the system capacity. Beamforming, which allows the signals to be directed towards the targeted users alone and away from the interferers, is one method that interference may be reduced. This will also raise the SINR. Enhancing the channel condition, which may be accomplished through the use of spatial multiplexing, is one way to reduce the negative effects of fading channels. In addition, it is well knowledge that the capacity of a network increases with the number of antennas does as well.

Spectral efficiency is the relationship between the throughput or net data rate and the channel bandwidth. The frequency of a channel's bandwidth is measured in Hz, whereas the data rate, or throughput, is measured in bps. The quantity of data that can be communicated over a specific bandwidth is proportional to a wireless communication system's spectral efficiency, which is measured in bps/Hz. Massive MIMO is able to achieve great spectrum efficiency because it uses a large number of antennas that are individually controlled. This allows the system to increase the amount of accessible spatial data streams, as well as throughput and multiplexing gain [115].

$$SE = \frac{Throughput[bits/sec/km^2]}{B[Hz].D[cells/km^2]} \tag{3.11}$$

iv. Energy efficiency:

According to [116], the relationship between transmitted power (P_t) and number of antennas (n_t) is inverse as a consequence of coherent combining. As the transmit power decreases significantly as nt increases, the power per antenna must be inversely proportional to nt. Throughput is demonstrated to be directly proportional to the number of transmitting antennas in [116], where the transmitted power is held constant. In addition, [117] specifies the minimum power consumption (in mW). Hybrid precoding is a sophisticated signal processing method that effectively combines digital and analog precoding to reduce the computational complexity of the base station while maintaining high performance levels.

v. Cost effectiveness:

Massive MIMO technology is cost-effective because it employs low-power consumption components such as power amplifiers and has the potential to drastically reduce the quantity of radiated power (by a factor of a thousand) [118]. Also By employing multiple antennas, the power per transmitted information bit can be decreased, resulting in reduced energy consumption and costs. Massive MIMO technology provides support for a substantially larger number of users than conventional single-antenna systems.

vi. Signal processing:

Massive MIMO technology streamlines signal processing by reducing the effects of interruption, rapid fading, and distortion. Utilizing a large number of antennas enables spatial processing technology, which increases spectrum utilization and data rate[119]. In addition, the use of multiple antennas in massive MIMO systems reduces the processing burden at each antenna, and linear processing techniques significantly reduce the complexity of signal processing, resulting in enhanced performance and decreased costs. Massive antenna arrays at base stations provide crucial "channel hardening" properties. When fading channels behave more predictably, the enormous MIMO channel matrix approaches the predicted values, or the number of antennas approaches infinity [120].

Let the **q** single antenna users be supported by **p** base station antennas sharing the same time-frequency resources.

Let the **p×1** transmitted signal vector from **p** antennas be represented by **t,** then the **q×1** received signal vector **s** at the user side is given as,

$s = (\mathbf{H}t\sqrt{\varphi} + \mathrm{n})$, Where **H** belongs to $\mathbb{C}^{q\times p}$, is a channel matrix between transmitter and receiver. In this downlink channel model, at the base station, The channel is predicted to have perfect channel state information, be ergodic, and exhibit Rayleigh fading. The components of H are viewed as independent, identically distributed (i.i.d.) Gaussian random functions in the complex space with a mean of zero and a variance of one. **t**=WZ is the recognized signal at q^{th}user after using the linear precoding. Where Z belongs to$\mathbb{C}^{q\times 1}$.

3.2.4 Hybrid beamforming in massive MIMO

Hybrid beamforming is implemented to attain good flexibility, control over amplitude and power consumption, and cost. The objective of hybrid analog-digital beamforming systems is to simultaneously modify analog and digital beamformers in order to increase the achievable rate or imitate a full-digital precoder. Due to its significance in creating enormous MIMO cost- and energy-efficient, hybrid beamforming has experienced a significant increase in popularity over the past five years. Hybrid systems seek to accomplish digital beamforming-like performance while minimizing the complexity of hardware and signal processing. In partially connected hybrid beamforming, a subset of antennas are coupled with an RF chain, whereas in a fully connected hybrid beamforming system, every antenna is connected to every RF chain. Whether wholly or partially coupled, hybrid analog-digital precoding and combining designs involve a compromise between complexity and efficacy. The implementation of these strategies increases spectrum efficiency and spectrum efficiency at the expense of a rise in computing complexity. Ultimately, the precise requirements and constraints of the system in question determine whether fully connected or partially connected architectures should be employed [121].

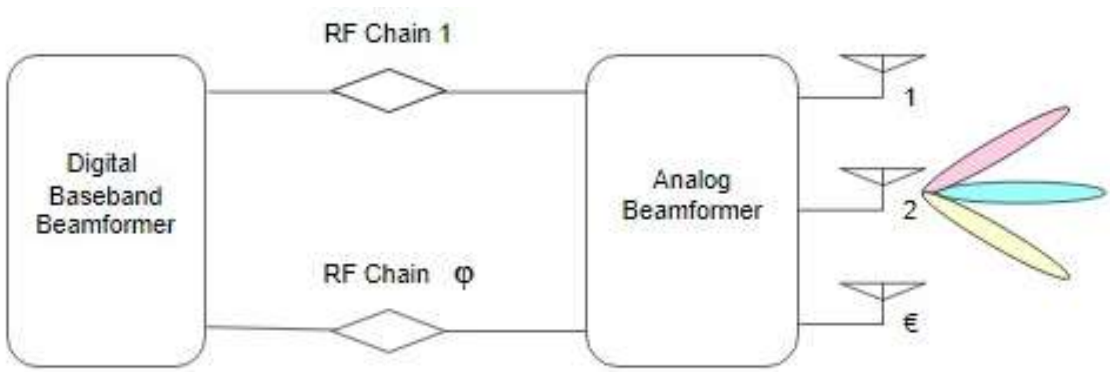

Figure 3.5. Hybrid beamforming.

Hybrid beamforming is a very intriguing method for large MIMO systems that incorporates digital and analog beamforming. When the number of base station antennas surpasses that of user device antennas, it is anticipated that future communication systems will utilize hybrid beamforming more often as shown in figure 3.5. Utilizing enormous MIMO improves channel estimation and spatial resolution. For hybrid beamforming, the base station divides the RF chain into a digital portion and an analogue portion. The digital component precodes a limited number of data streams, while the analogue component combines the signals from the digital component to generate a beam delivered through the analogue beamforming network. This technique maintains a high level of performance despite requiring fewer RF connections. Low-resolution analog-to-digital converters can also be utilized, which further reduces costs and energy consumption. Hybrid beamforming is ideally suited for massive MIMO systems due to its capacity to achieve high spatial resolution and circumvent the hardware limitations of conventional digital beamforming. Broad consensus exists that large MIMO and hybrid precoding techniques will be essential for achieving faster data rates, optimizing spectral efficiency, and reducing energy consumption as the world enters a new phase of broadcasting systems, such as the fifth wave of wireless communication and beyond. It is anticipated that these innovations will play a crucial role in meeting the ever-increasing demand for modern communications operations, making it simpler to serve more consumers and enhancing the quality of service.

The number of data processing paths is ($€ \times \varphi^2$) for a completely linked design with € transmit antennas and φ RF chains compared to ($€ \times \varphi$) for a sub-connected architecture [122]. However, the beamforming gain of the entirely linked architecture is times greater than that of the sub-connected architecture [123]. Using a hybrid analog-digital beamforming approach that is entirely connected, each antenna can receive the entire beamforming gain [122]. The use of multiple RF chains permits the construction of beam patterns with enhanced flatness over the service area as a result of hybrid analog-digital precoding and combining techniques, as well as fewer overlaps between beams, similar to those generated by a fully digital architecture. Fully connected hybrid beamformer utilizes all Angles of Departure (AoD) to accomplish the mapping via a system of phase.

In massive MMO grouping and selection of antenna according to the channel behavior and calculation of SNR with best optimal solutions has been discussed [124-126].

3.3 Result and Discussion

The amount of available received signal power, or, more commonly, the received signal power to noise power ratio, always limits the data rates that may be given in a mobile communication system where noise is the primary source of radio-link damage (a noise-limited scenario). Any increase in the data rate that can be achieved within a given bandwidth necessitates at least a corresponding proportionate increase in signal strength. The conclusion drawn from utilization of various antenna pairs, ranging from 4x4 to 32x32, is that the achievable able rate increases as we increase the pair of antennas while maintaining the same SNR value. The simulation results in figure 3.6 demonstrate that the beamforming with MIMO faces least BER as compared to MIMO without beamforming. And figure 3.7, describes the performance of different precoding technique using the parameters, achievable sum rate and average SNR, where the hybrid regularized zero forcing(HRZF) precoding technique out performs all other mentioned algorithms like zero forcing, matched filter and regularized zero forcing.

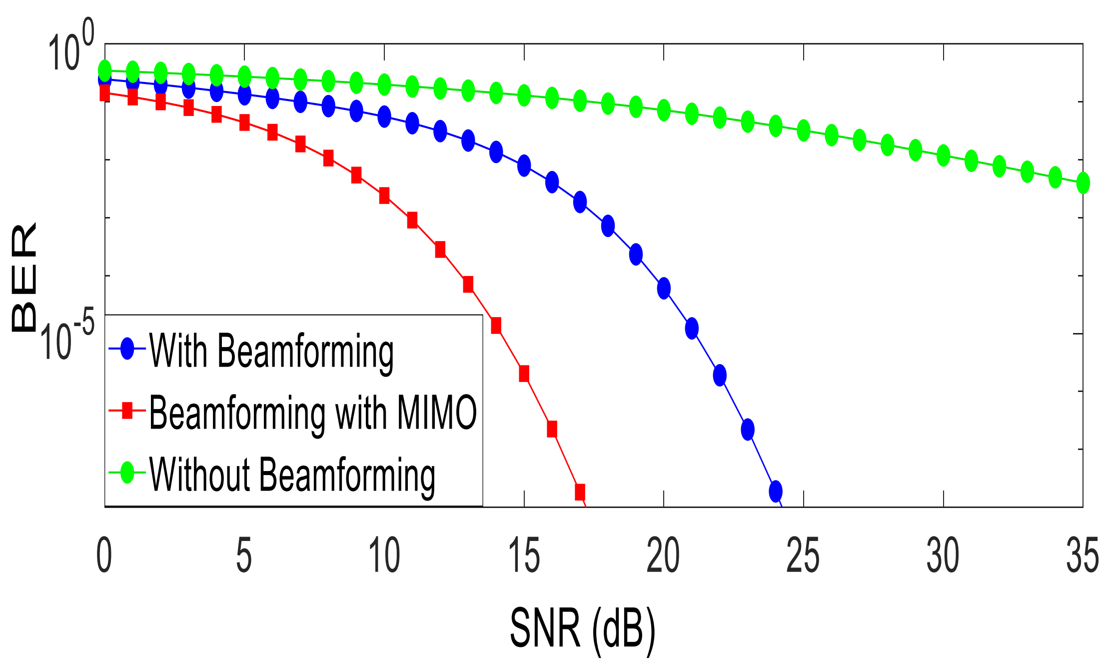

Figure 3.6. BER versus SNR for different methods

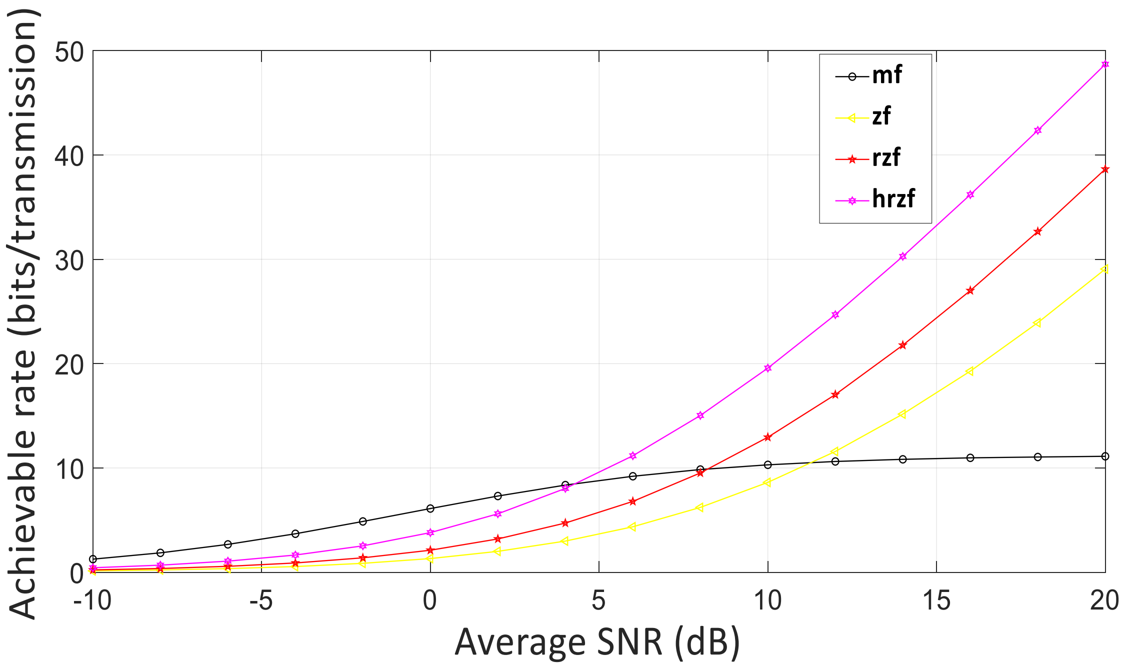

Figure 3.7. Achievable rate versus SNR for different precoding methods

On analyzing figure 3.7 it is evident that matched filter dominated the process at lower SNR values (here up to 5dB), where at different values of SNR and fixed number of antennas(m), performance based on four precoding techniques is compared. HRZF dominated performance at all levels of the comparison above 5dB SNR.

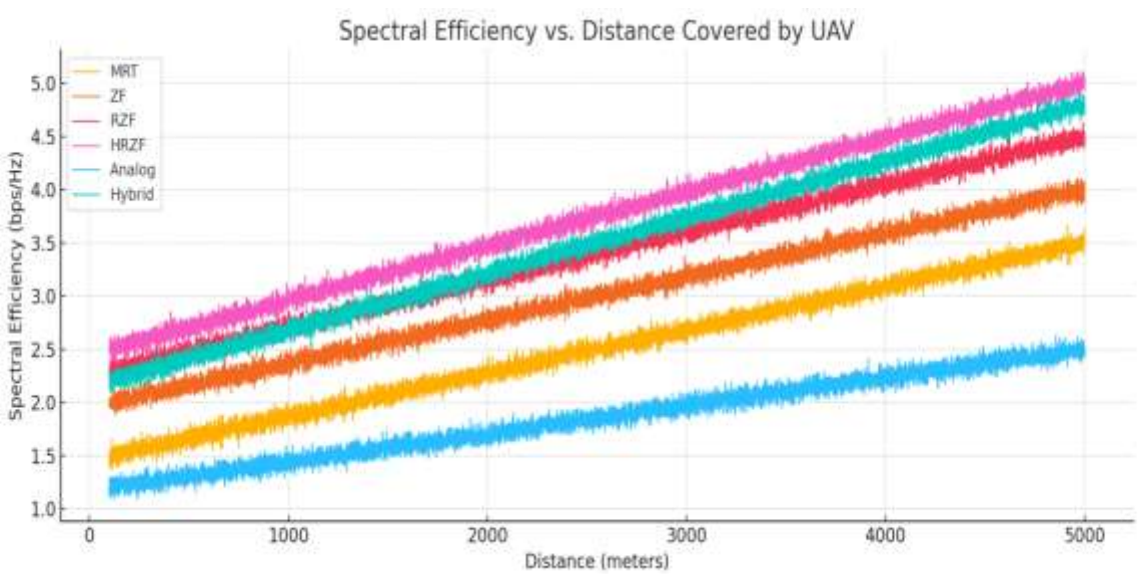

Figure 3.8. Spectral efficiency versus distance covered by UAV for different beamforming techniques.

In figure 3.8, the key observation from the analysis reveals an unusual yet significant trend: spectral efficiency increases with the distance covered, contrary to typical expectations where it usually decreases. This implies that the UAV follows a trajectory that progressively enhances its channel conditions possibly by moving closer to ground users or improving line-of-sight communication. Among the techniques compared, HRZF stands out as the best performer, starting around 2.4 bps/Hz and reaching up to 5.0 bps/Hz. RZF follows closely behind, maintaining strong performance across the range. In the mid-tier, Hybrid beamforming generally outperforms ZF, which is affected by noise amplification due to suboptimal channel conditions. MRT, though effective in boosting signal power, ranks lower as it lacks interference cancellation. Analog beamforming performs the worst, limited by its inherent inability to efficiently support multi-user scenarios. The energy efficiency (EE) showing in figure 3.9 of all beamforming techniques increases with distance, primarily because the UAV's achievable data rate improves along its path while power consumption remains constant, resulting in a higher rate-to-power ratio. Analog beamforming emerges as the most energy-efficient method, starting at approximately 0.35 bps/Joule and rising to around 0.75 bps/Joule; despite its low data rate, its minimal power usage requiring just one RF chain makes it superior in terms of energy use.

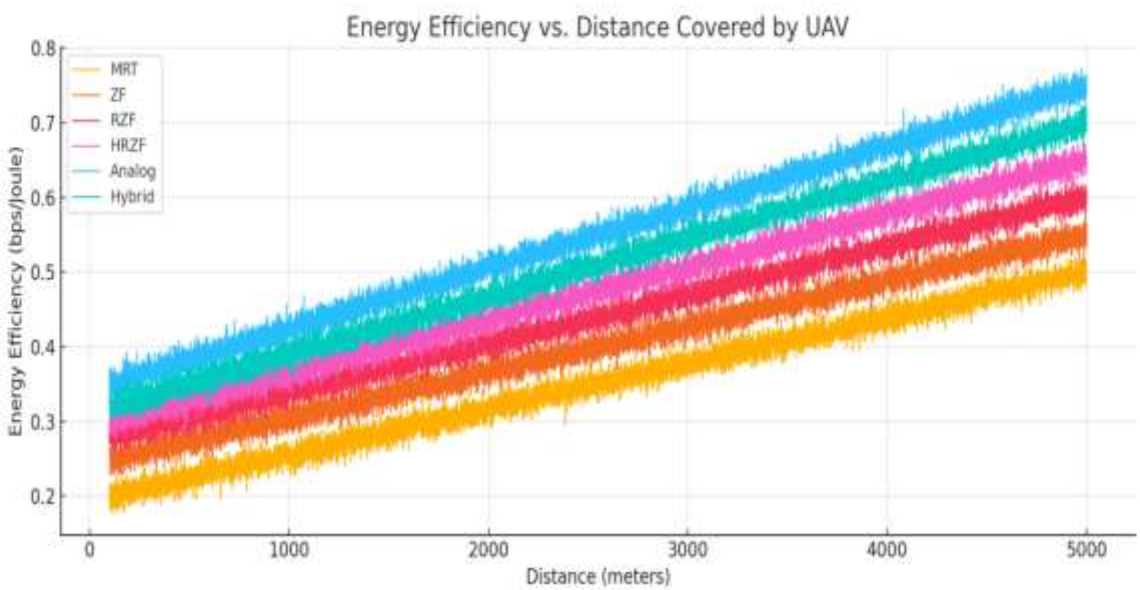

Figure 3.9. Energy efficiency versus distance covered by UAV for different beamforming techniques.

Hybrid beamforming follows, offering a practical balance between moderate power consumption and respectable data rates. Fully digital methods like HRZF, RZF, ZF, and MRT, although delivering higher throughput, suffer from poor energy efficiency due to their heavy RF chain usage and high power demands. This analysis highlights the essential trade-off between throughput and power consumption, emphasizing that for energy-constrained platforms such as UAVs, analog and hybrid beamforming provide more efficient and sustainable solutions than fully digital alternatives. The data rate for all beamforming techniques steadily increases as the UAV moves along its trajectory, indicating an improvement in channel quality likely due to better proximity to ground users or enhanced line-of-sight. In figure 3.10 among the techniques, HRZF consistently achieves the highest throughput, starting around 10 Mbps and surpassing 18 Mbps. Hybrid beamforming and RZF follow closely, with Hybrid outperforming the fully digital RZF, thanks to its balanced design. ZF and MRT perform moderately, with ZF being more affected by non-ideal channel conditions. Analog beamforming ranks lowest, delivering under 6 Mbps due to its limited capability in handling multiple users effectively.

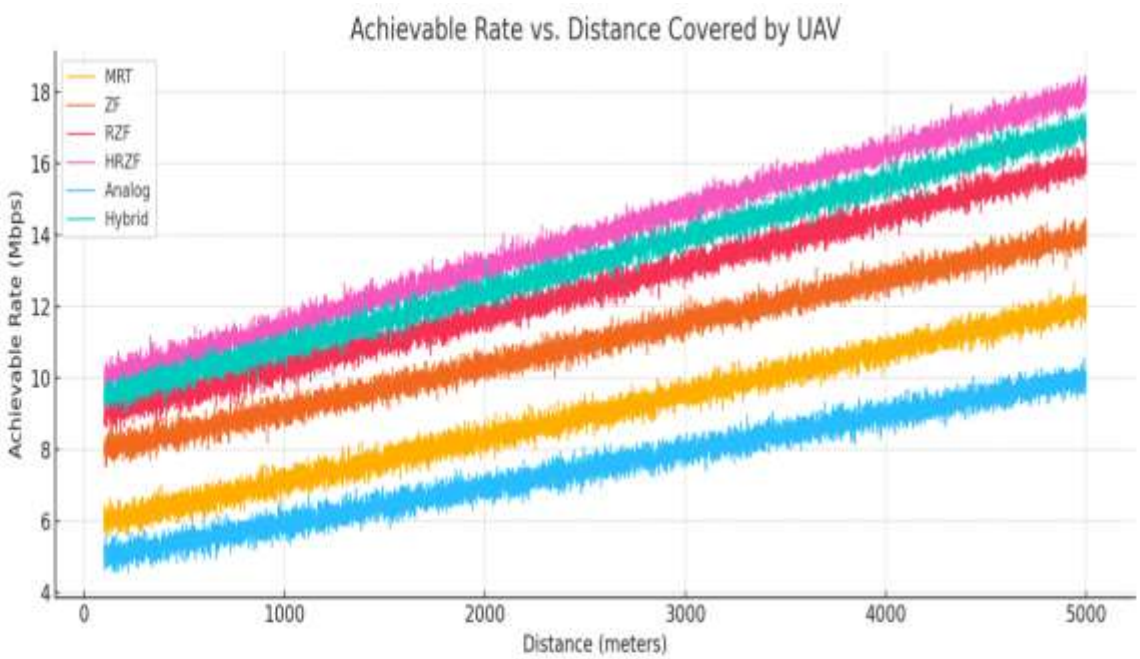

Figure 3.10. Achievable rate versus distance covered by UAV for different beamforming techniques.

This analysis underscores that for maximizing data throughput in UAV-assisted communication, advanced methods like HRZF and Hybrid beamforming offer the best performance, combining technical efficiency with practical applicability. In figure 3.11, the analysis reveals distinct power consumption tiers among beamforming techniques, primarily driven by hardware complexity. Analog beamforming is the most power-efficient, consuming only about 10–12.5 Watts due to its minimal hardware requirements. In contrast, fully digital and advanced hybrid techniques demand significantly more power: Hybrid uses approximately 18–21 W, MRT around 20–22.5 W, ZF between 22–24 W, RZF about 23–25 W, and HRZF is the highest at 24–26 W. Although power consumption remains mostly stable, a slight upward trend with distance suggests marginal increases in processing or transmission demands as the UAV progresses. Overall, this clearly indicates that beamforming architecture plays a critical role in determining power usage, making Analog and Hybrid beamforming highly advantageous for energy-efficient UAV communication systems.

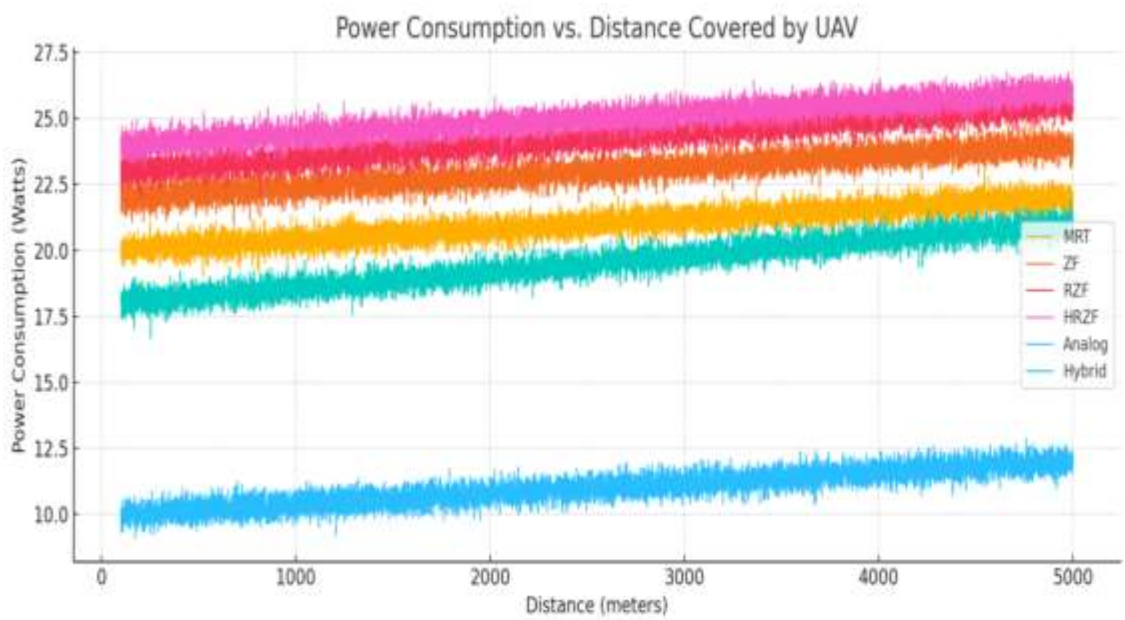

Figure 3.11. Power consumption versus distance covered by UAV for different beamforming techniques.

Table 3.1 Comparatative Analysis of Beamforming Techniques

Technique	Spectral Efficiency (bps/Hz)	Achievable Rate (Mbps)	Energy Efficiency (bps/Joule)	Power Consumption (Watts)	Remarks
HRZF	2.4 – 5.0	~10 – >18	0.21 – 0.41	24 – 26	Best overall in performance, but power-hungry
RZF	2.5 – 4.8	~11 – 17.5	0.22 – 0.42	23 – 25	Strong performer, but high power cost
Hybrid	2.0 – 4.0	~10 – 17	0.32 – 0.72	18 – 21	Good balance between rate and efficiency, suitable for UAV assisted wireless communication network
ZF	2.4 – 4.5	~10 – 16	0.23 – 0.43	22 – 24	Performs well but sensitive to channel conditions
MRT	2.2 – 4.3	~9 – 15	0.25 – 0.45	20 – 22.5	High signal strength but lacks interference handling
Analog	1.2 – 2.5	<6 – 12	0.35 – 0.75	10 – 12.5	Lowest power usage, poor multi-user support

3.4 Summary

In conclusion, the results clearly indicate that HRZF beamforming offers the best overall performance across all parameters, including SINR, throughput, latency, PDR, energy efficiency, and user connectivity. While analog beamforming is most energy-efficient, it lags in throughput and user handling. Hybrid beamforming, closely following HRZF, provides a highly practical balance between performance and efficiency. Therefore, for real-world UAV-assisted 5G deployments, HRZF and hybrid beamforming emerge as the most effective solutions, providing optimal trade-offs between complexity, power usage, and communication quality.

CHAPTER 4

DEPLOYMENT OF UAV USING MULTI-AGENT REINFORCEMENT LEARNING

4.1 Introduction

Following major natural disasters, ground-based communication infrastructure is often severely damaged, resulting in communication breakdowns and the loss of critical information, thereby jeopardizing the safety of affected individuals and complicating post-disaster rescue efforts. Unmanned Aerial Vehicles (UAVs), due to their swift deployment and adaptability, offer a viable solution by establishing Line of Sight communication coverage in disaster-stricken areas. This approach holds significant potential for emergency communication [127]. As mobile Internet and Internet of Things (IoT) technologies have rapidly advanced, numerous digital devices and equipment have been deployed in emergency services, including but not limited to rescue operations and intelligent healthcare. Additionally, a plethora of sensors and auxiliary devices are now in place for continuous monitoring of disaster-stricken regions [127]. Consequently, the emergence of the 6G network has ushered in the demand for larger-scale, higher-density, and faster coverage in the realm of emergency communication [128]. Moreover, this network must address the challenges arising from the high dynamics and diverse service requirements resulting from large-scale user connectivity [129]. In response to the 6G landscape, the concept of an intelligent emergency communication network [130-131] characterized by "node intelligence and network simplification" has emerged. By incorporating intelligent technologies, particularly the convergence of communication and computing [132], network nodes are equipped with intrinsic intelligence. This transformation leads to a simplified protocol structure within the network, promoting native simplicity. Furthermore, it facilitates on-demand, real-time adjustments in communication links and network configurations, driven by endogenous intelligence. This Intent-Driven Emergency Communication Network possesses the ability to dynamically adapt to user conditions, modify network deployments on the fly, and allocate network resources according to specific user service requirements.

Conventional non-intelligent emergency communication networks often rely on non-convex optimization techniques to enhance coverage performance. In such networks, coverage performance is heavily influenced by the real-time positions of UAV base stations relative to ground users. This necessitates solving the non-convex optimization problem related to the flight trajectory of UAV base stations. For instance, Kang et al. [133] developed a model for multi-user communication involving multiple UAV base stations and optimized the flight trajectories of these stations using iterative Gibbs sampling and block coordinate descent methods. This approach efficiently improved the network's maximum-minimum rate. Yin et al. [134] employed a continuous convex approximation method to jointly optimize the hover positions of ground clustering and multi-UAV base stations in large-scale ground user scenarios, thereby enhancing network spectral efficiency. Zhang et al. [135] tackled power allocation and trajectory optimization issues for multiple UAV base stations, considering the communication characteristics and requirements of emergency communication scenarios. Their goal was to maximize the capacity of emergency communication networks.

However, the aforementioned traditional non-intelligent coverage optimization methods rely on precise network environment state information (e.g., user locations, data sizes, channel conditions, etc.) as fixed parameters throughout the optimization process. As a result, these methods are primarily suitable for entirely static network scenarios where all network status information and service requirements of users in the future are known in advance. They are ill-suited to handling the dynamics and service variations of users in the aftermath of large-scale disasters.

Deep reinforcement learning is recognized as a pivotal technology for addressing network dynamics. UAV base stations equipped with deep reinforcement learning agents can adapt their flight trajectories based on real-time network conditions to maximize the network's long-term performance benefits. To derive the optimal coverage optimization strategy, the deep reinforcement learning agent undergoes iterative training and execution phases, which are crucial for adapting to the dynamic network environment and real-time regulation of UAV base station flight trajectories.

Different approaches to the training and execution phases have led to various coverage optimization methods based on deep reinforcement learning. For instance, in [136], the deep reinforcement learning proximal policy optimization algorithm is employed, resulting in improved communication rates for single UAV base stations and reduced flight energy consumption. Liu et al. [137] utilized the deep deterministic policy gradient (DDPG) algorithm to optimize the deployment of multiple UAV base stations without considering interference. However, when interference occurs between multiple UAV base stations, the single-agent learning environment becomes unstable, making it challenging for the algorithm to converge.

To address these issues, Challita et al. [138] integrated game theory into the echo state network (ESN) and jointly optimized the flight trajectories of multiple UAV base stations. In contrast to the value function-based reinforcement learning method in [138], [139-140] employs the multi-agent deep deterministic strategy gradient (MADDPG) algorithm. This approach generalizes the action space using strategy gradients and can continuously output actions to accurately regulate UAV flight trajectories, avoiding the problem of dimension explosion [141]. However, as the scale of the emergency communication network grows, the input dimension of the MADDPG algorithm, based on the "centralized training-distributed execution" framework, increases significantly, leading to heightened learning complexity, reduced stability [142], and limited effectiveness in dealing with the coverage optimization challenges of large-scale post-disaster user scenarios. After a disaster, site information should be quickly trans mitted from the incident area to the rescue centre, with post-disaster communications able to perceive environmen tal and personnel information. Rebuilding the distributed intent-based coverage optimization architecture for wireless networks is, therefore, a practical way to serve a large num ber of post-disaster consumers. Effectively monitoring the fully mechanized mining face is completed when the source node gathers data about the mine catastrophe and utilizes a multi-hop routing data transmission mechanism to deliver the data packet to the sink node. In contrast to typical mining set tings, nodes that survive in post-disaster dispersed networks possess copious amounts of energy that are not readily regen erated. Distributed intent-based coverage optimization design for several post-disaster users is shown in Figure 4.1. Post disaster communications may typically resume by installing cables or additional communication equipment in accident tunnels. Post-disaster communications should also be able to sense personnel andenvironmental data andquicklyrelaysite information from the incident site to the rescue centre.

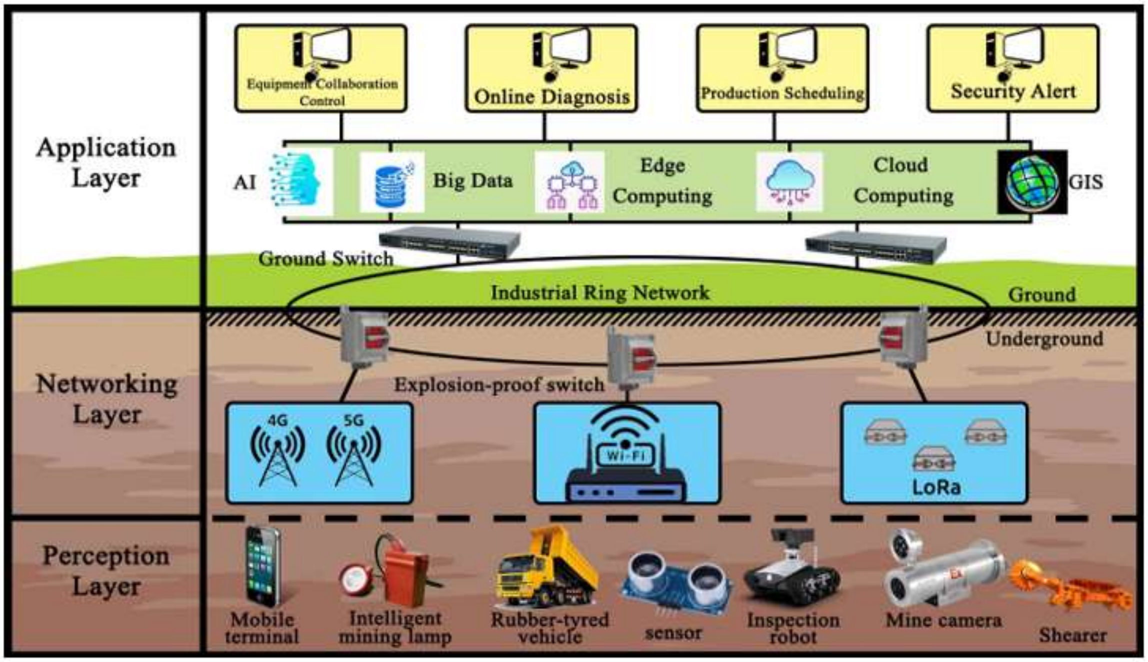

Figure 4.1 Distributed intent-based coverage optimization architecture for large-scale post-disaster users

4.2. Problem Formulation and System Model

Figure 4.2 demonstrates two sections, Space and Ground section in which the Space section facilitates communication between Earth stations or between Earth stations and spacecraft, communication satellites serve as the primary means of receiving and transmitting signals from satellite communication Earth stations and Ground section enable user connection, the ground segment consists of a tracking, telemetry, and command station, satellite transponder, gateway station, and satellite control center. The user sector is primarily made up of different terminal user devices, including as handheld terminals, mobile terminals installed on vehicles, ships, and aircraft, and Very Small Antenna Terminal stations. It also includes a variety of satellite communication-based applications and services. Satellite communication is highly suitable for emergency communications because it is not constrained by ground conditions and offers a wide range of communication coverage, large capacity, high reliability, long transmission distance, independent communication ability, and strong resistance to damage.

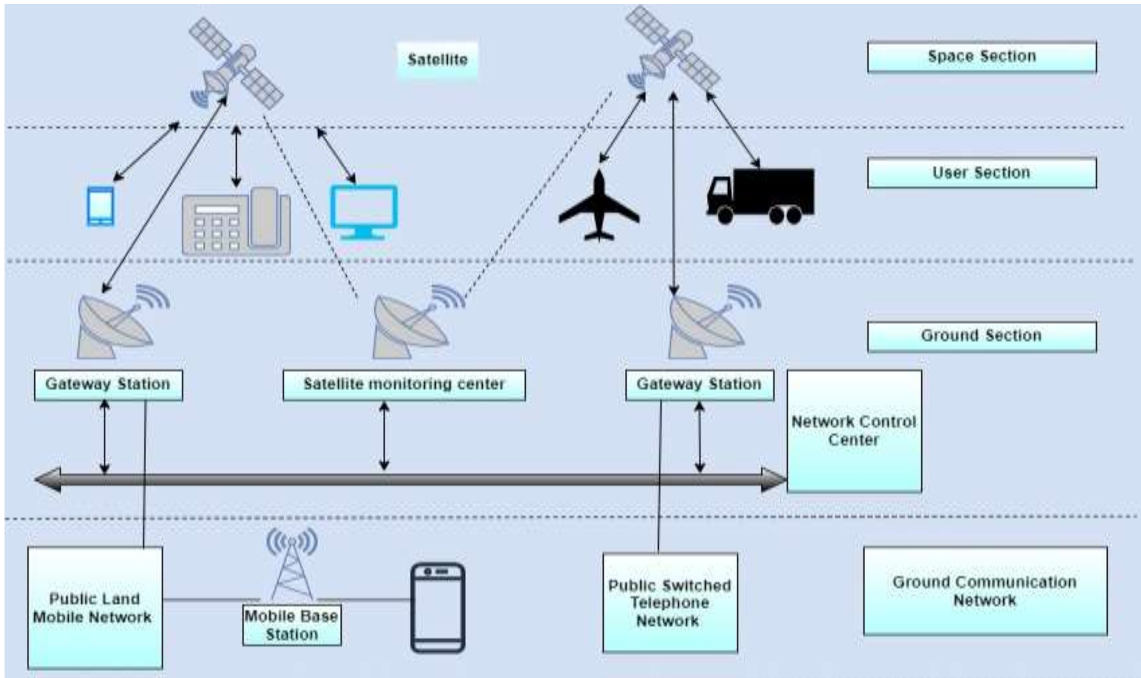

Figure 4.2. Emergency communication network system model

In Figure 4.3, we observe a large-scale dynamic population of diverse ground users within the disaster-affected area. To cater to their communication needs, multiple UAV base stations are strategically deployed to form an emergency communication network. Let's assume there are N users in the disaster-affected region, and M UAV base stations have been deployed. The users are logically grouped into M distinct clusters, each serviced by a specific UAV base station to reestablish communication services. In each user cluster, there exists a designated cluster center directly connected to the UAV base station serving that cluster. Communication from other users within the cluster is routed through this central user. We denote the user set as N and the UAV base station set as M. Within the expansive emergency communication network, the utilization of cluster center users for aggregating and forwarding information offers distinct advantages in three key areas: processing capacity, energy efficiency, and interference mitigation. Firstly, considering the limited processing capacity of UAV base stations, user clustering reduces the number of users directly connected to these stations.

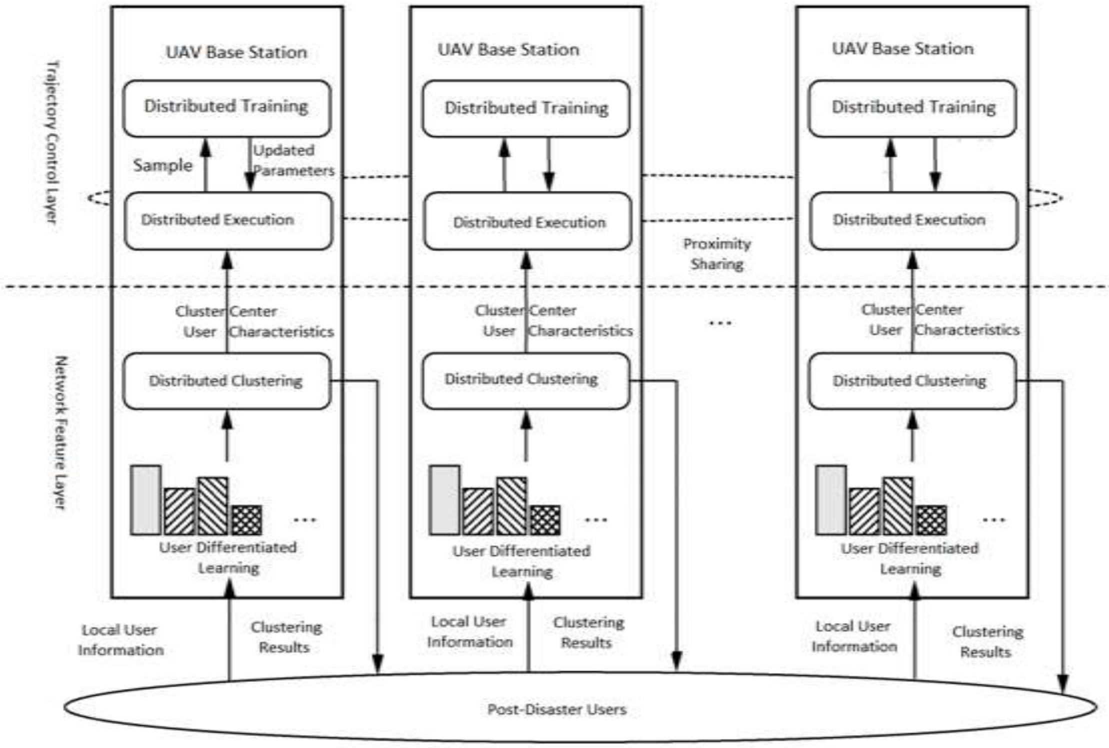

Figure 4.3. Architecture for distributed intent-based coverage optimization in large-scale post-disaster user scenario

This effectively reduces the dimensional of the neural network, preventing network paralysis. Secondly, user clustering leads to a decrease in the number of users directly connected to UAV base stations. This reduction results in lower communication and computing energy consumption for the UAV base stations, thus extending their continuous operational duration.

Lastly, the reduction in the number of air-ground communication links, facilitated by user clustering, minimizes interference between air-ground communication clusters. This, in turn, enhances the overall communication capability of the network. Here, we delve into the detailed description of the user model, ground transmission model, air-ground transmission model, and the comprehensive coverage optimization architecture design as outlined in this article.

4.2.1. User Model

In the actual and intricate emergency communication network environment, it's evident that large-scale post-disaster users exhibit substantial dynamism and variations in service requirements. This dynamism is primarily observed in the real-time fluctuations in the users' positions and the temporal randomness of their activation states. When a user becomes active at a specific moment, a new data transfer task emerges. The activation state of user i follows a Beta distribution within the time interval $t \epsilon [0, T]$, where

$$f_i(t) = \frac{t^{k_1-1}(T-t)^{k_2-1}}{T^{k_1+k_2-1}B(k_1+k_2)} \tag{4.1}$$

$$B(k_1+k_2) = \int_0^1 t^{k_1-1}(1-t)^{k_2-1}dt \tag{4.2}$$

The parameters k_1 and k_2 define the characteristics of the Beta distribution. Importantly, a user's activation status is contingent upon the presence of a new transfer task. Even when a user is inactive, they can still complete the transfer of any remaining data from previous tasks and may subsequently be designated as the cluster center user. Upon being assigned as the cluster center user, they bear the responsibility of relaying information for all users in the cluster and typically require higher transmission power. Since this article focuses on coverage optimization to restore communication for a large number of users, it does not delve into energy balancing for users. The central consideration is the disparity in information due to diverse service types and task requirements, particularly variations in the data sizes that users need to transmit. For an activated user i at time t, the data size of their new transfer task, denoted as $d_i(t)$, follows a Gaussian distribution [143].

$$f_d\big(d_i(t)\big) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(\frac{(d_i(t)-\mu_i)^2}{2\sigma_i^2}\right) \tag{4.3}$$

Here, μ_i and σ_i represent constant values that define the mean and standard deviation, respectively, characterizing the transfer task size for user i and their specific service type. The value of $d_i(t)$ can vary over time due to semantic changes in the transmission task.

4.2.2. Ground-Based Transmission Model

In this large-scale disaster scenario, ground users are grouped into M clusters, aligning with the number of UAV base stations. Each user initiates data transmission to the designated cluster center user, and subsequently, the data is routed to the UAV base station through the forwarding of the cluster center user. The communication between user i and cluster center user u_i operates on ground-to-ground communication links within the sub-6 GHz band, where non-line-of-sight (NLoS) conditions significantly impact the wireless link. The path loss, following the Rayleigh fading channel model [144], is expressed as:

$$L_{i,u_i}^{ground}(dB) = 37.6\, log\left\|p_i - p_{u_i}\right\| + 21\, log f_c^{ground} + 58.8 \tag{4.4}$$

In this equation, f_c^{ground} represents the central frequency used for terrestrial communications, p_i and p_{u_i} are the positions of user i and cluster center user u_i, $\left\|p_i - p_{u_i}\right\|$ denotes the Euclidean distance between these two locations. The coefficients 37.6 and 21 account for the distance attenuation and frequency attenuation factors in the path loss model for non-high-rise urban or suburban scenarios. The constant term 58.8 is an additional path loss constant that considers the height difference between users. Notably, due to the considerable distance between cluster users, interference between clusters can be effectively minimized through appropriate spectrum resource allocation techniques. However, this work does not delve into spectrum resource allocation. The SINR for the communication link between user i and cluster center user u_i within the cluster can be expressed as

$$SINR_{i,u_i}^{ground} = \frac{P_1 G_{i,u_i}^{ground}}{N_0} \tag{4.5}$$

In this equation (4.5), P_1 represents the transmit power of user i, and ground, $G_{i,ui}^{ground}$ represents the channel gain between user i and the cluster center user u_i. N_0 represents the noise power. The channel gain ground,$G_{i,ui}^{ground}$ is influenced by path loss and can be described as follows:

$$P_1 G_{i,u_i}^{ground}(dB) = P_1(dB) - L_{i,u_i}^{ground}(dB) \tag{4.6}$$

Spectral efficiency of data transmission by user i at time t can be represented as follows:

$$R_{i,u_i}(t) = lb\left(1 + SINR_{i,u_i}^{ground}(t)\right) \tag{4.7}$$

The overall transfer task size of user i at time t is denoted as $D_i(t)$ and encompasses the remaining task from time (*t-1*), denoted as $D_i(t-1)$, and the new task size $D_i(t)$ at time t. If there's no remaining task at the start, i.e., $D_i(1)0 = 0$, then

$$D_i(t) = max\left(0, D_i(t-1) - n_i(t-1)BR_{i,u_i}(t-1) + d_i(t)\right) \tag{4.8}$$

Here, B signifies the bandwidth of the ground resource block, and $n_i(t)$ represents the number of resource blocks allocated to the user, which is determined by the total transmission task size and spectral efficiency at time t.

$$n_{i,u_i}(t) = min\left(N_c, \left[\frac{D_i(t)}{R_{i,u_i}(t)}\right]\right) \tag{4.9}$$

Where N_c represents the threshold for resource block load, which prevents users from excessively consuming spectrum resources due to low spectral efficiency. We define the evaluation index for average load efficiency as

$$\eta = \frac{1}{TN}\sum_{t=0}^{T}\sum_{i=0}^{N}\frac{BR_{i,u_i}(t)}{n_{i,u_i}(t)} \tag{4.10}$$

The efficiency of load averaging, denoted as η, serves as an effective metric for evaluating the quality of ground clustering results across various scenarios characterized by different user dynamics and information disparities.

4.2.3. For Model Transmission between Air and Ground

Communication between the emergency UAV base station and the cluster center user occurs through air-to-ground communication links in the sub-6 GHz band, where Line of Sight (LoS) conditions prevail, significantly influencing the wireless link. The average path loss between UAV base station J and cluster center user u_j is formulated as follows

$$L_{j,u_j}^{air}(dB) = 20lg\left(\frac{4\pi f_c^{air}\left\|p_j - p_{u_j}\right\|}{c}\right) + \eta_{LoS} \tag{4.11}$$

Here, f_c^{air} denotes the central frequency of air-ground communication, P_j signifies the position of the drone base station, c represents the speed of light, and η_{LoS}denotes the additional spatial propagation loss for LOS and is treated as a constant. It's important to note that cluster center users may introduce interference to other UAV base stations, and the SINR for the communication link between UAV base station J and cluster center user u_j for the service is given by:

$$SINR_j^{air} = \frac{P_2 G_{j,u_j}^{air}}{N_0 + \sum_{j' \neq j, j' \epsilon M} P_2 G_{j,u_{j'}}^{air}} \tag{4.12}$$

Here, P_2 represents the transmit power of the cluster center user and $L_{j,uj}^{air}$ represents the channel gain between the UAV base station j and the cluster center user u_j. The channel gain $G_{j,uj}^{air}$ is influenced by path loss and can be expressed as

$$P_2 G_{j,u_j}^{air}(dB) = P_2(dB) - L_{j,u_j}^{air}(dB) \tag{4.13}$$

The Doppler Effect induced by drone movement can be effectively compensated for using existing technologies, such as phase-locked loop technology. The spectral efficiency of UAV base station J can be represented as

$$R_j(t) = lb\left(1 + SINR_j^{air}(t)\right) \tag{4.14}$$

The average spectral efficiency of an emergency communication network can be expressed as:

$$R(t) = \sum_{j\epsilon M} lb\left(1 + SINR_j^{air}(t)\right) \tag{4.15}$$

In this study, the optimization goal is set as the average spectral efficiency defined in Equation 4.15. The optimization problem is formulated while taking into account the constraints imposed by the maximum flight speed limit, flight safety limitations, and communication interruption limits of UAV base stations.

$$\mathrm{OP:} \max_{\mathrm{p_j(t), j\epsilon M, t=1,\dots,T}} \sum_{\mathrm{t=1}}^{\mathrm{T}} \sum_{\mathrm{j\epsilon M}} \mathrm{lb}\left(1 + \mathrm{SINR_j^{air}(t)}\right)$$

$$\text{s.t } C_1: \left\| p_j(t) - p_j(t+1) \right\| \leq V_{max}\Delta t, \forall j \in M \tag{4.16}$$

$$C_2: \left\| p_j(t) - p_{j'}(t) \right\| < 0, \qquad \forall j \neq j' \in M$$

$$C_3: P_{outage}(t) \leq P_{outage}^{max}$$

In the optimization problem, the communication interruption probability (P_{outage}) and the maximum communication interruption probability limit (max P_{outage}) at time-t are represented by the outage function P(t). The average spectral efficiency of the emergency communication network in this optimization problem is determined by the signal-to-noise ratio between each UAV base station and the cluster center users. Since air-ground communication mainly involves a direct path, the signal-to-noise ratio is primarily influenced by the distance between the two. Additionally, constraint C_3, which relates to communication interruption, is closely linked to the selection of ground user clustering and cluster center users. Therefore, the trajectory adjustment in a large-scale multi-UAV emergency communication network depends on the outcomes of ground user clustering, and the flight trajectory adapts to the dynamic changes in user selections for the cluster center.

4.2.4. Optimization Scheme Overrides

Based on the previously discussed user and communication models, the average spectral efficiency of the emergency communication network depends on various factors such as the positions of UAV base stations (p_j), the locations of cluster center users (p_u), and the results of ground user clustering. To address this, we have developed a distributed intent-based large-scale post-disaster user coverage optimization architecture comprising two layers: the network feature layer and the trajectory regulation layer.

Compared to the traditional end-to-end coverage optimization structure, the hierarchical coverage optimization structure proposed in this work offers several advantages:

i. Reduction in input dimension: By reducing the input dimension of the reinforcement learning state at the UAV base station, we can decrease the scale of the deep neural network and simplify problem training.

ii. Hierarchical design: Through this hierarchical approach, we separate air communication optimization and ground communication optimization, making it easier to adjust performance and parameters in practical engineering applications.

This hierarchical design aligns with the typical implementation of deep reinforcement learning algorithms in various industries.

Specifically, each UAV base station is equipped with a distributed computing terminal that serves the layered optimization architecture mentioned above. In the network feature layer, the UAV base station leverages locally acquired network status information to accommodate the service differences among large-scale post-disaster users. It autonomously groups local users based on this information and selects user features from the cluster center as the input state for multi-agent reinforcement learning.In the trajectory control layer, multi-agent reinforcement learning technology is employed to address the state input for time series dynamics, with UAV base stations autonomously optimizing their flight trajectories within the framework of distributed training and execution. This optimization aims to reduce communication interruptions and maximize network spectral efficiency. It's worth noting that, in each timeframe, along with user information, the characteristics of the cluster center user, who relays information in the transmission process, are aggregated. These characteristics are also required as input for reinforcement learning and are transmitted to the UAV base station as auxiliary communication overhead.

4.3 Network Feature Layer - Ground User Clustering

In the network feature layer, the process of ground user clustering and the selection of cluster center users are essential to address the varying service requirements among the large-scale user population. This part introduces a user differentiation learning algorithm based on Bayesian inference to address this challenge. As obtaining information about all the large-scale users can be challenging for UAV base stations, we also present a distributed K-SUMS clustering algorithm that takes into account these user differences. This algorithm results in clustering outcomes characterized by improved load efficiency and a more balanced distribution of users across clusters.

4.3.1 User Differentiated Learning

"Bayesian Inference" is a statistical machine learning method that establishes a connection between an observer and an estimator using Bayesian formulas [145]. In the process of user differentiation learning, the UAV base station can acquire the new task size of the user's latest activation at time T_0 as an observation $d_i^*$and estimate the user's priority parameter λ_i. In this work, the priority parameter λ_i represents a numerical representation of the average traffic demand of user i, considering information differences, with the aim of allocating higher-quality spectrum resources to users with higher priority. λi follows a Gaussian distribution with mean μ_i and variance σ^2.

Suppose the number of local users observable by UAV base station j is Nj, represented by the set Nj, and the definition vector is x = (x, y, z), where d* is the observation vector, λ is the estimation vector, and μ and σ^2 are parameter vectors.

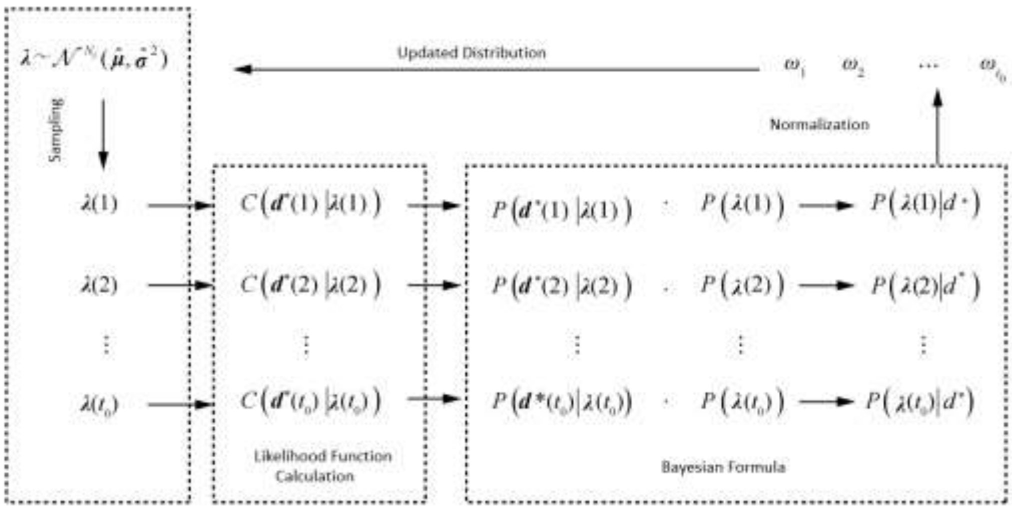

Figure 4.4. Bayesian inference flow

The Bayesian inference process is illustrated in Figure 4.4. Initially, the estimation vector λ, which has the same number of dimensions as the observation vector, is obtained through sampling from the prior distribution λ ~ N(μ, σ^2), where P(λ) is the prior probability distribution. Then, using the vectors d* and λ, the loss function is computed as follows

$$C(d^*|\lambda) = -\frac{1}{N_j}\sum_{i=0}^{N_j}\frac{(d_i^* - \lambda_i)^2}{d_i^*\lambda_i} \tag{4.17}$$

The likelihood function can be derived by normalizing the loss function with respect to the estimation vector λ given the observation vector d*, as follows:

−C(d |λ)Where Z(d) is the normalization constant.

$$\mathrm{P}(\mathrm{d}^*|\lambda) = \frac{\mathrm{e}^{-\mathrm{C}(\mathrm{d}^*|\lambda)}}{\int \mathrm{e}^{-\mathrm{C}(\mathrm{d}^*|\lambda)}\,\mathrm{dd}^*} \tag{4.18}$$

$$\mathrm{P}(\lambda|\mathrm{d}^*) \propto \mathrm{P}(\mathrm{d}^*|\lambda)\mathrm{P}(\lambda) \tag{4.19}$$

Based on equation (4.19), the product of the prior probability and likelihood function is normalized to obtain the posterior probability ω for the estimated vector λ. Consequently, the mean and variance of the prior distribution are updated.

$$\hat{\mu} = \sum_{t=1}^{t_0} \lambda(t)\,\omega \tag{4.20}$$

$$\hat{\sigma}^2 = \sum_{t=1}^{t_0} (\lambda(t) - \hat{\mu})^2\,\omega \tag{4.21}$$

Algorithm 1: *User Differentiation Learning Algorithm Based on Bayesian Inference*

Input:

- *Observation vector, d**
- *Parameter vectors to be optimized, μ and 2 σ*

Output:

Optimized parameter vectors, μ and 2 σ

1. *Initialize the priority parameters for t_0 group users from the prior distribution: λ(1), λ(2), ..., λ(t_0) ~ N(μ, 2σ).*
2. *For t = 1 to t_0:*
3. *Calculate the loss function using Equation (4.17): C(t, d*, λ) to characterize the gap between the observation vector and the sampled priority parameter vector.*

i. *Normalize the loss function using Equation (4.18) to obtain the likelihood function: P(t | d*, λ).*

ii. *Use Equation (4.19) to calculate the product of the loss function and the likelihood function based on Bayesian inference.*

6. *End for*

7. *Multiply all loss functions with likelihood functions and normalize to obtain the posterior probability: $\omega(t)$, $t = 0, 1, 2, ..., t_0$.*

8. *Update the posterior distribution using Equation (4.20) and Equation (4.21) to obtain parameters μ and σ^2.*

Algorithm 1 computes the priority parameter λ for each user, allowing for differentiated communication services during clustering. Prioritizing higher λ users for spectral efficiency can effectively reduce the network spectrum resource load.

4.3.2. Ground users clustering

The k-sums algorithm is chosen over traditional clustering methods like k-means and spectral clustering due to its lower computational complexity, which is O(NM), making it efficient even when users and cluster centers change rapidly. Moreover, the k-sums algorithm effectively reduces intra-cluster distances, improving the balance of users between clusters. These characteristics are crucial for optimizing average spectral efficiency and load balancing in an emergency communication network. In general, the k-sums algorithm is well-suited to handle the dynamic and diverse nature of users in the aftermath of large-scale disasters. The general matrix expression for clustering algorithms can be expressed as:

$$\min_{Y \in R^{N \times M}} \mathrm{Tr}\left((Y^T Y)^{-\frac{1}{2}} Y^T G Y (Y^T Y)^{-\frac{1}{2}}\right) \tag{4.22}$$

Figure 4.5. Overall process optimized for distributed coverage for large-scale post-disaster users

The matrix notation used in the clustering algorithm is as follows:

i. Matrix Y represents the cluster assignment matrix with dimensions N×M. When user i belongs to service cluster J of UAV base station, the element is set to 1 ($y_{i,j} = 1$); otherwise, it's set to 0 ($y_{i,j} = 0$).

ii. Matrix G is the cluster kernel matrix, and its definition varies depending on the clustering algorithm. For the k-sums algorithm, it involves neighbor dissimilarity measures between nodes. Elements gii represent the dissimilarity between user i_1 and user i_2. The smaller the dissimilarity, the larger the value of g_i, and only one element in each row (N_j) is set to 1, representing the smallest dissimilarity, while the other elements are replaced by a maximum dissimilarity constant.

iii. The Tr( ) operator represents the trace operation of the matrix.

To ensure clustering results' balance, the k-sums algorithm introduces the constraint Y^TY=nI to equation (22), where I is the identity matrix, and n is an arbitrary constant. Equation (22) can be transformed into:

$$\begin{gathered}\min_{Y \in R^{N \times M}} \mathrm{Tr}(Y^{T}GY) \\ \mathrm{s.t.} Y^{T}Y = \bar{n}I\end{gathered} \tag{4.23}$$

In the case of large-scale post-disaster users as shown in figure 4.5, obtaining information about all users for a single UAV base station is challenging. Therefore, calculating dissimilarity measures between all global users is infeasible. Adopting a centralized clustering approach in this scenario would result in significant communication overhead for user information. To address this issue, this work introduces a distributed K-Sums clustering algorithm, allowing UAV base stations to perform clustering using only locally observed information from large-scale post-disaster users.

The clustered kernel matrix G in the distributed K-Sums algorithm is defined based on the proximity dissimilarity measure of observable users. The dimension of the clustered kernel matrix for UAV base station j is represented as N_j×N, where N_j is the number of users observable by UAV base station j. The dissimilarity measure between users is calculated as the product of the number of load resource blocks required to transmit from user i_1 to user i_2 at the current moment ($n_{i1,\ i2}$) and the user's priority parameter λ_i. In mathematical terms, this dissimilarity measure is represented as:

$$g_{i_1,i_2} = n_{i_1,i_2}\lambda_{i_1} \tag{4.24}$$

This design aims to consider both the instantaneous and long-term characteristics of user transmission information traffic requirements. It allocates load resource blocks to users based on their information differences, providing better resource blocks to users with higher business needs. This approach effectively reduces the probability that high-priority user communication cannot be covered under limited load. It's important to note that the design of the cluster kernel matrix in this work primarily focuses on differences in user traffic demand. If you need to consider business differences arising from variations in other communication requirements, you would need to redefine the physical meaning of the elements in the cluster kernel matrix to accommodate those differences.

For each UAV base station, the distributed K-Sums clustering algorithm only needs to obtain the user cluster it serves. Therefore, it defines the local portion of the cluster identification matrix as Yp $\subseteq$ Nj $\times$ 2, where $y_{i,0}$ indicates whether user i is in the user cluster N_j served by the UAV base station. To ensure the balance of user clustering results and meet the conditions of equation (23), the elements of the matrix Y_p must satisfy:

$$y_{i,0} = \begin{cases} 1, & i \in N_j \\ 0, & i \notin N_j \end{cases} \tag{4.25}$$

$$y_{i,1} = \begin{cases} 1, & i \in N_j \\ \sqrt{\dfrac{N}{M(M-1)}}, & i \notin N_j \end{cases} \tag{4.26}$$

The local partial cluster identification matrix must satisfy the constraint Y^TY=nI of the global cluster identification matrix. Additionally, the number of observable users N_j for the UAV base station needs to be greater than the average number of users serviced by UAV base stations, i.e., jNN> M. Similar to the row iteration method used in the K-Sums algorithm [20], the local partial cluster of each user is optimized in sequence to identify the row vector, which is represented as $0 \leq y_i \leq 1$ for each row vector. The problem equation (23) can then be transformed into:

$$\min_{y_i} \mathrm{Tr}\left(Y_p^T \mathrm{GY}\right) \Leftrightarrow \min_{y_i} y_i^T \tilde{Y}_p^T g_i \tag{4.27}$$

The distributed K-Sums clustering algorithm, which takes user differences into consideration, is presented in Algorithm 2:

Algorithm 2*: Distributed K-Sums Clustering Algorithm with User Differences*

Input: User dissimilarity metric matrix G, local part cluster identification matrix pY
Output: Local part cluster identification matrix Yp after optimization

1. Initialize Yp and pY such that they are different from each other.

2. While p ≠ pY:

i. p ← pY

ii. For each j in [1, N]:

a) Perform row-wise optimization of the cluster identification matrix Yp according to Equation (27) to obtain the optimized yi.

iii. End for

3. End while

By calculating the result Yp from Algorithm 2, filter the users for whom yi,0 = 1 as the users serviced by UAV base station j, and select the user with the least similarity measure as the cluster center user, i.e., the user with the smallest gi,i value.

$$\min_{i_2 \in N_j, y_{i_2,0}=1} \sum_{i_1 \in N_j} g_{i_1,i_2} \tag{4.28}$$

Based on the distinctive information of cluster center users, UAV base stations have the capability to dynamically adjust their flight trajectories in real-time to optimize coverage for ground users.

4.3.3. Complexity analysis

The standard k-means algorithm requires iterative assignments of users to the nearest cluster center, recalculating cluster centers for each user cluster, and thus calculating distances between each user and all cluster center users with a complexity of O(NM).

However, the standard k-means algorithm has a limited scope of applicability, as it can only handle linearly separable data and is highly sensitive to initialization. The enhanced k-means algorithm first non-linearly maps the input data to a higher-dimensional space to accommodate non-linearly separable data types and then performs the k-means algorithm with a computational complexity of O(2N).

Spectral clustering algorithm, on the other hand, leverages the nearest neighbor map of users for analysis, making it capable of processing non-linearly separable data with superior clustering performance. However, due to the initial construction of the proximity map and subsequent spectral decomposition operations, its computational complexity is high, reaching $O(N^2M)$. In contrast, the clustered kernel matrix of the k-SUMS algorithm utilizes neighbor dissimilarity measures, and most of the values in g_i are constant. Employing the row iterative optimization method as described in equation 4.27, the complexity is approximately O(M), resulting in an overall computational complexity of O(NM). Moreover, to learn the business differences of users online, Bayesian inference algorithms require t0 steps to compute both the loss function (C(t)|(d*(t), λ)) and the likelihood function (P(t)|(d*(t), λ)), where the computational complexity of the loss function is associated with the number of locally observable users, N_j. Consequently, the computational complexity of the user differentiation learning algorithm based on Bayesian inference is $O(t_0N_j)$. In summary, the network feature layer, which encompasses the entire ground user clustering, accounting for user differences, has a complexity of $O(t_0N_j)$.

4.4 Control of UAV Trajectory at the Base Station Level

The conventional approach to optimizing UAV base station trajectories is inadequate for addressing the dynamic and long-term aspects of large-scale user scenarios. Simultaneously, single-agent reinforcement learning methods struggle to adapt to the unstable learning conditions arising from multiple UAV base stations. To tackle these challenges effectively, we introduce a multi-agent reinforcement learning-based optimization approach. This method makes intelligent decisions regarding flight trajectories by considering the current state of the network environment. In this research, we present the Multi-Agent Soft Actor-Critic (MASAC) algorithm, which offers superior convergence and stability compared to the existing Multi-Agent Deep Deterministic Policy Gradients (MADDPG) algorithm.

4.4.1. Design of a Multi-Agent Reinforcement Learning-Based Distributed Regulation and Control System for UAV Base Stations

In addressing the coverage optimization challenge for a large-scale post-disaster user scenario, This part introduces a distributed intent-based coverage optimization framework. Within this architecture, the network feature layer assumes responsibility for clustering the extensive ground user population, selecting key user feature data from the cluster centers, and serving as the input layer for the trajectory control module in the multi-agent reinforcement learning system.

The trajectory regulation layer employs a multi-agent deep reinforcement learning approach, utilizing the Markov decision process to remodel the trajectory regulation problem. This transformation turns the global optimization problem into a series of reinforcement learning optimization objectives, focusing on maximizing network spectral efficiency over time. The design leverages reward functions and value functions to iteratively adjust the flight trajectory of the UAV base station.

Consequently, the distributed regulation design for UAV base stations based on multi-agent reinforcement learning operates as follows:

State: Each UAV base station extracts specific observable information as an input state. This information includes:

- The coordinates of the UAV base station itself.
- Two-dimensional relative positioning with respect to the ground cluster's central user.
- Signal-to-noise ratio of user information received by the cluster center.
- Three-dimensional relative positioning with neighboring drones (Mj).

Action: Considering the UAV base station's freedom of movement in three-dimensional space, its output actions are characterized by its speed in three directions: x-axis, y-axis, and z-axis.

Reward: The reward function comprises three components:

- Flight safety penalty value.
- Communication interruption penalty value.
- Spectrum efficiency reward value.

These components work together to guide the optimization process.

$$r_j = R_j(t) - \xi_{collision} I^j_{collision} - N_j P^j_{outage}(t)\, \xi_{outage} I^j_{outage} \qquad (4.29)$$

In the given context, where "outage Pj(t)" represents the instantaneous communication interruption probability and "j(Rt)" signifies the instantaneous network spectral efficiency, "$\xi_{collision}$" and "ξ_{outage}" serve as constants for security and communication penalties when the UAV base station "j" encounters collisions or exits the specified area. When "I_{outage}" equals 1, it diminishes the reward function's magnitude in response to these events during the multi-agent reinforcement learning training process. This, in turn, aids in minimizing the likelihood of such occurrences and guides the UAV base station's flight strategy.

Furthermore, "$\xi_{collision}$" and "ξ_{outage}" are predefined hyper-parameters that remain constant throughout the optimization process. Regarding interactions, the multi-agent reinforcement learning MASAC algorithm necessitates fitting the adjacent action-state value function. The reward function also relies on the communication signal-to-noise ratio and spectrum utilization efficiency of neighboring UAV base stations in its calculation process. To achieve this, it engages with "M_j" neighboring UAV base stations, including:

- The coordinates of the UAV base station itself.
- The UAV base station's output actions.
- Two-dimensional relative positioning with respect to the central user within the ground cluster.
- The signal-to-noise ratio of user information received by the cluster center.
- The spectral efficiency of the UAV base station at the current time.

This part will introduce the Multi-Agent Soft Actor-Critic (MASAC) algorithm, a form of multi-agent maximum entropy reinforcement learning, based on the aforementioned trajectory regulation design using multi-agent reinforcement learning. Additionally, it will explore fusion ensemble learning and course learning techniques aimed at enhancing the training stability and convergence speed of the algorithm.

4.4.2. Maximum Entropy Reinforcement Learning for Multiple Agents

In the face of a dynamic and uncertain emergency communication network environment, reinforcement learning leverages the Markov decision process to create a model. It acquires observations from the environment, which form the state s_t. Subsequently, it selects a strategy based on the action $\pi(a_t|\ s_t)$, produced by the policy π, to control the flight trajectory of the UAV base station. The agent then executes these actions, engages in interactions with the environment, assesses communication network coverage performance, and computes the reward function r_t.

As the environment transitions from its current state st to the next state s_{t+1}, facilitated by the state transition distribution $P(s_{t+1}|s_t, a_t)$ at time t, the action selection strategy of the reinforcement learning agent becomes closely tied to the state-action value function $Q(s_t, a_t)$. This function characterizes the expected cumulative reward over the long term when selecting action at for the UAV base station under state s_t, taking into account the extended period of emergency communication network coverage.

$$Q(s_t, a_t) = r_t + \gamma E_{S_{t+1} \sim p_s}[V(s_{t+1})] \tag{4.30}$$

The function $V(s_t)$ at time t represents the state value function, which serves as a metric to describe the anticipated value of long-term rewards for emergency communication network coverage performance that the UAV base station can achieve, starting from state st. The parameter γ denotes the discount factor, and it ensures the convergence of the reinforcement learning strategy iteration when it satisfies the condition $0 < \gamma \leq 1$. The state value function is essential for this convergence process.

$$V(s_t) = E_{a_t \sim \pi}[Q(s_t, a_t) - \alpha log\pi(a_t|s_t)] \tag{4.31}$$

The term $\alpha log\pi(a_t|s_t)$ at time t represents an entropy regularization component. This entropy regularization aligns with the optimization process of the action selection strategy. The algorithm's strategy output exhibits multi-modal characteristics, effectively addressing the dynamics and complexity of the learning environment, ultimately enhancing algorithm convergence stability. The parameter α in the entropy regularization term is the temperature factor, and its influence weight can be self-adjusted.

In scenarios with multiple agents within the network, agent i can solely access local observations o_i^t. The environmental state transition is influenced by the collective action outputs of multiple agents simultaneously. Consequently, the environmental state transition distribution changes to agent i. In such a non-stationary state, conventional single-agent reinforcement learning struggles to converge. The multi-agent reinforcement learning MADDPG algorithm addresses this issue by fitting the global state-value function $Q(o_i^t, a_i^t, o_{-i}^t, a_{-i}^t)$ using observations and output actions of other agents, stabilizing agent i's learning environment. Here, -i represents all agents other than agent i.

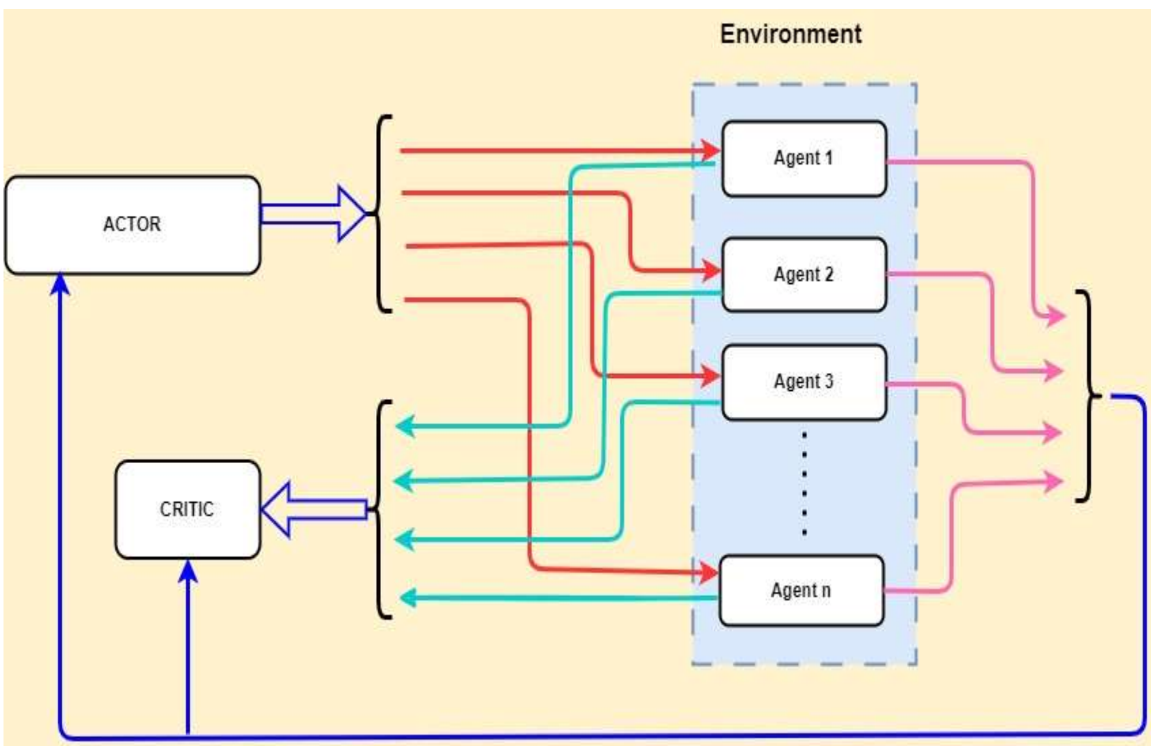

Figure 4.6. Multi-agent reinforcement learning MASAC agent structure

Figure 4.6 illustrates a Multi Agent Soft Actor-Critic (MASAC) framework used in reinforcement learning for environments involving multiple agents. In this setup, the centralized Actor module generates actions based on the current state observations and sends them to each agent (shown by red arrows). These agents (Agent 1 to Agent n) interact with the environment, execute their respective actions, and receive updated observations and rewards (shown by pink arrows). The Critic module evaluates the effectiveness of the agents' actions by collecting feedback from all agents (green and cyan arrows), calculating value functions or advantages, and sending learning signals back to the Actor (blue arrows) to improve its decision-making policy. This closed-loop structure allows continuous learning and coordination among agents, ensuring optimized behavior in dynamic and cooperative environments

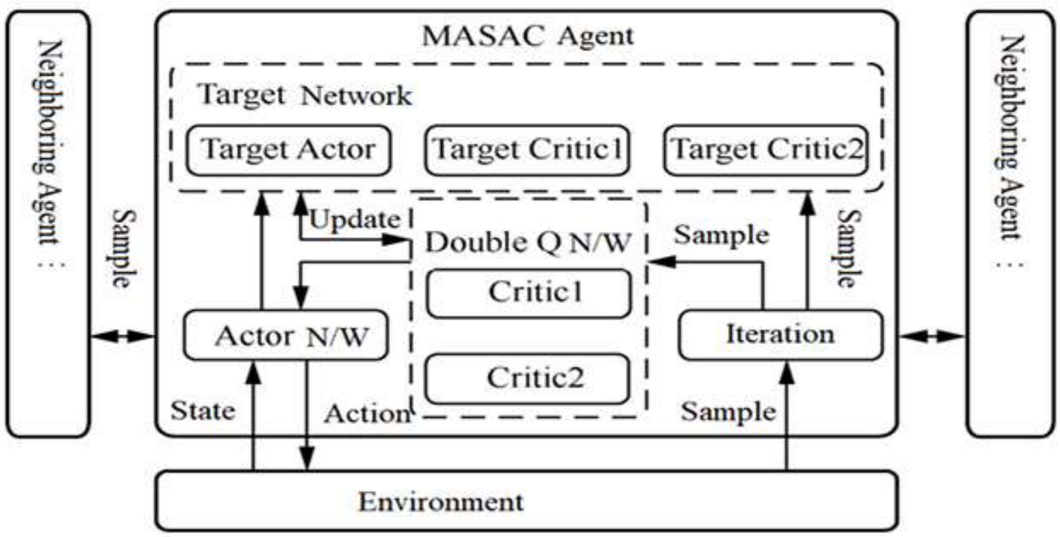

Figure 4.7. Detailed block diagram of multi-agent reinforcement learning MASAC agent structure

This work, building upon the Maximum Entropy Reinforcement Learning Soft Actor-Critic (SAC) algorithm and the Multi-Agent Deep Deterministic Policy Gradients (MADDPG) algorithm, adapts and enhances the adjacent state value function fitting from the SAC algorithm. This adaptation reduces communication overhead while ensuring algorithm convergence, facilitating distributed deployment of the algorithm.

As depicted in Figure 4.7, each MASAC agent comprises six neural networks and one empirical replay buffer. The Actor network defines the action selection policy, denoted as $\pi^{\theta}{}_{i}$, with θ_i representing its neural network parameters. It takes the local observation state oti as input and generates the mean ($\mu_{\theta i}$) and standard deviation ($\sigma_{\theta i}$) of the action output distribution for the observed state. This distribution is represented as $\pi_{\theta i}$ and serves as the action selection strategy for agent i at time t.

The Double Q network consists of two neural networks: Critic1 and Critic2 networks, which estimate the state-value functions as $Q_{\theta_2^i}$ and $Q_{\theta_3^i}$, respectively. These neural networks have parameters θ_1^i and θ_3^i, respectively. By fitting two state-value functions, they mitigate the overestimation issue associated with a single Critic network, as discussed in reference [22].

The Target network encompasses three neural networks: Target Actor $\pi_{\theta_4^i}$, Target Critic1 $\pi_{\theta_5^i}$, and Target Critic2 $Q_{\theta_6^i}$. These networks share the same architecture as the Actor network and the Critic networks but update their parameters at a slower rate. This deliberate slowing of parameter updates enhances training stability and accelerates algorithm convergence. The experience replay buffer is employed to store samples of agent interactions, where information about neighboring agents is obtained through inter-agent communication. During training, the agent samples from this replay buffer and randomly selects a sample set D to compute gradients for optimizing its objectives.

The objective of action selection strategy is to maximize the state-action value function. Therefore, the optimization objective for network can be formulated as follows

$$J_\pi(\theta_1^i)=E_{(o_t,a_t)\sim D}\left[\alpha \log \pi_{\theta_1}\left(\hat{a}_t^i \middle| o_t^i\right) - \min_{i=2,3} Q_{\theta_i}\left(o_t^i, a_t^i, o_t^{-i}, a_t^{-i}\right)\right] \tag{4.32}$$

Given that the Actor network generates a distribution function rather than a precise action value, it becomes necessary to represent the output action numerically when computing the gradient for the optimization objective. To accomplish this, we employ the weighted parameter technique to derive an estimated action value.

$$\hat{a}_t^i = \tanh\left(\mu_{\theta_i}\left(o_t^i\right) + \sigma_{\theta_i}\left(o_t^i\right)\epsilon_t^i\right) \tag{4.33}$$

Here,ε_t^i represents a Gaussian noise vector with a mean of 0, which is independent of the action selection strategy. The Critic network is designed to approximate the state-action value function, and thus, the optimization objective can be described in terms of the temporal difference error.

$$J_Q(\theta_{2,3}^i) = E_{(o_t,a_t,r_t,o_{t+1})\sim D}\Bigg[\Bigg(Q_{\theta_{2,3}^i}(o_t^i, a_t^i, o_t^{-i}, a_t^{-i}) - \Bigg(r_t + \gamma\ \Bigg(\min_{j=5.6} Q_{\hat{\theta}_{2,3}^i}(o_{t+1}^i, a_{t+1}^i, o_{t+1}^{-i}, a_{t+1}^{-i}) - \alpha \log\Big(\hat{\pi}_{\theta_4^i}\big(a_{t+1}^i \big| o_{t+1}^i\big)\Big)\Bigg)\Bigg)\Bigg)^2\Bigg]_{a_{t+1\sim\hat{\pi}_{\theta_4^i}}} \tag{4.34}$$

Based on the above optimization objectives, the network parameters are updated to

$$\theta_1^i \leftarrow \theta_1^i + \eta_1 \nabla_{\theta_1^i} J_\pi(\theta_1^i) \tag{4.35}$$

$$\theta_{2,3}^i \leftarrow \theta_{2,3}^i + \eta_{2,3} \nabla_{\theta_{2,3}^i} J_Q(\theta_{2,3}^i) \tag{4.36}$$

$$\theta_{4,5,6}^i \leftarrow \eta_{4,5,6}\theta_{4,5,6}^i + (1 - \eta_{4,5,6})\theta_{1,2,3}^i \tag{4.37}$$

Here, η represents the neural network update step. During the iterative exploration and training process, the agent acquires fresh samples from the environment and stores them in the experience replay buffer. Subsequently, it randomly selects batch samples from this buffer for training, following Equation (4.42) through Formula (4.34), enabling the agent to learn the optimal action selection strategy.

4.4.3. Combining learning and curriculum learning

The multi-agent reinforcement learning algorithm effectively addresses the non-stationary in multi-agent learning environments, and the MASAC algorithm adapts to complex dynamic settings. However, both multi-agent and maximum entropy reinforcement learning algorithms introduce complexity to neural networks. Therefore, this work employs ensemble learning [23] and curriculum learning [24] techniques to enhance the speed and stability of algorithm convergence.

Stable Convergence Technique Based on Ensemble Learning: This approach combines ensemble learning, where multiple sets of neural networks are trained through bootstrapping. It collects feedback during the decision-making process, identifies sub-optimal networks for pruning, and retains high-performing networks to prevent catastrophic forgetting. This technique enhances the stability of the algorithm convergence process. Figure 4.8 provides a detailed overview of the implementation architecture for stable convergence technology based on ensemble learning. Each UAV base station's agents simultaneously train multiple sets of neural networks, forming an ensemble learning neural network set W. In the "distributed training" phase, independent sample sets from W groups, denoted as W1, W2, ..., WD, are drawn from the experience replay buffer, and all neural networks within W undergo training.

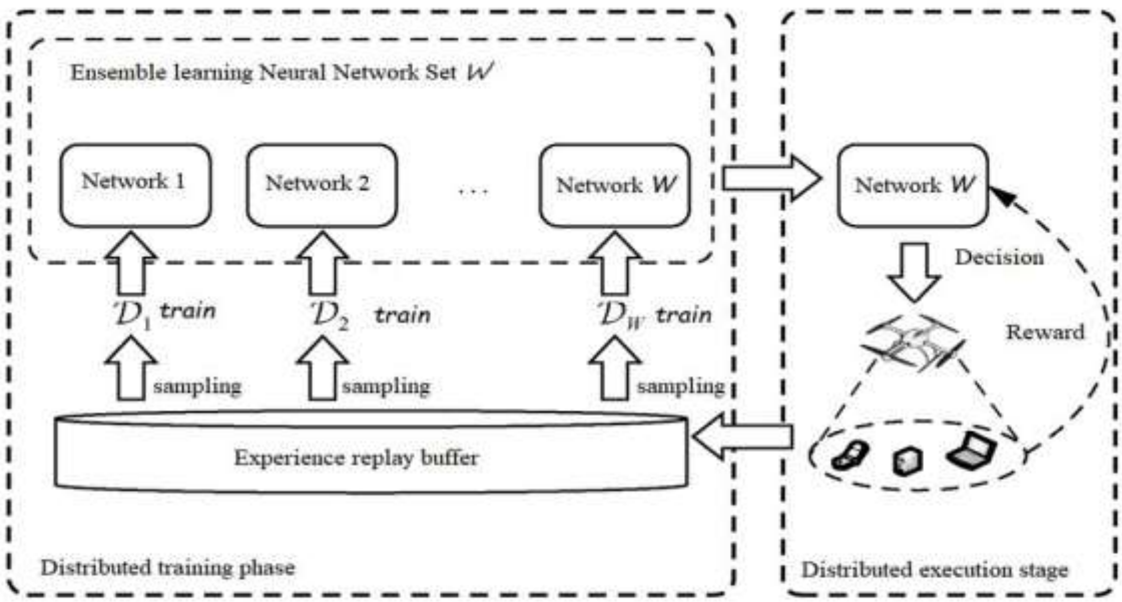

Figure 4.8. Implementation architecture of stable convergence technology based on ensemble learning

During the "distributed execution" phase, an agent randomly selects a neural network w from W to make decisions for the UAV base station, receive a reward rm, and update the cumulative reward w for the chosen neural network w.

$$r_m^{(w)} = \tau_w r_m^{(w)} + (1 - \tau_w) r_m \tag{4.38}$$

Here, τ_w represents the update step for the cumulative reward of the neural network. Furthermore, update the maximum cumulative reward r_m^{Wmax}within the neural network set W.

$$r_m^{W_{max}} = max\left(r_m^{W_{max}}, r_m^{(w)}\right) \tag{4.39}$$

If the cumulative reward r_m^w of neural network w significantly lags behind the maximum cumulative reward (r_m^{Wmax}) within the neural network set, pruning is initiated on neural network w. The neural network with the highest cumulative reward value among the remaining networks in W is then duplicated to replace the pruned neural network w. Through this ensemble learning design, MASAC agents can identify and prune neural networks that have suffered catastrophic forgetting, leading to significant performance degradation during training. This selection of neural network inheritance helps expedite the algorithm's convergence process.

- Accelerated Convergence Technique Based on Curriculum Learning: This approach divides learning tasks into multiple sub-tasks, arranged from easy to difficult based on their physical significance. It designs reward functions for each sub task, ranging from simple to complex, to reduce learning complexity and enhance algorithm convergence speed. Employing the concept of curriculum learning.
- UAV base station's task of maintaining flight within a fixed area.
- The objective of reducing communication service interruptions by adjusting the UAV base station's flight trajectory, where interruptions occur when the signal-to-noise ratio at the UAV base station receiving user information from the cluster center falls below a threshold.
- Optimizing flight trajectories of the UAV base station to maximize network spectral efficiency.

Consequently, the reward functions for these three sub-tasks can be designed as follows:

$$r_A = -\xi_{collision} I_{collision}^j \tag{4.40}$$

$$r_B == -\xi_{collision} I_{collision}^j - N_j P_{outage}(t) \xi_{outage} I_{outage}^j \tag{4.41}$$

$$r_C = R_j(t) - \xi_{collision} I_{collision}^j - N_j P_{outage}(t) \xi_{outage} I_{outage}^j \tag{4.42}$$

It's important to highlight that learning more complex course material may lead neural networks to forget what they've learned in simpler lessons, potentially resulting in catastrophic forgetting. In the reward design for these advanced courses, it's essential to incorporate rewards from simpler courses, as demonstrated in Equation (41) and Equation (42). This collaborative approach, combined with the sub-network pruning technique of integrated learning, helps mitigate the impact of catastrophic forgetting.

The MASAC-based multi-UAV trajectory distributed regulation algorithm, which integrates ensemble learning and curriculum learning techniques, is presented in Algorithm 3. This algorithm effectively reduces the frequency of communication interruptions within the network, ultimately enhancing network spectral efficiency.

Algorithm 3*: MASAC-based Multi-UAV Trajectory Distributed Regulation Algorithm*

1. *Initialize the time step t to 0.*
2. *Loop while t is less than or equal to t:*
3. *Retrieve the observed state o_i^t from the environment.*
4. *Randomly select a set of neural networks from the ensemble learning neural network set W and input the observation state o_i^t into the actor network to produce the action a_i^t.*
5. *Execute the selected actions, interact with the environment, and obtain the signal-to-noise ratio and spectral efficiency of user information at the cluster center at the current moment.*
6. *Communicate with neighboring drones, calculate the reward for the current curriculum learning task, and update the state o_i^t+1.*
7. *Record samples and store them in the experience replay buffer.*
8. *Update the cumulative reward r_m^w and the maximum cumulative reward r_m^{Wmax} based on Equation (4.38) and Equation (4.39) to determine whether to proceed to the next curriculum learning stage.*
9. *If r_m^w is significantly lower than r_m^{Wmax}, perform pruning and inheritance operations on neural network w.*

10. *For each neural network in W $(1 \leq n \leq N)$, do:*

11. *Retrieve a batch of samples DN from the experience replay buffer.*

12. *Update the MASAC multi-agent reinforcement learning neural network parameters following Equation (4.35) to Equation (4.37).*

13. *Increment t by 1.*

14. *End the loop when t reaches T.*

4.4.4. Complexity Analysis

During the "distributed execution" stage, each UAV base station must acquire its own local state information and share it with neighboring UAV base stations. This complexity is directly related to the number of adjacent UAV base stations, denoted as M_j. Therefore, the algorithm's complexity at this stage can be expressed as $O(M_j)$.

In the "distributed training" phase, each UAV base station is required to update all W neural networks within the ensemble learning neural network set W. The number of times each neural network needs to calculate gradients is proportional to the batch sample size taken from the experience replay buffer, denoted as ND. Consequently, the complexity of the algorithm during this phase can be represented as O(WN). Given that the number of adjacent UAV base stations, M_j, is significantly smaller than the number of batch samples, ND, the overall complexity of Algorithm 3 can be described as O(WN).

4.4.5. Distributed Coverage Optimization Process for Large-Scale Post-Disaster Users

The proposed distributed intent-based coverage optimization architecture in this work can be categorized into two main layers: the network feature layer and the trajectory regulation layer. The network feature layer serves as the feature extraction stage for multi-agent reinforcement learning and is jointly realized through two algorithms: the user difference learning algorithm based on Bayesian inference (Algorithm 1) and the distributed k-sums algorithm considering user difference (Algorithm 2).

On the other hand, the trajectory regulation layer functions as the strategy implementation stage for the multi-agent reinforcement learning segment and is executed by the MASAC-based multi-UAV trajectory distributed regulation algorithm (Algorithm 3).

4.5 Simulation Analysis

This section evaluates the proposed aerial coverage architecture for large-scale post-disaster users, which is based on multi-agent reinforcement learning, and assesses the effectiveness of the corresponding algorithm through simulation experiments. We assume a scenario with 500 ground users located within a 1km × 1km area in the disaster-stricken region. The flight altitude range for the UAV base station is set between 100 m to 1,000 m.

For the MASAC algorithm, both the Actor and Critic networks employ three fully connected layers in the hidden layer, with 512, 256, and 128 hidden neurons, respectively. The verification of the proposed large-scale post-disaster user distributed coverage optimization scheme based on multi-agent reinforcement learning is conducted on the Python 3.7 platform. NumPy Toolkit is used for the Bayesian inference and distributed K-SUMS clustering algorithms, providing high-speed matrix operations, statistical computations, and efficient handling of large user datasets. NumPy enabled rapid computation of user priority parameters, dissimilarity matrices, and iterative clustering updates through vectorized operations, ensuring low computational overhead. Tensor Flow Toolkit is used to develop and train the Multi-Agent Soft Actor-Critic (MASAC) algorithm. Tensor Flow's deep-learning framework facilitated building neural networks for Actor, Critic, and Target models, enabling GPU-accelerated training and automatic gradient computation. It also supported ensemble and curriculum learning for improved convergence and stability of multi-UAV trajectory optimization. The computing environment comprises Windows 10, an Intel 7th CPU, and a GTX 1060 GPU. Firstly, we validate the effectiveness of the distributed K-Sums clustering algorithm, which considers user differences in underlying optimization. We conduct simulation experiments under varying maximum priority parameters λ_{max} and compare the results with the K-Sums algorithm and the K-Means algorithm.

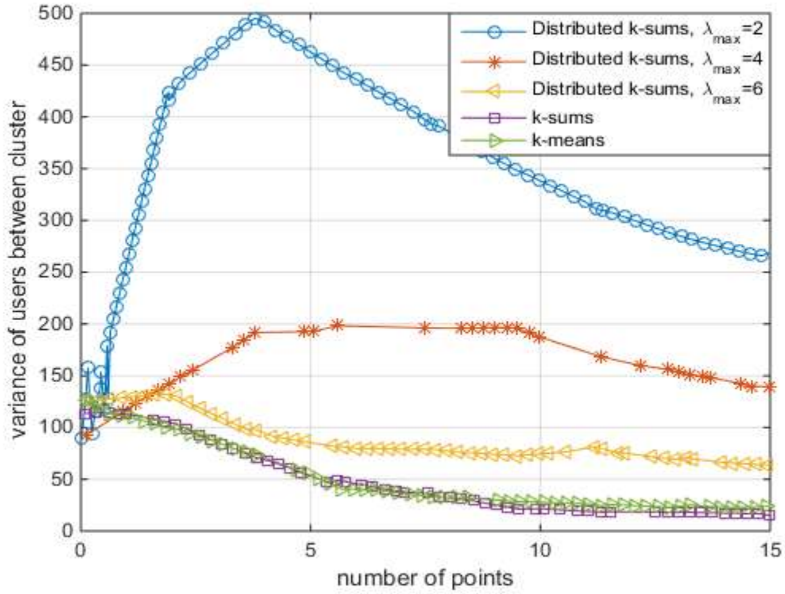

Figure 4.9. Effect of different clustering algorithms on the variance of the number of users between clusters

Figure 4.9 illustrates the impact of different clustering algorithms on the variance in the number of users between clusters. It is evident from Figure 4.9 that the proposed distributed K-Sums algorithm maintains cluster balance similar to the K-Sums algorithm. When user information differences are not considered (λ_{max} = 1), the variance in the number of users between clusters in the distributed K-Sums algorithm is nearly the same as that in the K-Sums algorithm, and considerably smaller than that in the K-Means algorithm. However, as the maximum priority parameter λ_{max} increases, the proposed algorithm tends to prioritize users with higher priority parameters, potentially sacrificing some cluster balance. Consequently, the variance in the number of users between clusters increases.

Figure 4.10 presents the convergence performance of the MASAC algorithm's average cumulative reward, showcasing the impact of ensemble learning and curriculum learning on MASAC's convergence rate and stability within the same simulation environment. The average cumulative reward serves as a crucial indicator for assessing the convergence of reinforcement learning algorithms [151]. It represents the average value of the reward function obtained across all time slots within a training round. Its specific physical interpretation depends on the design of the reward function. In this work, the average cumulative reward reflects the sum of average spectral efficiency, average communication interruption penalties, and security penalties within a training round. As observed both ensemble learning and curriculum learning contribute to increased algorithm convergence rates. However, ensemble learning directly tackles complex tasks and may converge to local optimal strategies with only average performance. Curriculum learning, on the other hand, exhibits catastrophic forgetting after learning Task 1 and Task 2, limiting further improvements in convergence performance. In contrast, MASAC algorithms that combine ensemble learning and curriculum learning can converge to superior strategies with faster convergence while mitigating the impact of catastrophic forgetting. Figure 4.11 demonstrate the impact of various reinforcement learning algorithms on the trajectory regulation learning process of UAV base stations.

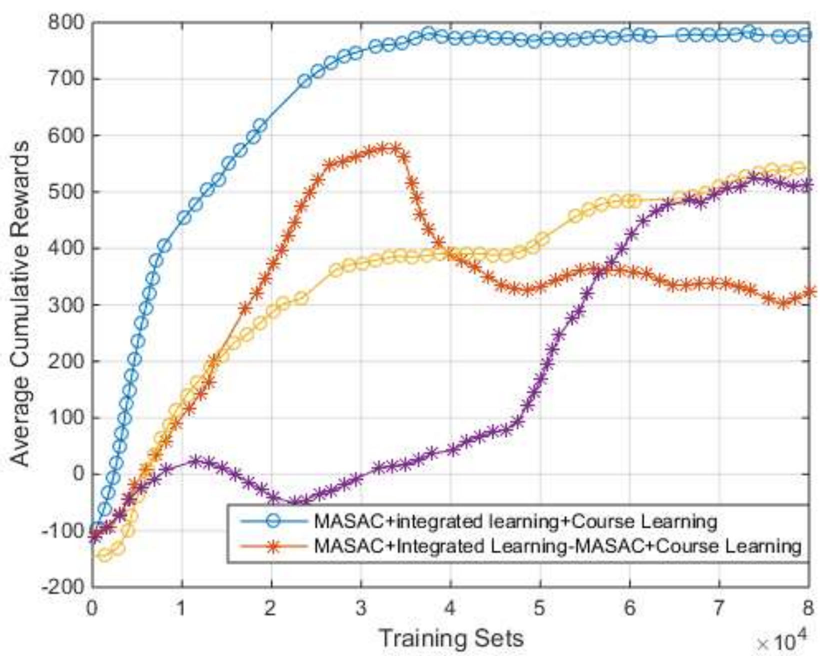

Figure 4.10 Convergence performance of MASAC algorithm averaging cumulative rewards

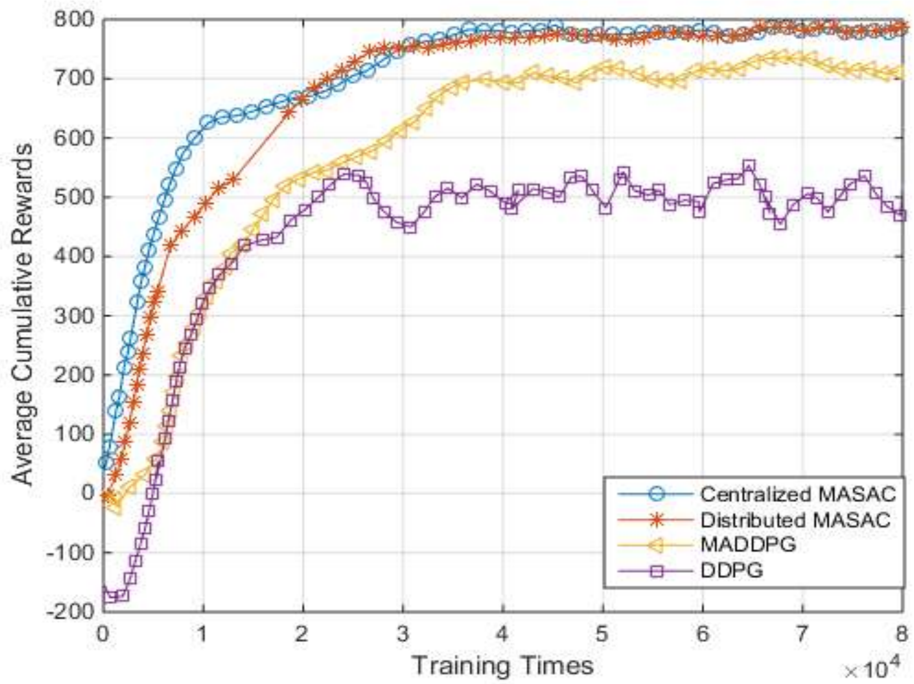

Figure 4.11: Convergence performance of average cumulative reward of different reinforcement learning algorithms

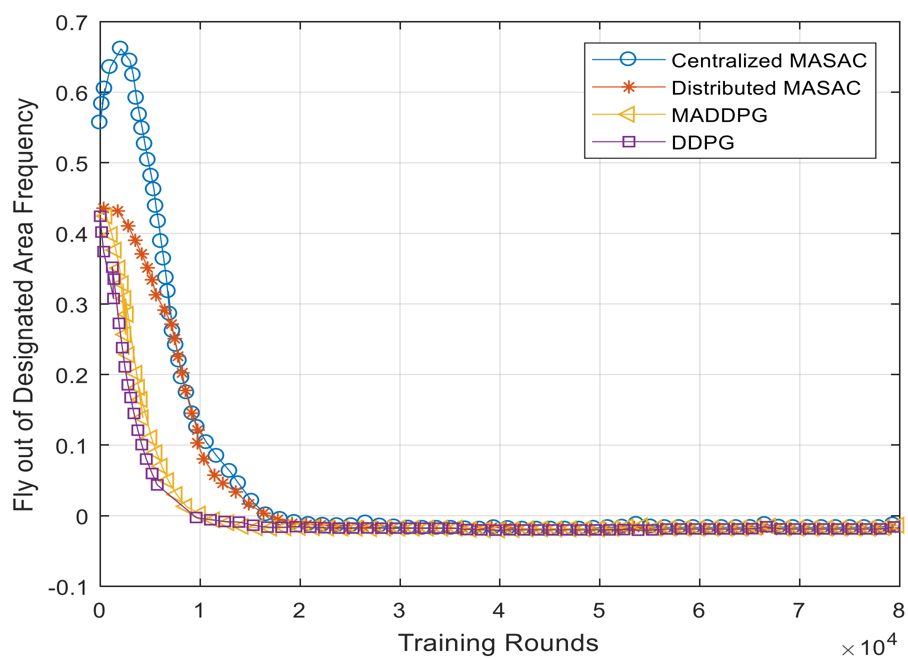

Figure 4.12. The learning effect of different reinforcement learning algorithms on the frequency of task 1− flying out of the specified region

The primary comparison involves the proposed MASAC algorithm with the MADDPG algorithm [139] and the DDPG algorithm [137]. Figure 4.11 illustrates the convergence performance of the average cumulative reward for different reinforcement learning algorithms. Meanwhile, Observing Figure 4.12, it becomes evident that the single-agent reinforcement learning DDPG algorithm rapidly accomplishes the learning for Task 1, which involves flying within the confined 1 km × 1 km area. However, it encounters difficulties in further learning Task 2 and Task 3. This is primarily because the strategic learning for the flight area of each UAV base station does not influence the flight areas of other UAV base stations, rendering the learning environment stable. In contrast as shown in figure 4.13, for Task 2, the changes in UAV base station flight strategies affect the communications of other UAV base stations, creating an unstable learning environment.

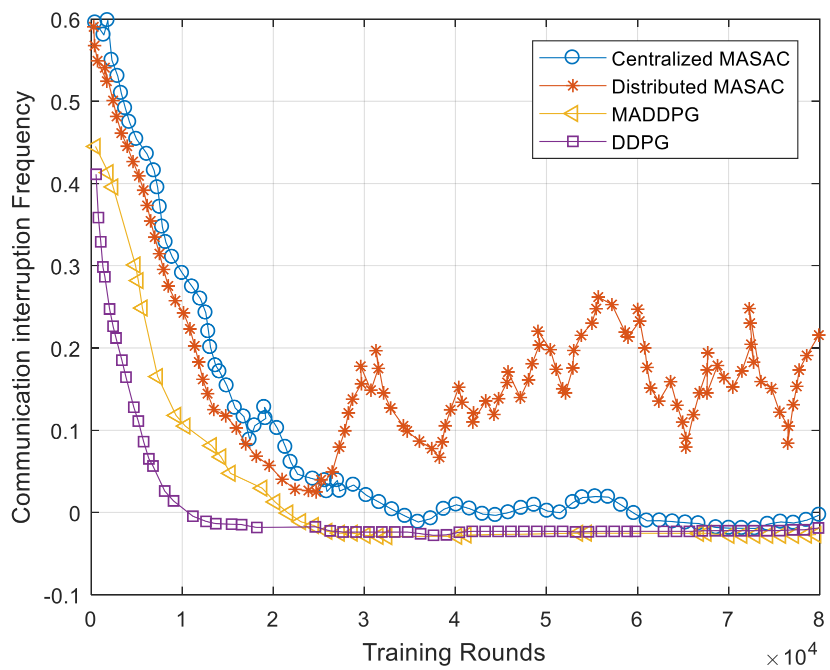

Figure 4.13. Learning effect of different reinforcement learning algorithms on task 2-communication interruption probability

When comparing the multi-agent reinforcement learning MASAC algorithm and the MADDPG algorithm, both algorithms successfully complete the learning for Task 1 and

Task 2. However, the MADDPG algorithm exhibits poor convergence performance and stability due to its deterministic strategy algorithm.

Additionally, the MADDPG algorithm's learning performance for Task 3, focusing on spectral efficiency, lags behind that of the MASAC algorithm. Furthermore, the simulation compares the centralized MASAC algorithm, which obtains the global state, with the distributed MASAC algorithm, which acquires the adjacent state. It is noteworthy that the distributed MASAC algorithm achieves a similar level of convergence as global optimization while substantially reducing communication overhead, as it only requires the status of neighboring drone base stations.

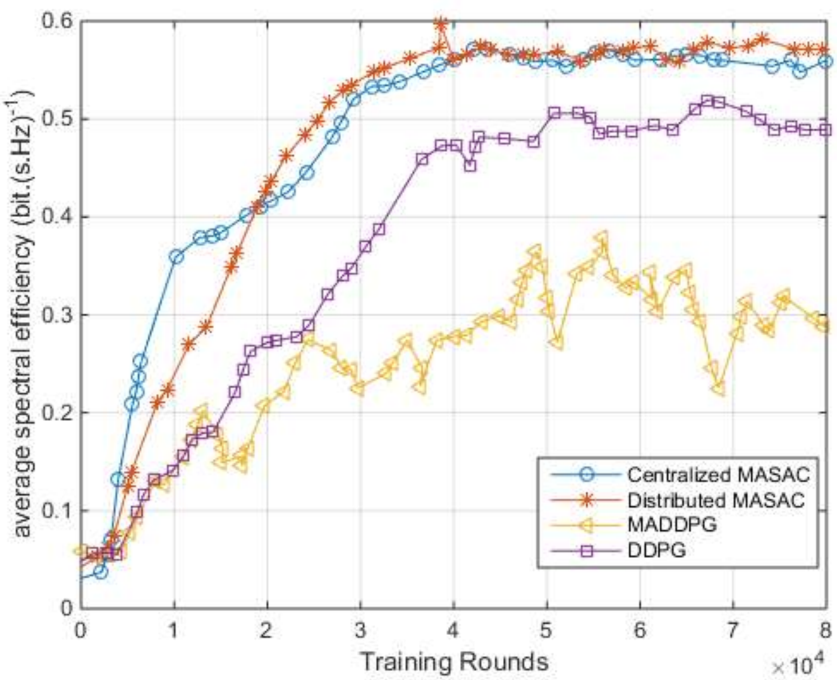

Figure 4.14. Learning effect of different reinforcement learning algorithms on task 3-average spectral efficiency

Figure 4.14 illustrates the impact of the number of UAV base stations on average spectral efficiency. From Figure 4.14, it becomes evident that the spectral efficiency of the DDPG and MADDPG algorithms decreases as the number of UAV base stations increases. This decline can be attributed to the increased complexity and non-stationary of the learning environment, which challenges the effectiveness of these algorithms. As the number of

UAV base stations rises, both DDPG and MADDPG algorithms exhibit reduced spectral efficiency. Conversely, the MASAC algorithm proposed in this work, achieves higher spectral efficiency by jointly regulating the flight trajectories of UAV base stations when the number of UAV base stations is small. However, as the number of UAV base stations continues to increase, each UAV base station experiences interference from more neighboring UAV base stations, resulting in a decline in spectral efficiency. Furthermore, when comparing the centralized MASAC algorithm with the distributed MASAC algorithm, distributed optimization can achieve similar or even improved performance compared to global optimization. This advantage arises due to lower state input dimensions and smaller neural network sizes in scenarios with a large number of drones.

4.6 Summary

The contribution of this research is the deployment of UAVs using the Multi-Agent Soft Actor-Critic (MASAC) algorithm, which establishes a distributed learning framework for optimal trajectory planning and user service allocation in dynamic environments. Unlike traditional optimization methods that rely on static parameters and fail to adapt to real-time user mobility and interference, MASAC enables decentralized decision-making where each UAV functions as an autonomous agent with partial observability but shared learning objectives, thereby reducing computational overhead and enhancing responsiveness. Its entropy-regularized exploration strategy ensures continuous policy improvement and avoids convergence to suboptimal solutions. Integrated with distributed K-SUMS clustering algorithm, MASAC allows UAVs to group users intelligently based on service demands and signal quality, ensuring balanced load distribution and efficient resource utilization. This approach makes UAVs highly adaptable to real-world challenges such as user fluctuations and environmental disruptions common in post-disaster scenarios. Simulation results demonstrate that MASAC significantly outperforms conventional models like DDPG and MADDPG in terms of spectral efficiency, reduced communication interruptions, and effective cluster formation, presenting a robust and scalable solution for resilient UAV-assisted wireless networks.

CHAPTER 5

AI-BASED APPROACH FOR POWER OPTIMIZATION OF UAV

5.1 Introduction

Unmanned Aerial Vehicles (UAVs), sometimes known as drones, have recently become a disruptive technology with great potential in various applications, including wireless communication networks. These possess the capacity to offer adaptable and immediate connectivity options, rendering them a useful asset in forthcoming wireless communication networks. Nevertheless, UAVs' effective implementation and energy efficiency in these networks provide intricate obstacles that require creative resolutions. Within this particular context, an approach exhibits significant potential for effectively tackling these issues and unleashing the complete capabilities of UAVs in upcoming wireless communication systems. UAVs can serve multiple functions in future wireless communication networks as shown in figure 5.1. An essential use of UAVs in this situation is expanding networks. Network expansion through UAVs entails deploying aerial vehicles to establish temporary or long-term wireless access in areas lacking sufficient network coverage. This technique has numerous benefits and has substantial potential to tackle connectivity obstacles in diverse situations. UAVs can be deployed to regions with restricted or nonexistent network coverage, providing temporary connectivity during crises or special occasions. UAVs can help reduce the burden on overwhelmed base stations in highly crowded regions, thus improving network efficiency. In addition, UAVs can quickly and efficiently create impromptu networks in areas affected by disasters or in remote locations while keeping costs low. They also fulfil functions such as surveillance, monitoring, and data collection, improving network administration and security. Effective power management is essential for the sustainable and efficient functioning of UAVs. As they usually depend on batteries, managing their energy resources carefully for their deployment and performance is crucial. Within this context, we explore the complexities of maximizing power efficiency for UAVs operating in wireless communication networks. Future UAVs are expected to reap the advantages of progress in battery chemistries, increased energy densities, and improved charging capabilities. This will allow them to store more energy on board and quickly recharge between missions. UAV makers consistently work towards improving energy efficiency by developing lightweight materials, efficient motors, and low-power electronics. These hardware enhancements directly contribute to longer flight periods and less power usage. UAVs also benefit from carefully designed flight paths and mission strategies that attempt to maximize energy efficiency. These plans consider target distances, necessary heights, wind conditions, and the energy consumption linked to different flight maneuvers.

UAVs can be directed along optimal routes to minimize energy consumption. In addition, power optimization involves the dynamic allocation of UAVs to particular tasks according to their battery levels and mission priorities. UAVs with larger battery capacities can be designated for activities that need longer flight periods. In contrast, UAVs with lower battery levels can be used for shorter missions. In the future, UAVs may use energy-collecting technology like solar panels or wind turbines to replenish their batteries while flying. These technologies possess the capacity to greatly increase the duration of flights, particularly in areas with ample sunshine or wind resources. UAVs with sensors and communication devices gather up-to-date information about network conditions, user requests, and environmental elements. Analyzing this data enables the making of well-informed judgments regarding mission adjustments. For example, an unmanned aerial vehicle UAV may opt to hover or stay still in a specific location when there is less network activity to preserve energy until necessary. Adaptive algorithms can adjust and accommodate changing situations when a UAV faces unforeseen obstacles, such as unfavorable while carrying out a mission.

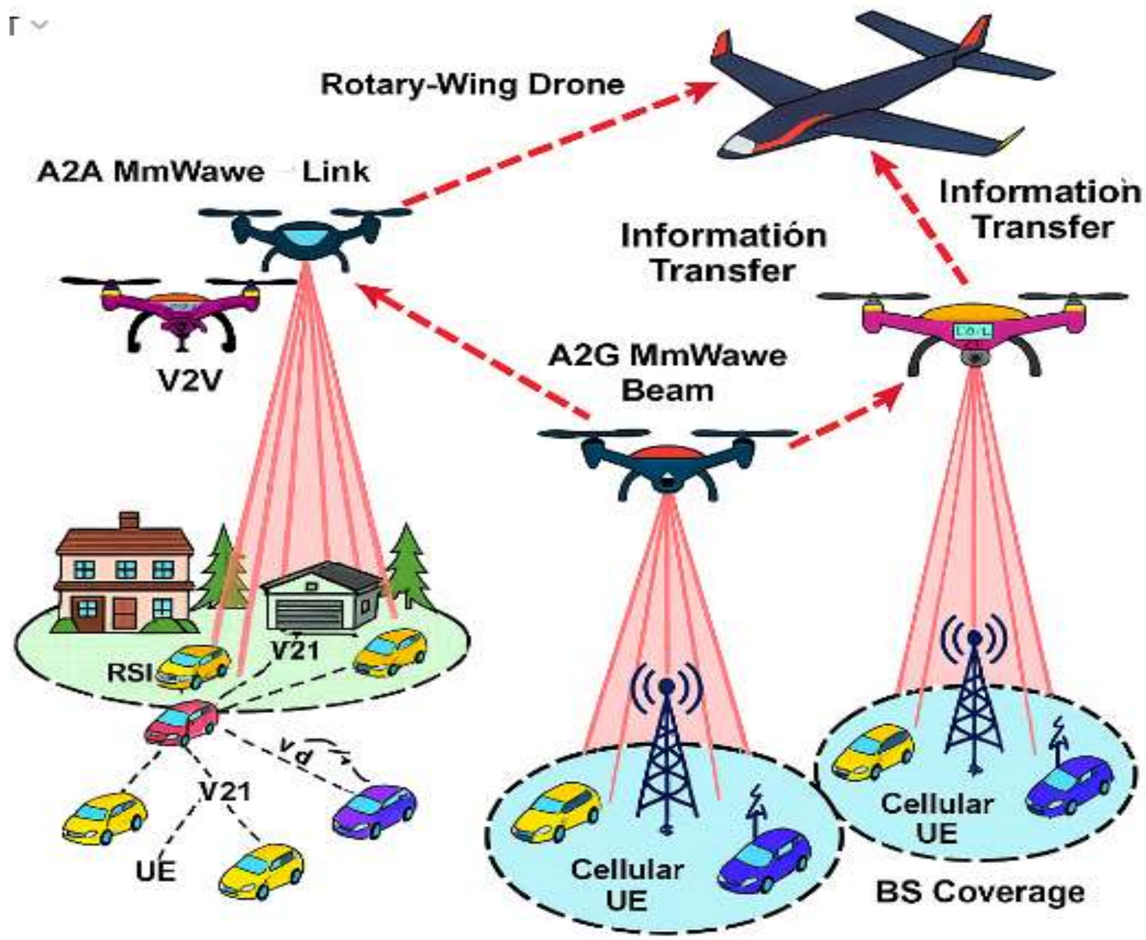

Figure 5.1 UAV-Assisted wireless communication network

In the presence of weather conditions or signal interference, the algorithm can adjust the flight plan to optimize energy usage and guarantee the accomplishment of the goal.

Monitoring the battery health in limited wireless networks is of utmost importance. Predictive maintenance algorithms can assess battery performance and lifespan, thereby preventing catastrophic failures and prolonging the total lifecycle of the UAV. Power optimization also considers user demand patterns. UAVs can be strategically positioned in regions with high user activity or network congestion to reduce wasted flights and conserve energy. UAVs establish and maintain communication with ground stations, which continuously offer up-to-date information on network conditions and mission parameters. This communication enables UAVs to make well-informed decisions to optimize their power consumption. Therefore, the optimization of power for UAVs in upcoming wireless communication networks requires technological improvements, effective energy management, and strategic decision-making. UAVs can travel large distances, stay connected continuously, and operate for longer periods of time by optimizing their power usage.

5.2. Leveraging Random Forests (RF) and Support Vector Machines (SVM)

To address the aforementioned challenges, this chapter considering the deployment and power optimization of UAVs in future wireless communication using AI-based approaches like RRF and SVM, several unique aspects and differentiation points can be highlighted

5.2.1. Unique Features of Random Forests (RF):

- *Collaborative Learning and Robustness:*

Random Forest is an ensemble learning method that combines many decision trees to improve accuracy and generalizability. By merging results from many trees, RF can provide trustworthy predictions in the context of UAV deployment to handle noise and variability in wireless communication conditions.

- *Qualitative Relevance and Readability:*

Radiofrequency offers a feature importance metric that can be utilized to identify critical factors affecting UAV deployment and power optimization. This interpretability can assist make it easier to understand how different variables relate to one another and how that affects performance.

- *Non-linear Links:*

In complicated settings where traditional linear approaches may not fully capture the dynamics of UAV deployment and optimization, RF's ability to capture non-linear linkages between input variables and output responses is essential.

5.2.2. Unique Features of Support Vector Machines (SVM):

i. Margin Maximization for Reliable Classification of Communication States

In UAV-assisted wireless communication systems, it's critical to accurately classify network states, such as LoS vs. NLoS conditions, user demand levels, or interference zones. SVM's unique margin maximization property ensures that these different communication states are classified with the highest confidence and separation. By identifying a hyperplane that provides the maximum margin between classes, SVM helps UAVs make robust and accurate decisions, such as where to reposition, how to adjust transmission power, or which user cluster to serve. This is especially vital in dynamic environments like post-disaster areas, where ground conditions are highly variable.

ii. Kernel Trick for Handling Non-Linear Wireless Environments

UAV communication environments are inherently non-linear due to multipath fading, obstacles, user mobility, and irregular terrains. SVM addresses this by using the kernel trick, which transforms the non-linear spatial or signal features into a higher-dimensional space where they become linearly separable. For instance, classifying user connectivity quality (high/medium/low) based on parameters like altitude, distance, SNR, and angle of arrival may not be linearly separable. Here, a radial basis function (RBF) kernel can help learn these complex boundaries, allowing UAVs to optimize their beamforming angles or resource allocation strategies effectively.

iii. Sparse Support Vector-Based Decisions for Fast Real-Time Operation

In a UAV-assisted system, computational efficiency is critical, especially when UAVs operate with limited onboard processing power and energy constraints. SVM is uniquely suited for such scenarios because it builds its decision boundary using only the support vectors, i.e., a subset of critical training data. Once trained, the model ignores all other data points, leading to fast prediction times with minimal memory and power usage. This allows UAVs to make real-time decisions for example, whether to act as a relay node, change flight path, or reassign bandwidth without requiring extensive computation.

ii. Global Optimization Ensures Stable and Trustworthy UAV Decisions

In safety-critical applications like emergency rescue or military communication, the reliability of UAV decisions is paramount. SVM offers a significant advantage because its training involves a convex optimization problem, which guarantees a unique and globally optimal solution. This means that once trained, the SVM model will always produce the same output for the same input, offering predictable and stable behavior. UAVs relying on such models can consistently select optimal routes, communication modes, or user scheduling plans without being affected by random training variations, as may occur in neural network-based systems.

5.2.3. Hybrid Approach of Random Forest and SVM Technique in Wireless Communication

In wireless communication, combining a hybrid technique of Random Forest and Support Vector Machines has the following benefits:

- *Increased Classification Accuracy**:***

Random Forests are renowned for their resilience and capacity to manage big, highly dimensional datasets. On the other hand, SVMs work well for determining the ideal decision border between classes. The hybrid model, which combines these two methods, can take advantage of each one's advantages to outperform either model alone in terms of classification accuracy.

- *Enhanced Robustness:*

Random Forests are less prone to overfitting due to their ensemble nature (combining multiple decision trees). SVMs, with proper regularization parameters, can also generalize well to new data. Combining them can mitigate individual weaknesses, resulting in a more robust model that performs well on various types of wireless communication data.

- *Feature Selection and Interpretability:*

Random Forests naturally perform feature selection by evaluating the importance of different features in the classification process. SVMs, with proper kernel selection and regularization, can also focus on the most relevant features. The hybrid approach can leverage this dual capability to identify and utilize the most informative features for classification tasks in wireless communication.

- *Scalability:*

Both Random Forests and SVMs are scalable to large datasets, which is beneficial in wireless communication scenarios where data volume can be significant. The hybrid approach can maintain computational efficiency while handling complex data structures commonly found in wireless communication systems.

- *Versatility:*

Wireless communication data often exhibits complex patterns and non-linear relationships. SVMs excel in capturing non-linear relationships through kernel methods, while Random Forests handle non-linearities implicitly through ensemble learning. Integrating these two approaches allows the hybrid model to handle a wider range of data patterns and complexities effectively.

- *Adaptability to Noise and Variability:*

RF-SVM hybrids can handle noisy data more effectively. Random Forests are robust to noisy data due to their averaging effect over multiple decision trees, while SVMs can minimize the impact of outliers by focusing on the support vectors that define the decision boundary.

5.3 System Model

It is one of the ML framework's data mining instruments. It can be applied to time series forecasting, regression issues, and classification. A group of decision trees from the random training set make up the RF classifier. To ascertain the test object's ultimate class, it aggregates the votes from many decision trees.

From the node to the final leaf, it has a number of decision pathways that are protected by a sub-feature. The mean value of the uppermost region covered by the training set plus the sum of the individual features makes up the prediction. In a training dataset= $(xi, yi), i = 1, 2, \ldots, n$, $(X, Y) \in Rm$ × R, the goal vector is represented by the output vector Y, while the input matrix X comprises n samples with m characteristics. Using the bootstrap resampling approach, the RF randomly selects N tree sample sets $Sk, k = 1, 2, \ldots, N$ tree) from the original sample set S. Sk has the same amount of elements as S (where k is the number of iterations).

About one-third of the data in the initial sample set S-referred to as out-of-bag (OOB) data-are not drawn in bootstrap samples; the remaining data are referred to as in-bag data shown in Eq. 5.1.

$$MSE_{OOB} = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_{iOOB})^2 \quad (5.1)$$

The Pi_{OOB} is the average of the OOB's predictions across all trees and "n" is the observation number.

Thus, the two main factors influencing the RF model's ability to estimate are the total number of trees in the forest and the amount of variables used to construct each tree. The OOB calculates the mean square error of the model, which is a technique for estimating prediction error and determining the significance of the variable.

The ensemble learning model Random Forest (RF), which is used for regression and classification, is built using several decision trees. Bootstrapping is used to increase the diversity of each tree. In RF, each decision tree is trained. The training set will be used as

$$T_d = \{(x_1, y_1), (x_2, y_2) \ldots\ldots (x_n, y_n)\} \quad (5.2)$$

$$E(X) = argmax\ y \in Y \sum_{t=1}^{T} D_t(x) = Y \quad (5.3)$$

The leaf node in the bootstrap represents the result after each node tests a specific property. The combined outcomes of every bootstrap set are represented as follows:

$$Z = \frac{1}{n_{train}}\sum_{i=1}^{n_{train}} Z_i(x) \quad (5.4)$$

$Z_i(x)$is the matching forecast for the input x, and Z is the average output of n trees. In the suggested model, the number of trees is divided into groups from the dataset. Trees are split into binary nodes, and the best split is chosen after the splits are examined to eliminate contaminants from the resulting tree. Here's how this dividing is carried out:

$$\overset{\Delta}{\rightarrow} e_r\ (sl, t) = e_r(t) - p_r[e(T_l) - e(T_r)] \quad (5.5)$$

The split portion at node t is represented by sl, the error reduction measure is represented by $\overset{\Delta}{\rightarrow} e_r\ (sl, t)$, the occurrence of errors before splitting the training dataset is indicated by $e_r(t)$, and the errors following splitting between the left and right nodes with the proportion are represented by $p_r[e(T_l) - e(T_r)]$.

The steps that follow summarize the entire scenario:

a) Initialize the RF model with hyper parameters (e.g., number of trees, depth of trees).

b) Train the RF model on the training dataset using the `fit` function.

c) Use cross-validation techniques to fine-tune hyper parameters if necessary.

d) Evaluate the RF model's performance on the validation/testing set using appropriate metrics (e.g., accuracy, mean squared error).

5.3.1 Train Support Vector Machine Model

One supervised learning model that looks into data and finds data samples that are utilized for classification is the SVM. An SVM training procedure creates a model that assigns labels to a fresh data set into a single class. By mapping the input vector x, the SVM constructs an optimized linear regression, assuming that prediction is a regression problem with training data consisting of the input matrix X, $X = [x_1, x_2, \ldots, x_n]$ and an output vector $Y = [y_1, y_2, \ldots, y_n]$. SVM in machine learning techniques demonstrates superior outcomes and incorporates various learning techniques. SVM handles both linear and nonlinear classification as well as uses of nonlinear regression. Manuscript look at a linear classifier for a binary classification problem with labels “y” and features “x” in order to simplify our discussion of SVMs. We’ll use $y \in \{-1, 1\}$ to denote the class labels and parameters w, b:

$$f(x) = w^T X + b \tag{5.6}$$

The hyperplane that divides the two regions and aids in data set classification is represented by the function f(x). The two zones that the hyperplane geometrically constructed match the two data categories with two class labels each. The region to which a data point "a" belongs depends on the value of f(a). A point is included in one zone if $f(a) > 0$ and in another region if $f(a) < 0$.

Assume that there are n data vectors in the input data and that each data vector is represented by the expression $x_i \in Rn$, where i = 1, 2,..., n. Let y_i represent the class label that must be applied to the data vectors to carry out supervised classification; y_i is +1 for one category of data vectors and -1 for the other category. A hyperplane can be used to geometrically divide the data collection. The hyperplane can be mathematically represented by the following since it is represented by a line:

$$w^T X + b \geq +1 \tag{5.7}$$

$$w^T X + b \leq +1 \tag{5.8}$$

Another mathematical representation of the hyperplane is

$$f(x) = sgn(w^T X + b) \tag{5.9}$$

and the following equation serves as the mathematical representation of sgn(), also known as a sign function.

$$sgn(x) = \begin{cases} 1 \; if \; x > 0 \\ 0 \; if \; x = 0 \\ -1 \; if \; x < 0 \end{cases} \tag{5.10}$$

The following formula can be used to calculate a data point x's distance D from the hyperplane:

$$D = \frac{|w^T X + b|}{|w|} \tag{5.11}$$

The steps that follow summarize the entire scenario:

a) Initialize the SVM model with hyper parameters (e.g., kernel type, regularization parameter).

b) Train the SVM model on the training dataset using the `fit` function.

c) Use cross-validation techniques to fine-tune hyper parameters if necessary.

d) Evaluate the SVM model's performance on the validation/testing set using appropriate metrics.

5.3.2 Combining RF and SVM Models

This step introduces the hybrid approach. Combine the predictions from RF and SVM models using various methods:

a) Simple Ensemble: Take a weighted average or majority vote of the predictions from both models.

b) Stacking: Train another machine learning model (e.g., logistic regression) on top of the predictions of RF and SVM to make a final prediction.

c) Meta-learner: Train a meta-learner (e.g., RF or SVM) on top of the predictions of RF and SVM models.

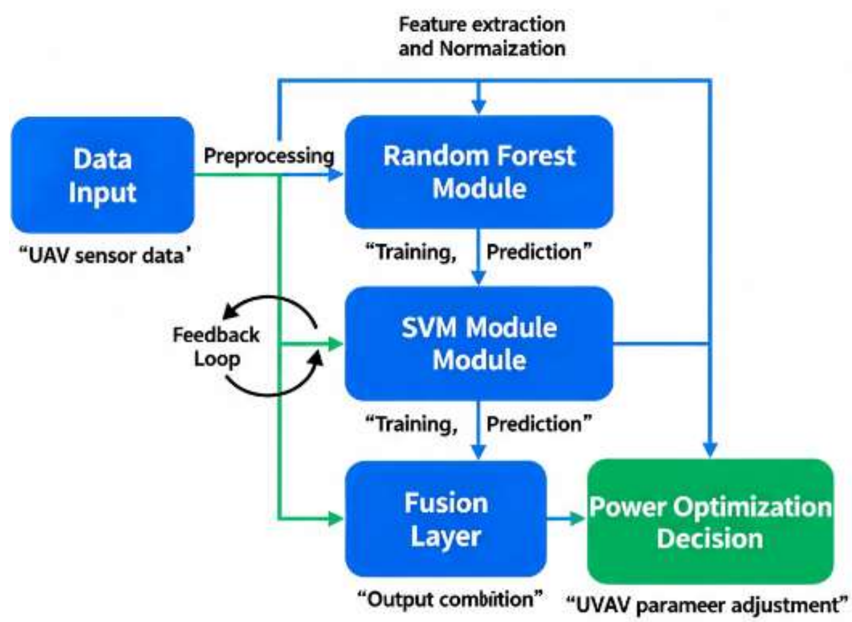

Figure 5.2. Block diagram of hybrid Random Forest and SVM algorithm for UAV power optimization

The hybrid Random Forest and Support Vector Machine (RFSVM) block diagram Figure 5.2, illustrates an AI-based power optimization process for UAVs. The system starts with input data, which is divided into random subsets using the Random Forest approach for feature selection and ensemble learning. Each subset is then trained using Support Vector Machine classifiers that identify optimal decision boundaries for classification. After each run, sample weights are updated to emphasize misclassified data, following a boosting mechanism. This iterative process repeats until classification accuracy stabilizes or a set limit is reached. Finally, results from all SVM models are combined through majority voting, leading to a robust final output with improved accuracy, energy efficiency, and reliability in UAV control within wireless networks.

5.4. Model Training Validation/Evaluation

The standard metrics for measuring model performance, mean absolute error (MAE) and mean square error (MSE), were used to evaluate the models' performances. The MAE and MSE were employed to assess the effectiveness of the SVM and RF models as well as nonlinear regression applications.

In this modelling scenario, which is a regression problem, the MAE serves as a practical risk metric. It represents the expected value of the absolute error, a key factor in determining the correlations between the predictor and response variables.

$$MAE = \frac{1}{n}\sum_{1}^{n}|y_i - \widehat{y_i}| \tag{5.12}$$

The Mean Squared Error (MSE) is calculated using the

$$MSE = \frac{1}{n}\sum_{1}^{n}(y_i - \widehat{y_i})^2 \tag{5.13}$$

Assess the hybrid model's performance on the testing/validation set using appropriate metrics. Ensure it aligns with the objectives of power optimization for UAVs in wireless communication networks.

5.5. Power Optimization in UAV-Based Future Wireless Networks:

Power optimization in UAV-based wireless networks involves complex mathematical expressions that consider various factors, ensuring compatibility with UAV mobility, communication constraints, and network performance requirements. Here, we present a simplified derivation highlighting the key components of this optimization problem.

Let's introduce the following variables, ensuring their compatibility with the optimization framework:

P_{total}: Total power consumption within the network.

P_{UAV}: Power dissipated by the UAV, encompassing propulsion, avionics, and other onboard systems.

$P_{transmit}$: Power expended by the UAV's communication transmitter.

$P_{receive}$: Power utilized by the receiver(s) within the network.

Process: Power employed for data processing and control operations within the UAV and ground station(s).

P_{misc}: Miscellaneous power consumption, accommodating sensor power, navigation, and networking equipment.

Q: Quality of Service (QoS) metric characterizing network performance.

Q_{min}: Minimum acceptable QoS threshold.

The total power consumption (P_{total}) can be represented as the sum of these compatible components:

$$P_{total} = P_{UAV} + P_{transmit} + P_{receive} + P_{process} + P_{misc} \qquad (5.14)$$

Eq. 5.14 represents the total power consumption in a system involving a UAV where power is consumed in various components such as transmission, reception, processing, and miscellaneous tasks.

To optimize the total power consumption P_{total} in the context of a hybrid model involving Random Forest, SVM, and beamforming, the paper considers each component to contributes to the overall power consumption equation.

Furthermore, the power consumed by the UAV's communication transmitter $P_{transmit}$ can be expressed in compatibility with the UAV's transmit power P_{tx} and the distance (d) between the UAV and the receiver(s):

$$P_{transmit} = f(P_{tx}, d) \qquad (5.15)$$

$$0 \leq P_{tx} \leq P_{max}$$

In constructing a power optimization problem, our objective is to minimize P_{total}, maintaining compatibility with the condition that (Q) either equals or surpasses Q_{min}. This can be represented as a compatible optimization problem:

Minimize: P_{total}

Subject to: $Q > Q_{min}$

These compatible constraints within the optimization framework can be intricate, involving various parameters, including:

- UAV flight paths and trajectories (e.g., x(t), y(t), z(t)).
- UAV transmit power control strategies (e.g., ($P_{tx}(t)$).
- Resource allocation among UAVs and users.
- Signal-to-noise ratio (SNR) constraints ensuring reliable communication.
- Data rate requisites for diverse service types (e.g., voice, video, data).
- Network topology and interference management.

Received Power Calculation is:

$$P_{rx} = P_{tx} - P_{interference} - P_{noise} \tag{5.16}$$

$$P_{noise} \leq P_{noise\_max}$$

$$P_{interference} \leq P_{interference\_max}$$

$$P_{rx} > P_{min}$$

5.6 Experimental Results

The experimental analysis, a pioneering endeavour, delves into the deployment and power optimization of Unmanned Aerial Vehicles (UAVs) in future wireless communication networks. It harnesses a cutting-edge hybrid machine learning approach, specifically Random Forest and Support Vector Machine. The analysis entails a systematic process of testing and evaluating the proposed solution. Here is a comprehensive examination of how this paper conducted a thorough analysis of the experimental data:

Our first step was to provide a clear definition of the problem. This case involves the implementation and enhancement of UAVs in upcoming wireless communication networks, with a focus on their deployment and power optimization. Subsequently, we establish a hypothesis that articulates our anticipated outcomes from the experimental investigation. For instance, one may propose that the integration of machine learning techniques with hybrid systems can greatly enhance the power efficiency and network performance of unmanned aerial vehicles (UAVs). Now, it is of utmost importance to meticulously collect pertinent data for your trials. The data encompasses historical performance records of unmanned aerial vehicles (UAVs), wireless network logs, meteorological data, specifications of UAV hardware, and information on network topology. Subsequently, we employed network simulation software tools in conjunction with AI-based models necessary for data pre-processing, modelling, and analysis. Popular options for machine learning include Python, together with libraries such as sci-kit-learn and TensorFlow, as well as many data visualization tools. Subsequently, we constructed a Random Forest model to enhance power optimization. Optimize hyperparameters with methods such as grid search or random search. Furthermore, we have created a Support Vector Machine model specifically designed for power optimization. Optimize hyperparameters as well. Subsequently, we merge the forecasts generated by the Random Forest and Support Vector Machine models through ensemble methodologies such as straightforward averaging, stacking, or meta-learners. The performance evaluation measures are employed to assess the predetermined datasets. Performance measures utilized for power optimization and network performance assessment encompass Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR), and Quality of Service (QoS) assessments. Subsequently, we will meticulously analyze the experimental findings by comparing the efficacy of the hybrid machine learning model with that of individual models, while also considering the absence of AI-based existing solutions. An analysis of the node transmit power and Mean Squared Error (MSE) provides useful information into wireless networks that utilize Unmanned Aerial Vehicles (UAVs). The term "Node Transmit Power (dBm)" refers to the specific values of the power at which nodes transmit. On the other hand, "Mean Squared Error" is a metric that measures the accuracy of predictions by quantifying the differences between the actual transmit power values and the expected ones. By analyzing this comparison, we may assess the efficacy of a model or strategy in predicting node transmit power. Smaller MSE values indicate more precise predictions, whereas larger MSE values reflect less precise ones. Utilizing charts or statistical analysis to visualize the correlation between transmit power and mean squared error (MSE) enhances understanding. In addition, it is important to take into account different evaluation metrics such as Root Mean Squared

Error (RMSE) or Mean Absolute Error (MAE), depending on the unique objectives of the analysis. Figure 5.3 shows that random forests manage complex interactions well in the system hybrid model. They may be beneficial for forecasting indirect MSE behaviors.

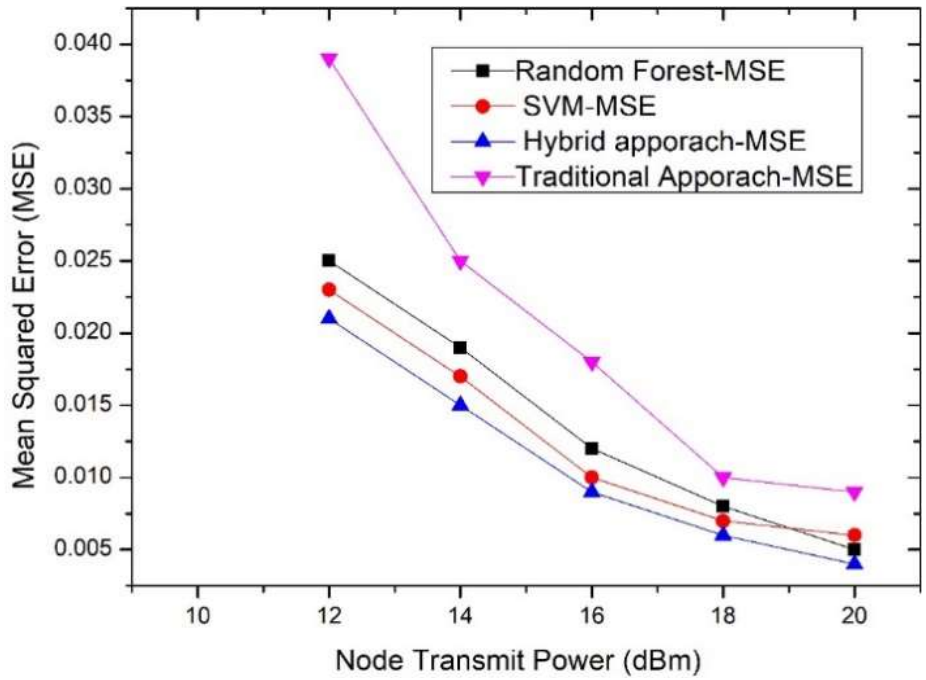

Figure 5.3 Node transmit power (dBm) with respect to Mean Squared Error (MSE)

SVMs are good at managing high-dimensional data and optimizing margins to directly improve node transmit power levels to minimize MSE.

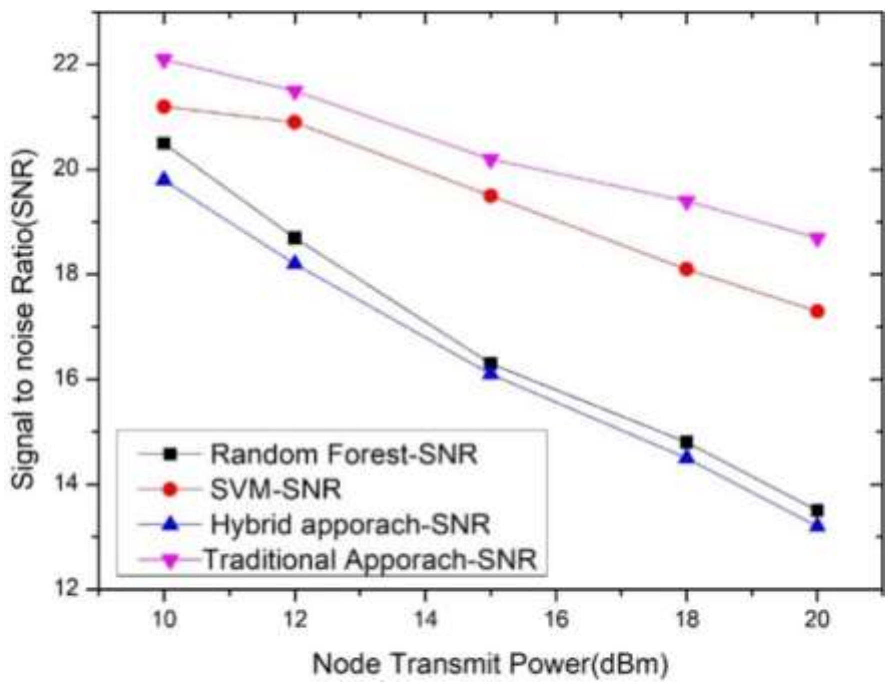

Figure 5.4 Node transmit power (dBm) with respect to Signal to Noise Ratio (SNR)

As node transmit power increases, MSE decreases. In particular, the hybrid strategy (SVM + Random Forest) lowers MSE better than SVM, Random Forest, and traditional methods.

Increasing node transmit power increases signal-to-noise ratio (SNR), as seen in Figure 5.4. This is key to wireless communication. Signal-to-noise ratio measures the relationship between signal and noise in a communication channel. Node Transmit Power (dBm) measures node data transmission. More transmit power usually means a stronger signal for the recipient. SNR measures signal quality relative to channel noise or interference. A higher signal-to-noise ratio (SNR) indicates a more reliable, noise-free signal. In UAV-based wireless networks, node distance, obstacles, and outside interference affect SNRs. Therefore, despite maximizing transmit power, these pragmatic difficulties must be addressed to ensure consistent communication. The hybrid technique in Figure 5.4 has a worse signal-to-noise ratio (SNR) as node transmit power increases. The proposed hybrid methodology has a lower signal-to-noise ratio (SNR) than current methods.

The power level directly impacts parameters such as the range and quality of the signal, as well as the connectivity of UAVs within the network. Aggregate Network Throughput measures the total rate at which data is transferred in a network, usually expressed in kilobits per second (kbps). It refers to the total data rates achieved by all network nodes, including UAVs and terrestrial nodes. By increasing the transmit power of nodes, the signal coverage area of UAVs can be expanded, allowing them to communicate over longer distances. This expansion positively affects the overall network throughput by improving connectivity. It is imperative to consider the balance between Node Transmit Power and distance. Although higher power levels can enhance connectivity and data transfer rates over longer distances, they can also result in higher energy consumption and the possibility of causing interference with other devices.

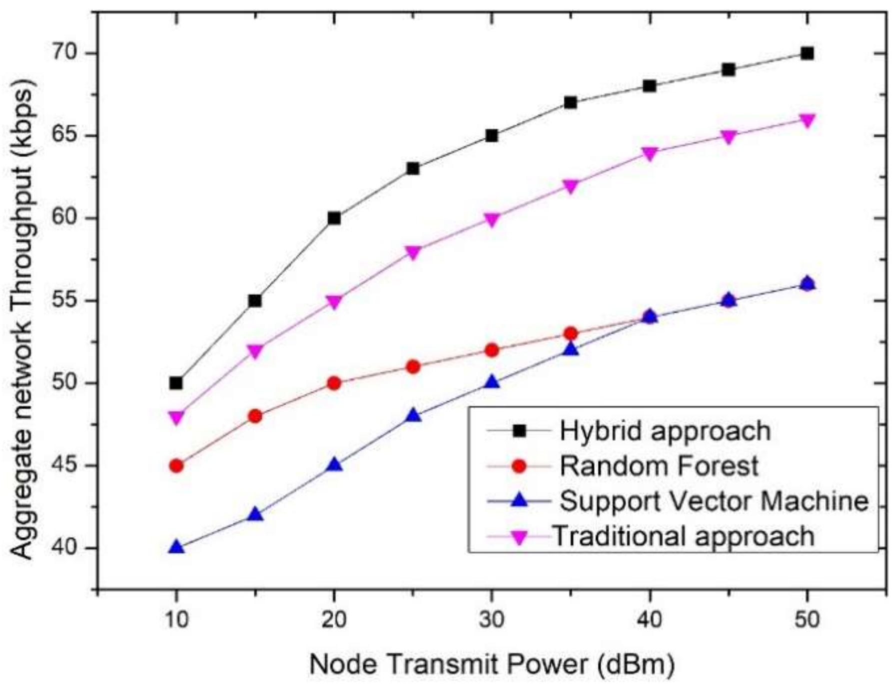

Figure 5.5. The node transmits power with Aggregate Network Throughput

Dynamic modifications to Node Transmit Power in UAV-based networks can enhance coverage and throughput by considering parameters such as UAV position, network load, and communication requirements. Increased transmission power levels can cause signal interference, particularly in locations with high population density or congestion. Maintaining optimal signal quality while reducing interference is crucial to ensuring balanced power levels. The network throughput achieved in Figure 5.5 rises as the transmit power of the nodes increases. Furthermore, the suggested hybrid method achieves the best network throughput when the transmit power of the nodes is increased. Figure 5.6 illustrates the relationship between the number of UAV nodes and the aggregate network throughput in the wireless network. As shown in Figure 5.6, there is a drop in network throughput as the number of UAV nodes in the coverage region increases at the same time higher throughput for hybrid approach as compare to traditional/RF/SVM as in hybrid approach of Random Forest and SVM offers less training time, fast prediction time and high scalability.

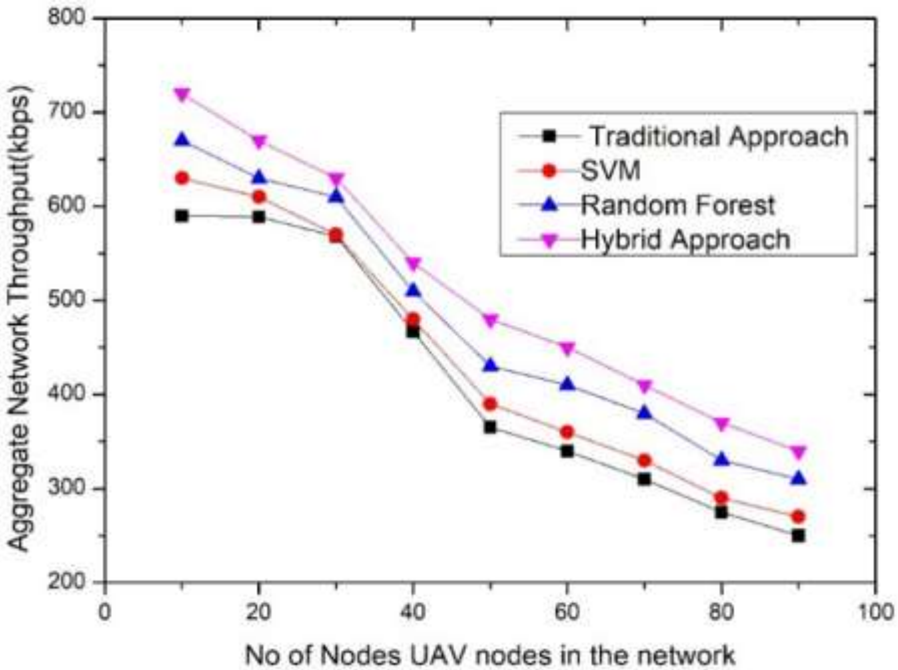

Figure 5.6. No. of UAV nodes with Aggregate Network Throughput

5.7 Summary

In summary, the RF–SVM hybrid model provides an effective solution for UAV-assisted wireless communication by combining Random Forest's robust feature selection with SVM's precise classification. This hybrid approach ensures high prediction accuracy, strong generalization, and fast real-time decision-making, making it ideal for dynamic and complex environments. Its superior performance in terms of throughput, SNR, and reduced error rates highlights its suitability for next-generation 5G/6G aerial networks. Particularly in emergency, rural, or high-mobility scenarios, where communication reliability is critical, the RF–SVM model stands out as a powerful tool for intelligent, adaptive, and efficient UAV-based network control.

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CHAPTER 6

CONCLUSION AND FUTURE SCOPE

The integration of Unmanned Aerial Vehicles (UAVs) into next-generation wireless communication networks marks a pivotal evolution in addressing modern connectivity challenges especially in post-disaster scenarios, remote areas, and highly dynamic user environments. This comprehensive research effort, spanning two complementary studies, successfully demonstrates how UAV enabled wireless systems can be optimized for resilience, scalability, and energy efficiency.

From one perspective, the adoption of distributed multi-agent reinforcement learning (MARL), specifically through the Multi-Agent Soft Actor-Critic (MASAC) framework, empowers UAVs to autonomously learn and adapt to changing network conditions. By introducing a distributed K-SUMS clustering mechanism, the architecture intelligently segments users based on service priority and load balancing, thereby ensuring efficient resource allocation and minimal interference. This decentralization of decision-making allows each UAV to act as an intelligent node, enabling robust, fault-tolerant communication even in large-scale disaster-stricken areas. Simulation results confirm a significant improvement in spectral efficiency, reduced communication dropouts, and better system stability compared to traditional centralized or static models. The proposed distributed K-SUMS clustering and Multi-Agent Soft Actor-Critic (MASAC) algorithms were validated solely under controlled simulation conditions. The absence of hardware or field-based experimentation limits the verification of their effectiveness in real-world conditions, such as fluctuating weather, GPS drift, or signal interference. The MASAC model requires extensive computational capacity, memory storage, and power consumption. Such requirements are impractical for many UAVs that operate with constrained onboard processors, restricting real-time adaptability and mission duration.

On the other hand, the second study addresses the critical issue of power optimization in UAV-assisted networks by leveraging hybrid beamforming within Massive MIMO frameworks. UAVs, constrained by limited battery life, benefit immensely from the hybrid combination of digital and analog beamforming, which minimizes RF chain usage

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while maintaining high-quality transmission. The analysis of various performance metrics including bit error rate (BER), achievable sum rate, signal-to-noise ratio (SNR), and energy efficiency demonstrates that with appropriate antenna scaling and beam steering, UAV networks can achieve substantial throughput gains with minimal power trade-offs. Furthermore, hybrid beamforming reduces hardware complexity and cost, making the solution practical for real-world deployment.

Together, these approaches form a comprehensive and intelligent architecture for UAV-assisted communication networks. The synergy between AI-based autonomous decision-making and hardware-aware communication optimization makes the proposed solution highly adaptable to 5G and 6G ecosystems. The outcomes underline that UAVs are not just temporary stop-gaps but strategic components in the future wireless landscape, capable of self-learning, efficient energy management, and autonomous network management.

In summary, this combined work offers a robust framework for the design, deployment, and optimization of UAV-based networks. It lays the groundwork for resilient, scalable, and intelligent communication systems suitable for a wide range of applications, from disaster response and rural connectivity to smart city infrastructure and beyond. Future research can build upon this foundation by incorporating satellite-UAV integration, blockchain-secured data exchange, and real-time edge intelligence to create even more agile and secure communication ecosystems.

Future Work

This study lays the groundwork for AI-driven UAV-assisted wireless network research. Key topics for future investigation may improve network performance, energy efficiency, and scalability. This document outlines the main directions for future activities based on this investigation.

a. Real-World Execution and Evaluation

AI-based architecture shows promise in simulations, but further testing is needed to determine its real-world application. Future study should apply the proposed AI

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algorithms to UAVs to test the system's performance in different situations. This document discusses UAV deployment issues like weather, physical impediments, and wireless network interference. Researchers can improve AI algorithms utilizing field data to optimize system performance under varied scenarios.

b. Sixth-generation technology integration

6G networks offer a great chance to improve AI-driven UAV-assisted networks. Research should examine how AI can optimize UAV deployment and power usage for 6G, which is projected to boost data rates, ultra-low latency, and broad connection. Advanced AI models are needed to meet 6G network requirements. Ultra-dense network deployments, mmWave and THz frequencies, and sophisticated communication paradigms like reconfigurable intelligent surfaces (RIS) and quantum communications are required.

c. Coordinating Multiple UAVs and Swarm Intelligence

Focusing on single UAV deployment tactics and power efficiency limits this research. Future study should focus on multi-UAV coordination, where a swarm of UAVs improves network coverage and operating efficiency. Ant colonies and bird flocks demonstrate swarm intelligence. UAVs can autonomously collaborate to share information and resources to improve performance using this idea. This method may improve UAV-assisted network scalability and adaptability, especially in large-scale deployments that require numerous UAVs to cover a vast area.

d. Renewable energy harvesting and integration

The limited battery life of UAVs makes UAV-assisted networks difficult. Future study should investigate using renewable energy sources like solar power to extend UAV operation and reduce recharging. UAVs can harvest energy from solar radiation and ambient RF waves. These strategies must be tested to improve UAV-assisted network sustainability. Renewable energy sources in the AI optimization framework can minimize UAV power consumption and increase their lifespan. This is especially important in distant or disaster-stricken places with limited charging infrastructure.

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e. Privacy and Security Considerations

Data transfer must be secure and private as UAV-assisted wireless networks grow. UAVs are vulnerable to spoofing, jamming, and unwanted access, which could compromise network integrity. AI-powered security systems that detect and eliminate threats in real time should be the focus of future research. The implementation may include machine learning algorithms to detect network irregularities and UAV-specific encryption methods. Next steps should focus on network security and UAV data collecting and transmission privacy to secure sensitive data.

f. Advanced AI and Hybrid Methods

This study's AI algorithms optimize UAV deployment and power usage, although they can be improved. Deep learning, reinforcement learning, and hybrid AI models should be studied in the future. Deep learning algorithms can manage big datasets and understand complicated patterns, improving UAV deployment accuracy and efficiency. Reinforcement learning uses feedback and environment interaction to work. This approach is useful in real-time deployment settings where unmanned aerial vehicles (UAVs) must make judgments based on changing conditions. UAV-assisted networks may benefit from hybrid machine learning-optimization methods like genetic algorithms and particle swarm optimization.

g. UAV-Assisted Network Cross-Layer Optimization

Cross-layer optimization, which improves communication protocol stack interactions, is a study possibility. Power control, resource allocation, and routing evaluation may increase network performance and efficiency. Due to their dynamic nature, UAV-assisted networks require significant cross-layer optimization. AI-based cross-layer optimization can improve UAV deployment and operation and network performance. This strategy considers energy expenditure, delay, and service quality.

h. Cognitive Radio System Spectrum Efficiency and Integration

As wireless networks evolve, spectrum efficiency will become more crucial. Cognitive radio lets devices find and use spectrum resources. AI-driven UAV-assisted networks

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may increase spectrum use. Artificial intelligence techniques allow UAVs to locate underused spectrum in real time. UAVs can modify their communication channels in real time, reducing user interference. This is especially useful in densely populated urban areas with limited spectrum. AI-driven cognitive radio solutions for UAV-assisted networks may be developed to optimize spectrum efficiency and provide reliable communication linkages.

LIST OF PUBLICATIONS

1. **Rahul Sharma**, Shakti Raj Chopra, Akhil Gupta “Power Optimization Of Unmanned Aerial Vehicle-Assisted Future Wireless Communication Using Hybrid Beamforming Technique In Disaster Management”, 1st International Conference on Sustainable Energy Sources, Technologies and Systems (ICSESTS2023), 2023 **[Scopus]**

2. **Sharma, Rahul**, Shakti Raj Chopra, Akhil Gupta, Rupendeep Kaur, SudeepTanwar, Giovanni Pau, Gulshan Sharma, Fayez Alqahtani, and Amr Tolba. "Deployment of Unmanned Aerial Vehicles in Next-Generation Wireless Communication Network using Multi-Agent Reinforcement Learning." *IEEE Access* (2024). **[SCOPUS Q1]**

3. **Sharma, Rahul**, Shakti Raj Chopra, and Akhil Gupta. "UAV Assisted Next Generation Wireless Communication Network." In *2024 International Conference on Emerging Smart Computing and Informatics (ESCI)*, pp. 1-5. IEEE, 2024. **[Scopus]**

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BIBLIOGRAPHY

[1] F. Khan, “Multi-comm-core architecture for terabit-per-second wireless,” IEEE Commun. Mag., vol. 54, no. 4, pp. 124– 129, Apr. 2016.

[2] X. Zhang, Y. Zhang, R. Yu, W. Wang, and M. Guizani, “Enhancing spectral-energy efficiency for LTE-advanced heterogeneous networks: A users social pattern perspective,” IEEE Wireless Commun., vol. 21, no. 2, pp. 10–17, Apr. 2014.

[3] Y. Zeng, R. Zhang, and T. J. Lim, “Wireless communications with unmanned aerial vehicles: Opportunities and challenges,” IEEE Commun. Mag., vol. 54, no. 5, pp. 36–42, May 2016.

[4] Y. Huo, X. Dong, T. Lu, W. Xu, and M. Yuen, “Distributed and multi-layer UAV network for the next-generation wireless communication,” arXiv preprint arXiv:1805.01534, 2018.

[5] M. Mozaffari et al., “Wireless communication using unmanned aerial vehicles (UAVs): Optimal transport theory for hover time optimization,” IEEE Trans. Wireless Commun., vol. 16, no. 12, pp. 8052–8066, Dec. 2017.

[6] Y. Zeng, R. Zhang, and T. J. Lim, “Throughput maximization for UAV-enabled mobile relaying systems,” IEEE Trans. Commun., vol. 64, no. 12, pp. 4983–4996, Dec. 2016.

[7] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Mobile unmanned aerial vehicles (UAVs) for energy-efficient Internet of Things communications,” IEEE Trans. Wireless Commun., vol. 16, no. 11, pp. 7574–7589, Nov. 2017.

[8] B. Li, Z. Fei, Y. Dai, and Y. Zhang, “Secrecy-optimized resource allocation for UAV-assisted relaying networks,” in Proc. IEEE GLOBECOM, Abu Dhabi, UAE, Dec. 2018, pp. 1–6.

[9] X. Qi, B. Li, Z. Chu, K. Huang, H. Chen, and Z. Fei, “Secrecy energy efficiency performance in communication networks with mobile sinks,” Physical Communication, vol. 32, pp. 41–49, Feb. 2019.

`

[10] Y. Zeng, J. Lyu, and R. Zhang, "Cellular-connected UAV: Potentials, challenges and promising technologies," arXiv preprint arXiv:1804.02217, 2018.

[11] M. Mozaffari, A. T. Z. Kasgari, W. Saad, M. Bennis, and M. Debbah, "Beyond 5G with UAVs: Foundations of a 3D wireless cellular network," IEEE Trans. Wireless Commun., vol. 18, no. 1, pp. 357–372, Jan. 2019.

[12] S. Hayat, E. Yanmaz, and R. Muzaffar, "Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint," IEEE Commun. Surveys Tuts., vol. 18, no. 4, pp. 2624–2661, Fourthquarter 2016.

[13] S. Sekander, H. Tabassum, and E. Hossain, "Multi-tier drone architecture for 5G/B5G cellular networks: Challenges, trends, and prospects," IEEE Commun. Mag., vol. 56, no. 3, pp. 96–103, Mar. 2018.

[14] W. Shi, H. Zhou, J. Li, W. Xu, N. Zhang, and X. Shen, "Drone assisted vehicular networks: Architecture, challenges and opportunities," IEEE Network, vol. 32, no. 3, pp. 130–137, May/Jun. 2018.

[15] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," arXiv preprint arXiv:1803.00680, 2018.

[16] S. A. R. Naqvi, S. A. Hassan, H. Pervaiz, and Q. Ni, "Drone-aided communication as a key enabler for 5G and resilient public safety networks," IEEE Commun. Mag., vol. 56, no. 1, pp. 36–42, Jan. 2018.

[17] N. Zhang, S. Zhang, P. Yang, O. Alhussein, W. Zhuang, and X. S. Shen, "Software defined space-air-ground integrated vehicular networks: Challenges and solutions," IEEE Commun. Mag., vol. 55, no. 7, pp. 101–109, Jul. 2017.

[18] M. Agiwal, A. Roy, and N. Saxena, "Next generation 5G wireless networks: A comprehensive survey," IEEE Commun. Surveys Tuts., vol. 18, no. 3, pp. 1617–1655, Thirdquarter 2016.

[19] N. Cheng, W. Xu, W. Shi, Y. Zhou, N. Lu, H. Zhou, and X. Shen, "Air-ground integrated mobile edge networks: Architecture, challenges and opportunities," IEEE Commun. Mag., vol. 56, no. 8, pp. 26–32, Aug. 2018.

`

[20] Al-Hourani, A.; Kandeepan, S.; Lardner, S. Optimal LAP Altitude for Maximum Coverage. IEEE Wirel. Commun. Lett. 2014, 3, 569–572.

[21] Holis, J.; Pechac, P. Elevation Dependent Shadowing Model for Mobile Communications via High Altitude Platforms in Built-Up Areas. IEEE Trans. Antennas Propag. 2008, 56, 1078–1084

[22] Kawamoto, Y.; Nishiyama, H.; Kato, N.; Ono, F.; Miura, R. An efficient throughput-aware resource allocation technique for data transmission in unmanned aircraft systems. In Proceedings of the 2017 IEEE International Conference on Communications (ICC), Paris, France, 21–25 May 2017.

[23] Medina-Pazmiño, W.; Jara-Olmedo, A.; Valencia-Redrován, D. Analysis and determination of minimum requirements for a data link communication system for unmanned aerial vehicles- UAV's. In Proceedings of the 2016 IEEE Ecuador Technical Chapters Meeting (ETCM), Guayaquil, Ecuador, 12–14 October 2016.

[24] Azari, M.M.; Rosas, F.; Chen, K.C.; Pollin, S. Joint Sum-Rate and Power Gain Analysis of an Aerial Base Station. In Proceedings of the 2016 IEEE Global Communications Conference (GLOBECOM) Workshops, Washington, DC, USA, 4–8 December 2016.

[25] Al-Hourani, A.; Kandeepan, S.; Jamalipour, A. Modeling air-to-ground path loss for low altitude platforms in urban environments. In Proceedings of the 2014 IEEE Global Communications Conference (GLOBECOM), Austin, TX, USA, 8–12 December 2014.

[26] Khawaja, W.; Guvenc, I.; Matolak, D. UWB Channel Sounding and Modeling for UAV Air-to-Ground Propagation Channels. In Proceedings of the 2016 IEEE Global Communications Conference (GLOBECOM), Washington, DC, USA, 4–8 December 2016.

[27] Zeng, Y.; Zhang, R.; Lim, T.J. Wireless Communications with Unmanned Aerial Vehicles: Opportunities and Challenges. IEEE Commun. Mag. 2016, 54, 36–42.

[28] Kalantari, Elham, Halim Yanikomeroglu, and Abbas Yongacoglu. "On the number and 3D placement of drone base stations in wireless cellular networks."

`

In *2016 IEEE 84th vehicular technology conference (VTC-Fall)*, pp. 1-6. IEEE, 2016.

[29] Košmerl, Jože, and Andrej Vilhar. "Base stations placement optimization in wireless networks for emergency communications." In *2014 IEEE international conference on communications workshops (ICC)*, pp. 200-205. IEEE, 2014.

[30] Dogancay, Kutluyil. "UAV path planning for passive emitter localization." *IEEE Transactions on Aerospace and Electronic systems* 48, no. 2 (2012): 1150-1166.

[31] Rucco, Alessandro, A. Pedro Aguiar, and John Hauser. "Trajectory optimization for constrained UAVs: A virtual target vehicle approach." In *2015 International Conference on Unmanned Aircraft Systems (ICUAS)*, pp. 236-245. IEEE, 2015.

[32] Horwath, Joachim, Nicolas Perlot, Markus Knapek, and Florian Moll. "Experimental verification of optical backhaul links for high-altitude platform networks: Atmospheric turbulence and downlink availability." *International Journal of Satellite Communications and Networking* 25, no. 5 (2007): 501-528.

[33] Fidler, Franz, Markus Knapek, Joachim Horwath, and Walter R. Leeb. "Optical communications for high-altitude platforms." *IEEE Journal of selected topics in quantum electronics* 16, no. 5 (2010): 1058-1070.

[34] Alzenad, Mohamed, Muhammad Z. Shakir, Halim Yanikomeroglu, and Mohamed-Slim Alouini. "FSO-based vertical backhaul/fronthaul framework for 5G+ wireless networks." *IEEE Communications Magazine* 56, no. 1 (2018): 218-224.

[35] Wang, Wei, Xinrui Li, Miao Zhang, KanapathippillaiCumanan, Derrick Wing Kwan Ng, Guoan Zhang, Jie Tang, and Octavia A. Dobre. "Energy-constrained UAV-assisted secure communications with position optimization and cooperative jamming." *IEEE Transactions on Communications* 68, no. 7 (2020): 4476-4489.

[36] P. Li and J. Xu, "UAV-Enabled Cellular Networks with Multi-Hop Backhauls: Placement optimization and Wireless Resource Allocation," *2018 IEEE International Conference on Communication Systems (ICCS)*, Chengdu, China, 2018, pp. 110-114, doi: 10.1109/ICCS.2018.8689218.

`

[37] Wu, Qingqing, Yong Zeng, and Rui Zhang. "Joint trajectory and communication design for multi-UAV enabled wireless networks." *IEEE Transactions on Wireless Communications* 17, no. 3 (2018): 2109-2121.

[38] Zhang, Long, Hui Zhao, ShuaiHou, Zhen Zhao, Haitao Xu, Xiaobo Wu, Qiwu Wu, and Ronghui Zhang. "A survey on 5G millimeter wave communications for UAV-assisted wireless networks." *IEEE Access* 7 (2019): 117460-117504.

[39] Hosseinalipour, Seyyedali, Ali Rahmati, and Huaiyu Dai. "Interference avoidance position planning in UAV-assisted wireless communication." In *ICC 2019-2019 IEEE International Conference on Communications (ICC)*, pp. 1-6. IEEE, 2019.

[40] Zhao, Nan, Weidang Lu, Min Sheng, Yunfei Chen, Jie Tang, F. Richard Yu, and Kai-Kit Wong. "UAV-assisted emergency networks in disasters." *IEEE Wireless Communications* 26, no. 1 (2019): 45-51.

[41] Liu, Xiao, Yuanwei Liu, Yue Chen, and Lajos Hanzo. "Trajectory design and power control for multi-UAV assisted wireless networks: A machine learning approach." *IEEE Transactions on Vehicular Technology* 68, no. 8 (2019): 7957-7969.

[42] Perera, Tharindu D. Ponnimbaduge, DushanthaNalin K. Jayakody, Sahil Garg, Neeraj Kumar, and Ling Cheng. "Wireless-powered UAV assisted communication system in Nakagami-m fading channels." In *2020 IEEE 17th annual consumer communications & networking conference (CCNC)*, pp. 1-6. IEEE, 2020.

[43] Lakew, DemekeShumeye, Arooj Masood, and Sungrae Cho. "3D UAV placement and trajectory optimization in UAV assisted wireless networks." In *2020 International Conference on Information Networking (ICOIN)*, pp. 80-82. IEEE, 2020.

[44] Ji, Jiequ, Kun Zhu, DusitNiyato, and Ran Wang. "Joint cache placement, flight trajectory, and transmission power optimization for multi-UAV assisted wireless networks." *IEEE Transactions on wireless communications* 19, no. 8 (2020): 5389-5403.

`

[45] Zhang, Tiankui, Yu Xu, Jonathan Loo, Dingcheng Yang, and Lin Xiao. "Joint computation and communication design for UAV-assisted mobile edge computing in IoT." *IEEE Transactions on Industrial Informatics* 16, no. 8 (2019): 5505-5516.

[46] Shahzadi, Rizwana, Mudassar Ali, HumayunZubair Khan, and Muhammad Naeem. "UAV assisted 5G and beyond wireless networks: A survey." *Journal of network and computer applications* 189 (2021): 103114.

[47] Masroor, Rooha, Muhammad Naeem, and Waleed Ejaz. "Resource management in UAV-assisted wireless networks: An optimization perspective." *Ad Hoc Networks* 121 (2021): 102596.

[48] Jiang, Xu, Xinying Chen, Jie Tang, Nan Zhao, Xiu Yin Zhang, DusitNiyato, and Kai-Kit Wong. "Covert communication in UAV-assisted air-ground networks." *IEEE Wireless Communications* 28, no. 4 (2021): 190-197.

[49] Luong, Phuong, François Gagnon, Le-Nam Tran, and Fabrice Labeau. "Deep reinforcement learning-based resource allocation in cooperative UAV-assisted wireless networks." *IEEE Transactions on Wireless Communications* 20, no. 11 (2021): 7610-7625.

[50] Matracia, Maurilio, Mustafa A. Kishk, and Mohamed-Slim Alouini. "On the topological aspects of UAV-assisted post-disaster wireless communication networks." *IEEE Communications Magazine* 59, no. 11 (2021): 59-64.

[51] Xiong, Zehui, Yang Zhang, Wei Yang Bryan Lim, Jiawen Kang, DusitNiyato, Cyril Leung, and Chunyan Miao. "UAV-assisted wireless energy and data transfer with deep reinforcement learning." *IEEE transactions on cognitive communications and networking* 7, no. 1 (2020): 85-99.

[52] Elnabty, Israa A., Yasmine Fahmy, and Mai Kafafy. "A survey on UAV placement optimization for UAV-assisted communication in 5G and beyond networks." *Physical Communication* 51 (2022): 101564.

[53] Atif, Muhammad, Rizwan Ahmad, Waqas Ahmad, Liang Zhao, and Joel JPC Rodrigues. "UAV-assisted wireless localization for search and rescue." *IEEE Systems Journal* 15, no. 3 (2021): 3261-3272.

`

[54] Basharat, Mehak, Muhammad Naeem, ZakriaQadir, and AlaganAnpalagan. "Resource optimization in UAV-assisted wireless networks—A comprehensive survey." *Transactions on Emerging Telecommunications Technologies* 33, no. 7 (2022): e4464.

[55] Fu, Shu, Meng Zhang, Min Liu, Chen Chen, and Fei Richard Yu. "Toward energy-efficient UAV-assisted wireless networks using an artificial intelligence approach." *IEEE Wireless Communications* 29, no. 5 (2022): 77-83.

[56] Pogaku, Arjun Chakravarthi, Dinh-Thuan Do, Byung Moo Lee, and NhanDuc Nguyen. "UAV-assisted RIS for future wireless communications: A survey on optimization and performance analysis." *IEEE Access* 10 (2022): 16320-16336.

[57] Lakew, DemekeShumeye, Woongsoo Na, Nhu-Ngoc Dao, and Sungrae Cho. "Aerial energy orchestration for heterogeneous UAV-assisted wireless communications." *IEEE Systems Journal* 16, no. 2 (2021): 2483-2494.

[58] Jeganathan, Anandpushparaj, BalajiDhayabaran, Tharindu D. PonnimbadugePerera, DushanthaNalin K. Jayakody, and P. Muthuchidambaranathan. "Harvest-on-sky: An AoI-driven UAV-assisted wireless communication system." *IEEE Internet of Things Magazine* 5, no. 1 (2022): 142-146.

[59] Liu, Yaqun, Jun Xie, Changyou Xing, and ShengxuXie. "Access control and deployment design for multi-UAV assisted wireless networks." *IEEE Wireless Communications Letters* 11, no. 11 (2022): 2380-2384.

[60] Liu, Xiaojie, Xingwei Wang, JieJia, JianhuiLv, and Novella Bartolini. "Distributed deployment in UAV-assisted networks for a long-lasting communication coverage." *IEEE Systems Journal* 16, no. 3 (2021): 4130-4138.

[61] Gu, Xiaohui, and Guoan Zhang. "A survey on UAV-assisted wireless communications: Recent advances and future trends." *Computer Communications* 208 (2023): 44-78.

[62] Sonny, Amala, Sreenivasa Reddy Yeduri, and Linga Reddy Cenkeramaddi. "Autonomous UAV path planning using modified PSO for UAV-assisted wireless networks." *IEEE Access* (2023).

`

[63] Wang, Yatong, Mu Yan, Gang Feng, Shuang Qin, and Fengsheng Wei. "Autonomous on-demand deployment for UAV assisted wireless networks." *IEEE Transactions on Wireless Communications* 22, no. 12 (2023): 9488-9501.

[64] Zhang, Qianqian, Mohammad Mozaffari, WalidSaad, Mehdi Bennis, and MerouaneDebbah. "Machine learning for predictive on-demand deployment of UAVs for wireless communications." In *2018 IEEE Global Communications Conference (GLOBECOM)*, pp. 1-6. IEEE, 2018.

[65] Klaine, Paulo V., João PB Nadas, Richard D. Souza, and Muhammad A. Imran. "Distributed drone base station positioning for emergency cellular networks using reinforcement learning." *Cognitive computation* 10, no. 5 (2018): 790-804.

[66] Wang, Zhe, LingjieDuan, and Rui Zhang. "Adaptive deployment for UAV-aided communication networks." *IEEE transactions on wireless communications* 18, no. 9 (2019): 4531-4543.

[67] Yao, Miao, MunawwarSohul, VukMarojevic, and Jeffrey H. Reed. "Artificial intelligence defined 5G radio access networks." *IEEE Communications Magazine* 57, no. 3 (2019): 14-20.

[68] Wang, Li-Chun, Chuan-Chi Lai, Hong-Han Shuai, Hsin-Piao Lin, Chi-Yu Li, Teng-Hu Cheng, and Chiun-Hsun Chen. "Communications and networking technologies for intelligent drone cruisers." In *2019 IEEE Globecom Workshops (GC Wkshps)*, pp. 1-6. IEEE, 2019.

[69] Dai, Haibo, Haiyang Zhang, Baoyun Wang, and Luxi Yang. "The multi-objective deployment optimization of UAV-mounted cache-enabled base stations." *Physical Communication* 34 (2019): 114-120.

[70] Alsamhi, Saeed H., Ou Ma, and Mohd Samar Ansari. "Survey on artificial intelligence based techniques for emerging robotic communication." *Telecommunication Systems* 72 (2019): 483-503.

[71] Yang, Helin, ArokiaswamiAlphones, ZehuiXiong, DusitNiyato, Jun Zhao, and Kaishun Wu. "Artificial-intelligence-enabled intelligent 6G networks." *IEEE network* 34, no. 6 (2020): 272-280.

`

[72] Bithas, Petros S., Emmanouel T. Michailidis, Nikolaos Nomikos, Demosthenes Vouyioukas, and Athanasios G. Kanatas. "A survey on machine-learning techniques for UAV-based communications." *Sensors* 19, no. 23 (2019): 5170.

[73] Liu, Xiao, Yuanwei Liu, Yue Chen, and Lajos Hanzo. "Trajectory design and power control for multi-UAV assisted wireless networks: A machine learning approach." *IEEE Transactions on Vehicular Technology* 68, no. 8 (2019): 7957-7969.

[74] Al-Ahmed, Shahriar Abdullah, Muhammad ZeeshanShakir, and Syed Ali Raza Zaidi. "Optimal 3D UAV base station placement by considering autonomous coverage hole detection, wireless backhaul and user demand." *Journal of Communications and Networks* 22, no. 6 (2020): 467-475.

[75] Ullah, Zaib, Fadi Al-Turjman, UzairMoatasim, Leonardo Mostarda, and Roberto Gagliardi. "UAVs joint optimization problems and machine learning to improve the 5G and Beyond communication." *Computer Networks* 182 (2020): 107478.

[76] Wang, Cheng-Xiang, Marco Di Renzo, SlawomirStanczak, Sen Wang, and Erik G. Larsson. "Artificial intelligence enabled wireless networking for 5G and beyond: Recent advances and future challenges." *IEEE Wireless Communications* 27, no. 1 (2020): 16-23.

[77] Ali, Samad, WalidSaad, NandanaRajatheva, Kapseok Chang, Daniel Steinbach, Benjamin Sliwa, Christian Wietfeld et al. "6G white paper on machine learning in wireless communication networks." *arXiv preprint arXiv:2004.13875* (2020).

[78] Zhang, Chen, Leyi Zhang, Yanming Liu, Lipeng Zhu, and Zhenyu Xiao. "A Deployment Method Based on Artificial Bee Colony Algorithm for UAV-Mounted Base Stations." In *International Conference on Internet of Things as a Service*, pp. 143-155. Cham: Springer International Publishing, 2020.

[79] Lin, Mengting, and Youping Zhao. "Artificial intelligence-empowered resource management for future wireless communications: A survey." *China Communications* 17, no. 3 (2020): 58-77.

`

[80] Liu, Xiao, Mingzhe Chen, Yuanwei Liu, Yue Chen, Shuguang Cui, and Lajos Hanzo. "Artificial intelligence aided next-generation networks relying on UAVs." *IEEE Wireless Communications* 28, no. 1 (2020): 120-127.

[81] Shehzad, Muhammad K., Arsalan Ahmad, Syed Ali Hassan, and Haejoon Jung. "Backhaul-aware intelligent positioning of UAVs and association of terrestrial base stations for fronthaul connectivity." *IEEE Transactions on Network Science and Engineering* 8, no. 4 (2021): 2742-2755.

[82] Shafik, Wasswa, S. MojtabaMatinkhah, SolagbadeSaheedAfolabi, and MammanNurSanda. "A 3-dimensional fast machine learning algorithm for mobile unmanned aerial vehicle base stations." *International Journal of Advances in Applied Sciences* 2252, no. 8814 (2020): 8814.

[83] Ben Aissa, Sana, and Asma Ben Letaifa. "UAV communications with machine learning: challenges, applications and open issues." *Arabian Journal for Science and Engineering* 47, no. 2 (2022): 1559-1579.

[84] Mandloi, Dilip, and Rajeev Arya. "Seamless connectivity with 5G enabled unmanned aerial vehicles base stations using machine programming approach." *Expert Systems* 39, no. 5 (2022): e12828.

[85] Khan, Shah Khalid, Usman Naseem, HarisSiraj, Imran Razzak, and Muhammad Imran. "The role of unmanned aerial vehicles and mmWave in 5G: Recent advances and challenges." *Transactions on Emerging Telecommunications Technologies* 32, no. 7 (2021): e4241.

[86] Elnabty, Israa A., Yasmine Fahmy, and Mai Kafafy. "A survey on UAV placement optimization for UAV-assisted communication in 5G and beyond networks." *Physical Communication* 51 (2022): 101564.

[87] Lim, Wei Yang Bryan, Sahil Garg, ZehuiXiong, Yang Zhang, DusitNiyato, Cyril Leung, and Chunyan Miao. "UAV-assisted communication efficient federated learning in the era of the artificial intelligence of things." *IEEE network* 35, no. 5 (2021): 188-195.

`

[88] Lahmeri, Mohamed-Amine, Mustafa A. Kishk, and Mohamed-Slim Alouini. "Artificial intelligence for UAV-enabled wireless networks: A survey." *IEEE Open Journal of the Communications Society* 2 (2021): 1015-1040.

[89] Fatemidokht, Hamideh, MarjanKuchaki Rafsanjani, Brij B. Gupta, and Ching-Hsien Hsu. "Efficient and secure routing protocol based on artificial intelligence algorithms with UAV-assisted for vehicular ad hoc networks in intelligent transportation systems." *IEEE Transactions on Intelligent Transportation Systems* 22, no. 7 (2021): 4757-4769.

[90] Lins, Silvia, Kleber Vieira Cardoso, Cristiano Bonato Both, Luciano Mendes, José F. De Rezende, Antonio Silveira, Neiva Linder, and AldebaroKlautau. "Artificial intelligence for enhanced mobility and 5G connectivity in UAV-based critical missions." *IEEE Access* 9 (2021): 111792-111801.

[91] Hu, Jinna, Chen Chen, Lin Cai, Mohammad R. Khosravi, Qingqi Pei, and Shaohua Wan. "UAV-assisted vehicular edge computing for the 6G internet of vehicles: Architecture, intelligence, and challenges." *IEEE Communications Standards Magazine* 5, no. 2 (2021): 12-18.

[92] Yang, Helin, Jun Zhao, JiangtianNie, Neeraj Kumar, Kwok-Yan Lam, and ZehuiXiong. "UAV-assisted 5G/6G networks: Joint scheduling and resource allocation based on asynchronous reinforcement learning." In *IEEE INFOCOM 2021-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 1-6. IEEE, 2021.

[93] Parvaresh, Nahid, Michel Kulhandjian, HovannesKulhandjian, Claude D'Amours, and BurakKantarci. "A tutorial on AI-powered 3D deployment of drone base stations: State of the art, applications and challenges." *Vehicular Communications* 36 (2022): 100474.

[94] Rolly, Rinju Mariam, PandyMalarvezhi, and Thomas D. Lagkas. "Unmanned aerial vehicles: Applications, techniques, and challenges as aerial base stations." *International Journal of Distributed Sensor Networks* 18, no. 9 (2022): 15501329221123933.

`

[95] Baig, Bisma, and Abdul QaharShahzad. "Machine learning and AI approach to improve UAV communication and networking." In *Computational intelligence for unmanned aerial vehicles communication networks*, pp. 1-15. Cham: Springer International Publishing, 2022.

[96] Wang, Changyu, Weili Yu, Jinrong Lu, Fusheng Zhu, Lihua Fan, and Shengping Li. "UAV-Based Physical-Layer Intelligent Technologies for 5G-Enabled Internet of Things: A Survey." *Wireless Communications and Mobile Computing* 2022, no. 1 (2022): 4351518.

[97] Khan, Muhammad Asghar, Neeraj Kumar, Syed Agha HassnainMohsan, WaliUllah Khan, Moustafa M. Nasralla, Mohammed H. Alsharif, JustynaŻywiołek, and InsafUllah. "Swarm of UAVs for network management in 6G: A technical review." *IEEE Transactions on Network and Service Management* 20, no. 1 (2022): 741-761.

[98] Dastranj, Parinaz, VahidSolouk, and Hashem Kalbkhani. "Energy-efficient deep-predictive airborne base station selection and power allocation for UAV-assisted wireless networks." *Computer Communications* 191 (2022): 274-284.

[99] Fu, Shu, Meng Zhang, Min Liu, Chen Chen, and Fei Richard Yu. "Toward energy-efficient UAV-assisted wireless networks using an artificial intelligence approach." *IEEE Wireless Communications* 29, no. 5 (2022): 77-83.

[100] Fu, Shu, Meng Zhang, Min Liu, Chen Chen, and Fei Richard Yu. "Toward energy-efficient UAV-assisted wireless networks using an artificial intelligence approach." *IEEE Wireless Communications* 29, no. 5 (2022): 77-83.

[101] Rezwan, Sifat, and Wooyeol Choi. "Artificial intelligence approaches for UAV navigation: Recent advances and future challenges." *IEEE access* 10 (2022): 26320-26339.

[102] Chen, Chengbin, Jin Xiang, Zhuoya Ye, Wanyi Yan, Suiling Wang, Zhensheng Wang, Pingping Chen, and Min Xiao. "Deep learning-based energy optimization for edge device in UAV-aided communications." *Drones* 6, no. 6 (2022): 139.

`

[103] Pasandideh, Faezeh, Fabricio E. Rodriguez Cesen, Pedro Henrique Morgan Pereira, Christian Esteve Rothenberg, and Edison Pignaton de Freitas. "An improved particle swarm optimization algorithm for UAV base station placement." *Wireless Personal Communications* 130, no. 2 (2023): 1343-1370.

[104] Yazici, İbrahim, IbraheemShayea, and Jafri Din. "A survey of applications of artificial intelligence and machine learning in future mobile networks-enabled systems." *Engineering Science and Technology, an International Journal* 44 (2023): 101455.

[105] Zuo, Yiping, JiajiaGuo, Ning Gao, Yongxu Zhu, Shi Jin, and Xiao Li. "A survey of blockchain and artificial intelligence for 6G wireless communications." *IEEE Communications Surveys & Tutorials* (2023).

[106] Sarkar, Nurul I., and Sonia Gul. "Artificial intelligence-based autonomous UAV networks: A survey." *Drones* 7, no. 5 (2023): 322.

[107] Gu, Xiaohui, and Guoan Zhang. "A survey on UAV-assisted wireless communications: Recent advances and future trends." *Computer Communications* 208 (2023): 44-78.

[108] Dai, Minghui, Ning Huang, Yuan Wu, JieGao, and Zhou Su. "Unmanned-aerial-vehicle-assisted wireless networks: Advancements, challenges, and solutions." *IEEE Internet of Things Journal* 10, no. 5 (2022): 4117-4147.

[109] Cheng, Nan, Shen Wu, Xiucheng Wang, Zhisheng Yin, Changle Li, Wen Chen, and Fangjiong Chen. "AI for UAV-assisted IoT applications: A comprehensive review." *IEEE Internet of Things Journal* 10, no. 16 (2023): 14438-14461.

[110] Björnson, E., Hoydis, J., & Sanguinetti, L. (2017). Massive MIMO networks: Spectral, energy, and hardware efficiency. *Foundations and Trends® in Signal Processing*, *11*(3-4), 154-655

[111] Molisch, A. F., Ratnam, V. V., Han, S., Li, Z., Nguyen, S. L. H., Li, L., &Haneda, K. (2017). Hybrid beamforming for massive MIMO: A survey. *IEEE Communications magazine*, *55*(9), 134-141.

`

[112] Han, S., Chih-Lin, I., Xu, Z., & Rowell, C. (2015). Large-scale antenna systems with hybrid analog and digital beamforming for millimeter wave 5G. *IEEE Communications Magazine*, *53*(1), 186-194.

[113] Roh, W., Seol, J. Y., Park, J., Lee, B., Lee, J., Kim, Y., ...&Aryanfar, F. (2014). Millimeter-wave beamforming as an enabling technology for 5G cellular communications: Theoretical feasibility and prototype results. *IEEE communications magazine*, *52*(2), 106-113.

[114] Zheng, K., Ou, S., & Yin, X. (2014). Massive MIMO channel models: A survey. *International Journal of Antennas and Propagation*, *2014*.

[115] Björnson, E., Larsson, E. G., &Debbah, M. (2015). Massive MIMO for maximal spectral efficiency: How many users and pilots should be allocated?. *IEEE Transactions on Wireless Communications*, *15*(2), 1293-1308.

[116] He, Q., Xiao, L., Zhong, X., & Zhou, S. (2014). Increasing the sum-throughput of cells with a sectorization method for massive MIMO. *IEEE Communications Letters*, *18*(10), 1827-1830.

[117] Larsson, E. G., Marzetta, T., &Rusek, F. (2013). Scaling up MIMO: Opportunities and challenges with very large arrays. *Sig Process Mag IEEE*, *30*(1), 40-60.

[118] Larsson, E. G., Edfors, O., Tufvesson, F., & Marzetta, T. L. (2014). Massive MIMO for next generation wireless systems. *IEEE communications magazine*, *52*(2), 186-195.

[119] Jin, S., Wang, X., Li, Z., Wong, K. K., Huang, Y., & Tang, X. (2015). On massive MIMO zero-forcing transceiver using time-shifted pilots. *IEEE Transactions on Vehicular Technology*, *65*(1), 59-74.

[120] Gunnarsson, S., Flordelis, J., Van der Perre, L., &Tufvesson, F. (2020). Channel hardening in massive MIMO: Model parameters and experimental assessment. *IEEE Open Journal of the Communications Society*, *1*, 501-512.

[121] Ahmed, I., Khammari, H., Shahid, A., Musa, A., Kim, K. S., De Poorter, E., &Moerman, I. (2018). A survey on hybrid beamforming techniques in 5G:

`

Architecture and system model perspectives. *IEEE Communications Surveys & Tutorials*, *20*(4), 3060-3097.

[122] Uwaechia, A. N., Mahyuddin, N. M., Ain, M. F., Latiff, N. M. A., &Za'bah, N. F. (2019). On the spectral-efficiency of low-complexity and resolution hybrid precoding and combining transceivers for mmWave MIMO systems. *IEEE Access*, *7*, 109259-109277.

[123] Kutty, S., & Sen, D. (2015). Beamforming for millimeter wave communications: An inclusive survey. *IEEE communications surveys & tutorials*, *18*(2), 949-973.

[124] Chopra, Shakti Raj, and Akhil Gupta. "Error analysis of grouped multilevel space-time trellis coding with the combined application of massive MIMO and cognitive radio." *Wireless Personal Communications* 117, no. 2 (2021): 461-482.

[125] Chopra, Shakti Raj, Akhil Gupta, SudeepTanwar, CalinOvidiuSafirescu, TraianCandinMihaltan, and Ravi Sharma. "Multi-User Massive MIMO System with Adaptive Antenna Grouping for Beyond 5G Communication Network." *Mathematics* 10, no. 19 (2022): 3621.

[126] Chopra, Shakti Raj, Akhil Gupta, and HimanshuMonga. "An LTE approach with MIMO by using suboptimal selection of antenna." In *2018 International Conference on Intelligent Circuits and Systems (ICICS)*, pp. 167-172. IEEE, 2018.

[127] Matracia, Maurilio, Nasir Saeed, Mustafa A. Kishk, and Mohamed-Slim Alouini. "Post-disaster communications: Enabling technologies, architectures, and open challenges." *IEEE Open Journal of the Communications Society* 3 (2022): 1177-1205.

[128] Fascista, Alessio. "Toward integrated large-scale environmental monitoring using WSN/UAV/Crowdsensing: A review of applications, signal processing, and future perspectives." *Sensors* 22, no. 5 (2022): 1824.

[129] Zhou, Yiqing, Ling Liu, Lu Wang, Ning Hui, Xinyu Cui, Jie Wu, Yan Peng, Yanli Qi, and Chengwen Xing. "Service-aware 6G: An intelligent and open

network based on the convergence of communication, computing and caching." *Digital Communications and Networks* 6, no. 3 (2020): 253-260.

[130] Yang, Wanting, Hongyang Du, Zi Qin Liew, Wei Yang Bryan Lim, ZehuiXiong, DusitNiyato, Xuefen Chi, Xuemin Shen, and Chunyan Miao. "Semantic communications for future internet: Fundamentals, applications, and challenges." *IEEE Communications Surveys & Tutorials* 25, no. 1 (2022): 213-250.

[131] Ping, Z. H. A. N. G., X. U. Xiao-dong, H. A. N. Shu-jun, N. I. U. Kai, X. U. Wen-jun, and L. A. N. Yue-heng. "Entropy reduced mobile networks empowering industrial applications." *Journal of Beijing University of Posts and Telecommunications* 43, no. 6 (2020): 1.

[132] Zhou, Yiqing, Lin Tian, Ling Liu, and Yanli Qi. "Fog computing enabled future mobile communication networks: A convergence of communication and computing." *IEEE Communications Magazine* 57, no. 5 (2019): 20-27.

[133] Chen, Qinbo. "Joint position and resource optimization for multi-UAV-aided relaying systems." *IEEE Access* 8 (2020): 10403-10415.

[134] S. Yin, Y. Zhao, and L. Li, ‘‘Resource allocation and basestation placement in cellular networks with wireless powered UAVs,’’ IEEE Trans. Veh. Technol., vol. 68, no. 1, pp. 1050–1055, Jan. 2019

[135] T. Zhang, J. Lei, Y. Liu, C. Feng, and A. Nallanathan, ‘‘Trajectory optimization for UAV emergency communication with limited user equipment energy: A safe-DQN approach,’’ IEEE Trans. Green Commun. Netw., vol. 5, no. 3, pp. 1236–1247, Sep. 2021.

[136] K. Li, W. Ni, E. Tovar, and M. Guizani, ‘‘Deep reinforcement learning for real-time trajectory planning in UAV networks,’’ in Proc. Int. Wireless Commun. Mobile Comput. (IWCMC), Jun. 2020, pp. 958–963.

[137] W. Zhang, Q. Wang, X. Liu, Y. Liu, and Y. Chen, ‘‘Three-dimension trajectory design for multi-UAV wireless network with deep reinforcement learning,’’ IEEE Trans. Veh. Technol., vol. 70, no. 1, pp. 600–612, Jan. 2021.

`

[138] U. Challita, W. Saad, and C. Bettstetter, ‘‘Interference management for cellular-connected UAVs: A deep reinforcement learning approach,’’ IEEE Trans. Wireless Commun., vol. 18, no. 4, pp. 2125–2140, Apr. 2019.

[139] N. Zhao, Y. Cheng, Y. Pei, Y.-C. Liang, and D. Niyato, ‘‘Deep reinforcement learning for trajectory design and power allocation in UAV networks,’’ in Proc. IEEE Int. Conf. Commun. (ICC), Jun. 2020, pp. 1–6.

[140] H. V. Abeywickrama, Y. He, E. Dutkiewicz, B. A. Jayawickrama, and M. Mueck, ‘‘A reinforcement learning approach for fair user coverage using UAV mounted base stations under energy constraints,’’ IEEE Open J. Veh. Technol., vol. 1, pp. 67–81, 2020.

[141] R. Lowe, ‘‘Multi-agent actor-critic for mixed cooperative-competitive environments,’’ in Proc. Adv. Neural Inf. Process. Syst., vol. 30, 2017, pp. 1–9.

[142] K. Sharma, B. Singh, E. Herman, R. Regine, S. S. Rajest, and V. P. Mishra, ‘‘Maximum information measure policies in reinforcement learning with deep energy-based model,’’ in Proc. Int. Conf. Comput. Intell. Knowl. Economy (ICCIKE), Mar. 2021, pp. 19–24.

[143] W. Jiang, B. Han, M. A. Habibi, and H. D. Schotten, ‘‘The road towards 6G: A comprehensive survey,’’ IEEE Open J. Commun. Soc., vol. 2, pp. 334–366, 2021.

[144] E. Dahlman, S. Parkvall, and J. Skold, 4G, LTE-Advanced Pro and The Road to 5G. New York, NY, USA: Academic, 2016.

[145] C. Li, T. Trinh, L. Wang, C. Liu, M. Tomizuka, and W. Zhan, ‘‘Efficient game-theoretic planning with prediction heuristic for sociallycompliant autonomous driving,’’ IEEE Robot. Autom. Lett., vol. 7, no. 4, pp. 10248–10255, Oct. 2022.

[146] Y. Wang, ‘‘McDPC: Multi-center density peak clustering,’’ Neural Comput. Appl., vol. 32, pp. 13465–13478, Feb. 2020.

[147] W. Shi, S. Song, and C. Wu, ‘‘Soft policy gradient method for maximum entropy deep reinforcement learning,’’ 2019, arXiv:1909.03198.

`

[148] O. Peer, ‘‘Ensemble bootstrapping for Q-learning,’’ in Proc. Int. Conf. Mach. Learn. (PMLR), 2021, pp. 1–10.

[149] H. M. Gomes, J. P. Barddal, F. Enembreck, and A. Bifet, ‘‘A survey on ensemble learning for data stream classification,’’ ACM Comput. Surveys, vol. 50, no. 2, pp. 1–36, Mar. 2018.

[150] M. E. Taylor and P. Stone, ‘‘Transfer learning for reinforcement learning domains: A survey,’’ J. Mach. Learn. Res., vol. 10, no. 7, pp. 1–53, 2009.

[151] P. R. Montague, R. S. Sutton, and A. G. Barto, ‘‘Reinforcement learning: An introduction,’’ Trends Cognit. Sci., vol. 3, no. 9, p. 360, 1999.

[152] Q. Hou and J. Dong, ‘‘Robust adaptive event-triggered fault-tolerant consensus control of multiagent systems with a positive minimum interevent time,’’ IEEE Trans. Syst., Man, Cybern., Syst., vol. 53, no. 7, pp. 4003– 4014, Jul. 2023.

[153] Q. Hou and J. Dong, ‘‘Distributed dynamic event-triggered consensus control for multiagent systems with guaranteed performance and positive inter-event times,’’ IEEE Trans. Autom. Sci. Eng., vol. 21, no. 1, pp. 746–757, Jan. 2024.