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Development of Air-to-Ground Connectivity for 5G
UAV Networks

School of Aerospace, Transport and Manufacturing
Aerospace

PhD

Academic Year: 2020–2024

Supervisors: Professor Saba Al-Rubaye
Professor Gokhan Inalhan
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Academic Integrity Declaration

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- that all content, including primary and/or secondary data, is true to the best of my knowledge.
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Abstract

This thesis explores novel methodologies aimed at addressing critical challenges in the integration of Unmanned Aerial Vehicles (UAVs) within heterogeneous networks, particularly in the context of fifth-generation (5G) communication systems. The primary focus revolves around achieving seamless connectivity and mitigating interference to enhance the performance and reliability of UAV operations. As such, this thesis contributes three novel components across these domains. The first novel component of this thesis investigates the development of an algorithmic framework grounded in the Received Signal Strength (RSS) criterion for network selection, augmented by the Entropy Weighted Method (EWM) decision-making process. Through comprehensive simulation-level analyses, the efficacy of this approach in facilitating seamless handover (HO) between 5G and long-term evolution (LTE) networks for UAVs is demonstrated. This component represents a significant contribution to addressing the mobility challenges inherent in heterogeneous networks, thus advancing the state-of-the-art in UAV-5G communication. However, ensuring uninterrupted connectivity for UAVs operating in remote or dynamic environments remains a significant hurdle. The second component introduces a novel approach to achieving seamless HO for UAVs

transitioning between terrestrial and satellite communication networks, leveraging graph theory to develop a decision-making algorithm aimed at optimising HO decisions. Evaluation through extensive simulations and comparison with existing solutions underscores significant improvements in various performance metrics, such as RSS, Signal-to-Noise Ratio (SNR), throughput, latency, and overall UAV connectivity. The proposed graph-method (GM)-based seamless HO solution represents a pivotal advancement in enabling reliable and uninterrupted communication for UAVs operating in remote and challenging environments, thereby advancing the state-of-the-art in UAV technology. The third component delves into interference mitigation strategies to ensure optimal UAV performance within 5G networks. A novel deep Q learning (DQL) algorithm is proposed to address interference from neighbouring 5G base stations (gNBs). By formulating and solving a Signal-to-Interference and Noise Ratio (SINR) optimisation problem using the DQL algorithm, interference is effectively mitigated, resulting in improved link performance. This Ph.D. research contributes to the advancement of knowledge in the field of UAV-5G integration by presenting innovative solutions to key challenges. The findings pave the way for the seamless incorporation of UAVs into heterogeneous networks, unlocking their full potential across a diverse range of applications, from surveillance to communication infrastructure maintenance and beyond.

Keywords:

Fifth Generation (5G); Unmanned Aerial Vehicles(UAV); mobility; handover; het-

erogeneous networks; entropy weighted method; Interference Mitigation; Artificial Intelligence; Deep Q-Learning; vertical handover; satellite; graph method; non-terrestrial networks (NTN)

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List of Abbreviations

3D	Three-Dimensional
3GPP	Third Generation Partnership Project
4G	Fourth-Generation
5G	Fifth-Generation
6G	Sixth-Generation
ABS	Aerial Base Station
AI	Artificial Intelligence
AMF	Access Mobility Function
ANN	Artificial Neural Network
AOD	Angle of Departure
AP	Access Point
ARIMA	Auto-Regressive Integrated Moving Average
BS	Base station
BVLoS	Beyond Visual Line of Sight
CAA	Civil Aviation Authority
CCDF	Complement Cumulative Distribution Function
CNN	Convolutional Neural network

CoMP	Coordinated Multi-Point
CSI	Channel State Information
DBS	Drone Base Station
DDQL	Double Deep Q-Learning
DQL	Deep Q-Learning
ECI	Earth Centric Inertial Reference
eMBB	Enhanced Mobile Broadband
ETSI	European Technical Standards Institution
EWM	Entropy Weighted Method
FAA	Federal Aviation Authority
FPA	Fixed Power Allocation
FSPL	Free Space Path Loss
GEO	Geostationary Orbit
GHz	Gigahertz
GM	Graph Method
gNB	Next generation e-Node B
GPS	Global Positioning System
GSM	Global System for Mobile Communications
HAPS	High Altitude Platform Systems
HO	Handover
HOF	Handover Failure
ICIC	Inter Cell Interference Cancellation
IoT	Internet of Things

KPI	Key Performance Indicators
LEO	Low Earth Orbits
LoS	Line of Sight
LTE	Long Term Evolution
Mbps	Mega bits per second
MDP	Markov Decision Process
MEC	Multi-Edge Cloud Architecture
MHz	Megahertz
MIMO	Massive Input and Massive Output
ML	Machine Learning
mmTC	Massive Machine-Type Communications
mmWave	Millimeter Wave
MR	Mixed Reality
MSE	Mean Square Error
NEF	Network Exposure Function
NLoS	Non Light of Sight
NN	Neural Network
NOMA	Non Orthogonal Multiple Access
NR	New Radio
NRF	Network Repository Function
NSA	Non-Standalone
NSSF	Network Slice Selection Function
NT-BS	Non Terrestrial Base Station

NTN	Non Terrestrial Networks
OFDM	Orthogonal Frequency Division Multiplexing
OWC	Optical Wireless Communications
PCF	Policy Control Function
PPP	Poisson Point Process
PRB	Physical Resource Block
PSO	Particle Swarm Optimization
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
RAN	Radio Access Network
RAT	Radio Access Technology
RLF	Radio Link Failure
Rma	Rural Macro
RN	Relay Node
RQ	Request
RSRP	Reference Signal Received Power
RSS	Received Signal Strength
RWP	Random Waypoint
SATCOM	Satellite Communications
SATM	School of Aerospace, Technology and Manufacturing
SAW	Simple Additive Weight
SBA	Software Based Architecture
SDN	Software Defined Network

SGD	Stochastic Gradient Descent
SGP4	Simplified General Perturbations
SINR	Signal to Noise Plus Interference Ratio
SMF	Session Management Function
SN	Sequence Number
SNR	Signal to Noise Ratio
SWAP	Size, Weight and Power
TCP	Transport Control Protocol
THz	Terahertz
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TPC	Joint Trajectory and Power Control
TTT	Time to Trigger
UAV	Unmanned Aerial Vehicles
UDM	Unified Data Management
UDP	User Datagram Protocol
UE	User Equipment
UK	United Kingdom
UMa	Urban Macro
UMi	Urban Micro
UPF	User Plane Function
uRLLc	Ultra Reliable Low Latency Communications
V2X	Vehicle to Everything
VLoS	Visual Line of Sight

VNF Virtual Network Function

Publications

Published

1. A. Warrier, L. Aljaburi, H. Whitworth, S. Al-Rubaye and A. Tsourdos, "Future 6G Communications Powering Vertical Handover in Non-Terrestrial Networks," in IEEE Access, vol. 12, pp. 33016-33034, 2024, doi: 10.1109/ACCESS.2024.3371906.
2. Warrier A, Al-Rubaye S, Inalhan G & Tsourdos A (2023) AI-enabled interference mitigation for autonomous aerial vehicles in urban 5G networks, Aerospace, 10 (10) Article No. 884.
3. Warrier A, Al-Rubaye S, Panagiotakopoulos D, Inalhan G & Tsourdos A (2022) Interference mitigation for 5G-connected UAV using deep Q-learning framework. In: 2022 IEEE/AIAA 41st Digital Avionics Systems Conference (DASC), Portsmouth, Virginia, 18-22 September 2022.
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6. Subasu S, Al-Rubaye S, Warrier A, Whitworth, H "Unmanned Air Vehicle Operational Framework for Public Safety Communications". In: 2024 IEEE/AIAA 43rd Digital Avionics Systems Conference (DASC), San Diego, September 29- October 3 2024 (*Accepted*).

Submitted

1. Day J, Al-Rubaye S, Whitworth H, Warriar A, & Samie M (2024) "Towards Autonomy for Transportation Systems: Collaborative Agent Performance Analysis", Electronics.
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Chapter 1

Introduction

This chapter provides an overview of the various components of air-to-ground connectivity with respect to fifth-generation (5G) technology and Unmanned Aerial Vehicles (UAVs). It introduces UAVs, 5G technology, integration of UAVs with satellites, mobility in urban and rural areas, and interference. Additionally, the chapter examines the standardization of UAVs and 5G communication technology, elucidating its implications on this research.

1.1 Unmanned Aerial Vehicles (UAVs)

In the past decade, rapid technological advances within the UAV industry have caused a transformative disruption in aviation, introducing unprecedented capabilities. Over the past decade, rapid technological advances in the UAV industry have significantly impacted various sectors of aviation. In the military, UAVs have enhanced surveillance, reconnaissance, and combat capabilities. Commercially, they are revolutionizing delivery services, agriculture, and infrastructure

inspection. In emergency response, drones aid in search and rescue operations and disaster assessment. The recreational market has expanded with hobbyist drones, and innovations in aerial photography. Technological progress in AI, battery life, and autonomy has improved UAV functionality. Additionally, regulatory frameworks have evolved to ensure safety and manage UAV traffic. UAVs also support environmental monitoring and wildlife conservation, while driving aerospace innovations that benefit the broader aviation industry. This surge in innovation has led to a substantial increase in applications for access to low-level airspace by various states and regulators. Forecasts indicate that civil UAV operations are poised to surpass manned aircraft operations in the near future. Air navigation service providers (ANSPs) [1] anticipate a diverse range of operations, spanning controlled and uncontrolled airspace, including trans-boundary flights. Integrating UAVs safely into crowded airspace, ensuring robust cybersecurity, and addressing privacy concerns are critical issues. Additionally, developing infrastructure, establishing technological standards, and gaining public acceptance are essential for widespread UAV adoption. Insurance, liability, and environmental sustainability further complicate the landscape, necessitating collaborative efforts between regulatory bodies, industry stakeholders, and technology developers to create a balanced and effective framework. The lack of harmonization among states and regulators in UAV operations can lead to operational inefficiencies, safety risks, and economic fragmentation, as operators navigate complex and varying regulations. This inconsistency hampers cross-border operations, stifles innovation, and creates legal and compliance challenges. It also

results in uneven safety, security, and privacy standards, potentially undermining public trust and environmental protections. Moreover, it can delay technological advancements and diminish global competitiveness, highlighting the need for international cooperation and standardized regulatory frameworks.

The swift and widespread adoption of cutting-edge technologies poses a formidable challenge to the establishment of timely standards. Traditional methods of certification and operational approval face impracticality due to the lack of stability in aircraft design and equipage, coupled with the utilisation of non-traditional aviation-related communication and navigation technologies. In response to this burgeoning demand, there is a call for states and regulators to adopt an innovative and proactive approach to swiftly review and approve proposals. However, this urgency has resulted in a lack of harmonisation, potentially impacting critical aspects such as safety, security, environmental considerations, system reliability, and economic efficiency.

UAVs are a new and developing component of the aviation system that offers a multitude of potential applications and obstacles. UAVs come in a variety of forms and dimensions, from small portable devices to large aircraft about the size of commercial aeroplanes. They can be designed with fixed wings, rotary wings, or a combination of both, just like their manned counterparts [2], [3], [4]. All UAVs have the same basic design; however, they differ in size and shape, and all have no pilot on board. UAVs, vary widely in form and dimension, from tiny micro and nano drones used for indoor inspections to large drones for military surveillance and environmental monitoring. While they share similarities with

manned aircraft in terms of aerodynamic principles and control systems, UAVs differ significantly in crew requirements, size, payload capacity, endurance, and regulatory standards. UAVs are remotely operated or autonomous, reducing costs and risks to human life. They are designed for specific tasks with varying degrees of complexity and are subject to different safety and operational regulations compared to manned aircraft. But much like with conventional aircraft, it is still necessary to fly unmanned aircraft properly to protect both airborne traffic, people and property on the ground.

UAV operations are categorized as follows:

1. Within the Visual Line of Sight (VLoS): Operating within Visual Line of Sight (VLoS) requires the remote pilot to maintain a clear and unobstructed view of the unmanned aircraft and its surrounding airspace throughout its airborne trajectory. The primary objective of VLoS operations is to prevent collisions, ensuring that the remote pilot can continuously observe the UAV's flight path and take corrective action to avoid potential obstacles. Although corrective lenses are permissible, the use of binoculars, telescopes, or other image-enhancing devices is prohibited. Essentially, when operating within VLoS, the UAV must remain visible to the unaided eyes of the remote pilot [5]. The VLoS requirement is satisfied even if the UAV is flown horizontally up to 500 m from the remote pilot, provided it remains visible at that distance [6]. The "operating height" is limited to a maximum distance of 400 feet (120 m) from the nearest point of the Earth's surface. Operations beyond this range may be permitted if an acceptable safety case

is submitted to the Civil Aviation Authority (CAA), the regulatory body for UAVs. Larger aircrafts may justify visual monitoring at distances greater than 500 m, while smaller aircraft may require closer proximity to ensure adequate visual contact. Pilots of manned aircraft face significant challenges in visually detecting small UAVs, especially in high-density, low-level air traffic areas. These challenges include the small size and poor visibility of UAVs, high workload for pilots, rapid closing speeds, and difficult lighting and weather conditions. Utilizing proper position lights and markings on the UAV aids in enhancing its visibility to manned aircraft. Remote pilots should also stay informed about weather conditions and adhere to operational limits to avoid flying in adverse weather. Leveraging technology like GPS-based planning tools and collision avoidance systems enhances situational awareness and helps in proactive risk management. Compliance with local regulations, continuous monitoring of airspace conditions, and thorough pre-flight risk assessments further contribute to safe and responsible UAV operations. For UAVs, the terminology "height" denotes the vertical distance of an object from a specified point above the earth's surface. To accommodate instances where a UAV is flown over hilly/undulating terrain or near a cliff edge, regulations stipulate a requirement to maintain a distance of 400 feet (120 m) from the earth's surface, as illustrated in Figure 1.1. The small size and structure of most UAVs operated within VLOS, especially the multi-rotor models, pose a challenge in terms of visibility for pilots of manned aircraft. These UAVs are often difficult to discern un-

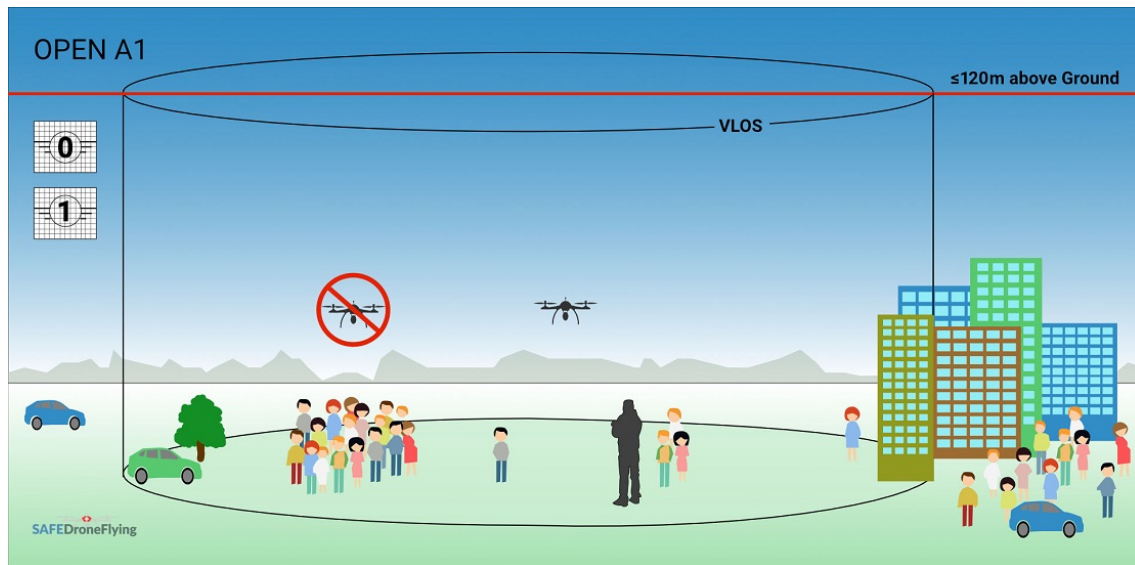


Figure 1.1: Representation of maximum allowed height for VLoS operation

til they are in close proximity, unlike the typical visibility range associated with manned aircraft sightings. This challenge becomes more pronounced when the UAVs are hovering or moving at slow speeds. The visual detection of a small unmanned aircraft from the vantage point of another aircraft is likely to occur as a 'late sighting,' providing limited time for the pilot to alter course and avert a potential collision. This issue is particularly pertinent in areas with a higher density of low-level air traffic. In such scenarios, remote pilots are advised to operate their aircraft at altitudes no higher than strictly necessary for the intended operation. Advanced sensors and collision avoidance systems enhance UAVs' ability to detect and evade obstacles, reducing collision risks. Autonomous capabilities driven by AI improve decision-making and operational control, potentially minimizing human error. Enhanced cybersecurity measures safeguard against unauthorized access and data breaches, crucial for protecting sensitive information. Economically, advancements lead to reduced operational costs

through improved efficiency in energy usage and maintenance. Moreover, these technologies open new markets and opportunities, boosting productivity across sectors like agriculture, infrastructure, and logistics. Overall, the integration of these technologies promises to elevate UAV capabilities, driving innovation and safety while fostering economic growth. This precautionary measure is essential to mitigate the risk associated with the reduced visibility of small UAVs and allows for increased reaction time for pilots of manned aircraft, contributing to overall airspace safety.

2. Beyond the Visual Line of Sight (BVLOS): Beyond Visual Line of Sight (BVLOS) is the most talked about thing in the UAV industry. Countries around the world are amending their drone policies so that they can allow UAVs to fly BVLOS for maximum efficiency. Unlike VLOS flights, which are operated within the pilot's line of sight, BVLOS flights are flown beyond the visual range. BVLOS capabilities enable UAVs to cover far greater distances. The BVLoS architectures is shown in Figure 1.2

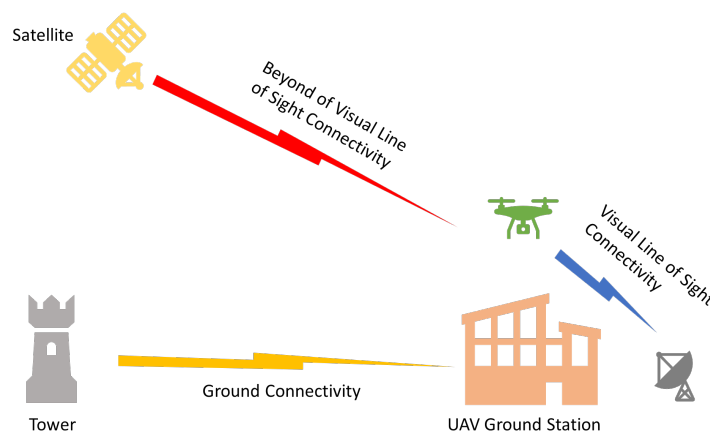


Figure 1.2: Beyond Visual line of Sight Architecture

BVLoS flying UAVs are controlled by data provided by on-board instru-

ments. Information is transmitted via a telemetry link that informs the operator about the position, altitude, speed, and direction of flight as well as all relevant parameters of the aircraft. However, BVLoS flying UAVs can also change flight parameters and control sensors to collect data [7], [8], [9], [10].

BVLoS flight will normally require either:

- a technical ability which is equivalent to the ability of a pilot of a manned aircraft uses to 'see and avoid' potential conflicts; this is referred to as a Detect and Avoid (DAA) capability.
- a block of airspace to operate in which the unmanned aircraft is 'segregated' from other aircraft – where the other aircraft are not permitted to enter this airspace block, thus allowing the unmanned aircraft can operate without the risk of collision, or the need for other collision avoidance capabilities

1.2 5G Technology

The 5G standard for broadband cellular networks was introduced in 2019 by mobile phone operators around the world [11]. According to the Global System for Mobile Communications Association (GSMA) [12], 5G networks are expected to have more than 1.7 billion subscribers worldwide by 2025. 5G networks are positioned as the planned successor to fourth generation (4G) networks, which currently provide connectivity to most cell phones. Like its predecessors, 5G divides

the service area into small geographic units called cells to function as a cellular network. Every 5G wireless device in a cell uses a local antenna to send radio waves to the Internet and phone network.

The larger capacity of 5G networks allows faster download speeds, up to 10 gigabits per second (Gbit/s), which is by far their main advantage. As a result, the anticipated architecture of 5G radio access networks in the future is well-positioned to link and support a wide range of needs, including 1000-fold traffic volumes, 100 billion wireless devices connected, and a variety of criteria for latency, dependability, and battery life. As seen in Figure 1.3, this permits support for several devices and applications. Compared to current 4G cellular networks, this is different. An increase in mobile data traffic is expected to exceed 1 zettabyte per month globally by 2028 as a result of the growing popularity of the Internet of Things (IoT), which presents serious problems for current infrastructure and imposes a considerable cost burden [13]

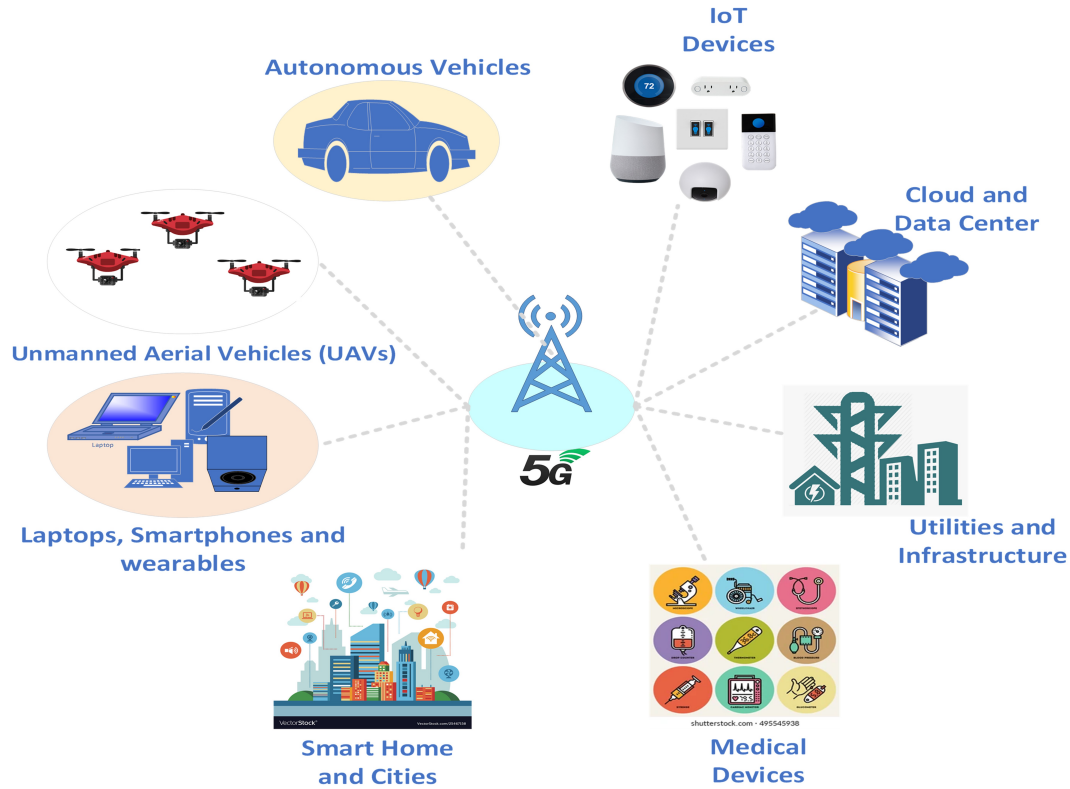


Figure 1.3: Multi device connectivity in 5G

Efforts to address the increasing demands include the deployment of heterogeneous networks (HetNets), which incorporate various small cells [14]. However, in unforeseen or emergency situations, such as disaster relief and service recovery, the deployment of current infrastructure becomes economically infeasible and logistically challenging. To tackle this issue, an intelligent heterogeneous architecture leveraging UAVs, emerges as a promising paradigm. This approach aims to facilitate three central usage scenarios in future wireless networks: enhanced mobile broadband (eMBB) with bandwidth-consuming applications, ultra-reliable low-latency communication (URLLC), and massive machine-type communications (mMTC) [15].

Using higher-frequency radio waves in addition to the low and medium-band frequencies used in earlier cellular networks helps 5G attain its faster speeds. Smaller geographic cells are necessary because higher-frequency radio waves have a shorter usable physical range. Up to three frequency bands—low, medium, and high can be used by 5G networks. Three different cell types are used in 5G networks, each of which has unique requirements for antenna designs and offers a trade-off between download speed, range, and service area. Smartphones and other wireless devices with 5G use the fastest antenna in their area to connect to the network.

Implementation options for 5G encompasses the following frequencies [16]:

- Low-band: 5G uses a similar frequency range to 4G cell phones, 600–900 MHz, giving download speeds a little higher than 4G, between 30–250 megabits per second (Mbit/s). Low band cell towers have a range and coverage area similar to 4G towers.
- Midband: 5G uses microwaves of 2.3 to 4.7 gigahertz (GHz), allowing speeds of 100 to 900 Mbit/s, with each cell tower providing service up to several kilometres in radius.
- High-band: 5G operates at frequencies of 24–47 GHz, achieving download speeds in the gigabit-per-second range, comparable to cable internet.

However, millimetre waves (mmWave) have a more limited range, requiring numerous small cells, and their propagation can be hindered by materials in walls or windows [17]. Due to higher costs, these cells are planned for deployment primarily in dense urban environments and areas with large crowds.

1.3 5G-enabled UAV Communications

The use of UAVs has experienced rapid growth in recent years. However, conventional UAV systems predominantly rely on simplistic direct communication between the UAV and the ground pilot over unlicensed spectrum, such as the Industry, Science and Medical (ISM) 2.4 GHz band [18]. This communication method is characterised by low data rates, unreliability, insecurity, vulnerability to interference, challenging monitoring and management, and a very limited operational range. Ensuring the safe and reliable operation of UAVs when dependent on ground-based wireless connectivity requires several key considerations. It is essential to maintain strong and consistent signal strength throughout the UAV's operational range, minimizing latency for real-time control responses. Implementing redundancy in communication systems and employing fail-safe mechanisms such as backup channels or satellite communication enhances reliability and mitigates risks of signal loss. Security measures like encryption and authentication protect against unauthorized access and cyber threats, safeguarding data integrity and confidentiality. Managing interference from other wireless devices and complying with regulatory requirements for spectrum usage are critical to maintaining uninterrupted communication. Thorough testing and validation under various conditions validate system performance and identify potential vulnerabilities, ensuring that UAV operations are conducted safely and effectively. To address these constraints, there has been considerable interest in integrating UAVs into cellular networks, notably 5G networks.

One way in which UAVs can take advantage of the widespread accessibility

of advanced cellular technologies and cellular networks is by connecting them to cellular networks as unique aerial users with specific tasks. However, in order to enhance terrestrial wireless communications from the air, specialised UAVs can be strategically deployed as aerial base stations (ABSs), access points (APs), or relays. This will result in the development of UAV-assisted communications. The potential for on-demand deployment, high reconfiguration flexibility in the network, and increased probability of Line-of-Sight (LoS) communication links are only a few of the prospective benefits of UAV-assisted communications. Both models are closely related to 5G use cases, including mMTC, eMBB, and ultra-reliable low-latency (URLLC) communications. They either give UAVs stable, uninterrupted connectivity, or use UAVs to improve communication.

In addition, the sensing and computing capabilities related to UAVs play a crucial role in achieving efficient and reliable communication, such as avoiding coverage gaps, as well as in facilitating intelligent UAV coordination, positioning, and trajectory design. However, wireless networks of 5G and beyond, integrated with UAVs, diverge significantly from conventional communication systems. This is attributed to the elevated altitude and mobility of UAVs, the distinctive channel characteristics of UAV-ground links, the asymmetric quality of service (QoS) requirements for downlink command and control and uplink mission-related data transmission, the stringent constraints imposed by the size, weight, and power (SWAP) limitations of UAVs, and the additional degrees of freedom of design enabled by joint UAV mobility control and communication resource allocation [19].

1.4 Standardization

The industry consortium setting standards for 5G is the 3rd Generation Partnership Project (3GPP), defining any system using 5G New Radio (5G NR) software as "5G." Minimum standards are set by the International Telecommunication Union (ITU) [20].

1.4.1 Standards for 5G Communication

Originally working together to develop international specifications and standards for 3G technology, the 3GPP is an alliance of telecoms standards organisations. As of right now, 3GPP is still in operation and is focused on developing new releases that will eventually provide standardised features and specifications for 5G technology. According to projections, 5G technology—including all of its releases—will be completed and commercially available faster than previous cellular generations.

3GPP is still working on strategic planning and developing new releases that add new standardised functionality to previous versions while also improving and refining them. Notably, Releases 15, 16, 17, and 18 are the upcoming releases that are intended for 5G.

1.4.1.1 Release 15

Timeline: March 2017 - June 2019

3GPP Release 15, approved in March 2017, marked the initial step in standardising 5G. It focused on non-standalone (NSA) 5G architecture, where 5G relies on

a 4G foundation, introducing enhancements like increased speed, capacity, and groundwork for technologies like massive input and massive output (MIMO). The release also brought in 5G NR technology and specifications for 5G NR hardware. The second phase introduced standalone (SA) 5G architecture, enabling independent 5G operation without 4G reliance, incorporating the entire suite of 5G functionalities, including core network architecture and ultra-reliable low latency. The final version introduced various standardised architectures for a simplified migration from 4G to 5G, although not mandatory. Although it was the first step, Release 15 did not support UAV operations in 5G networks, but it laid the foundation for future releases to add support for UAV applications [21].

1.4.1.2 Release 16

Timeline: June 2018 - June 2020

3GPP Release 16, completed in 2020, represents a significant progression in 5G technology by introducing the 5G-SA architecture, allowing complete 5G functionality independently of 4G. Notable improvements include advancements in Ultra-Reliable Low Latency Communication (URLLC) for critical applications, a focus on Vehicle-to-Everything (V2X) communication, expanded support for unlicensed spectrum, and specialized features for Industrial IoT applications. The release also enhances multimedia broadcast services to improve content delivery efficiency and reinforces security features against evolving threats. Although it does not establish standards for 5G-UAV communications, Release 16 lays the foundation for future releases, contributing to a more versatile, efficient, and se-

cure 5G ecosystem, facilitating innovative applications across industries [22].

1.4.1.3 Release 17

Timeline: December 2019 - June 2022

3GPP Release 17 signifies a pivotal moment in cellular communication evolution, specifically tailored UAVs. This release introduces groundbreaking features that enhance UAV capabilities within cellular networks, address challenges, and unlock diverse applications. Key enhancements include height-dependent measurements for accurate altitude determination, improved UAV tracking capabilities for situational awareness, and direct UAV-to-UAV and UAV-to-ground communications. The release also extends coverage, reduces handover (HO) latency, and introduces optimized mobility signalling for seamless UAV connectivity, even in remote areas. Additionally, interference mitigation techniques are introduced for efficient spectrum utilization. These advances will significantly impact UAV communication, enabling longer-range operations, greater autonomy, and new use cases such as BVLoS operations, package delivery, and search and rescue missions. The standardised communication approach in Release 17 improves safety, security, and encourages further innovation in UAV applications and services, marking a milestone in the continuous evolution of cellular communications for UAVs [23].

1.4.1.4 Release 18 and further releases

Timeline: December 2021 - March 2024

Legacy technologies such as 4G underwent a decade-long development in six 3GPP releases to achieve their current capabilities. Similarly, 5G is expected to undergo multiple releases to realise its full potential. Release 18 was formally designated as part of the 5G series after a December 2020 meeting, but its progression has been hampered by the COVID-19 pandemic, which has affected in-person meetings crucial to specifying Release 18. Optimistically, 3GPP anticipates in-person meetings to resume by June 2021, with the aim of approving Release 18's initial package by December 2021. The timeline depends on physical meetings, and the potential for continued reliance on virtual meetings is a factor to consider in the foreseeable future [24].

1.4.2 UAV Safety Standards

CAA is the regulating body in the UK for UAVs. As such, these regulations impact various aspects such as maximum altitude of flying, LoS operation, restricted zones and UAVs are typically restricted from flying above a certain maximum altitude, often specified in feet or meters above ground level. In the UK, it is up to 120 m (approximately 400 feet). Certain areas, such as airports, military zones, and sensitive locations, may have specific altitude restrictions or be designated as no-fly zones. Special permissions or authorisations may be required to fly in restricted areas. Operators are generally required to maintain visual contact with the drone during flight, when flying VLoS while, when flying BVLoS may be restricted without special permissions. Regulations limit how close UAVs can fly to people, buildings, and other structures. These regulations imposed by CAA,

have a significant impact on communications, which are discussed below:

- **Altitude Limitations:** Maximum-altitude restriction directly influences the operational range of drone communications. UAVs are limited in how high they can fly, affecting the reach and coverage of communication signals.
- **Communication Range:** UAV communication systems, including RF or wireless communication, are designed to operate within specific ranges. Altitude restrictions can limit the effective range of communication between the UAV and its operator or ground control station.
- **Signal Strength and Reliability:** As UAVs ascend, atmospheric conditions and the distance from the operator can impact signal strength and reliability. Adherence to altitude regulations helps ensure that the UAV maintains a reliable connection with the ground control system.

Understanding and adhering to altitude regulations are essential for responsible UAV operation. Communication systems must be designed to operate within specified altitude limits, promoting safe and compliant flights. As technology and regulations evolve, UAV communication systems are likely to continue to adapt to meet changing requirements [25].

1.5 Mobility Overview for Urban Areas

The integration of UAVs into 5G heterogeneous networks marks a revolutionary step in the evolution of modern communication systems. The seamless operation of UAVs within these networks, however, introduces a critical challenge known

as the HO problem. HOs are transitions of communication links from one network node to another, essential for maintaining connectivity as UAVs traverse diverse geographical areas. This intersection of UAVs and 5G heterogeneous networks brings about a myriad of complexities that demand innovative solutions to ensure uninterrupted communication and optimal performance. Following are some associated challenges [26] [27]:

- **Mobility and Dynamics:** UAVs, by nature, exhibit dynamic mobility and varying altitudes, creating challenges for seamless HOs. Rapid changes in location and altitude demand a robust HO mechanism capable of adapting to these dynamic scenarios without compromising connection quality.
- **Network Heterogeneity:** 5G heterogeneous networks consist of diverse cells, each with different characteristics and capabilities. Coordinating HOs between these varied cells poses a significant challenge, which requires intelligent algorithms and protocols to manage transitions effectively.
- **Latency and Reliability:** The stringent requirements of UAV applications, such as surveillance or delivery services, demand low latency and high reliability in communication. HOs must be executed swiftly and efficiently to minimise data transmission delays and ensure uninterrupted mission-critical operations.
- **Interference:** In 5G heterogeneous environments, interference from neighbouring cells and competing devices can disrupt HOs. Effective spectrum management strategies are imperative to mitigate interference, optimise

bandwidth utilisation, and ensure a smooth transition during HOs.

Overcoming the HO problem in UAVs operating within 5G heterogeneous networks facilitates enhanced connectivity in remote and inaccessible regions. This has profound implications for applications such as disaster response, environmental monitoring, and precision agriculture. Efficient HO mechanisms contribute to optimal use of network resources. This not only enhances the overall performance of UAVs but also ensures that 5G networks can accommodate the increasing demand for aerial communication services without compromising quality [28] [29]. Additionally, addressing the HO problem paves the way for advancements in autonomous UAV operations. Seamless transitions between network cells enable UAVs to navigate diverse environments with minimal human intervention, unlocking new possibilities for automation and efficiency.

The HO problem in UAVs operating within heterogeneous 5G networks presents formidable challenges and transformative opportunities. Addressing these challenges is essential for unlocking the full potential of aerial communication technologies, ushering in a new era of connectivity, and fostering innovation across various industries [30].

1.6 Mobility Overview for Rural Areas

The integration between UAVs and satellites holds the promise of extending the operational capabilities of both platforms, unlocking transformative possibilities in various applications. At its core, UAV-satellite HO encapsulates the seamless transition of communication links between UAVs and satellites, introducing

a critical dimension to the autonomy and reach of these airborne systems. As UAVs evolve beyond conventional applications, such as surveillance and reconnaissance, their reliance on real-time data exchange and uninterrupted connectivity becomes increasingly pronounced. The integration of satellite communication provides a strategic solution to overcome the limitations imposed by ground-based infrastructure, extending the operational range of UAVs into remote or inaccessible areas.

The challenges inherent in UAV-satellite HO are multifaceted. One primary hurdle lies in the dynamic nature of UAV missions. These unmanned platforms often traverse through different altitudes, speeds, and geographical locations, necessitating adaptive HO protocols to manage the dynamic connectivity requirements. Swift and seamless transitions are imperative, especially in applications such as real-time surveillance or disaster response, where low-latency, high-throughput communication links are crucial.

Interoperability and standardisation represent another significant challenge. The diversity in UAV and satellite configurations demands the establishment of common communication protocols to ensure seamless HOs across different platforms and satellite constellations. Achieving interoperability is vital for fostering collaboration and maximizing the potential of UAV-satellite integration in various mission scenarios.

The orbital dynamics of satellite constellations introduce complexities in maintaining continuous communication links with UAVs. As satellites orbit the Earth, HOs must account for variations in their positions, requiring sophisticated algo-

rhythms and coordination mechanisms to facilitate smooth transitions between different satellites. Addressing these challenges is pivotal for establishing a reliable and efficient HO process that can adapt to the dynamic nature of UAV missions.

Despite these challenges, the impact of UAV-satellite HO is profound. It extends the operational range of UAVs, allowing them to operate beyond the limitations of the ground-based communication infrastructure. This has significant implications for applications such as environmental monitoring, long-range surveillance, and BVLoS operations. The integration also enhances global connectivity, providing a resilient communication infrastructure that is not bound by terrestrial limitations. In disaster-stricken or remote regions, where ground-based networks may be compromised, UAV-satellite HOs ensure continuous communication and data dissemination. Furthermore, the seamless HO between UAVs and satellites contributes to the creation of dynamic and responsive space-based sensor networks. This networked approach enhances the collective capabilities of UAVs and satellites, fostering collaborative data acquisition and dissemination for a wide array of applications, from scientific research to disaster management.

UAV-satellite HO represents a nexus of challenges and transformative potentialities, underscoring the ever-evolving synergy between autonomous aerial platforms and space-based communication infrastructure. As technological advancements continue to propel these domains forward, the seamless integration of UAVs with satellites not only redefines the scope of airborne missions, but also contributes to the broader narrative of an interconnected and resilient aerospace ecosystem.

1.7 Overview of Mobility Interference

The integration of UAVs into 5G networks, while promising enhanced connectivity and novel applications, presents a challenge unique to altitude-based LoS interference of UAVs in 5G networks. This introduces a nuanced set of complexities related to maintaining interference-free LoS connections at varying altitudes.

At the core of the challenge lies the intricate trade-off between the altitude of UAVs and the direct visual line between the UAV and the 5G communication infrastructure. In 5G-UAV networks, LoS communication is a fundamental requirement, enabling high data rates and low-latency connectivity. However, as UAVs traverse through different altitudes, the potential for interference in the LoS becomes a multifaceted issue that demands careful consideration and innovative solutions.

Understanding the technological nuances of altitude-based LoS interference requires a grasp of the dynamic interactions between UAVs and 5G infrastructure. At lower altitudes, where obstacles and terrain features may obstruct the direct line of sight, maintaining a consistent connection is challenging. Conversely, at higher altitudes, interference can arise from a variety of sources, including atmospheric conditions, signals from non associated base stations (BSs). The deployment of 5G networks relies on a dense network of small cells, each with a limited coverage area. As UAVs ascend or descend, the HO between these cells must be managed seamlessly to ensure uninterrupted communication. The intricate interplay of antenna configurations, beamforming technologies, and adaptive modulation schemes further complicates the equation, demanding sophisti-

cated solutions to mitigate interference and optimize performance.

UAVs, by their very nature, exhibit dynamic mobility and can operate at varying altitudes, depending on the requirements of the mission. This dynamicity poses a challenge for 5G networks to maintain a stable LoS connection, particularly when UAVs navigate through areas with diverse topography. As UAVs ascend to higher altitudes, they may encounter interference from other non-associated BSs, including ones that serve ground-based communication systems or neighbouring UAVs. Managing this interference is crucial to maintain reliable 5G connectivity.

Altitude-based LoS interference in 5G-UAV networks poses a multifaceted challenge that requires a holistic approach. The delicate balance between dynamic altitude changes and interference sources necessitates innovative technological solutions and adaptive strategies. As the integration of UAVs into 5G networks continues to unfold, addressing these challenges becomes imperative for unlocking the full potential of this transformative synergy. The development and implementation of sophisticated technologies, coupled with a comprehensive understanding of the nuanced interactions at play, will pave the way for a future where 5G UAV networks seamlessly navigate the skies, ensuring reliable and interference-free connectivity across diverse altitudes.

1.8 Problem Statement

UAVs, because of the numerous advantages they offer, are envisioned as new types of user equipment connected to cellular networks, thus promising revenue

through additional new subscribers and use cases, especially for the aviation sector. In addition, UAVs are accepted as an extension to BSs by boosting coverage, spectral efficiency, and user quality of experience. In this context, the main objective of this project is to provide high quality data link and smooth UAVs connectivity into cellular network infrastructure. The UAVs allow rapid deployment of a multi-hop communication backbone in challenging environments with applications for public safety, delivery, and monitoring. The integration of UAVs into cellular networks promises transformative impacts across public safety, delivery services, and monitoring applications. In terms of public safety, UAVs equipped with cellular connectivity enable swift deployment in emergencies, providing real-time data to enhance response efforts and surveillance capabilities. For delivery services, UAVs optimize routes based on current conditions, speeding up deliveries and expanding access to remote or congested areas. In monitoring applications, such UAVs facilitate precise environmental and infrastructure assessments, supporting agriculture, disaster response, and infrastructure maintenance. Therefore, UAVs can be used as complementary infrastructure to provide wireless services for the ground users or they may require wireless connectivity from the ground for a safe and reliable operation.

1.9 Research Gap

The air-ground data communication based on 5G communication technology has great development and application in the fields of aviation, transportation and UAVs. It can provide reliable signal coverage on land and a variety of altitudes

in air space. 5G based technology is expected to be an ideal data communication solution. Therefore, there is an urgent demand to accelerate the development of intelligent communication system that can address the tremendous challenges of data management, spectrum, HO, and guarantee a high quality of service. In particular, scenarios of important concerns in UAVs integrated with 5G wireless communication and networking including air-to-ground traffic management, mobility management, interference mitigation, unique constraints in UAVs networking, network level performance, optimal deployments of UAVs and important path guidelines. UAVs equipped with cellular connectivity have diverse applications that enhance wireless services for ground users across emergency response, remote connectivity, public events, search and rescue, surveillance, agriculture, and infrastructure maintenance. These applications leverage UAVs' mobility, flexibility, and ability to deploy quickly in challenging environments, expanding the reach and reliability of wireless communication and services where traditional infrastructure may be limited or unavailable.

1.10 Aim

This project aims to provide a seamless 5G-UAV communication architecture to enable integration so that the connected system can solve the main problems of UAV mobility using different operator services, mitigate interference and for seamless rural operation.

1.11 Objectives

Within the scope of this thesis, 5G networks are being integrated with UAVs by addressing the challenges associated with seamless HO and mitigating interference. To this aim, the following objectives are proposed:

1. Determine the current research gap by careful study and investigation of current literature and state of the art.
2. To design a novel entropy weighted method algorithm for performing seamless HO across heterogeneous networks.
3. To develop a new deep reinforcement learning framework and implement a power control scheme that mitigates the UAV network interference problem.
4. To achieve vertical integration that can enable NTN for UAVs, satellites, and 5G using a graph method-based algorithm.
5. To validate and evaluate the performance of the end-end system.

1.11.1 Contributions

Corresponding to the aim and objectives presented in the previous sections the following contributions are made as part of this PhD:

- A heterogeneous ground network encompassing 5G and LTE is established to ensure UAVs can access either BS seamlessly. UAVs can make these HO decisions independently.

- A three-stage HO with an appropriate signalling flow scheme is designed
- A novel EWM is developed for decision making that utilizes RSS as signal parameter for decision-making.
- A heterogeneous satellite-ground networks is established to ensure UAVs can access either satellites or BSs seamlessly. UAVs can make these HO decisions independently.
- The decision functions are designed to reflect the signal parameters, viz. RSS, SNR and elevation angle. This is multi-criteria decision-making problem implemented through the weighted summation model (WSM)
- A graph theory based algorithm is proposed, that implements the Dijkstra's algorithm for HO execution.
- Develops a power control optimization problem for the downlink direction to maximize the SINR experienced by the UAV.
- Develops a framework based on Deep Reinforcement Learning (DRL) that enables the concurrent execution of multiple actions and dynamically adjusts power levels to achieve optimal SINR by utilizing data from a given dataset.

1.12 Thesis Structure

UAVs have undergone rapid transformation, transitioning from their initial military applications to assuming versatile and impactful roles across various sec-

tors. Within the realm of communications, UAVs have emerged as potent tools, presenting innovative solutions to conventional challenges. The applications of UAVs in communication exhibit diversity, ranging from the establishment of temporary communication networks in remote or disaster-stricken areas to increasing the efficiency of existing infrastructures. This report delves into the integration of UAVs and 5G communication technology, as outlined in Chapter 1, providing an overview of the subject. Additionally, the chapter examines the standardization of UAVs and 5G communication technology, elucidating its implications on this research. Furthermore, the chapter addresses the challenges associated with the integration of UAVs into 5G and beyond cellular networks, with primary emphasis on mobility in urban and rural areas, as well as interference faced by these UAVs.

The organisation of this thesis proceeds with Chapter 2, offering a comprehensive literature review encompassing current works associated with challenges in integrating UAVs with 5G networks. This chapter formulates the problem statement derived from current academic gaps, subsequently defining the aim and presenting the objectives.

In Chapter 3, the challenges linked to mobility in urban areas and the significance of heterogeneous networks within urban settings are thoroughly discussed. The methodology employed to address these challenges is introduced, with emphasis on the proposed entropy-weighted method (EWM). The chapter concludes with a presentation of the simulation setup, results, and a detailed discussion of their implications.

Chapter 4 focusses on the challenges of mobility in areas devoid of ground-based infrastructure, specifically rural regions. A graph theory-based solution is proposed and explained, formulating the problem as a graph with decision parameters as edges. Dijkstra's algorithm is employed to calculate the shortest HO path. The chapter concludes by presenting the associated system, network, and channel models, followed by the simulation setup, results, and their impact.

Chapter 5 delves into the challenge of interference faced by UAVs from non-associated ground BSs, particularly intensifying with increasing altitude. The chapter outlines this challenge and proposes a mitigation strategy. The functionalities of 5G, next-generation Node B (gNB), and UAVs are described, introducing a reinforcement learning solution that incorporates deep learning components to implement power control and mitigate interference. Existing methods are explained, highlighting their drawbacks, and the chapter concludes with the simulation setup and detailed results.

Figure 1.4 visually depicted the organization of this report.

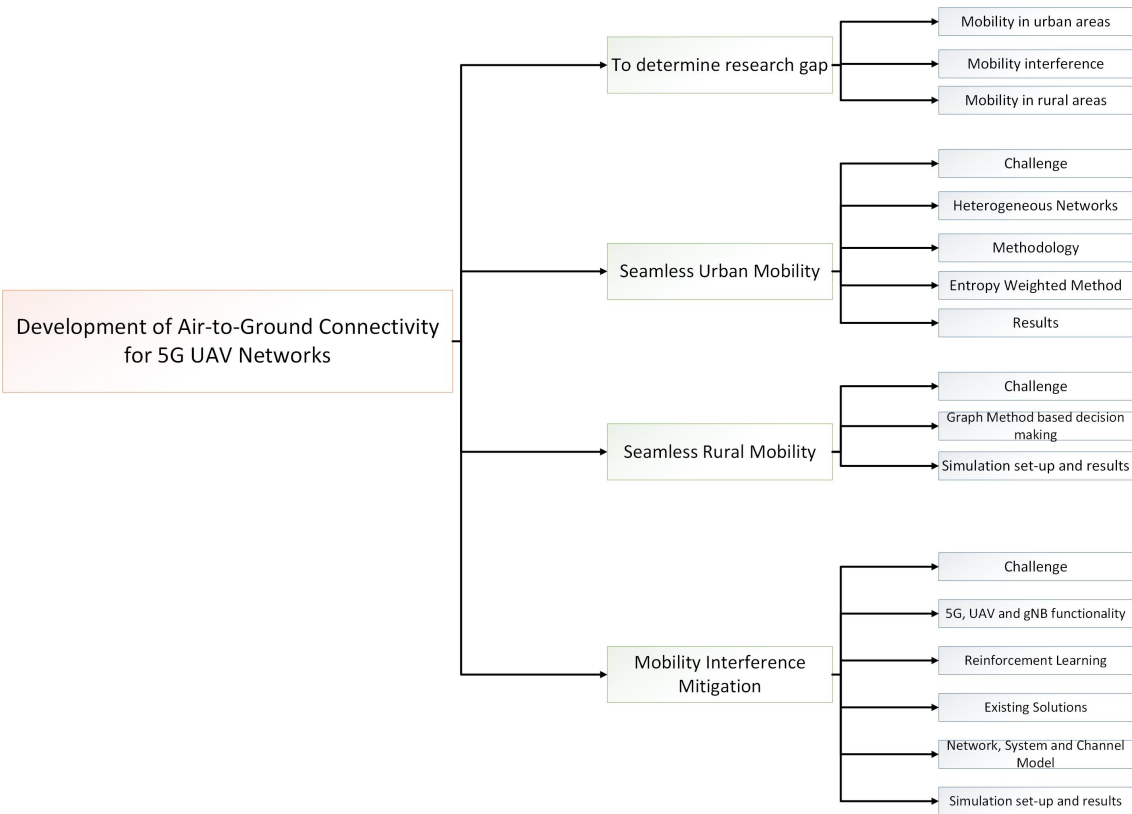


Figure 1.4: Organization Chart of the Thesis

Chapter 2

Background and Related Works

In this chapter, a comprehensive literature review encompassing current works associated with challenges in integrating UAVs with 5G networks is presented. This chapter forms the basis of the identified research gap, formulated problem statement, defined aim and objectives presented in chapter 1. Work presented in this chapter directly links to the first objective.

2.1 Mobility in Urban Areas

2.1.1 Background

In the realm of contemporary wireless communication, the proliferation of UAVs has sparked a paradigm shift in the way connectivity solutions are perceived and deployed [31]. The paradigm shift in connectivity solutions within contemporary wireless communication is driven by several key factors. The deployment of 5G technology stands out as a pivotal advancement, promising higher speeds,

lower latency, and massive device connectivity crucial for IoT and smart city applications. Concurrently, the proliferation of IoT devices necessitates robust and scalable networks capable of handling diverse data streams efficiently. Edge computing further accelerates this shift by demanding low-latency connections for real-time data processing closer to the source. Moreover, the integration of AI and ML applications requires fast and reliable connectivity to support data-intensive tasks. Security and privacy concerns amplify the need for enhanced protection mechanisms in new connectivity solutions. Finally, sustainability considerations are prompting innovations towards more energy-efficient network technologies. Collectively, these factors are reshaping the landscape of wireless communication, pushing towards faster, more secure, and sustainable connectivity solutions capable of meeting the evolving demands of modern digital ecosystems. As these aerial platforms navigate urban landscapes, the seamless HO of connectivity becomes a critical aspect of their operational efficiency and effectiveness [32]. The integration of HO mechanisms into 5G networks significantly enhances the operational efficiency of UAVs by ensuring seamless and reliable connectivity during flight. This is crucial for maintaining continuous communication and control, especially when UAVs traverse areas covered by different network cells. HO mechanisms in 5G provide low latency and high-speed data transfer, which are vital for real-time applications such as surveillance, delivery, and remote sensing. Additionally, 5G's advanced HO capabilities support high mobility and the dynamic nature of UAV operations, reducing the risk of communication interruptions and improving the overall reliability and safety of UAV missions. The

process of HO, or the seamless transition of communication links between different network nodes, is fundamental to maintaining uninterrupted connectivity, especially in dynamic environments where UAVs operate. This section delves into the intricate dynamics of HO mechanisms, with a specific focus on their integration into the fabric of 5G networks. The advent of 5G technology has not only revolutionized conventional communication systems but has also presented new challenges and opportunities for optimizing HO procedures, particularly in the context of UAVs.

The intersection of UAVs and 5G technologies introduces the concept of vertical HO in heterogeneous networks, a key area of exploration in this thesis. Vertical HO, involving the transition between different types of networks, becomes crucial in ensuring continuous and high-quality connectivity for UAVs, irrespective of their position within a given urban setting [33]. Heterogeneous networks, characterized by the coexistence of diverse communication technologies, further amplify the complexity of vertical HO processes, demanding innovative solutions for seamless integration.

This section aims to elucidate the challenges posed by vertical HO in heterogeneous networks, with a specific focus on its implications for UAVs navigating the dynamic and densely populated urban areas. By exploring the intricate interplay between UAVs, 5G technologies, and the unique demands of urban environments, a novel HO framework to enhance the efficacy of vertical HO procedures, ultimately fostering a more robust and resilient communication infrastructure for the evolving landscape of urban UAV networks is proposed.

2.1.2 Related Works

The current literature is the major factor that is essential in the process of integration of UAVs in future networks. This section gives a brief introduction of related studies. The specific research problem, their solutions and possible future enhancements within current literature is discussed in detail. The majority of the studies consider decision algorithms for the HO of UAVs as the research problem, and their techniques are based on either the mathematical model approach or machine learning (ML) methods. Innovations of new architectures where UAVs can be integrated as the part of a connected ecosystem is also discussed. This forms the basis of the novel work presented in this thesis as well as future work [34], [35].

In the paper [36], authors suggested an algorithm for coverage decision in UAV networks. A significant problem in the UAV network is the short battery life and a bad HO management which eventually causes the broken communication and the frequent HOs. Conventional HO algorithms, can't work on UAVs because they are at different altitudes and coverage areas in comparison to each other. The algorithm works on the basis of Received Signal Strength (RSS) and controls each drone's coverage by changing their height and separation distance. The algorithm performs well. While the above scenario is very much possible, the real-world scenario should also be considered by taking into account the UAV's payload, radio range of BSs. Furthermore, the coverage algorithm makes the RSS of each drone to be the same in the simulation, which might not be applicable in

reality.

In [37] an intelligent HO scheme for drones using a fuzzy inference system is introduced. The HO decision depends on parameters that include the radius, coverage, RSS, altitude, and speed. These parameters are fuzzified by assigning a linguistic variable to their normalized ranges. A set of predefined rules determine the HO decision. De-fuzzification occurs afterwards to evaluate the HO decision made. The results demonstrated that the proposed intelligent HO scheme performed better than the traditional approach. The HO probability was lower for the former simulations. Overall, factors such as speed and altitude affect the number of HOs for drones. The overall result of this proposed model seems to align with the fact that parameters (such as speed and altitude) affect the probability of disconnection, thus influencing the number of HOs. Additionally, the HO decision considers numerous parameters instantly, which is an advantage of fuzzy inference systems. Future works, however, must also consider the fact that multiple users and HetNets positively affect HO.

A deep learning-based system for trajectory prediction and an intelligent HO control approach for UAV cellular networks are provided in [38]. Cellular networks supported by aerial base stations (ABS) are widely used to enable wireless coverage. However, only one device's measurements are taken into account when the HO is triggered for a device moving to distinct ABSs. This implies that while making HO decisions, the relationships among users are disregarded, which causes communication to become congested and results in inaccurate HO assessments. The authors, thus, introduced an intelligent HO technique: the deep

learning-based HO technique, in UAV networks in response to this issue. The interplay between each person's movement patterns is captured through the use of social pooling and a hidden layer. Next, the model is trained by minimizing the loss function. Four key operations (measurement, reporting, judgment, and execution) are implemented to perform the HO decision. Unlike conventional HO, ML is used to predict the future trajectory, and a verification function decides whether the user should be switched to another ABS. A manually built dataset was applied for training and testing data. The model trained to learn the trajectories has 256 hidden layers. The values in the dataset come from real-world scenarios. The deep learning system employed Back-Propagation Through-Time (BPTT) to update the parameters in its hidden layers. To determine the accuracy of this solution, the Mean Squared Error (MSE) between the predicted value and the ground truth value was used. It is anticipated and demonstrated that the model's prediction accuracy is high since it accurately captured user interactions. When compared to other comparable models, the average MSE is lower. The success rate of the HO decision increases with decreasing Time-to-Trigger (TTT), up to 84.8%. Compared to other systems, an average improvement in accuracy of 8% has been achieved. In addition to preventing frequent HO triggering, circumstances where the coverage zones overlapped were taken into account. Overall, the proposed solution considers different scenarios and reaches an excellent overall result compared to related works. The power of deep learning in prediction proves its potential use in future. However, several issues should be considered such as spectrum, energy, and security management. To examine network per-

formance, four HO performance metrics were considered: successful HO, HO failure (HOF), link failure, and ping-pong HOs. The rate of link failure was observed through the process of radio link monitoring. Supplementary to the theoretical work, simulations were also accomplished. Two different traffic models have been considered: a full buffer model and a File Transfer Protocol (FTP) traffic model. HOF and link failure were counted in a mutually exclusive way to provide results. Urban-Macro (UMa) and Rural-Macro (RMa) scenarios have been considered for the simulations. Several observations were completed in the UMa scenario with full buffer traffic (100% resource utilization). The HO rate increases with speed, as expected [39].

In [40] a stochastic geometry-based drone cellular network model is investigated. The spread and trajectories of UAVs are irregular, so deploying tools from stochastic geometry is a potential solution that provides better insight for the network design. The initial positions of the UAVs were modeled as a Poisson Point Process (PPP), and a straight line movement with a constant velocity is performed. Two models are considered where the UAVs have been considered for serving the UEs. In the first model, the UE independent model, the serving UAV moves in a random straight line while serving the UE, thus, HO is required. For the UE dependent model, the serving UAV moves towards the UE, so no HO is needed. For the UE independent model, the positions of other UAVs is characterized as an in-homogeneous PPP. Simulations were performed for both noisy and not noisy environments. The results indicate that the coverage probability saturates very quickly after the UAVs begin to move in the UE-dependent model.

It is evident that this model is better than other. Moreover, the results from noisy and non-noisy environments demonstrate that the setup is limited due to interference. With the increase of the path loss exponent, the received rate increases due to the decrease in interference power. The solution of incorporating stochastic geometry in analyzing HO seems to be innovative and promising for the future of UAVs as BSs. The mathematical approach also seems accurate and helpful for works of a similar nature [41],[42].

In [43] a new solution (named the route-aware HO algorithm) to achieve reliability in drone communication systems is proposed. This solution utilizes flight path information to optimize the network so that unnecessary HOs are minimized, and the false HO probability is reduced. The pre-determined trajectory and the predictability of the aerial channel are employed to achieve mobility management. The proposed algorithm consists of two phases: offline and online. The former is only used when the HO is triggered during Signal to Interference Ratio (SINR) calculations. The latter consists of a periodic update of parameters which can improve the performance of dynamic wireless systems and reduce computational complexity. A system-level simulator was developed for the evaluation of HO performance. The scenario was assumed to be an Urban-Macro Aerial Vehicles (UMa-AV) case. The reference signal received power (RSRP) measurement was continuously updated (every 200 ms) and the update for online thresholds was made every 2 ms. As expected, the HO rate increases with the speed and altitude of drones. However, this rate also decreases from 4 to 32 times depending on the speed and altitude in comparison to other approaches. For 0 m height,

the ping pong effect is eliminated and for other height levels, it can reduce by up to 46 times. For aerial UEs at different speeds, the HOF can reduce by 5 to 24 times. Results can be further improved if a better granularity presents the radio link quality and if the estimation accuracy is enhanced

In [44] a ML based approach for the HO mechanism and resource management for cellular-connected drones is recommended. Drones cause severe interference to BSs when aerial and terrestrial users coexist in cellular networks, thus becoming problematic for the uplink communication service of terrestrial users. The above-mentioned challenge was represented using network data for Stockholm city. Several models were built upon the Key Performance Indicator (KPI) (e.g. communication delay and interference) to formulate an optimization problem called HO and Handover and Radio Resource Management(H-RRM). The problem used for making HO decisions was approached by ML solution techniques that aim to capture the correlations at the temporal and spatial levels. The effects of parameters, such as speed and altitude, were observed to solve this problem. The system model was represented by the air-to-ground channel where the LoS path is dominant. A buffer queue is used to characterize the arrival rate of data as well as the allocated spectrum and the interference from the BSs. Next, the optimization problem is formulated, and the algorithms are utilized to perform the decision-making as well as update the overall process. The Q-learning algorithm was applied, where the Q-function is trained and at each decision epoch, one of the actions is randomly taken. Increasing the delay coefficient (making delay less allowable) leads to more triggered HOs. Increasing the importance of

interference in the weighted sum's reward function increases the HO number as well. The contrary has been observed when speed increases. Several similar observations were noticed, but overall, the appropriate delay, interference, and HO coefficients effectively reduced the HO number, total delay, and acquired interference. The proposed solution is very accurate and considers several scenarios which makes it a prominent solution for the HO mechanism of UAVs to coexist in cellular networks with terrestrial users. The uplink scenario can be significantly affected by the usage of drones; therefore, this study proposes algorithm that can help optimize cellular networks.

The intersection of UAVs and 5G technologies presents several challenges concerning HO procedures. Firstly, the high mobility and varying altitudes of UAVs complicate the HO process, requiring more frequent and dynamic handovers compared to ground-based users. This increases the risk of communication disruptions, latency, and data loss. Additionally, the UAVs' diverse flight patterns and speeds can lead to unpredictable HO scenarios, making it difficult for the network to maintain seamless connectivity. Furthermore, the need for robust and reliable HO mechanisms can strain network resources and necessitate advanced algorithms and infrastructure upgrades, potentially increasing operational costs. Discuss the significance of vertical Handover (HO) in ensuring continuous and high-quality connectivity for UAVs, especially in densely populated urban areas.

The literature is summarized below in Table 2.1.

Table 2.1: Summary of Literature Survey - Mobility in Urban Areas

	Summary	Algorithm	Gap
[33]	The HO initiation techniques based on the RSS is used. In addition, the HO based on channel usage, micro-cellular and multi-layered systems and network characteristics are explained.	N/A	Studies HO in cellular networks with no mention of UAV
[45]	HO decision method is presented involving distance, coverage, speed, load, and RSS. These parameters are considered as input variables for fuzzy inference system based on which estimation level has evaluated and decision is taken	Fuzzy Algorithm	Fuzzy based decision algorithm, in horizontal HO
[46]	Techniques for analyzing the behaviour of HO algorithms using field-strength measurements. The rate of HO is studied as the level crossings of the averaged signal level process which is modelled as a Poisson's process	Poisson Process	Comparison study for analyzing different HO algorithms, does not discuss any implementations
[47]	This paper uses EWM to make a decision for assessing water quality from different sources and making decision on which source has the best quality using the EWM	Entropy Weighting	This is not used in the realm of communication systems, but can be adopted for UAV communication systems

Based on a literature survey it has been identified that, UAVs need to be seamlessly handed over across networks in a heterogeneous environment so that the capabilities of 5G and advantages of heterogeneous networks can be fully utilized. To this effect, a seamless HO scheme using the EWM algorithm was devel-

oped [48]. A UAV is considered to move across a 5G and Long Term Evolution (LTE) networks and the HO between them is simulated using the EWM algorithm. Chapter 3 successfully demonstrates the efficient working of the algorithm on a simulation level

2.2 Mobility Interference in 5G-Connected UAVs

2.2.1 Background

In the dynamic landscape of UAV communication networks, the ever-evolving integration of advanced technologies, such as 5G, presents both unprecedented opportunities and challenges. As UAVs become integral components of various applications, from surveillance and monitoring to delivery services, the issue of interference has emerged as a critical facet influencing the reliability and performance of these airborne platforms [49]. This literature survey undertakes a comprehensive exploration of existing research on interference.

The advent of 5G technology has ushered in a new era of wireless communication characterized by enhanced data rates, lower latency, and increased connectivity density. However, the deployment of 5G networks in proximity to UAVs introduces a novel set of challenges, including potential interference issues that may arise due to shared frequency bands or overlapping signal footprints and primarily the altitude of UAVs [50]. This survey critically examines the current state of knowledge regarding 5G interference in UAV communication networks, highlighting key findings, methodologies, and emerging trends in mitigating the

adverse effects on UAV operations.

Furthermore, the altitude at which UAVs operate presents a unique dimension to the interference landscape. As UAVs traverse varying altitudes, the propagation characteristics of wireless signals change, introducing challenges related to signal strength, connectivity, and interference from ground-based networks. Investigating the implications of UAV altitude on interference is pivotal for understanding the nuanced dynamics of communication in airspace [51]. This survey aims to synthesize existing literature on the impact of UAV altitude on interference and elucidate potential mitigation strategies tailored to altitude-related challenges.

In addressing these challenges, interference mitigation emerges as a critical area of focus within the literature. The survey explores a myriad of techniques and technologies proposed to alleviate interference in UAV communication networks, ranging from spectrum management and cognitive radio approaches to adaptive beamforming and ML-based solutions. By reviewing the current body of knowledge, this survey aims to provide a comprehensive overview of the state-of-the-art interference mitigation strategies and identify gaps that warrant further research attention.

In summary, this literature survey embarks on a journey through the rich tapestry of research surrounding interference in UAV communication networks, shedding light on the intricacies of 5G interference, altitude-related challenges, and the diverse landscape of interference mitigation strategies. Through this exploration, it is sought to contribute to a deeper understanding of the current state

of the field and provide insights that pave the way for future advancements in the resilient and efficient communication infrastructure of UAV networks.

2.2.2 Related Works

The utilization of UAVs for meeting the growing communication needs has been widely advocated. Despite this, operation of UAVs at high altitude would enable LoS links to be significantly pervasive within the viable communication channels; as a result, a UAV has a high likelihood of communicating with both associated gNB and interfering gNBs simultaneously. In the case of ground users, who are served by the primary lobe of the gNB antenna, an escalation in path loss typically correlates with a reduction in interfering signals. However, when UAVs are served by the side lobes of the gNB antenna, the relationship between increasing path loss and interference becomes less straightforward. This complexity arises because side lobes have the potential to introduce unintended coverage areas and additional propagation paths, thereby giving rise to interference with other systems or gNBs. Consequently, even when the main lobe signal strength is weakened due to path loss, these side lobes can still generate interference. This scenario increases the likelihood of interference as compared to ground-based users, posing a significant challenge for interference management in cellular networks that include UAVs. Several techniques have been proposed in extant literature to mitigate interference in terrestrial networks, including Inter-cell interference coordination (ICIC) [52], [53], and coordinated multi-point (CoMP) transmission [54], [55]. However, these techniques prove inadequate in handling new inter-

ference challenges arising from UAVs and the emergence of LoS-dominated air-ground links at high altitudes.

ICIC is a radio resource management technique used to enhance spectral efficiency. This is achieved by imposing constraints on the management block to improve favourable channel conditions for a subset of users significantly affected by interference. The coordination of resources may be achieved through fixed, adaptive, or real-time approaches, supported by additional inter-cell signalling, with the frequency adjusted based on specific requirements. A cooperative interference cancellation technique is proposed in [50] to minimise the sum rate to available gNBs and eliminate co-channel interference at each occupied gNB for multi-beam UAV uplink communication. Although similar techniques have been extensively studied in terrestrial cellular networks [51], they are not effective in mitigating strong UAV interference, leading to limited frequency reuse in the network and lower spectral efficiency for both UAVs and ground users [49]. In [56], the interference in directional UAV networks is characterised using stochastic geometry, considering UAVs equipped with directional antennas and situated in a three-dimensional (3D) environment. This work provides a comprehensive analysis of the interference in directional UAV networks, but no strategies are presented for mitigating it.

The approach of employing a path planning or trajectory design to avoid or minimise interference is a widely adopted strategy for interference management. In [57], the authors consider a relay-assisted UAV network overlaid with an existing network, and propose a joint power and 3D trajectory design approach to

reposition the UAVs in 3D space to circumvent interference. They propose a joint optimisation solution based on spectral graph theory and convex optimisation to address the problem of 3D trajectory design and power allocation. Simulation results demonstrate the proposed algorithm improves the maximum flow and reduces undesirable interference to the coexisting network [58].

The authors of [59] explore the joint trajectory and power control (TPC) design problem for multi-user UAV-enabled interference channels (UAV-IC). As the TPC problem is NP-hard and involves a significant number of optimisation variables, the authors propose effective sub-optimal algorithms. Although a multi-UAV setup is considered in both [58] and [59], the trajectory optimisation approach may not be optimal in situations where the path or trajectory of the UAV is unknown beforehand or changes during the mission.

In [60], an alternative solution to mitigate UAV-ground interference is proposed by utilizing Intelligent Reflective Surfaces (IRSs) near gNBs for both downlink and uplink communications. The authors suggest an optimal passive beamforming design using IRSs for the downlink to minimize terrestrial interference with UAVs, and a hybrid linear and nonlinear Interference Coordination (IC) scheme in the uplink to handle the strong interference from UAVs. The authors further investigate the optimal performance of this scheme. However, in 5G-UAV networks, using IRS to mitigate altitude-based LoS interference faces significant challenges. These include handling the dynamic mobility of UAVs, limited effective coverage range, increased path loss, complex synchronization, and en-

vironmental impacts. In [61], an interference-aware energy-efficient scheme is proposed to allow cellular-connected aerial users to reduce the interference they impose on terrestrial users while maximizing their energy efficiency and spectral efficiency. The optimization problem is formulated considering the KPI requirements for both aerial and terrestrial users, including energy efficiency, spectral efficiency, and interference. The problem is solved through the use of a DQL approach. However, it is critical to note the energy efficiency problem cannot be universally solved as it is dependent on various factors such as mission design, UAV capabilities, and UAV size.

In recent years, Artificial Intelligence (AI) has emerged as a critical technology for 5G-and-beyond wireless networks that include UAVs, as demonstrated in studies like [62]. This is primarily due to AI's capacity to handle complex problems and large amounts of data in system design and optimisation, making it a crucial tool for creating highly dynamic UAV communication networks. Conventional offline and model-driven trajectory design methods are limited in practical scenarios with variable traffic and open operating environments due to the requirement for accurate communication models and complete understanding of system parameters. However, with the use of deep reinforcement learning, UAVs can predict future network states in real-time and adjust communication resource allocation and UAV trajectories accordingly. Additionally, AI-embedded UAVs can play a significant role in edge computing applications, where multiple UAVs can collaborate as aerial edge servers or edge devices for efficient data and computation offloading.

Several research studies have investigated the application of DRL in the field of communications in recent years, as evidenced by publications such as [63], [64], [65], and [66]. In particular, [66] employs DRL for power regulation in millimeter-wave (mm-Wave) transmission, as an alternative to beamforming for enhancing non-line of sight (NLoS) performance. The authors employ DRL to tackle the power allocation problem with the objective of maximizing the aggregate rate of the user equipment (UE) while meeting quality and transmission power constraints. The proposed approach involves estimating the Q-function of the DRL problem using a convolutional neural network (NN). In another work, [67] introduces a policy framework that employs deep Q-learning (DQL) to maximize the number of transmissions in a multi-channel access network. In [68], the authors propose a joint optimization approach that employs a Q-learning algorithm to optimize power control, interference coordination, and communication performance for end-users in a 5G wireless network, enhancing the downlink SINR in a multi-access Orthogonal Frequency Division Multiplexing (OFDM) network from a gNB with multiple antennas to UEs with a single antenna. Finally, [69] uses DQL to develop a policy to maximize transmissions in a dynamic correlated multi-channel access scenario. It is important to note, however, that these studies only address interference in the context of mobile devices. NNs were used in [65] to forecast mm-Wave beams with low training overhead utilising received signals from nearby gNBs. [68] analysed voice signals for a multiple-access network consisting of many gNBs. The mid band 5G frequency was only discussed in [70] framework in a single gNB scenario. Deep NNs, which need channel knowledge

to make decisions were used in [70] to perform joint beamforming and interference cooperation at mm-Wave. The effectiveness of deep NNs for beamforming without using reinforcement learning was examined in [71]. These works have deployed ML algorithms to implement beamforming to solve the interference problem. Although beamforming improves the SINR of the system and resists interference, it is very complicated and expensive in terms of hardware to be deployed. Advanced techniques such as double DQL were discussed in [72]. The main difference between DQL and Double Deep Q-Learning (DDQL) is that DDQL uses two separate deep NNs to estimate the Q-values, whereas DQL uses only one. The idea behind DDQL is to reduce overestimation of Q-values that can occur in DQL. However, in some cases, such as when dealing with interference in 5G networks, overestimation may not be a problem and may even be desirable. In the case of interference in 5G networks, the goal is to minimize the interference between different channels and users. This can be achieved by optimizing the transmission power and frequency allocation of different users. In this scenario, DQL may be more suitable than DDQL because it allows for more exploration of the state-action space, which can lead to better performance in complex environments. Additionally, DQL has been shown to be more computationally efficient than DDQL, which can be a critical factor when dealing with large-scale 5G networks with many users and channels.

The literature review is summarised in Table 2.2 and the outcomes are discussed in the following section.

Table 2.2: Summary of literature survey - Mobility Interference

	Optimisation Problem	Algorithm	Gap
[66]	Power Control for Downlink SINR	Deep Reinforcement Learning	It only considers the interference problem with terrestrial UEs and does not consider UAVs.
[67]	Power control for uplink power and sum rate	deep NNs	It only considers the interference problem with terrestrial UEs and does not consider UAVs.
[73]	beamforming and power control for uplink sum-rate	convex optimisation	To ensure the optimal performance of the power domain concept at the receiver, it is imperative that the channel gain difference between users is appropriate. This requirement limits the effective number of user pairs that can be served by clusters.
[74]	beamforming for SINR	Q-learning	Q-learning becomes inefficient when the state action space becomes excessively large
[75]	SINR	Mean-Field Game Theory	When the number of users in game theory increases, it is challenging to implement
[76]	Power control for SINR and spectral efficiency	Convolved NN (CNN)	It deals with energy harvesting networks which is similar to a UAV, but still does not take into account parameters like altitude

UAVs are frequently touted as a promising solution for a wide range of applications, and as such, the future 5G networks are expected to be able to support UAVs flying at higher altitudes and speeds with minimal interference. Within existing literature, many works discuss interference mitigation techniques, however, they also have certain drawbacks and unsuitability to the problem at hand. Methods such as ICIC as discussed in [50],[51],[49],[56] is effective for reducing interference via coordination, however in dynamic and unpredictable environ-

ments such as UAVs in 5G networks they would be ineffective. In addition they also generate high overhead, thus increasing the complexity. Another method employed within the literature is path planning for UAVs as discussed in [57], [58]. This optimises the trajectory of the UAVs so it can take the path with the least interference possible. One clear disadvantage of this would relate to not knowing the path of the UAV beforehand. In addition dynamic routes could also render this method ineffective. Even though current AI/ML approaches such as [63],[64],[65],[66],[67] have been effective at mitigating interference, these methods have been deployed for UAVs in general or for users in 5G networks but not both, which is the unique problem that this thesis addresses in chapter 5. In Table 2.2, the literature is summarised and shown that current solutions for mitigating interference are not sufficient. To address this issue, an interference mitigation approach building upon the work presented in [77] is proposed.

2.3 Mobility in Rural Areas

2.3.1 Background

Remote and rural areas often grapple with limited access to traditional communication infrastructures, presenting a formidable barrier to economic development, education, and healthcare. UAVs, equipped with communication payloads, offer a promising solution to address this digital disparity. This section gives a background to the role of UAVs as aerial communication relays, extending their reach to serve remote communities with reliable and resilient connectivity solu-

tions, thereby unlocking new possibilities for socio-economic growth [78]. The collaboration between satellites and UAVs introduces a dynamic dimension to aerial communication networks. Satellites provide a backbone for global coverage, while UAVs offer agility and adaptability to address specific regional needs. Investigating the seamless integration of satellite and UAV technologies, this section explores how the two can work in tandem to create a pervasive communication network that transcends geographical barriers and optimizes resource utilization [31].

HO, the seamless transition of communication links between different network nodes, is pivotal for maintaining uninterrupted connectivity as UAVs traverse diverse terrains. This section delves into the challenges and opportunities associated with HO mechanisms in UAV networks, emphasizing the need for context-aware algorithms that can adapt to the unique demands of rural landscapes and provide a continuous and reliable communication experience [79].

The next section embarks on a comprehensive exploration of the integration between UAVs, satellite communication, HO mechanisms, and 5G technology. By investigating their collective potential, it is aimed to contribute insights that pave the way for designing efficient, scalable, and sustainable communication solutions tailored to the unique challenges and opportunities presented by rural areas.

2.3.2 Related Works

In recent years, there has been a surge of interest among various companies in providing widespread internet connectivity from space. This renewed focus gained momentum following the successful implementation of projects such as Starlink and OneWeb [80], [81], [79].

3GPP conducted comprehensive studies aimed at delineating the potential role of NTN within the 5G ecosystem during Release 15 [82]. Subsequently, in Release 16 [83] the 3GPP is proffering networking solutions to facilitate the seamless integration of non-terrestrial and terrestrial networks. A distinguishing feature among these proposed solutions lies in the allocation of functionalities on non-terrestrial objects. These objects may serve as relay nodes, connecting 5G UE and the 5G AP (5G-gNB), thereby extending the 5G Radio Access Network (RAN) coverage. Alternatively, they can act as a backbone support. Furthermore, an additional study is currently exploring the potential utilization of Satellite Communication (SatCom) networks as active nodes in 5G access operations, effectively generating 5G cells akin to 5G gNBs [84]. Several ongoing research projects are diligently investigating the role of satellites and UAVs within the 5G framework, with the intent of developing and testing solutions for future implementation within the 5G network. For instance, the work presented in [32] sheds light on the outcomes of the ongoing SAT5G project, which is funded by the European Commission. The project focuses on satellite communications positioning within 5G scenarios, particularly geared toward eMBB capabilities. The overarching objective is to provide cost-effective, plug-and-play SatCom solutions while expe-

editing 5G deployment across diverse geographical regions. The project has identified four distinct satellite use cases for eMBB, concentrating on efficient multi-cast/broadcast content delivery to network peripheries, augmenting terrestrial connectivity by providing 5G access to premises, extending 5G connectivity to mobile platforms such as airplanes, and provisioning 5G as a fixed backhaul in regions where deploying terrestrial connections is challenging, such as lakes and islands, among others.

Additionally, the work in [85] introduces a 5G-centric network architecture predicated on satellite communication and Multi-Edge Cloud Architecture (MEC). This architecture is designed to bolster eMBB applications and ensure an optimal Quality of Experience (QoE), particularly for live streaming applications. The evaluation of this approach was conducted using a real satellite link. Another noteworthy initiative, "SATis5", presents a demonstrator that showcases the integration of satellite and terrestrial 5G networks. A recently launched European Union (EU) project, "5G! Drones" [78], is dedicated to integrating UAVs into the 5G landscape. The ultimate goal of this endeavor is to design, implement, and conduct various examinations of UAV use cases atop the 5G infrastructure while validating critical 5G KPIs. The envisaged use cases encompass UAV traffic management, public safety, life-saving operations, situational awareness, and providing connectivity during densely attended events.

These studies provide useful background into the landscape of UAVs, satellites and 5G and provide a foundation in future directions. This however, does not dive specifically into the solutions to challenges presented in the different use

cases specifically HO between terrestrial networks and satellites.

One possible method to integrate terrestrial and non-terrestrial networks is discussed in [31], where a concept of relay nodes (RN) is presented. This facilitates the transportation of 5G downlink/uplink waveforms via a low earth orbit (LEO) satellite link to the designated BS or the ground earth station. From the perspective of the onboard equipment, whether it be the flight controller necessitating Cell-Network Plane Communication (CNPC) or payload equipment requiring a high-throughput link, the RN functions akin to a conventional ground station. In scenarios where multiple UAVs are deployed as a swarm, the UAV equipped with the satellite-enabled RN can effectively serve as a "cell tower" for the entire fleet. For the ground BS, which perceives the RN as transparent, it merely interacts with a group of users.

While this approach may not necessarily optimize channel capacity, it offers the advantage of reduced communication infrastructure requirements both on the UAV and ground station. It also streamlines the HO process from 5G to satellite, while capitalizing on the capabilities of 5G technology.

[36], presents an extensive survey on UAVs in sixth-generation (6G) networks. UAVs, when harnessed in conjunction with 6G communication services, exhibit immense utility across a diverse spectrum of civic and commercial applications. The integration of 6G communication services empowers smart automation and the seamless assimilation of AI, thereby ushering in a new era characterized by innovative services, including ultra-smart cities, the Internet of Everything (IoE), Extended Reality (XR) encompassing Augmented Reality (AR), Virtual Reality

(VR), and Mixed Reality (MR), autonomous connectivity such as autonomous vehicles, Wireless Brain-Computer Interaction (WBCI), and AI-driven services. The anticipated capabilities of 6G communication networks promise to deliver a wireless connectivity enhancement of up to 100-fold and significant performance amplification compared to its predecessor, 5G. The primary drivers of 6G advancements encompass satellite connectivity, drones, connected intelligence supplemented by ML, utilization of the terahertz (THz) band, Optical Wireless Communication (OWC), wireless power transfer, and the development of 3D networking [86], [87].

In the context of aerial communications, 6G introduces solutions that surmount several limitations inherent to prior generations of wireless communication technologies [88], [89], [90], [91], [92], [93], [94] and [95]. The core attribute of 6G communication lies in its fusion of non-terrestrial networks with 3D connectivity, seamlessly integrated with ubiquitous AI-based services within the 3D spatial domain, rendering it particularly well-suited for aerial communications [96]. 6G technologies promise to deliver uninterrupted connectivity, precision positioning capabilities, ultra-high bandwidth, and real-time remote control functionalities tailored for high-density aerial vehicle environments. While THz bands may pose challenges for drone operations due to elevated path loss and constrained coverage, their integration with satellite networks presents a viable solution to address these issues.

In a specific research endeavour presented in [97], the authors introduced an inter-satellite HO strategy grounded in potential game theory. The objective was

to minimize the average number of HO events and evenly distribute the load within the satellite constellation network. However, it did not consider a terrestrial network and HO from such a network. Addressing the critical issues of HO delay and signalling cost reduction, [98] proposed various HO procedures designed for a multi-layer network architecture encompassing geostationary (GEO) satellites, high altitude platform systems (HAPS), and terrestrial relay nodes. The use of GEO satellites reduce the number of satellites required for connectivity, but it has challenges relating to high latency and higher signal attenuation. [99] outlined a user-centric HO scheme tailored for ultra-dense LEO satellite networks. Their solution involved buffering user's downlink data across multiple satellites simultaneously, facilitating seamless HOs and mitigating the frequent HO issue. [100] introduced a reinforcement learning scheme wherein User Equipment (UE) autonomously made decisions to optimize long-term throughput while minimizing unnecessary HO events among non-terrestrial base stations. This work, does not consider HO for UAVs instead does it for UEs. Similar to conventional terrestrial wireless networks [101], NTN can involve a Non-Terrestrial Base Station (NT-BS) serving UEs. However, a fundamental distinction exists between NTNs and terrestrial wireless networks. In terrestrial wireless networks, BSs are typically stationed at fixed locations without mobility. Consequently, multiple BSs can easily coordinate with each other to support seamless services and optimize mobility management through a network-driven user access control approach. Conversely, NTNs introduce a challenge due to the mobility of NT-BSs, including satellites orbiting the Earth travelling over significant distances. These NT-BSs ex-

hibit high-speed mobility, with satellite speeds reaching up to 7,000 m/s. These rapid and continuous movements can disrupt the availability of links between NT-BSs, making it exceedingly difficult for them to directly coordinate with each other. Consequently, in NTN, a UE-driven user access control scheme, where each UE autonomously selects an appropriate NT-BS, becomes a viable solution to address this challenge. While network-driven user access control schemes have demonstrated superior performance in terrestrial networks, there have been discussions on the development of UE-driven access control schemes in terrestrial networks. These UE-driven schemes often focus on the RSS-based method [102], [103] where UEs typically connect to the base station (BS) with the strongest RSS. The work done in the realm of HAPs HO, also proves to be a critical point of advancement. HAPs can be considered to have similar characteristics to that of a UAV and therefore HO strategies developed for HAPs, can be adopted for use within UAVs with certain modifications. [104] proposes an adaptive hysteresis margin for HO within a LTE network, specifically attempting to reduce ping-pongs. The hysteresis margin is based on RSS between both target and serving BS, and its proper determination amongst other advantages mitigates the rate of unnecessary and repeated HO (ping-pong effect). The model presented in this research integrates the artificial NN (ANN) mechanism into the determination of hysteresis margin in the LTE HO process which is to minimise HO delay and ping-pong taking into consideration the speed of the UE. This method is effective in reducing ping-pongs for ground users but not for UAVs. [105] proposes a design with different HO procedures suitable for LEO-HAP system based on 5G

protocol and analyze the performance on delay and signalling cost. They employ a dynamic HO strategy to optimize the HO moment and resource allocation. Lagrange duality is used and a sub-gradient algorithm is presented. A prediction based HO decision algorithm with an adaptive threshold is presented in [106]. An auto-regressive integrated moving average model (ARIMA) algorithm is proposed, that predicts the values of RSS using time series analysis model and dynamically adjust the HO initiation time according to the prediction. This proves to be an effective method, but as with other aforementioned works, they cannot be implemented for UAVs. Even though, HAPs are similar to UAVs, they do have some fundamental differences that changes the pattern of HO algorithms. Firstly, HAPs are typically deployed at exceptionally high altitudes, often within the stratosphere. This elevated positioning affords a clear line of sight to extensive areas, minimizing obstacles and reducing signal blockages. Consequently, the channel can be modelled with relatively low path loss, rendering it well-suited for establishing long-range communication links. In contrast, UAVs operate at lower altitudes, and their line of sight may encounter obstructions such as buildings and terrain. Channel modelling for UAVs must therefore account for potential signal blockages, leading to increased path loss when compared to HAPs. Secondly, the development of a HO scheme involves managing the transition of communication links between BS. In the realm of airborne platforms like UAVs and HAPs, the development of HO schemes may vary due to disparities in their characteristics and operational environments. HAPs are engineered to maintain a stationary or quasi-stationary position for extended duration, resulting in rel-

actively predictable mobility characteristics. The associated mobility model may incorporate considerations for sustaining connectivity within a fixed coverage area. Conversely, UAVs are highly mobile platforms capable of rapid position changes. The mobility modelling for UAVs must adapt to the dynamic nature of their movement, encompassing scenarios involving HOs between ground stations and satellites. For UAVs, high mobility necessitates adaptive HO schemes to accommodate the UAV's changing location, ensuring seamless communication. Potential interference and obstacles in the communication path mandate mechanisms within the HO scheme to assess the QoS and mitigate interference or obstacles. Variability in communication range, influenced by factors like altitude, terrain, and interference, underscores the need for dynamically adjusting HO thresholds in real-time conditions [107] [108]. The following Table 2.3 summarises the existing works.

Table 2.3: Summary of Literature Survey - Mobility in rural areas

	Problem formulation	Technology	Decision Criteria	Gap
[104]	HO with a hysteresis margin	Adaptive hysteresis method	ANN-based prediction	ANN for prediction and implementing the adaptation, which is computationally intensive and requires complex hyper-parameter tuning and requirements of large datasets for training. Additionally, this method has also been used for ground based users and not UAVs
[109]	HO as a Resource Allocation problem	Deep Reinforcement Learning	Markov Decision Process	It carries out network selection by allocating resources in multi-Radio Access Technology (RAT) network scenario. Although multi-RAT HO is of interest, this paper does not consider HO at the signal level. Furthermore, only accounts for ground UEs and no UAVs
[110]	HO based on Antenna Gain manipulation	Network-controlled HO	Gain value based, network controlled	This paper compares state of art HO mechanisms for UE-LEO satellites. It proposes a new method for intra-satellite HO, but no methods were discussed for UAVs or in a heterogeneous network environment.
[106]	Monte Carlo Model	RSS-threshold algorithm combined with the ARIMA	Adaptive threshold	This is primarily implemented for HAPS, which is similar to UAVs. However, UAVs have different characteristics than HAPS.
[111]	HO based on QoS utility function optimization	Graph Theory	Multi-Attribute Decision Making (MADM)	Inter-satellite HO is discussed in this paper using GM. It does not include base station to satellite HO, only between satellites.

This section has delved into the multifaceted realm of HO mechanisms within diverse communication networks, focusing on specific domains such as rural HO, 5G, satellite HO, non-terrestrial networks, and the intricate interface between UAVs and satellite HO. Through a systematic review of existing research, this survey has aimed to distil key insights, identify emerging trends, and uncover gaps in our understanding, ultimately contributing to the collective knowledge base of seamless HOs in varied communication landscapes. The examination of rural HO mechanisms has revealed the nuanced challenges posed by sparse infrastructure, unique propagation characteristics, and the need for robust connectivity in remote areas. Existing literature emphasizes the importance of efficient HO algorithms and the integration of heterogeneous networks to address the specific challenges of rural environments. The section further highlights, the evolution of rural HO solutions and underscores the growing importance of technologies such as 5G in bridging the connectivity divide in rural regions. The investigation into satellite HO mechanisms has uncovered the pivotal role played by satellites in providing ubiquitous connectivity, especially in remote and challenging terrains. It emphasizes the importance of efficient HO algorithms to ensure continuous communication as satellites traverse the sky. Novel approaches, such as predictive HOs and intelligent satellite constellation management, emerge as promising solutions to enhance the reliability of satellite-based communication systems. The intersection of UAVs and satellite HO introduces a dynamic dimension to aerial communication networks. The literature survey elucidates the complexities arising from the integration of UAVs into satellite communication

ecosystems, emphasizing the need for tailored HO mechanisms. Insights include the impact of UAV altitude on HO dynamics, the role of satellite constellations in supporting UAV missions, and the potential synergy between satellite and UAV communication technologies.

Chapter 3

Development of New Vertical Handover for Urban Mobility

This chapter introduces the concept of heterogeneous networks and its relevance to 5G networks and the specific challenge of seamless HO across such networks. Further, it presents the EWM for vertical HO in urban areas. Lastly, it presents the results and its impact to the integration of 5G and UAVs. This chapter is linked to the second and fifth objective .

3.1 Introduction

With the increasing demands for new data and real-time services, wireless networks should support calls with different traffic characteristics and different Quality of Service (QoS) guarantees. In addition, various wireless technologies and networks exist currently that can satisfy different needs and requirements of mobile users. Since these different wireless networks act as complementary to each

other in terms of their capabilities and suitability for different applications, integration of these networks will enable the mobile users to be always connected to the best available access network depending on their requirements. This integration of heterogeneous networks will, however, lead to heterogeneities in access technologies and network protocols [112]. To meet the requirements of mobile users under this heterogeneous environment, a common infrastructure to interconnect multiple access networks will be needed. Although Internet Protocol (IP) has been recognized to be the de-facto protocol for next-generation integrated wireless, for inter-operation between different communication protocols, an adaptive protocol stack is also required to be developed that will adapt itself to the different characteristics and properties of the networks. Finally, adaptive, and intelligent terminal devices and smart BSs with multiple air interfaces will enable users to seamlessly switch between different access technologies. For efficient delivery of services to the mobile users, the next-generation wireless networks require new mechanisms of mobility management where the location of every user is proactively determined before the service is delivered. Moreover, for designing an adaptive communication protocol, various existing mobility management schemes are to be seamlessly integrated. The design issues of several mobility management schemes need to be identified and resolved. Efficient HO mechanisms are essential for ensuring seamless connectivity and uninterrupted service delivery [113].

BVLoS connectivity is key for use cases of low altitude small UAVs such as package delivery, infrastructure inspection, and rescue missions [114]. Cellular

networks stand ready to support flying UAVs by providing wide-area, quality, and secure connectivity for UAV operations [115],[116]. The reliable support of mobile connections is one of the distinguishing features of cellular networks and why mobile operators can command higher cellular subscription fees than other forms of telephony and data access. Ensuring a reliable connection to UAV user equipment (UE) in the presence of UAV movement is important for safety control and operations of the UAV.

3.2 Heterogeneous Networks

Future advanced networks, will lead to excessive capacity demands and impose a heavy burden on operators in terms of increased capital investments and operational costs. Early efforts were dedicated to heterogeneous networks (HetNets), to meet these growing demands [117], [118].

In unexpected or emergency situations (such as disaster relief and service recovery), terrestrial infrastructure is economically infeasible and difficult due to high operational expenditure, as well as sophisticated and volatile environments. To address this issue, intelligent heterogeneous architecture leveraging UAVs has been a promising new paradigm to facilitate three central usage scenarios of future wireless networks: eMBB with bandwidth-consumption, ultra-reliable low-latency communication (URLLC) and mMTC. When 5G is used for UAVs, air to ground (A2G) data links, higher carrier frequencies lead to higher path loss. This means beamforming and larger antenna arrays must be placed on both the transmitter and receiver, resulting in higher antenna gains, which offsets the path loss.

In [119] a 5G network is envisioned that, with the help of embedded resource support services such as UAV Non-Orthogonal Access (NOMA) and Software Defined Networks (SDN), the capabilities of communications, computing, and caching converge. Heterogeneous networks are defined as the integration of different telecommunication technologies with the aim of exploiting their additional characteristics. An example of a heterogeneous network is shown in Figure 3.1.

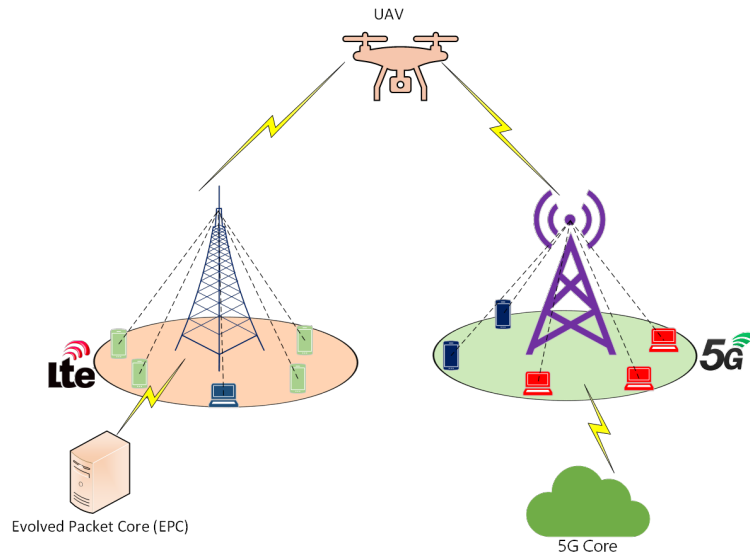


Figure 3.1: UAV in heterogeneous networks

Because of heterogeneous networks, users can transport connections between several APs of different types, benefiting from the best customized services depending on their preferences. Moreover, heterogeneous networks are an important solution to decreasing congestion in mobile networks by sharing traffic with other access technologies with higher flows. Owing to their fast and significant deployment, mobile networks consist of a set of heterogeneous systems managed by different operators and form distinct access networks [120]. Devices enabled with multiple wireless technologies enable the maintenance of seamless connec-

tivity in highly dynamic scenarios, such as UAVs, switching from one wireless network to another using vertical HO techniques. All user connections in this heterogeneous environment should occur without interruption and without service degradation when the user changes from one network to another. In this context, mobile terminals (UAVs) are network multi-interfaces that enable them to move transparently from one system to another during communication.

3.3 Challenges in Urban UAV Mobility

HO in cellular telecommunications refers to the transfer of an ongoing session from one channel connected to the core network to another channel, i.e., by transferring control from one BS to another. The session is automatically transferred to the new channel when a UAV moves to a new cell. HO operations include not only identifying a new BS, but also allocating data and control signals to the new BS's channels. The system must provide users with mobility that is dependable and does not result in the loss of any of their sessions or data. The two types of HOs are hard and soft HOs. In a hard HO, the user disconnects from the source cell before connecting to the target cell. The user connects to the target cell before disconnecting from the source cell in soft HO. HO is triggered by various types of events that are defined by specific aspects of the serving and target cells. 3GPP Release 15 details these events [121].

According to an European Technical Standards Institution (ETSI) report [122], the 5G system architecture is made up of Virtualized Network Functions (VNFs), each with their own set of capabilities. In the 5G architecture, Access, and Mobil-

ity Management Function (AMF) receives all connection and session information from the UAV. When the link degrades (falls below a certain threshold), the mobile terminal (UAV) sends measurement reports, and the network responds with a HO command. The HO command then begins the HO procedure (if necessary). The AMF is linked to the Session Management Function (SMF), which contains all session-related information and is in charge of transferring session-related information from the source node to the target node, effectively ending the current session and starting a new one.

As a result, providing continuous service in such networks has become a major problem, which is addressed in this thesis by achieving seamless HO, which enables a UAV to provide such a continuous service. de such a continuous service.

3.3.1 Contributions

To provide continuous service in heterogeneous networks is a challenge that requires efficient vertical HO algorithms to be addressed. With this aim, a vertical HO algorithm is proposed in this thesis with the following contributions

- A heterogeneous ground network encompassing 5G and LTE is established to ensure UAVs can access either BS seamlessly. UAVs can make these HO decisions independently.
- A three-stage HO with an appropriate signalling flow scheme is designed
- A novel EWM is developed for decision making that utilizes RSS as signal

parameter for decision-making.

3.4 Methodology and Proposed Solution

The number of BSs in urban areas is higher because they must serve cell phone users. Cell phone users should be able to connect to the 5G network. The same 5G BS can be used to support the UAV, which will communicate with the BSs via a 5G link [123]. A mobility architecture is intended for use in urban areas. In Figure 3.2, a UAV is connected to ground 5G BSs in urban areas, but as it travels out of the city to a rural area with no BSs, it switches to a satellite. In this chapter, only the urban environment use-case is considered.

In 5G, HOs are classified into two types based on the characteristics of the source and target cells: intra RAT and inter RAT. The HO is referred to as an inter-RAT HO when two networks belong to different RATs. This chapter only considers inter-RAT HO. A slightly higher signal level is used as a HO threshold once a signal level has been specified as the minimum usable signal for acceptable link quality at the BS receiver. Based on measurement reports, the BS decides whether to hand over the UAV as well as a variety of periodic and event-triggered methods for measuring the signal quality of the serving cell and neighbor cells. The RSS is used as a metric for HO decision making in this chapter [48].

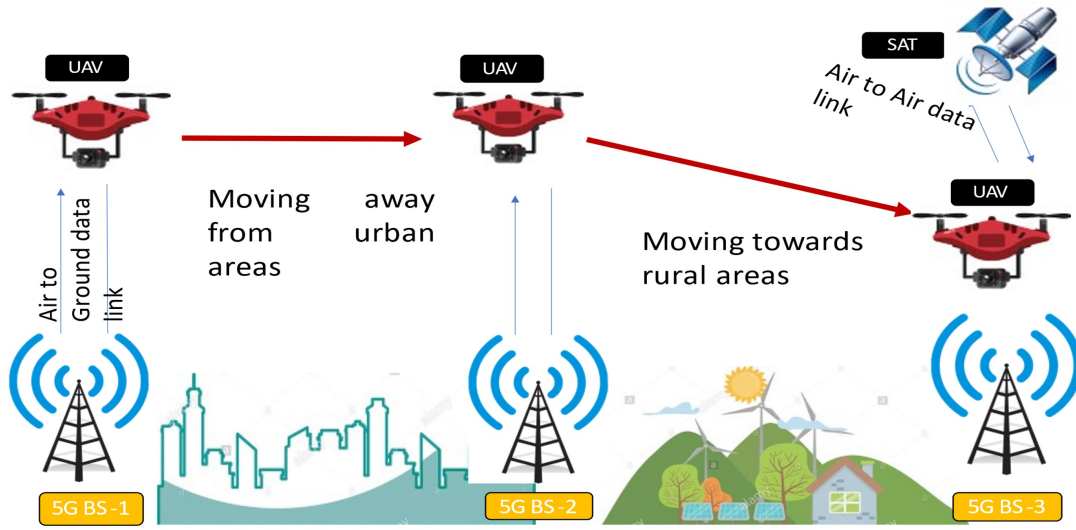


Figure 3.2: High level communication architecture for urban mobility

Various decision-making algorithms have been employed in the past, like the Simple Additive Weighted Algorithm (SAW) [124], Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) [125], Weighted Product Model (WPM) [126]. compares and distinguishes the aforementioned and other methods, outlining their benefits and challenges. Given the drawbacks of the previous methods, a new decision-making algorithm is proposed. The EWM is used in [127] to create an efficient decision-making algorithm for source water site selection. This approach was used in this chapter to develop a decision-making algorithm for HOs. The seamless HO procedure between two types of networks, 5G and LTE, is demonstrated using a MATLAB simulation setup. The network is chosen based on RSS, and the findings are presented in the form of two plots, one that shows the seamless transition (signal strength vs time) and the other time the UAV remains in each network before switching to the other one.

3.4.1 Air-Ground Connectivity for urban environments

This scenario is designed for urban environments where there are usually enough BSs to support UAVs and can thus be integrated with the already existing cellular network. Figure 3.3 depicts a high-level architecture depicting this scenario, in which two UAVs move in a cellular network and switch between BS, the first from A to B and the second from C to D. The BS will constantly measure and monitor a received signal parameter (such as RSS) from the UAV. If the threshold is exceeded in an urban area, the UAV will continue to communicate via the BS. If the threshold is not met, however, HO is initiated. One of the decision algorithms is used to make a decision (EWM). Event B2 from [128] is triggered when a primary serving cell deviates from the defined threshold for that cell while a neighbor inter-RAT cell improves. When the primary serving cell fails, this can be used to initiate inter-RAT mobility procedures. Measurements of inter-system neighbor cells are used to ensure that the target cell provides adequate coverage.

A UAV is flying through different cells in an urban area. It will constantly need to change BSs by ‘handing over’ as it moves. A signal parameter is determined. BS and the UAV are constantly exchanging measurement reports. The data flows from the UAV to the data plane of the 5G Core, i.e., User Plane Function (UPF), via a source BS. Signal quality is continuously measured and reported using Radio Resource Control (RRC) signaling. This is referred to as the HO monitoring/initiation phase. This parameter is assigned a threshold that is specified to be slightly higher than the minimum acceptable signal. If the signal parameter exceeds the threshold, the system returns to the monitoring phase. If it falls be-

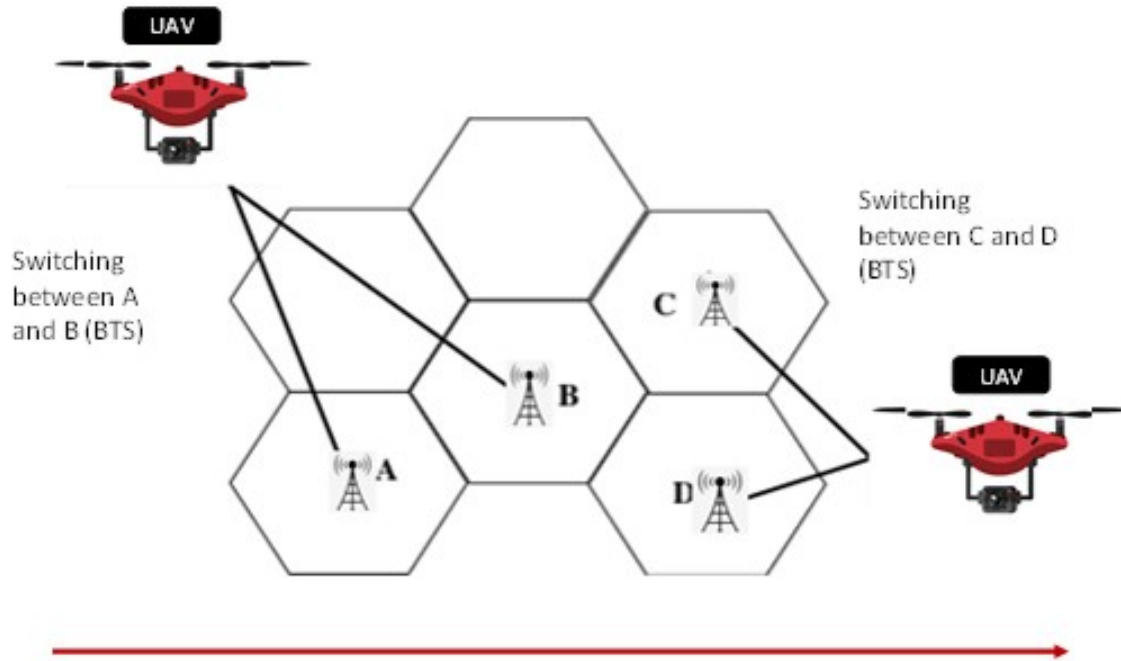


Figure 3.3: UAV mobility architecture in urban areas

low the threshold, the HO procedures are initiated. A decision algorithm is used to determine whether to hand over control. This is the decision phase. Following that, HO occurs, and UAV control is transferred from one BS to another. To begin the switching process, the UAV connects to the target BS. After the HO is performed a new route is defined and UAV's context released to the new BS by the AMF. The term "context" refers to all data and control signals associated with the UAV. A path switch request is sent from the target BS to the AMF, and once accepted, data can flow from the UAV through that target BS to the specified UPF. The execution phase begins when the HO is completed. It is seen that the HO request is initiated only after the signal parameter has been checked and ensured that it is less than the threshold.

The three stages of HO can therefore be summarized as follows:

1. Initiation

Measurement reports are constantly exchanged between the BS and the UAV via RRC, allowing it to be monitored. The data flows from the UAV to the data plane of the 5G Core via a source BS. Signal quality is continuously measured and reported using Radio Resource Control (RRC) signaling. The initiation procedure is depicted in Figure 3.4, where the UAV is currently connected to a 5G BS.

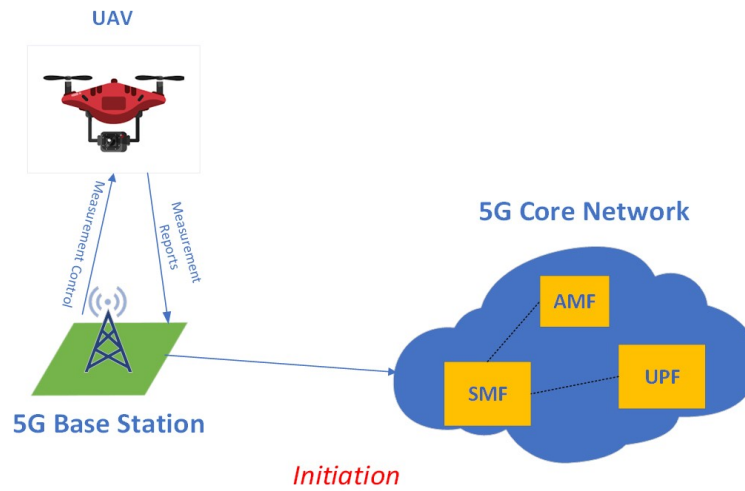


Figure 3.4: 5G handover Initiation for UAV

2. Decision Phase

The BS then uses a decision algorithm to make the HO decision based on the value (i.e., if it is less than the threshold). When a HO is required, the source BS transmits a HO request signal (RQ) to the target BS. The RQ signal contains information that identifies the UAV as well as protocols that will allow the UAV to be 'admitted' to a new BS. When the target BS recognizes the need for HO, it sends an acknowledgment signal back (ACK). Figure 3.5 depicts the decision, in which the UAV waits for the ACK signal before executing the HO.

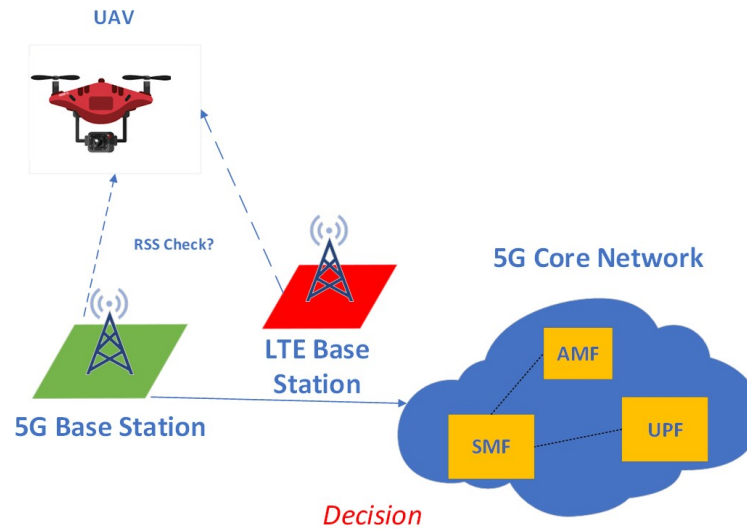


Figure 3.5: 5G-LTE Handover Decision for UAV

3. Execution

The ACK signal contains data that will allow the UAV to synchronize with the new BS. The SN Status is then transferred, allowing packets to be sent to the new BS. The UAV then disconnects from the old cell, synchronizes with the new cell, and transmits the packets to the target BS. The UAV then confirms the HO by sending a confirm signal to the target BS. The target BS sends a path change request signal to the AMF. Through the UPFs, the AMF switches the data links. The UAV then returns an ACK and switches to the target BS. Finally, the UAV context is released, and the HO is carried out. Figure 3.6 depicts this.

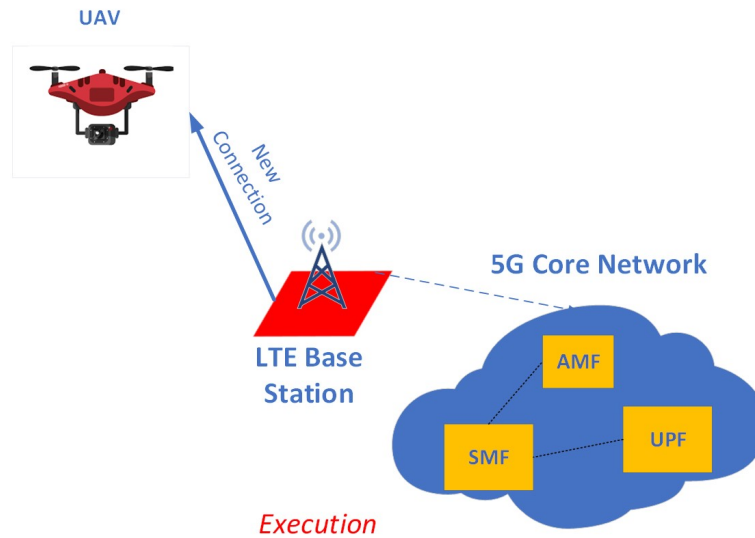


Figure 3.6: Handover Execution for UAV

In summary, the HO will take place in three steps in this proposed mobility scheme: (i) initiation- where measurement monitoring and reporting takes place, (ii) decision making- where the EWM is used to determine whether a HO is required or not, and (iii) execution- which carries out the HO and transfers complete control to the target BS.

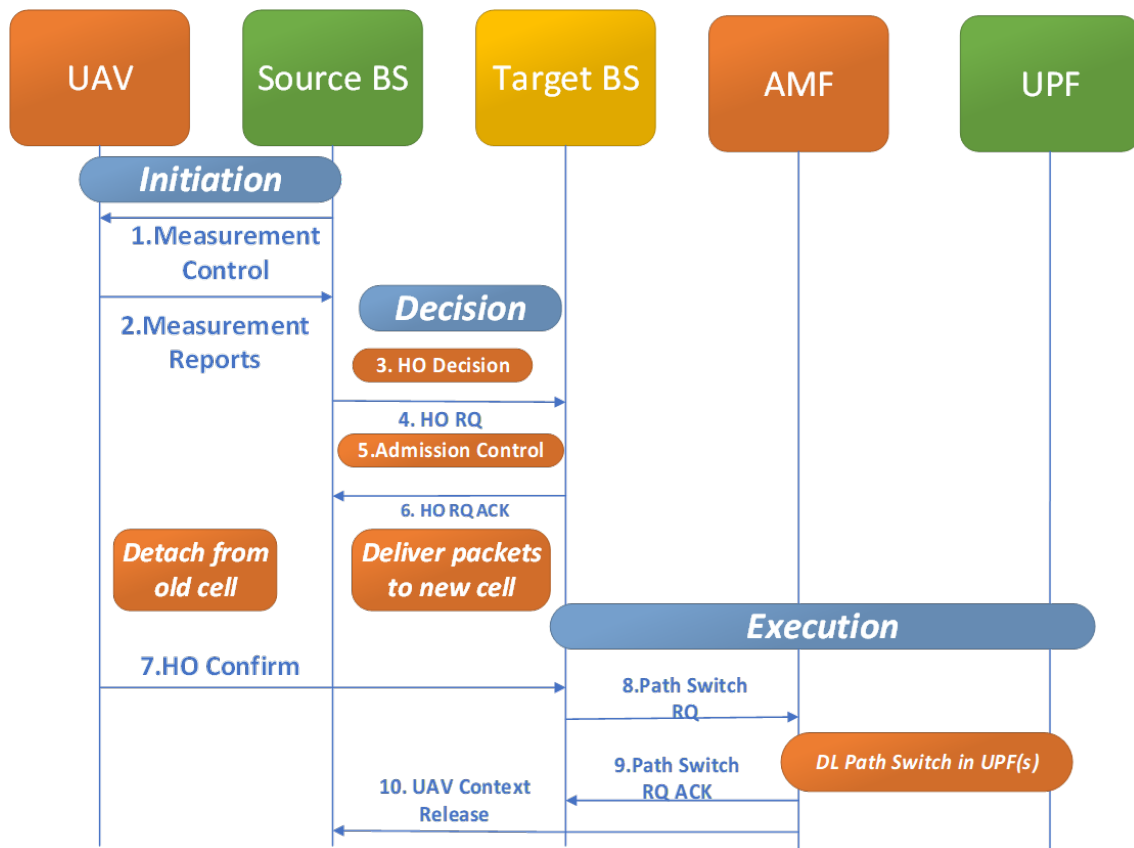


Figure 3.7: Signal flow diagram for handover in urban areas

A sequence diagram depicts the sequential flow through the three stages in Figure 3.7. The initiation and execution steps are considered to follow traditional mechanisms in this chapter, and the decision scheme is the focus. The decision algorithm used is known as EWM, and the process is explained in greater detail in the next section.

3.5 Entropy Weighted Method(EWM) for Decision Making

Based on the limitations of the existing methods described in [129], a novel decision-making algorithm is presented in this section. The EWM measures the degree of differentiation to determine the parameter value. This method computes the indicator's information entropy and employs the indicator's degree of difference to calculate the effective information and indicator weight contained in the known data. The greater the degree of dispersion of the measured value, the greater the degree of variation in the index; thus, more information can be derived. Furthermore, the index should be given more weight, and vice versa.

In the evaluation of this method, m indicators and n samples are set, and the measured value of the i^{th} index in the j^{th} sample denoted as p_{ij} is calculated as follows

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^n x_{ij}} \quad (3.1)$$

In the EWM, the entropy value E_i of the i^{th} index is defined as:

$$E_i = -\frac{\sum_{j=1}^n p_{ij} \cdot \ln p_{ij}}{\ln n} \quad (3.2)$$

In the actual evaluation using the EWM, $p_{ij} = 0$ is generally set, for the convenience of calculation. The entropy value E_i has a range of $[0, 1]$. The greater the value of E_i , the greater the degree of differentiation of index I , and thus more in-

formation can be extracted. As a result, the index should be given more weight. Consequently, in the EWM, the weight ω_i calculation method is determined by,

$$\omega_i = \frac{1 - E_i}{\sum_{i=1}^m (1 - E_i)} \quad (3.3)$$

In this algorithm, the RSS is regarded as an indicator for various types of networks and, as a result, is used as a decision-making factor for network switching. In an urban environment, the UAV navigates two networks: 5G and LTE. Path loss, RSS, and weight property entropy are calculated using BS and UAV coordinates as arguments to various functions in the algorithm. It first determines whether the network is a 5G or LTE network, and then calculates the RSS from both networks. Then, depending on the RSS value, a HO is performed to the network with a higher RSS.

The co-ordinates for both the BSs and the UAV along with the UAV speed are set. In next step, using function "is in 5G coverage" or "is in LTE coverage" the current state of the UAV is determined. Once the current state is defined a net state variable is either set (1) or reset (0) depending on which network the UAV is currently in. After this the RSS from both serving networks are calculated using "calculate RSS" function. After the RSS is measured, it is checked which network has higher value and that network is selected, i.e., HO is performed. After the decision is made, if the UAV is still in the past network, then a clock signal "handoff clock" is reset (0) else if HO is performed and the UAV is in the new network then "handoff clock" is set (1). After these two graphs are plotted, viz. RSS vs time and mark of the network vs time. The following functions are

used in this model:

- *calculate path loss*: This function calculates the free space path loss using the formula derived from Friis Transmission formula [130]:

$$\text{FSPL} = 32.44 + 20\log_{10}\left(\frac{d}{1000}\right) + 20\log_{10}\left(\frac{f}{10^6}\right) \quad (3.4)$$

- *calculate RSS*: Calculates RSS using UAV co-ordinates and switch case variable for determining the type of network. It uses the following formula:

$$\text{RSS} = P_{\text{tx}} + G_{\text{tx}} + G_{\text{rx}} - \text{FSPL} - k \quad (3.5)$$

where,

RSS: received signal strength

Ptx: Transmitted Power. It is assumed to be 38 dBm for 5G and 24 dBm for LTE

Gtx: Transmitter Antenna Gain. Assumed to be unity i.e., 0 dB

Grx: Receiver Antenna Gain. Also assumed to be unity.

k: slow fading margin. Assumed to be 8dB

FSPL: Free space path Loss as obtained from

- *is in 5G coverage* and *is in LTE coverage*: Checks which network UAV is in,

based on its co-ordinates

- *calculate weight property entropy*: To assign weights and perform decision making process.

This algorithm efficiently assigns weights to multiple criteria and then identifies RSS as the decision parameter.

3.6 Results and Analysis

In an urban environment, the UAV navigates two networks: 5G and LTE. The seamless HO procedure between the two networks is demonstrated using a MATLAB simulation setup. The strength of the received signal is used to select the network, and the decision to HO is made using the EWM. Table 3.1 summarizes the parameters used in this simulation.

Table 3.1: System Parameters

Parameter	5G	LTE
Frequency	6 GHz	2.5 GHz
BS Co-ordinates	[0,0,0]	[600,0,0]
UAV Co-ordinates	[100,100,100]	[100,100,100]
Initial Height of UAV	328ft.($\approx$ 100 m)	328ft($\approx$ 100 m)
Initial measured RSS	-89 dBm	-105.67 dBm

The analysis for seamless HO is simulated using RSS selection criteria based on an EWM decision model. As discussed already, one of the unique challenges of the UAV supported networks is reliable communications link at the high speeds, therefore the simulation is carried out for UAVs moving at different speeds.

1. UAV moving at 10 m/s

The UAV is flying at a speed of 10 m/s at a height of 328 feet. A graph depicting the difference between 5G, and LTE networks is plotted: time vs RSS. In Figure 3.8, the UAV is initially connected to the 5G network and records RSS of about -89 dBm, which gradually decreases as the UAV flies away. RSS begins measuring at -106 dBm in the LTE network after about 25 seconds and gradually increases. As the UAV approaches the LTE network, the RSS decreases for 5G and increases for LTE around the 48-second mark. Finally, the UAV switches to the LTE network at -100 dB as annotated in Figure 3.8. The RSS in LTE increases up to -99 dBm in a 3 s time frame, and then starts falling as the UAV further flies away into a 5G network. After 62 s, the RSS from 5G becomes more than LTE, and the UAV switches back to 5G, which now has RSS of -102 dBm. This is the second HO, as shown in Figure 3.8. To further illustrate the seamless HO, another graph is plotted where it is observed that the UAV switches seamlessly from 5G to LTE and then back to 5G. The switching is also represented in Figure 3.9.

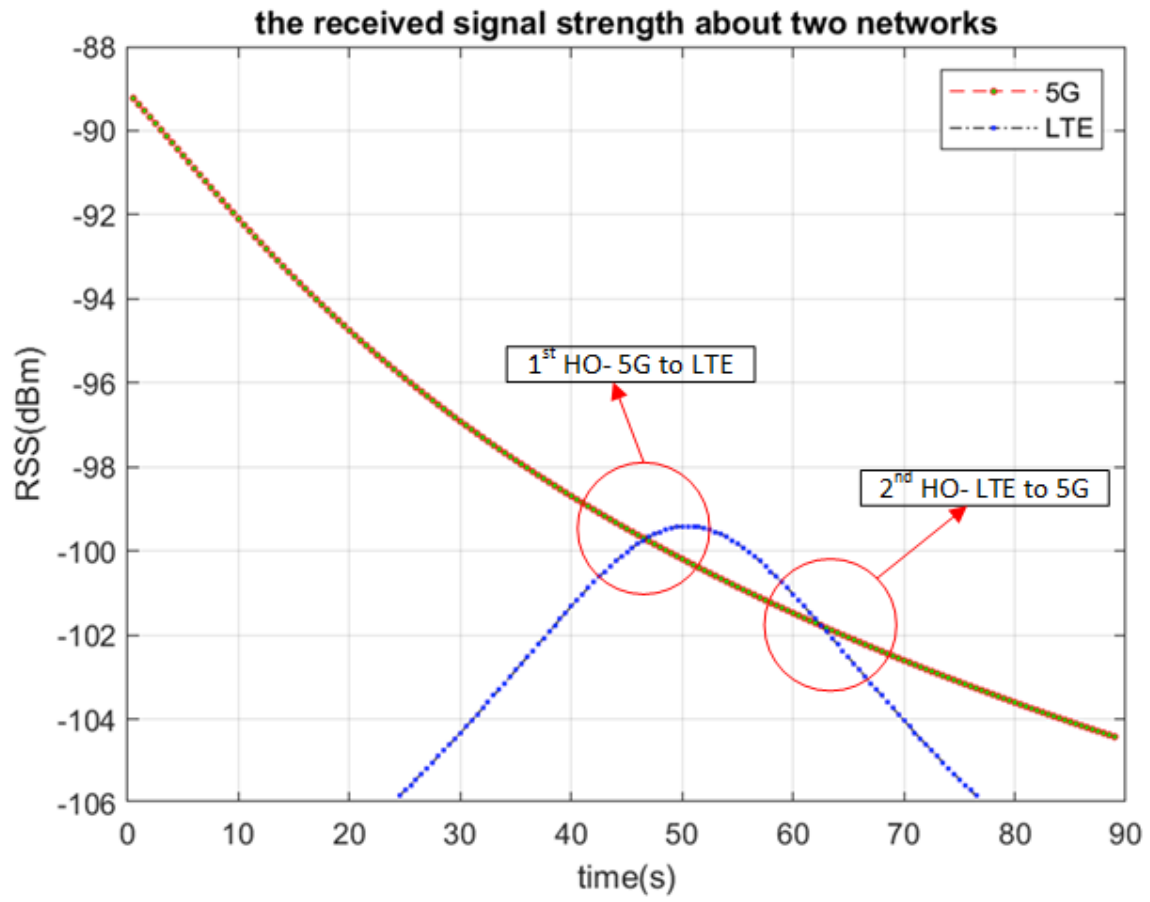


Figure 3.8: RSS switching between 5G and LTE networks with UAV at 10 m/s

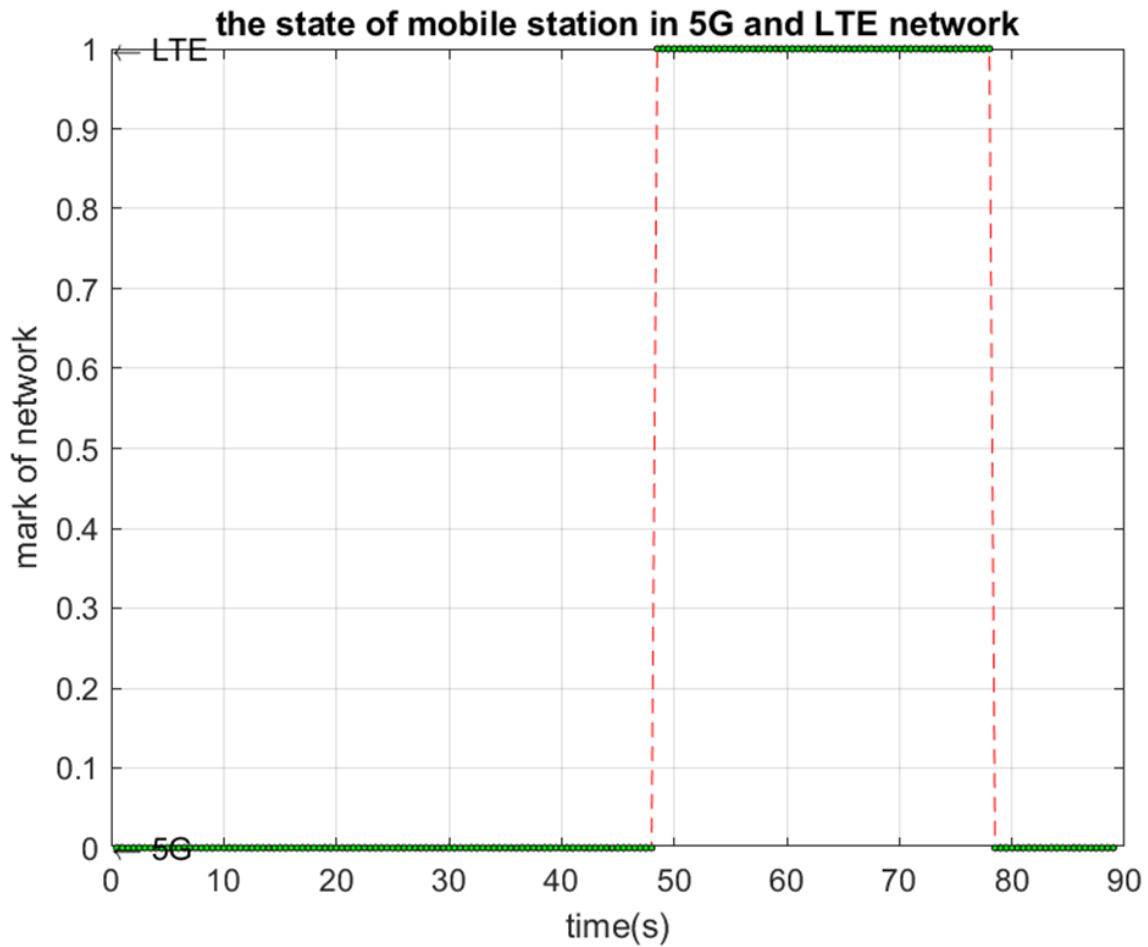


Figure 3.9: Switching between 5G and LTE networks

2. UAV moving at 20 m/s

In this scenario, the UAV is flying at a speed of 20 m/s at the same height of 328 ft. A graph is plotted: time vs RSS showing the change between 5G and LTE networks. In figure 3.10, the UAV is initially in the 5G network and records RSS of about -89 dBm and falls, as the UAV flies away. After 12.5 s the LTE network RSS starts measuring at -106 dBm slowly increasing. At about 23 s mark, the RSS is decreasing for 5G and increasing for LTE, due to the imminent approach of the UAV. At -100 dBm the UAV switches to the LTE network as annotated in Figure 3.10. The RSS in LTE increases up to

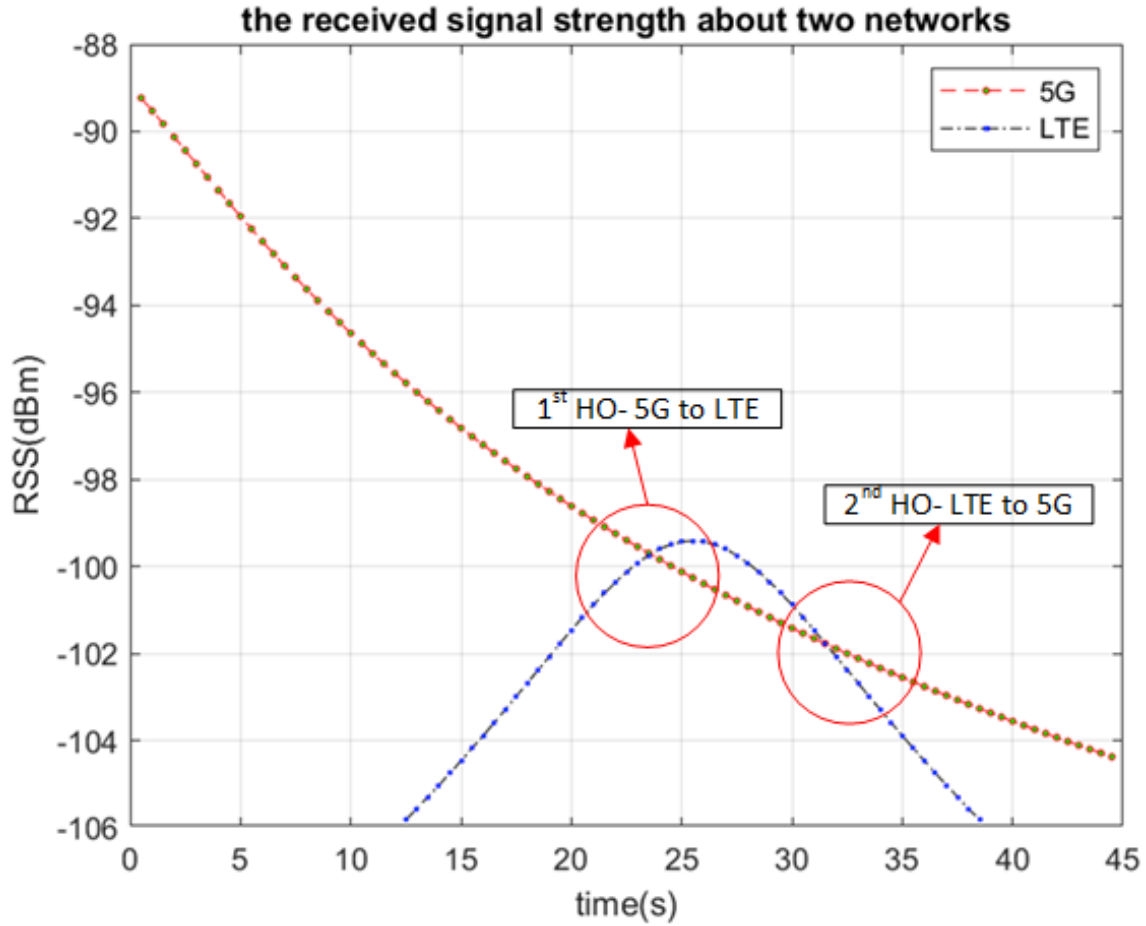


Figure 3.10: RSS switching between 5G and LTE networks with UAV at 20 m/s

-99 dBm in a 3 s time frame, and then starts falling. After 32 s the RSS from 5G becomes more than that of LTE and the UAV switches back to 5G which now has RSS of -101 dBm. This is the second HO, as annotated in Figure 3.10. To further illustrate the seamless HO another graph is plotted where it is observed that the UAV switches seamlessly from 5G to LTE and then back to 5G. The switching is also represented in Figure 3.11

As compared to the UAV flying at 10 m/s, when the speed is increased, the HO takes place faster to accommodate the faster UAV speed. Further, it is also seen that the signal level variations are the same as it is for the lower speed scenario, and the only change is observed in HO time.

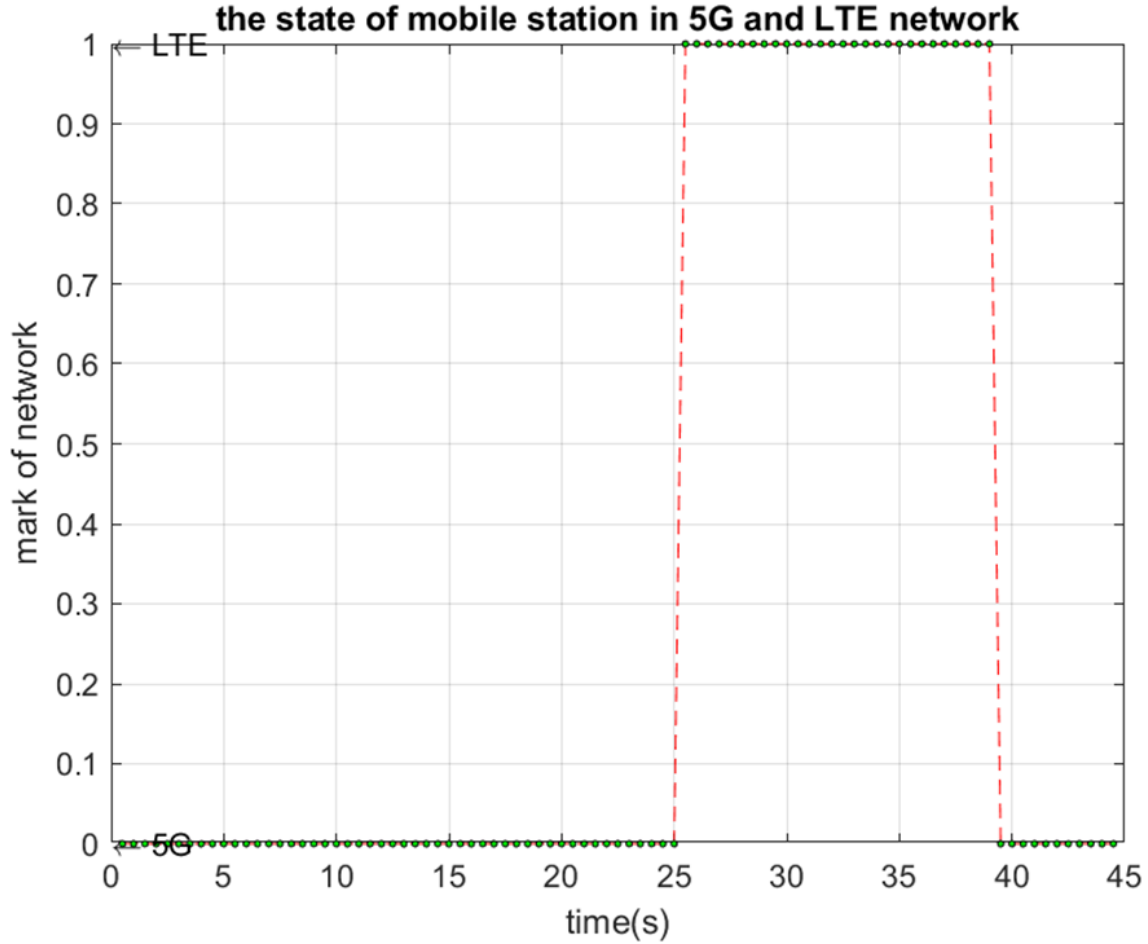


Figure 3.11: RSS switching between 5G and LTE networks with UAV at 20 m/s

3. UAV moving at 30 m/s

The UAV flight speed is further increased by 10 m/s to 30 m/s in this scenario. Once again, as shown in Figure 3.12, time vs RSS plot, the UAV is initially in the 5G network and records RSS of about -89 dBm falling as the UAV moves away. After 8 s the LTE network RSS starts measuring at -106 dBm, with the UAV approaching. At -99 dBm the UAV switches to the LTE network as annotated in Figure 3.12. The RSS in LTE increases up to -99 dBm in a 3 s time frame, and then starts falling. After 23 s the RSS from 5G becomes more than that of LTE and the UAV switches back to 5G which

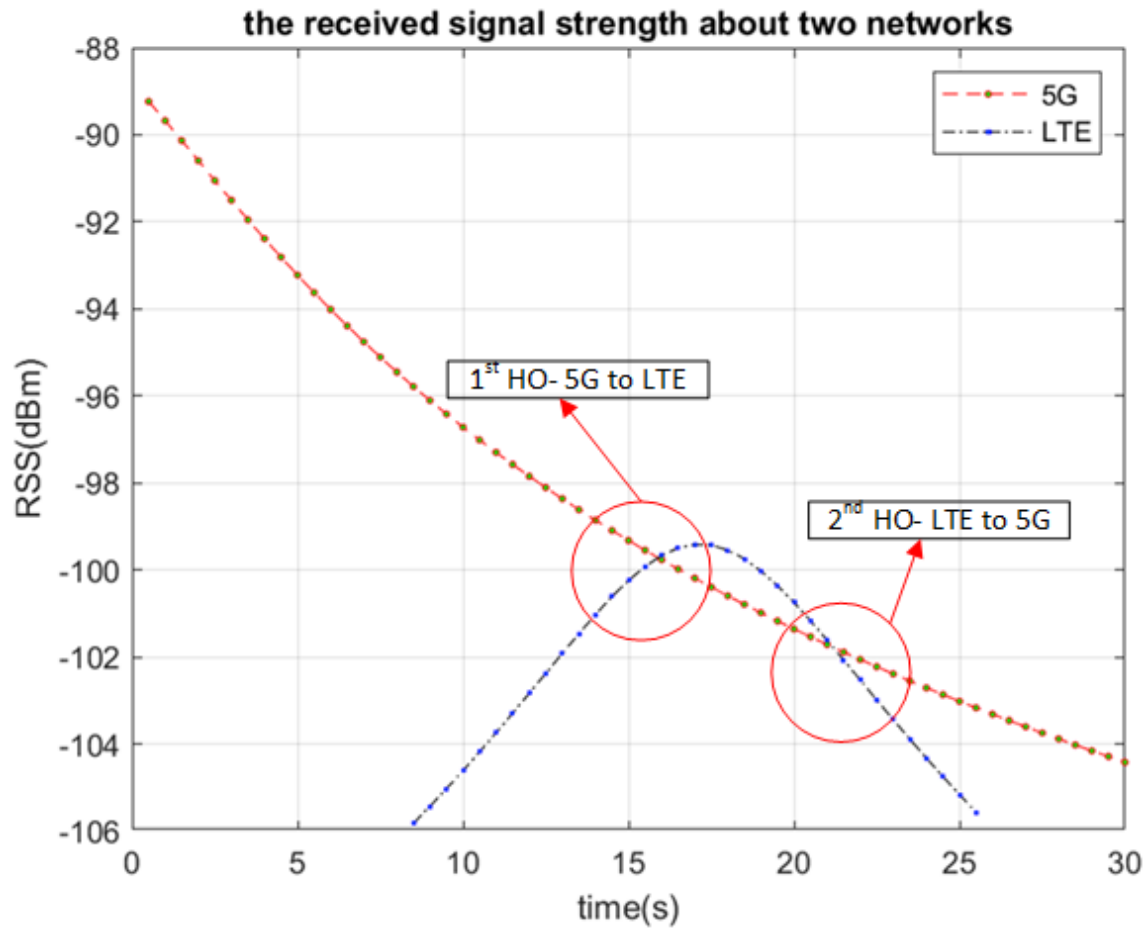


Figure 3.12: RSS switching between 5G and LTE networks with UAV at 30 m/s

now has RSS of -102 dBm. This is the second HO, as shown in Figure 3.12

To further illustrate the seamless HO another graph is plotted where it is observed that the UAV switches seamlessly from 5G to LTE and then back to 5G. The switching is also represented in Figure 3.13

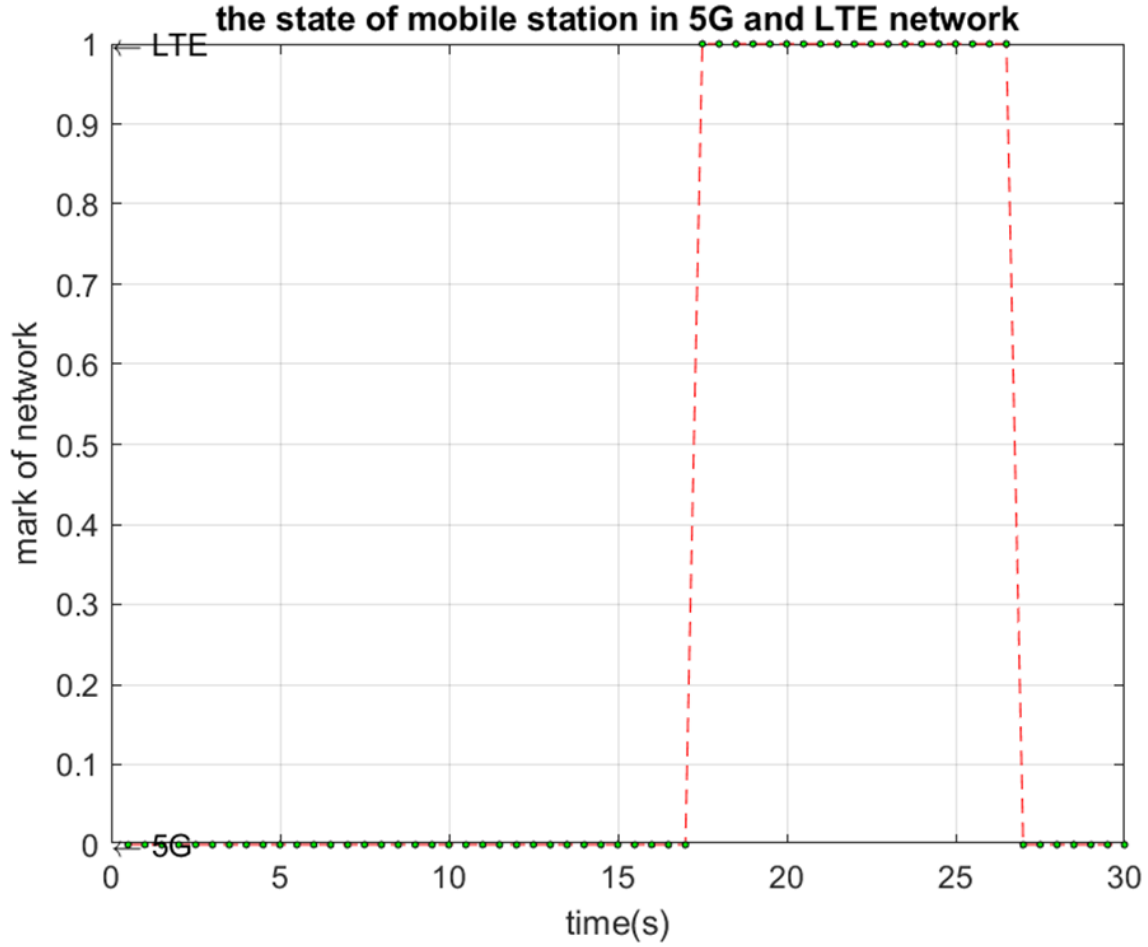


Figure 3.13: Switching between 5G and LTE networks with UAV at 30 m/s

As compared to the UAV travelling at 20 m/s HO times have once again decreased with the increase in the UAV speed. A comparison of the results is summarized in Table 3.2. It is evident that as the UAV speeds increase, a decrease in the time at which the HO takes place. This means the algorithm can accommodate high speeds of the UAV and still reliably perform HO. This solves one of the challenges, i.e., HO at high speeds of the UAV.

Table 3.2: Switching Times for UAV at different speeds

UAV Speeds	5G-LTE HO time	LTE-5G HO time
10 m/s	48 s	62 s
20 m/s	23 s	32 s
30 m/s	16 s	26 s

Additionally, a simulation is also carried out for UAV at 442 ft. At this altitude, the UAV is unable to reach the LTE base station, briefly connects to the 5G BS until it loses connection, these are shown in Figure 3.14 and Figure 3.15. Since the CAA regulations [131] states that maximum height at which the UAV is allowed to fly is at 400 ft., therefore this scenario highlights that, above the regulated height the communications link fails.

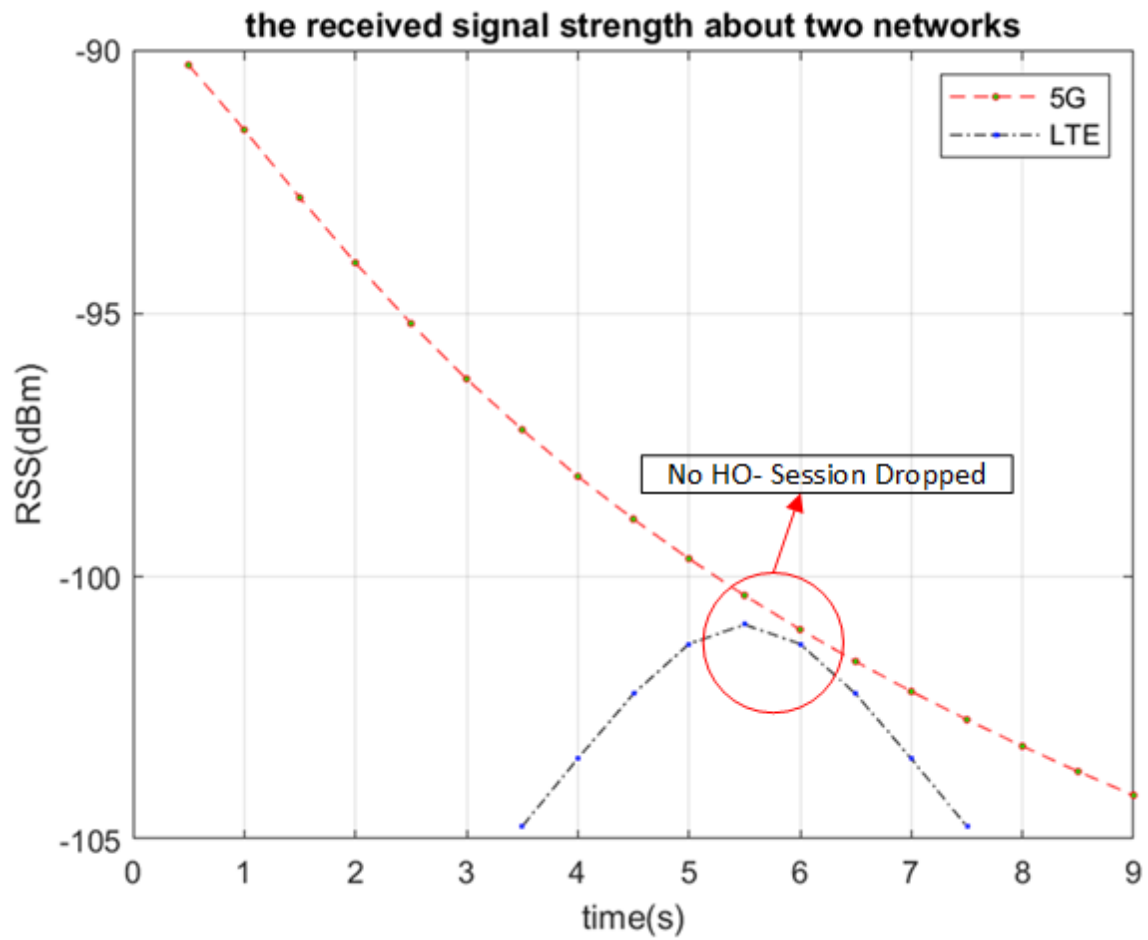


Figure 3.14: RSS switching between 5G and LTE networks with UAV at 442 ft

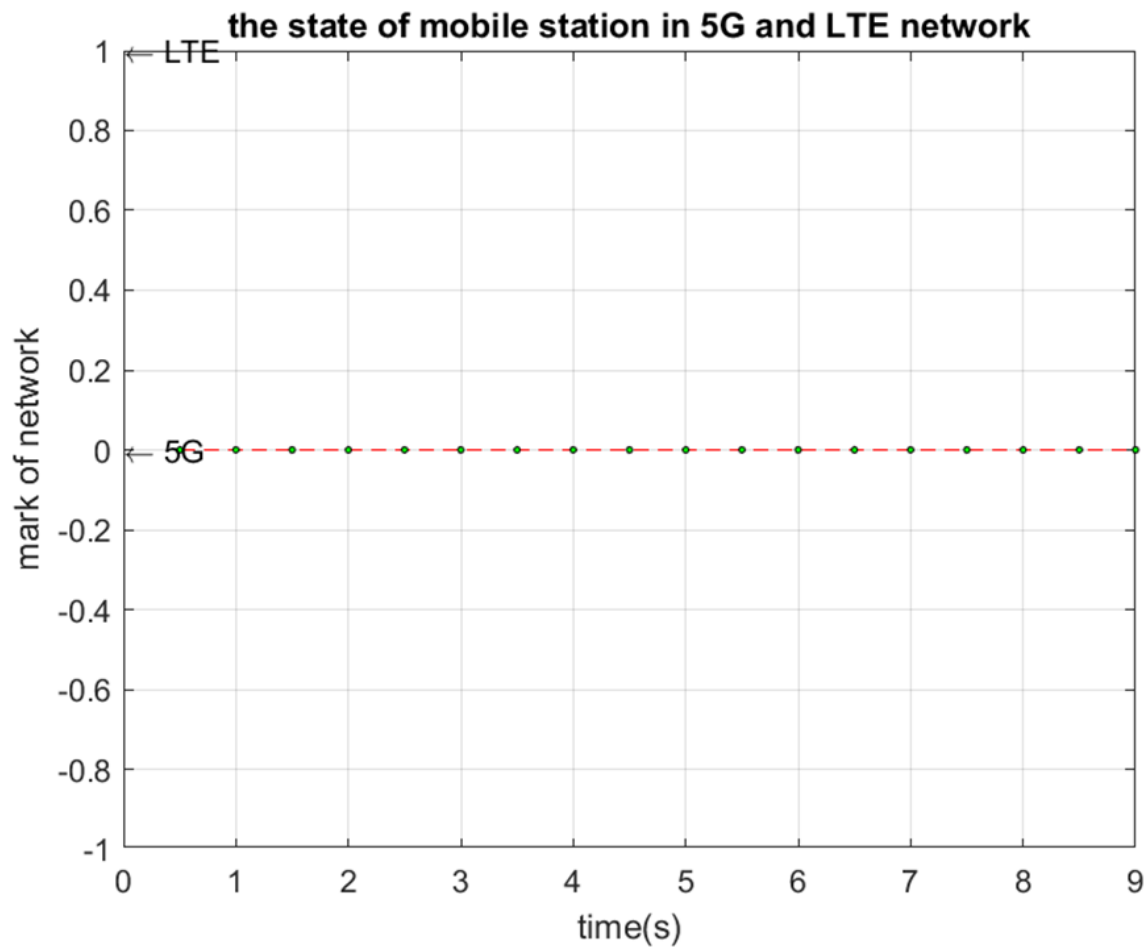


Figure 3.15: Switching between 5G and LTE networks at 442 ft

3.7 Chapter Summary

The prospective landscape of 5G networks anticipates seamless and ubiquitous connectivity, capable of supporting huge traffic volumes, accommodating 100 billion connected wireless devices, and addressing diverse requirements of reliability, latency, and battery lifetime. This evolution, however, poses significant challenges to the existing infrastructure, placing substantial demands on operators in terms of capital investments and operational costs. In response to these challenges, the widespread deployment of UAVs has emerged as a strategic solution.

The deployment of UAVs has been identified as a strategic solution to several challenges posed by the evolution of 5G networks in the following ways; UAVs can be used as aerial base stations to provide temporary network coverage in areas lacking infrastructure, such as rural or disaster-stricken regions. They can also help extend network coverage in urban areas with high demand, addressing gaps and ensuring comprehensive service. UAVs equipped with small cells can be deployed to boost network capacity during peak usage times, such as events or emergencies. This helps alleviate congestion and ensures a higher quality of service for users. Compared to building traditional ground-based infrastructure, deploying UAVs is quicker and more flexible. This enables rapid network expansion and the ability to address sudden increases in demand or changes in network topology. UAVs can be repositioned as needed to optimize network performance and coverage. This dynamic capability allows operators to adapt to changing network conditions and user demands in real-time. By leveraging UAVs, network operators can address some of the key challenges of 5G deployment, such as ensuring widespread coverage, managing high-capacity demands, and maintaining cost efficiency. The flexibility, mobility, and rapid deployment capabilities of UAVs make them a valuable asset in the evolution and optimization of 5G networks. The broad spectrum of applications that the UAV enables, necessitates increased data transfer rates and network traffic capacity, giving rise to the concept of heterogeneous networks. These networks encompass devices utilizing different radio access technologies, a particularly critical consideration for UAVs engaged in medical, delivery, and military applications. In urban heterogeneous

networks, UAVs face the imperative of seamlessly transitioning between different BS to maintain a reliable link. An extensive review of existing research and technologies reveals that achieving seamless HO in urban environments has become a significant challenge. This study aims to address this challenge through the development of an algorithm based on the RSS criterion for network selection. The decision-making process employs the EWM. Through simulation-level analysis, the successful implementation of EWM for a UAV navigating across 5G and LTE networks is demonstrated. Consequently, this study presents a viable solution for addressing the mobility challenges in heterogeneous networks, particularly in the context of UAV-5G communication. The findings of this research represent a significant stride toward enabling the integration of UAVs into the 5G architecture, marking a noteworthy advancement in this domain.

Chapter 4

Mobility Management in Rural Areas

In this chapter, the HO challenge in rural areas and its solution is presented. It builds on the work done in Chapter 3, by extending the integration of 5G and UAVs to include satellites. This chapter links to the fourth and fifth objective.

4.1 Introduction

The evolution of telecommunications networks toward 5G and beyond necessitates a significant overhaul in infrastructure and technological paradigms. Future networks are poised to accommodate a larger volume of users and devices with varying performance demands, alongside a burgeoning array of applications and use cases. Conventional terrestrial mobile networks encounter limitations in providing coverage, particularly in remote, non-land areas, and regions affected by disasters, owing to infrastructural constraints.

The integration of Non-Terrestrial Networks (NTNs) with upcoming networks offers a promising and cost-effective strategy to ensure seamless and ubiquitous

wireless coverage, thus facilitating scalability [79]. NTN serves as supplementary access nodes that augment the capabilities of existing terrestrial networks, addressing aspects such as capacity, coverage, and latency. Moreover, this approach has the potential to alleviate the shortcomings inherent in terrestrial infrastructure, enabling it to uphold requisite standards of reliability and widespread accessibility for forthcoming wireless applications.

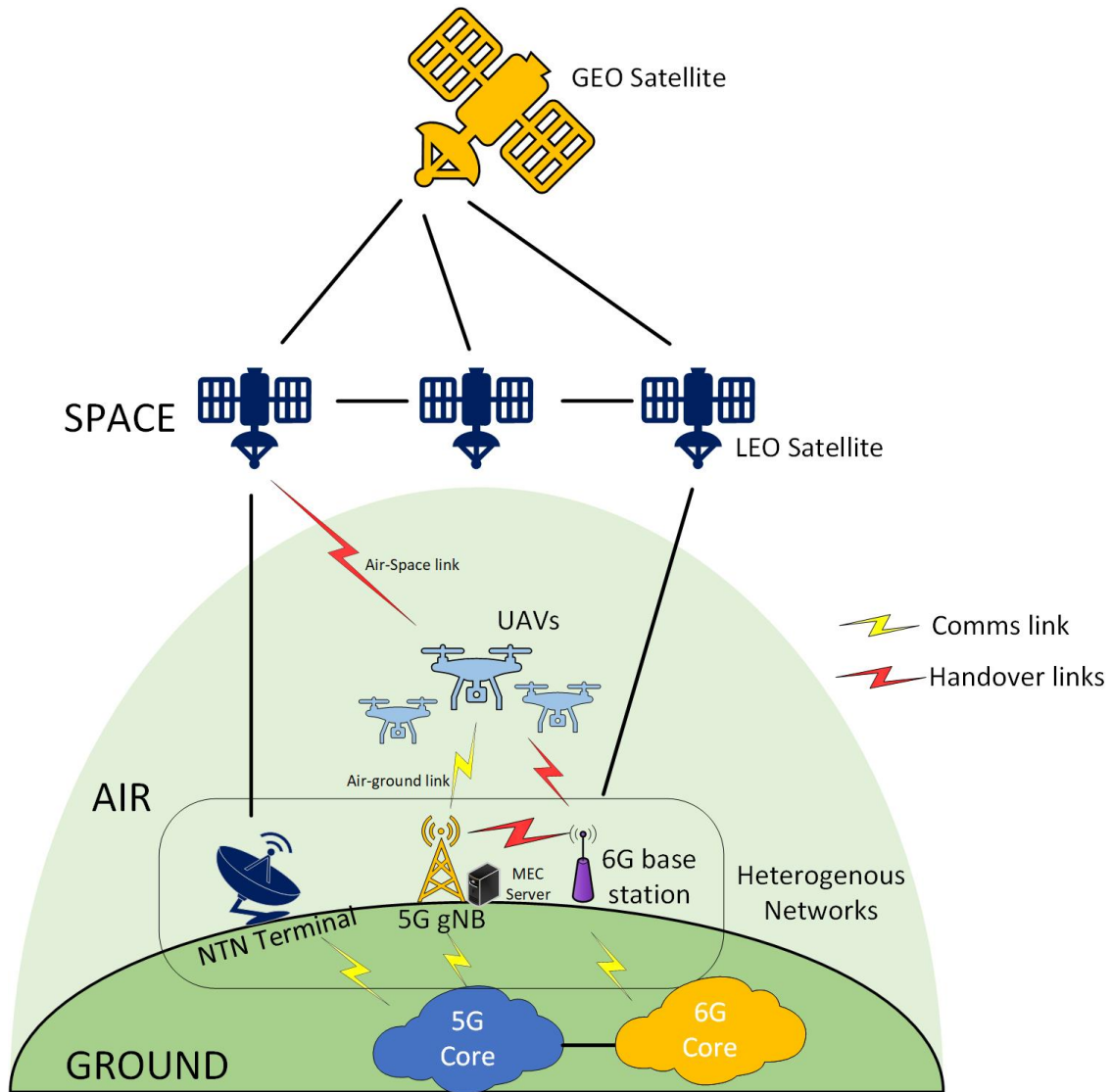


Figure 4.1: Integrated Vertical Heterogeneous Networks

Satellites offer a solution as they are not constrained by geographical environ-

ments and can provide global coverage. GEO satellites, located 35,786 km above the equator and moving synchronously with the Earth, cover almost one-third of the Earth's surface (excluding polar regions). The inevitable propagation delay of GEO satellites cannot meet the requirements of delay-sensitive services. On the other hand, LEO satellites, situated at altitudes between 300-1500 km, experience frequent HOs due to their rapid movement. Additionally, LEO satellites have limited coverage areas, and when the constellation size is small, certain regions may not be covered. However, in the upcoming era of integrated vertical heterogeneous networks [132], the provision of global communication and internet services will involve LEO satellites.

In the illustration depicted in Figure 4.1, a network configuration comprises three layers. The initial layer, referred to as the ground segment, incorporates terrestrial network components, including BSs, corresponding core networks, and MEC architecture. The second layer, termed the air segment, encompasses flying vehicles or UAVs. Lastly, the third layer, known as the space segment, is divided into two tiers: LEO satellites deployed in constellations and GEO satellites.

Achieving seamless vertical HO within such a network architecture, as illustrated in Figure 4.1, necessitates the development of efficient techniques and algorithms. Ground-based vertical HO solutions for UAVs have been extensively explored and documented [77], [133], [134], as elucidated in subsequent sections. However, the air-to-space transition for UAV networks remains relatively uncharted territory. Notably, commercial entities such as SpaceX and Amazon are launching LEO satellite constellations to ensure global connectivity [135]. Com-

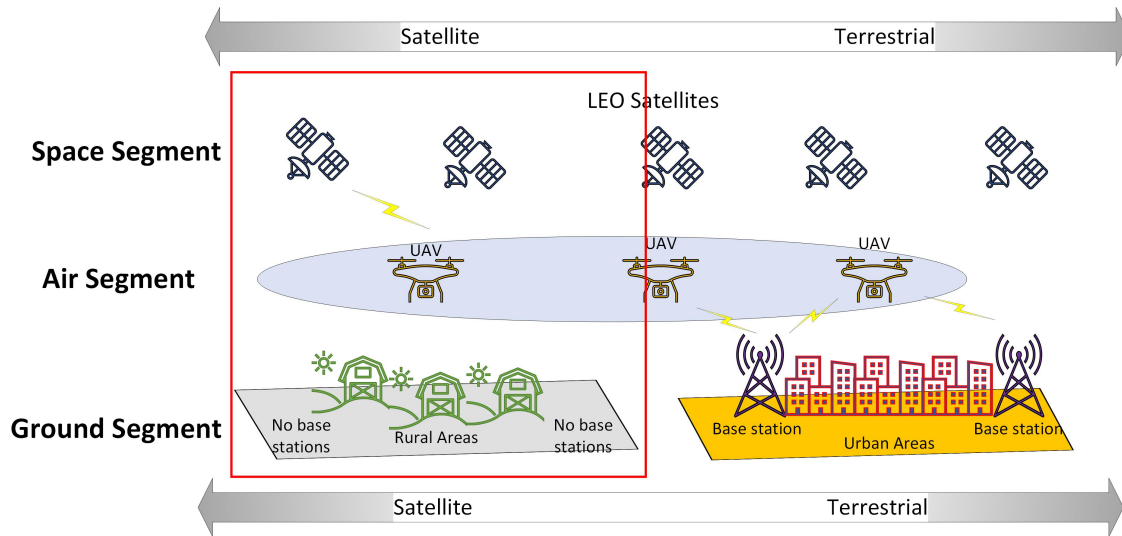


Figure 4.2: Satellite connectivity in rural areas

pared to GEO satellites, LEO satellites offer advantages such as lower propagation delays, reduced transmission power requirements, and diminished signaling attenuation.

This allows for direct communication with UAVs to be established easily. These satellite systems are intended to complement and extend the existing terrestrial networks to provide complete global coverage. They can interact with existing fixed networks to share instantaneous traffic overload. In general, satellite networks will extend the coverage area where terrestrial wireless systems are infeasible, both economically and geographically. The system model is shown in Figure 4.2 and the highlighted part represents a rural area where terrestrial systems become infeasible.

4.2 Handover Challenge in Air-to-Air Networks

HO technology, crucial for sustaining seamless connections as users move between cells, is impacted by various factors such as signal degradation, load distribution, and elevated error frequencies. UAVs, given their distinctive attributes, pose specific hurdles for efficient HO management within mobile networks. These obstacles encompass heightened system intricacies, the potential for LoS regulation, and accelerated transition frequencies owing to UAV velocity [119]. Additionally, UAVs commonly rely on terrestrial antenna sidelobes, resulting in frequent transitions that compromise Quality of Service (QoS) standards [136]. Managing UAV HOs necessitates a distinct approach compared to conventional UE HO techniques. Techniques designed for terrestrial UEs may not be directly applicable to UAV networks due to the unique aspects of UAV operations. The primary goal is to ensure high-quality, reliable communication while facilitating seamless HOs among UAVs.

Although prior research has made efforts to address these challenges, substantial hurdles remain. For instance, vertical HOs in urban environments were previously explored [48], whereas this chapter, focuses on UAV HOs in rural areas with limited terrestrial infrastructure. In this scenario, UAVs transition between urban and rural regions, connecting to a LEO satellite when terrestrial infrastructure is lacking. A graph-based decision-making HO algorithm, treating satellites and gNBs as vertices and using weighted summation models as edges for decision-making is proposed. HOs are executed within a framework similar to Dijkstra's shortest path algorithm.

The results indicate that our proposed algorithm outperforms existing solutions for similar networks, such as the adaptive threshold method and hysteresis method [137] and [106]. This research contributes to the advancement of effective HO management for UAVs operating in challenging, dynamic environments, ultimately enhancing the performance and reliability of drone communication networks.

4.2.1 Contributions

In this chapter, a novel graph-based HO algorithm is proposed. The decision-making is performed as part of a time-based directed weighted graph, where the satellites and BSs form the vertices and the signal parameters as edges. This chapter therefore makes the following contributions

- A heterogeneous satellite-ground networks is established to ensure UAVs can access either satellites or BSs seamlessly. UAVs can make these HO decisions independently.
- The decision functions are designed to reflect the signal parameters, viz. RSS, SNR and elevation angle. This is multi-criteria decision-making problem implemented through the weighted summation model (WSM)
- A graph theory based algorithm is proposed, that implements the Dijkstra's algorithm for HO execution.

4.3 Graph Method based Handover decision Algorithm

4.3.1 Graph Theory

In the dynamic realm of UAVs and terrestrial-satellite connectivity, maintaining uninterrupted transitions between diverse communication nodes is critical. This chapter introduces an innovative strategy known as the GM based seamless HO, tailored to tackle the distinctive challenges encountered by UAVs operating within terrestrial-satellite networks. Offering a range of key enhancements, this approach enhances the efficiency, dependability, and effectiveness of UAV communication within dynamic, multi-node settings.

At the core of this methodology lies graph theory, wherein communication nodes, UAVs, and satellites are depicted as nodes within a dynamic network graph. The edges connecting these nodes encapsulate decision-making parameters. This model furnishes a holistic depiction of network topology, facilitating streamlined HO decision-making processes. A primary goal is to achieve seamless transitions between terrestrial networks and satellite links as UAVs traverse their operational domain. Leveraging the graph-based framework, proactive HO decisions are made by evaluating signal metrics such as RSS, SNR, and elevation angles to ensure uninterrupted data transmission. Continuously assessing available routes and opting for the most suitable ones, this approach guarantees that UAVs maintain robust and consistent connections, even amidst challenging environments. Furthermore, the graph-based methodology exhibits scalability, accommodating a growing array of UAVs and communication nodes, thus ren-

dering it adaptable across various deployment scenarios.

In this chapter, graph theory is implemented to model the network encompassing the satellites and ground BSs as the nodes and the edges as the decision parameters as detailed in further sections.

4.3.2 Problem formulation

Firstly, the list of notations are presented in Table 4.1

The problem is formulated as a graph with distinct instances of satellites and BSs denoted as s_1, s_2, s_3 and s_4 across a time duration T , segmented into several short, equidistant time intervals $t_1, t_2, \dots, t_i$. The optimal time for HO from BS b_1 to any of the target satellites s_1, s_2, s_3 or s_4 is subject to various time-variable criteria. In the proposed framework, each satellite and BS is represented by multiple instances to account for changes in satellite communication status over time. For instance, in Figure 4.3 the notations of the BSs and satellites with respect to the time are shown. This means that BSs $BS_{1-1}, BS_{1-2}, BS_{1-3}, BS_{1-4}$ represent the BSs at time duration t_1, t_2, t_3 and t_4 . Similarly for BSs at time duration t_5, t_6, t_7 , and t_8 . In the case of satellites, they are represented at time duration t_9, t_{10} and t_{11} as s_{1-9}, s_{1-10} and s_{1-11} . Given the context of the Starlink satellite network with numerous LEO satellites and overlapping coverage periods, the global positioning system (GPS)-based approach outlined in [138] and the simplified general perturbations (SGP4) model from [139] are employed to determine UAV positions and LEO satellite information.

Let us suppose that for a given UAV, to maintain a connection, a sequence

Table 4.1: List of Notations

List of notations	Definition
T	Total time period of simulation
$s_1, s_2 \dots s_q$	satellite instances
$BS_1, BS_2, \dots BS_m$	Base station instances
δ	Relaxation Period
χ_{gNB}	Signal Parameter for BS
$\chi_{satellite}$	Signal Parameter for satellite
M	Decision Matrix
G	Graph
V	Vertices
E	Edges
W	Weight matrix
$P_{i,m}$	received power
$\overline{P_{i,m}}$	Mean Power
Π_0	Free space pathloss
σ^2	Variance of shadowing
P_s	Signal power
P_N	Noise Power
$s(t)$	signal
$R_n(t)$	Correlation function for noise
$ E[\cdot] $	Expected value
Δ	Delta Dirac function
v_{ij}	normalized matrix
K	Ratio of Power between direct and scattered paths
u^2	power from direct paths
$2\beta^2$	power from scattered paths
Ω	Total power from direct and scattered paths
$A(d)$	Atmospheric fading
χ	Attenuation through clouds and rain
d	Propagation distance
h	UAV altitude
(o_x, o_y)	position right to below the satellite
G	channel model
c	speed of light
f_c	Frequency
φ	Probability distribution function

of HOs is required from a BS to a satellite for a time duration, T . As mentioned earlier, T is split into q equally sized time duration t_i , so $\sum_{i=1}^q t_i = T$ and $t_i = (\mu_i \pm \delta)$ where μ_i is the mean value of t_i and δ is the relaxation period.

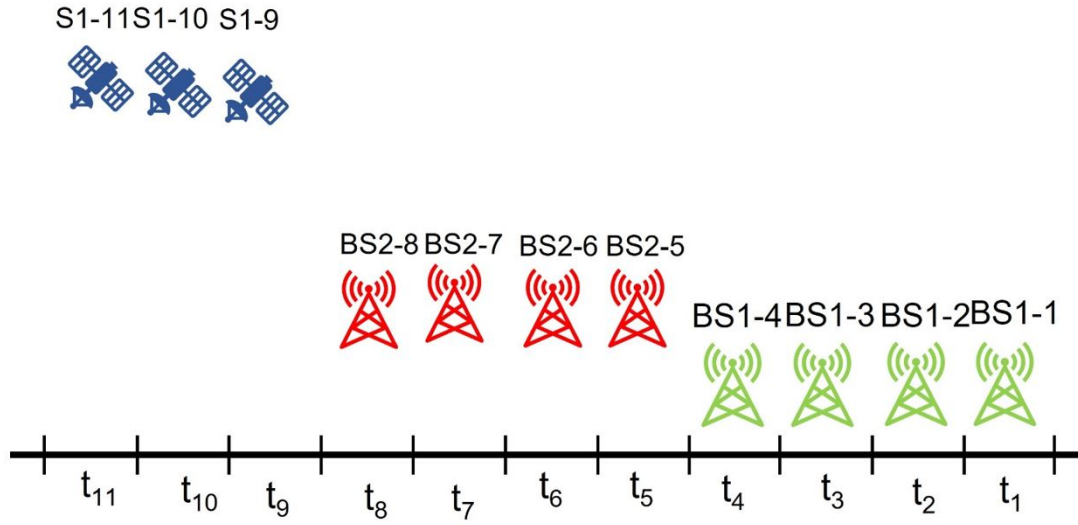


Figure 4.3: gNBs and satellites as time instances

By conceptualizing satellite instances as nodes within a graph and defining HO decision-making criteria as directed weighted edges, the sequence of HO occurrences and destinations within period T can be determined by identifying the most favorable path in the directed weighted graph. In Figure 4.4, the directed weighted time-based graph illustrates the relationships between LEO satellites and BSs. Within this directed graph, straight edges symbolize transitions between different instances of the same satellite or BS (indicating no HO), while diagonal edges represent HOs between instances of two distinct satellites or BSs with overlapping coverage periods. Each directed edge's weight in the graph is computed as a weighted summation of utility functions, collectively constituting the criteria for HO decision-making.

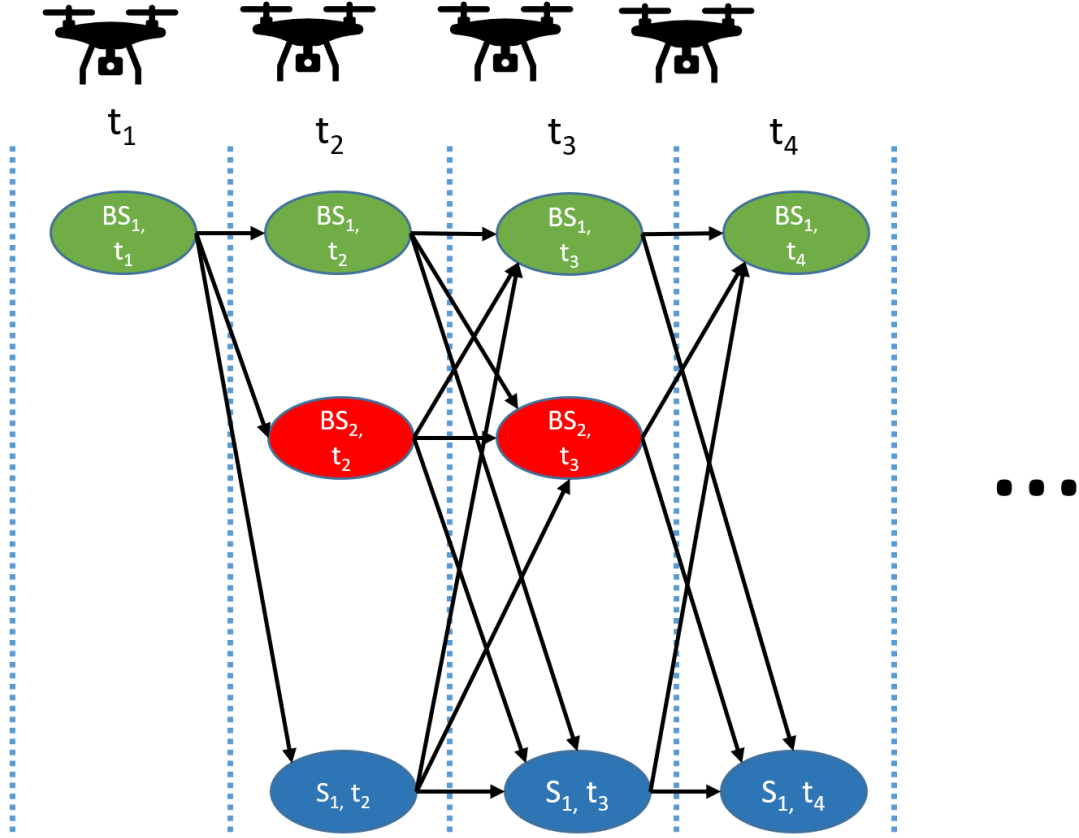


Figure 4.4: Representative graph for proposed model

Figure 4.5 provides a depiction of a sample graph alongside its real-world counterparts, which are symbolically represented by the graph's elements. Each vertex within the graph signifies an edge node that are either BSs or satellites. These vertices are, denoted by $V = b_m, s_q$.

The edges within the graph symbolize the times that take to HO from one BS to a satellite. Edge weights represent the time-weighted decision parameters RSS, SNR and elevation angle denoted by M , and the edges itself is represented by $E = x_{gNB}, x_{sat}$ where $x \in M$ encompassing all elements of M . The dotted lines represent the HO between the nodes. This is between either two BSs or between a BS and satellite. Within the scope of this chapter only HO between the last BS

and the satellite is considered. Nevertheless, our proposed strategy possesses the flexibility to accommodate both scenarios by the addition or removal of vertices within the graph.

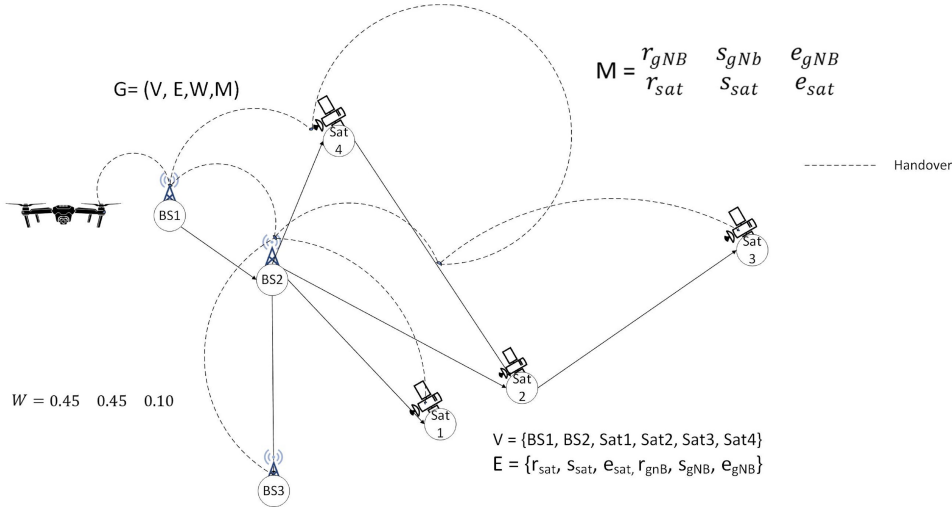


Figure 4.5: Graph representing the possible handovers

The favourable sequence of HOs in the graph is determined using the Dijkstra's Algorithm to find the shortest path between two selected nodes, where the shortest path is the path with the lowest summation of weight edges.

Thus, the graph is represented as a set of all nodes, edges, weights, and the performance matrix., shown as follows,

$$G = \{V, E, W, M\} \quad (4.1)$$

where, V is the set of all the nodes, i.e BSs and satellites.

$$V = \{b_1, b_2 \dots b_m, s_1, s_2 \dots s_q\} \quad (4.2)$$

E is the set of all decision parameters as defined in (4.11),

$$E = \{x_{gNB}, x_{sat}\} \quad (4.3)$$

where, $x \in M$.

4.3.3 Modelling the decision parameters

In this chapter, RSS is used as shown in (4.4), SNR as shown in (4.10) and elevation angle for the UAV to satellite are considered as decision making signal parameters.

The RSS is the measured received power at UAV i transmitted by BS j . $P_{i,j}$ is considered to be log-normal, thus the random variable $P_{i,j}$ is Gaussian [140]

$$P_{i,j}(\text{dBm}) \sim \mathcal{N}(\bar{P}_{i,j}(\text{dBm}), \sigma_{\text{dB}}^2) \quad (4.4)$$

where,

$$\bar{P}_{i,j}(\text{dBm}) = \Pi_0(\text{dB}) - 10n_p \log_{10}(d_{i,j}/\Delta_0) \quad (4.5)$$

Here, $\bar{P}_{i,j}(\text{dBm})$ is the mean power in dBm, σ_{dB}^2 is the variance of shadowing and Π_0 is calculated from the free space path loss formula [141].

The SNR is calculated as the ratio of signal power and the noise power. Therefore it is denoted as,

$$\text{SNR} = \frac{P_s}{P_N} \quad (4.6)$$

where, P_s is the signal power and P_N is the noise power.

If the signal is represented as $s(t)$, and it is deterministic then P_s is defined to be

$$P_s = \frac{1}{T} \int_0^T s^2(t) dt \quad (4.7)$$

where T is the observation duration interval. The T is equal to the period of $s(t)$ and the root mean square (rms) value equals the square root of its power.

The noise is represented as $N(t)$ and has a stochastic description. Thus, the correlation function for noise signal can be written as:

$$R_n(\tau) \equiv E[n(t)n(t + \tau)] \quad (4.8)$$

Here, $E[\cdot]$ denotes expected value. P_N is thus related to its correlation function as follows,

$$P_N = R_n(0) \quad (4.9)$$

In this chapter, however, a white noise system is assumed. This means the correlation function is equal to $N_0/2 \cdot \delta(t)$, where $\delta(t)$ is known as Dirac's delta function [142]. and $N_0/2$ is the spectral height of the white noise and corresponds to the value of noise power spectrum at all frequencies. The SNR changes to the following,

$$SNR = \frac{\int s^2(t) dt}{N_0/2} \quad (4.10)$$

Given below is the performance matrix M , which is a 3×2 matrix, represent-

ing the 3 different RF parameters and 2 different networks.

$$M = \begin{bmatrix} r_{gnb} & s_{gnb} & e_{gnb} \\ r_{sat} & s_{sat} & e_{sat} \end{bmatrix} \quad (4.11)$$

where, $r_{gnb}, s_{gnb}, e_{gnb}$ are the RSS, SNR and elevation angle probabilities associated with the gNB and $r_{sat}, s_{sat}, e_{sat}$ are the RSS, SNR and elevation angle probabilities associated with the satellite.

The decision making parameters are implemented as a weighted summation model (WSM). A WSM is a mathematical framework that combines multiple factors by assigning specific weights to each one. These weights reflect the relative importance or contribution of each factor to an overall outcome. The model computes the result by multiplying each factor by its corresponding weight and then summing these products. This approach allows for customised and flexible analyses, making it valuable in decision-making problems such as ours where different signal parameters must be considered with varying degrees of significance to make informed decisions.

For this, a weight matrix that assigns weighted probabilities to each parameters were defined. This is written as :

$$W = \begin{bmatrix} 0.45 & 0.45 & 0.10 \end{bmatrix} \quad (4.12)$$

The final step is to normalise the performance matrix and then add weights to the normalised matrix. If the normalised matrix is represented as v_{ij} , then,

$$v_{ij} = \frac{a_{ij}}{a_j^{\max}} \quad (4.13)$$

and,

$$v_{ij} = \frac{a_j^{\min}}{a_{ij}} \quad (4.14)$$

where, a is an element of (4.11).

From, above equations, the weighted summation model can be represented as follows,

$$v_i = \sum_j v_{ij} w_j \quad (4.15)$$

where, v_{ij} is the normalized performance matrix and w_j is an element

4.3.4 Dijkstra's Algorithm

Dijkstra's algorithm stands as a prevalent method for graph traversal and shortest path determination. It adeptly computes the shortest route from a designated source node to every other node within a weighted, directed graph. The algorithm's operation commences by initializing distances to all nodes from the source as infinite, except for the source node itself, which assumes a distance of zero. Subsequently, it maintains a collection of unvisited nodes and iteratively identifies the node with the smallest distance as the current focus. Upon selecting a current node, the algorithm explores its adjacent nodes and adjusts their distances accordingly. Should it uncover a shorter path to a neighbouring node, it promptly revises the corresponding distance value. This iterative process per-

sists until all nodes are visited or until the algorithm reaches the specified target node, if provided.

Algorithm 1 Dijkstra Algorithm for shortest path

Input: No. of nodes and weights of edges

Output: Shortest path to target node

- 1: Define the b_{m-1} as the source node in the built graph in the proposed method
- 2: Calculate the weight based cost to each node connected to b_{m-1} as:

$$v_i = \sum_j v_{ij} w_j$$

- 3: **if** $M = r_{gnb}, r_{sat}$ **or** s_{gnb}, s_{sat} **then**
 - 4: Mark node with highest v_i
 - 5: **else**
 - 6: Mark the node with lowest v_i
 - 7: **end if**
 - 8: **while** s_{m-n} is reached **do**
 - 9: Calculate v_i for each node connected to the marked node.
 - 10: **if** $M = r_{gnb}, r_{sat}$ **or** s_{gnb}, s_{sat} **then**
 - 11: Mark node with highest v_i
 - 12: **else**
 - 13: Mark the node with lowest v_i
 - 14: **end if**
 - 15: **end while**
 - 16: **end**
-

Dijkstra's algorithm uses a priority queue (min-heap) data structure to effi-

ciently select the node with the smallest distance. This data structure ensures that the algorithm runs in $O(E + V \log V)$ time complexity, where E is the number of edges and V is the number of vertices in the graph.

4.3.5 Proposed Method

As explained in the previous sections, a graph is built consisting of nodes that are BSs and satellites. The vertices are modelled as a WSM of the decision parameters.

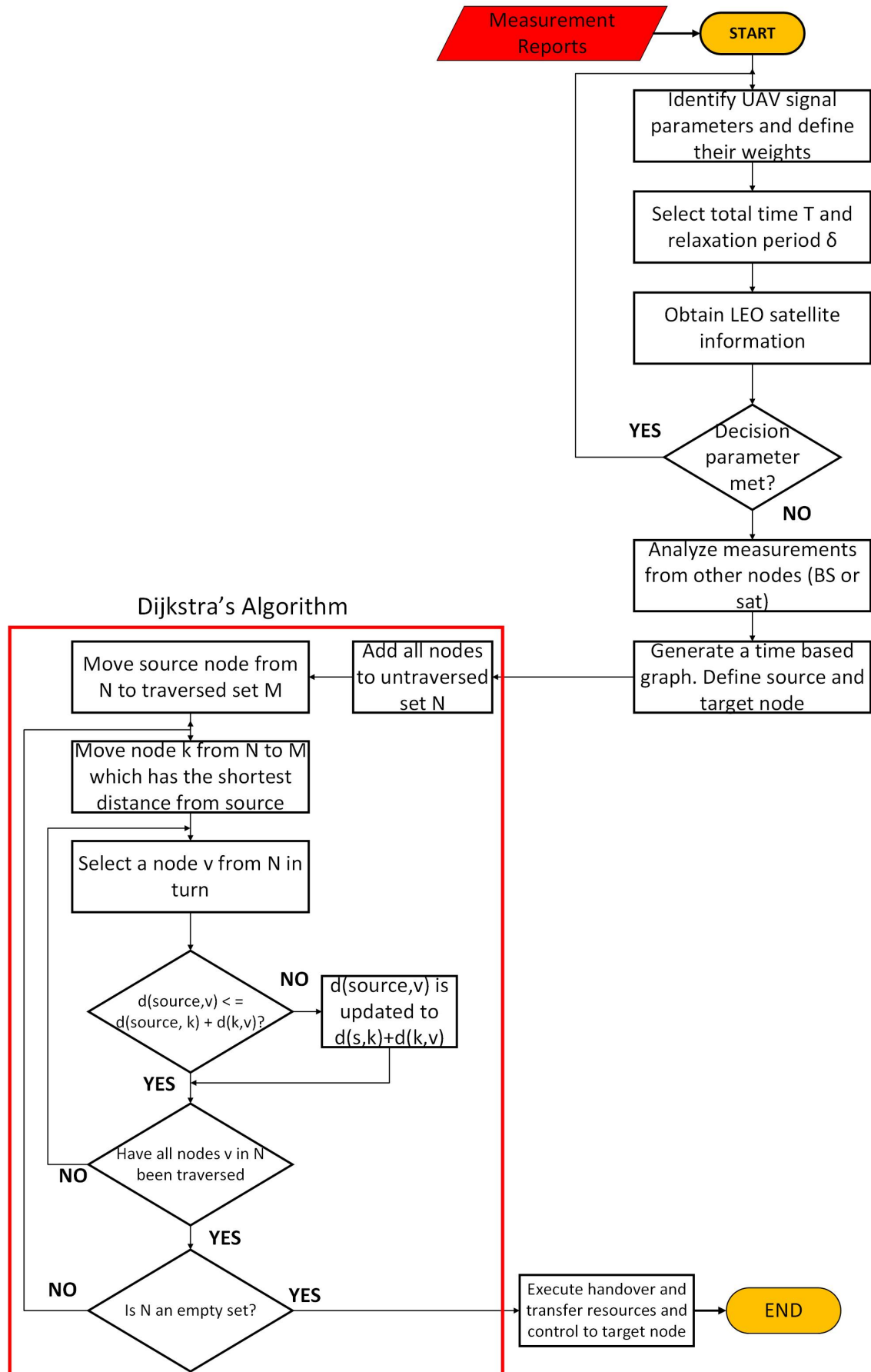


Figure 4.6: Graph-based algorithm flowchart

The diagram depicted in Figure 4.6 illustrates the flow of the proposed algorithm. The initial step involves acquiring measurement reports from both terrestrial BSs and satellites by the UAV, which serve as input to the algorithm. Decision parameters such as RSS, SNR, and elevation angle are identified, and their respective weights are analyzed. Subsequently, a relaxation period (δ) is chosen, which constitutes a fraction of the total time period. In graph theory, relaxation is a fundamental operation utilized to enhance estimates of the shortest path durations between vertices. In the context of a time-based graph, the shortest path effectively signifies the least time required to transfer control to the node with the optimal signal parameter, hence the term "relaxation period" is employed.

Following this, LEO satellite information is obtained, with the model utilizing the Starlink Phase 1 constellation data, sourced from the research conducted in [111]. Upon obtaining this information, a comparison is made to determine whether the decision parameter of the source node (terrestrial BS) is inferior to that of the destination node (satellite). If this condition is met, a HO is executed; otherwise, control remains with the source node, and the process iterates. This facilitates the creation of a time-based graph, wherein the BS is designated as the source and the satellite as the destination, and Dijkstra's algorithm is employed to ascertain the shortest duration for transferring control to the satellite. Further elaboration on the HO procedure is provided in Figure 4.7.

Dijkstra's algorithm maintains a set of BSs and satellites with tentative time instances from the source. Initially, all nodes, except the source gNB, have time weights set to infinity, while the source node's time weight is set to zero. The

algorithm then iteratively selects the node with the smallest time duration and explores its unvisited neighbors to potentially update their time durations. The subsequent steps briefly outline this process:

- Initialization: Set the time duration of the source node to 0 and all other nodes to infinity. Create a priority queue (or min-heap) to manage nodes with the smallest tentative time durations.
- Exploring Neighbors: While nodes remain in the priority queue, select the node with the smallest tentative time duration, marking it as visited. For each unvisited neighbor, calculate a tentative time duration by adding the duration from the source to the selected node and the edge weight between them. If this tentative duration is less than the current duration of the neighbor, update the neighbor's duration.
- Repetition: Continue this process until all nodes have been visited or the priority queue is empty.
- Shortest Paths: Upon termination of the algorithm, the shortest time durations from the source node to all other nodes are determined. These durations can be utilized to reconstruct the shortest paths themselves. and the edge weight between the selected node and the neighbor. If this tentative time periods is smaller than the current time periods of the neighbor, update the neighbor's time periods.

Algorithm 2 Graph Theory Algorithm for handover Sequence Selection

Input: UAV location, RSS, SNR and elevation angle

Output: Optimised handover sequence

- 1: Define signal performance parameters as decision parameters, RSS, SNR and elevation angle
- 2: Define performance matrix M
- 3: Define weight matrix W
- 4: Normalize the performance matrix M and obtain normalized performance matrix v_i
- 5: Select time duration T and relaxation time δ
- 6: Obtain LEO satellite information
- 7: Define Appropriate Channel Model

$$G = 20\log(c) - 20\log(4\pi df) + 10\log(A(d)) + \chi$$

- 8: Add a virtual beginning node b_{m-1} directed to the 1st node (in this case a BS instance)
 - 9: Add a virtual end node s_{m-n} in this case an instance of satellite
 - 10: Solve the graph from first to last node using the Dijkstra's Algorithm to obtain optimal handover sequence
-

Algorithm 2 explains the proposed algorithm in detail. As discussed, previously, the input to the algorithm are the signal parameters and the UAV location. Firstly, the RSS, SNR and elevation angles are defined as the decision parameters. A performance matrix M is defined as the first step to implement the weight summation model. The definition of M is given in (4.11). The weight matrix is

defined as in (4.12). Next, (4.11) is normalised to obtain the normalised performance matrix v_i . The time period for the simulation is set as 1800 s and relaxation period δ is set as 300 s.

The next step is to obtain the satellite information for the LEO Starlink Phase 1 constellation. The channel model is defined in the next step, this detailed in further sections. Finally Dijkstra's algorithm to perform the HO from the source to the target is implemented.

4.3.6 Handover Stages

Achieving seamless HO involves three primary phases: preparation, execution, and completion. These phases encompass multiple steps facilitating the transfer of UAV association from the BS to a satellite, as depicted in Figure \ref{signal}, and elaborated below.

Five key components facilitate seamless HO between the future gNB and satellite in future networks: the UAV, source future gNB, target satellite, AMF, and User Plane Function (UPF). The roles of AMF and UPF are delineated in [77].

1. Preparation: The initial phase of HO entails preparing the involved elements for the process. The AMF disseminates all mobility-related information to each component, while the UAV receives measurement reports from the source node. Parameters like RSS, SNR, and elevation angles are assessed for their significance and prioritized to make the HO decision. Subsequently, upon making the HO decision, a request is dispatched to transfer control from the future gNB to the satellite, mediated by the AMF. The

AMF acknowledges the request and issues an admission control command, allowing the UAV to connect to the satellite.

2. Execution: In the second phase, following preparation, the actual HO process is executed. Initially, all Radio Resource Control (RRC) connections are reconfigured, particularly the "mobilityControlInformation," responsible for conveying updated information. The UAV disengages from the old cell and synchronizes with the satellite. Any buffered or in-transit packets are rerouted to the satellite. Additionally, the future gNB sends the Sequence Number (SN) status transfer to the AMF, ensuring the transfer of the packet data convergence protocol from the source to the target \cite{TSGR2013}. The AMF forwards the SN status transfer to the satellite. Once RRC reconfiguration is finalized, the UAV synchronizes with the satellite, culminating in the final step of execution: the UAV requests the patch switch from the gNB to the satellite.
3. Completion: In this phase, the final procedures are conducted, marking the completion of the HO. Initially, upon receiving the path switch request, the UPF updates its plane to associate with the satellite. Subsequently, the path switch acknowledgment is transmitted to both the satellite and the UAV. Finally, the context is released from the gNB, signifying the release of network resources.

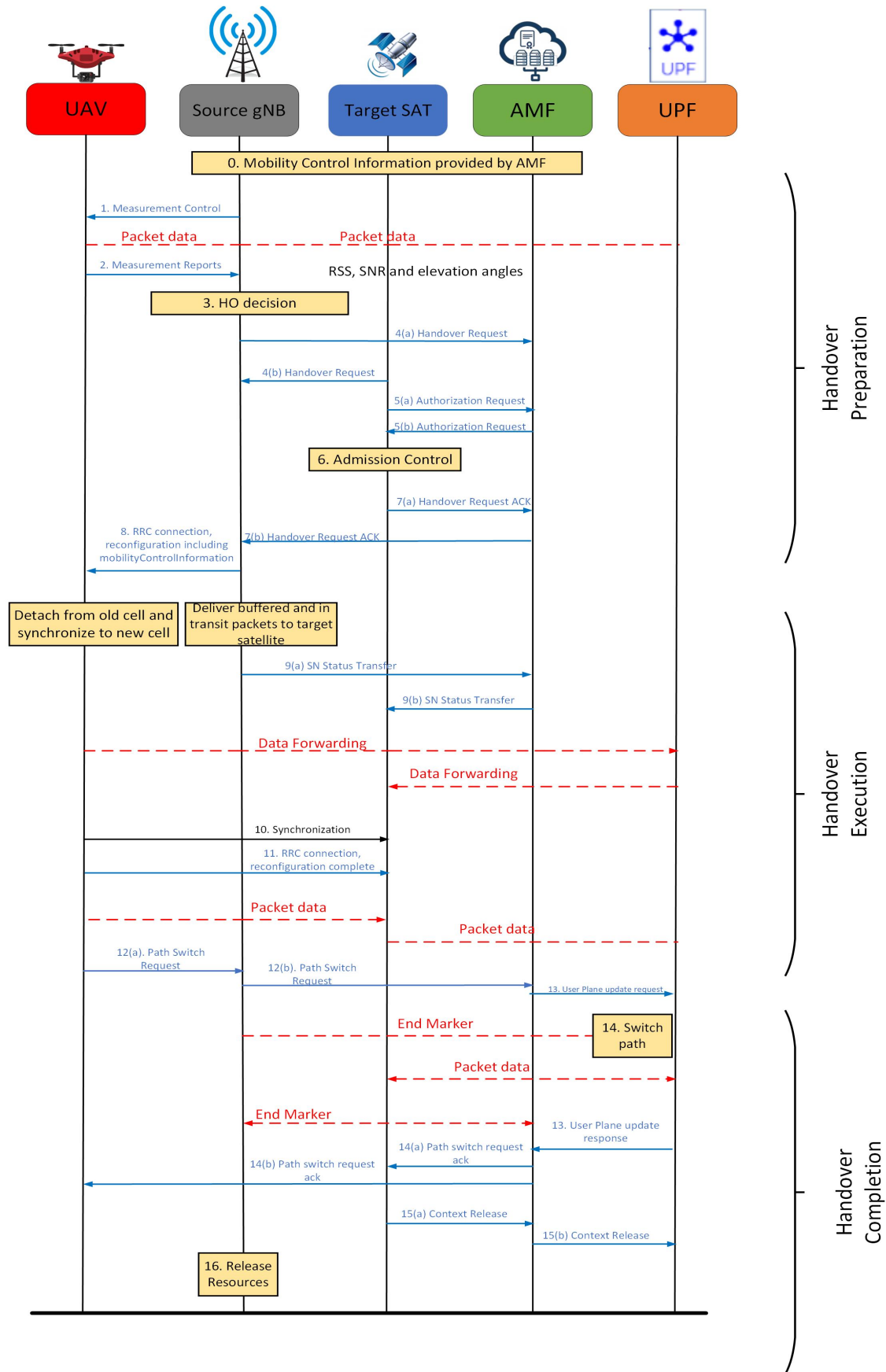


Figure 4.7: Satellite connectivity in rural areas

4.4 Simulation Set-up and Results

4.4.1 System Model

A three layer system, as shown in Figure 4.2 is considered. The ground segment consists of a 5G gNB, to which the UAV is initially associated with. The gNB and by extension the UAV associated with it is part of the cellular 5G network. The sub-6GHz frequency is used for the gNB, at maximum transmitting power of 5G. The satellite in-view periods lies between the 180 s and 750 s at an elevation angle of 10°. All the parameters are listed in Table 4.2 [143].

Table 4.2: 5G Parameters

Parameters	Value
Maximum gNB Power	46 dBm
Antenna Gain	8 dBi
Cellular geometry	Hexagonal
Cell Radius	150m
Frequency	6 GHz
Modulation type	QPSK
Satellite in-view periods (Max, Min)	(750 s @ 10° (180 s @ 10°

The air segment consists of the UAV, which is first associated with the gNB and then to the satellite. The proposed algorithm is deployed on-board of this UAV. It flies at an height of 100 m at an average speed of 20 m/s. It uses an omni directional antenna with a transmitting power of 23 dBm. These parameters are summarized in Table 4.3

Table 4.3: UAV parameters

Parameter	Value
UAV altitude	100 m
UAV transmitting power	23 dBm
Average UAV speed	20 m/s
Probability of P_{LOS}	0.8

Finally, the space segment consists of the LEO satellite constellation. In this model, the Starlink Phase 1 satellite constellation at 550 km orbit is considered. The UAV sees at a 10 levation angle. These parameters are shown in Table 4.4 [111].

Table 4.4: Satellite Parameters

Parameter	Value
Elevation angle	10°
Satellite Orbit	550 km
Orbit Inclination	53°
Orbit eccentricity	0 (circular orbit)
Frame of reference	Earth Centered Inertial (ECI)
Transmitting Power	30 dBm

4.4.2 Network Model

In this model, a scenario of a quasi-stationary fixed cell which does not consist BSs is considered. The UAV moving with a velocity of v moving out of a cellular

network with at least one gNB represented by $B = BS_1, BS_2, \dots, BS_n$ into the quasi-stationary cell as shown in Figure 4.8 is assumed.

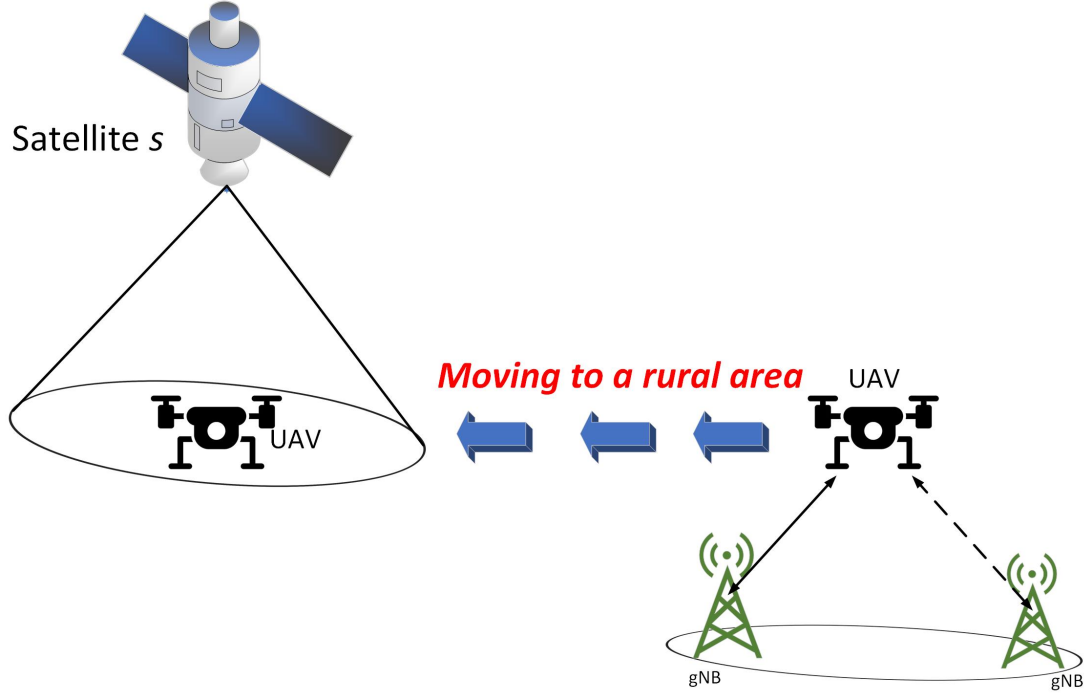


Figure 4.8: Handover Scenario

This area is covered covered by satellite represented by $S = s_1, s_2, \dots, s_m$. The satellite is seen by the UAV at an elevation angle of α as shown in Figure 4.9. This complete network is modelled as a graph $G = (n, E)$, where n represents the nodes, i.e. either satellite or gNB and E represents the edges that are the weighted summed functions explained earlier. Here, s_{m-q} is the satellite instance m at time instant t and f is the signal parameter that triggers HO.

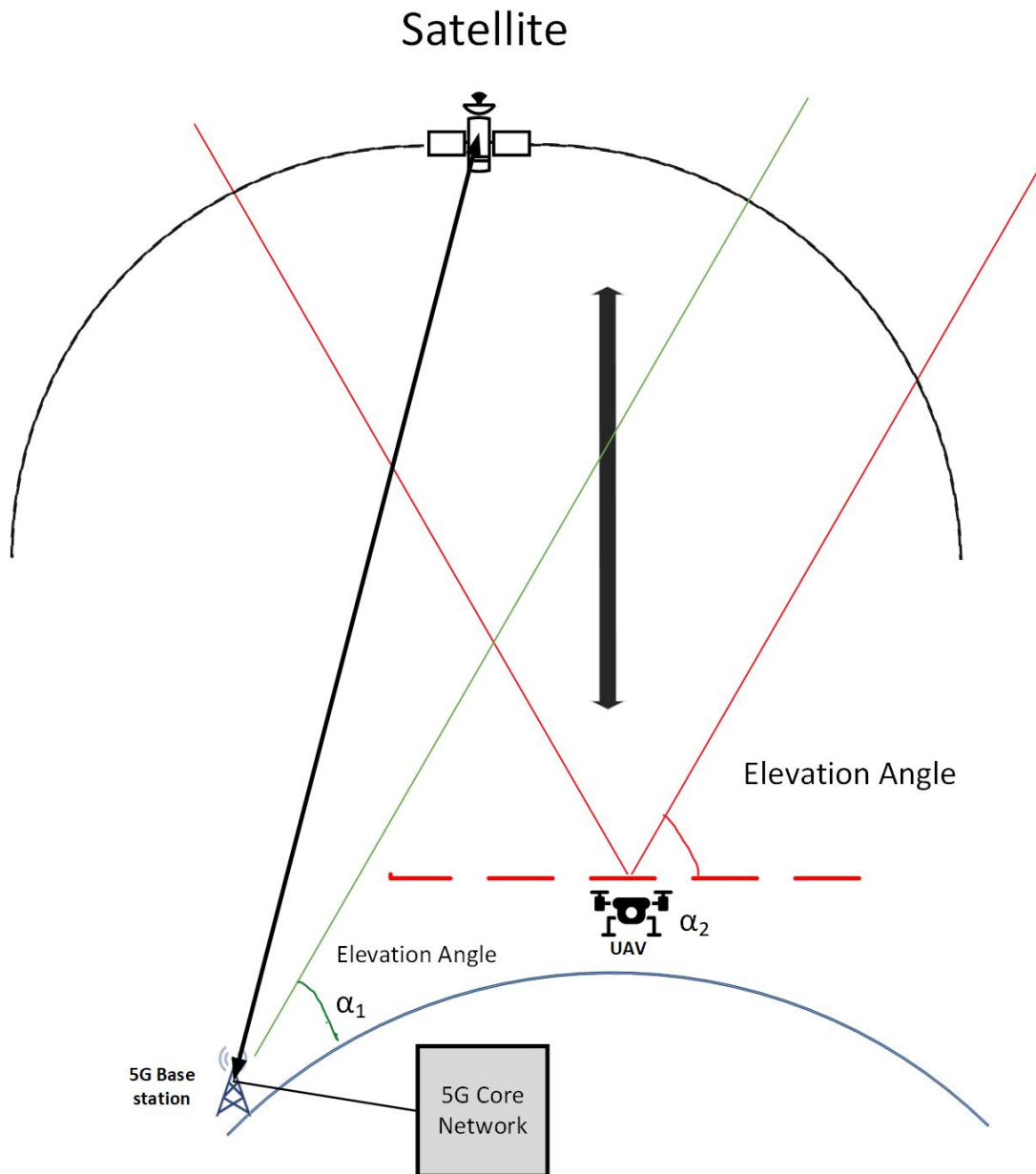


Figure 4.9: Network Model

4.4.3 Channel Model

The channel model takes into account Rician small-scale fading and atmospheric fading. The Rician fading is generally defined by two parameters. The first one, is the ratio between the power in the direct path and the power in the scattered paths,

$$K = \frac{u^2}{2\beta^2} \quad (4.16)$$

The second one, is the Ω is the total power from both paths and functions as a scaling factor to the distribution,

$$\Omega = u^2 + 2\beta^2 \quad (4.17)$$

The amplitude of the signal therefore is Rice distributed with these parameters,

$$u^2 = \frac{K}{1+K} \Omega \quad (4.18)$$

$$\beta^2 = \frac{\Omega}{2(1+K)} \quad (4.19)$$

The resulting probability distribution function (φ) is:

$$\varphi = \frac{2(K+1)\chi}{\Omega} \exp\left(-K - \frac{(K+1)\chi^2}{\Omega}\right) I_0\left(2\sqrt{\frac{K(K+1)}{\Omega}}\chi\right) \quad (4.20)$$

The atmospheric fading $A(d)$ is given by

$$A(d) = 10^{\frac{3d\chi}{10h}} \quad (4.21)$$

where, χ is the attenuation through the clouds and rain in dB/km, h is the UAV altitude and d is the propagation distance between satellite and the UAV, calculated by,

$$d = \sqrt{h^2 + (x - o_x)^2 + y - o_y^2} \quad (4.22)$$

where (o_x, o_y) is the position right below the satellite.

Combining 4.21 and 4.22, the channel model expression is written as,

$$G = \frac{c}{4\pi d f_c}^2 A(d) \varphi \quad (4.23)$$

where,

c : Speed of light (3×10^8 m/s)

d : transmission distance (as calculated in (4.22))

f_c : Operating frequency

$A(d)$: Atmospheric fading (as calculated in (4.21)

φ : Rician small scale fading (as calculated in (4.20)

4.4.4 Results

In the sections above, the use of the system, channel, and network model for conducting simulations are detailed. These simulations have a duration of 1800 seconds (30 minutes) with a relaxation period of 240 seconds.

4.4.4.1 Decision Parameters

This model employs three decision parameters: RSS , SNR, and elevation angle. The results of these simulations are analyzed by plotting these parameters in conjunction with QoS parameters.

- **RSS:** RSS is a measure of the received radio signal's power by a UAV, reflecting signal strength or intensity. Values typically range from -70 dB to -90 dB within the sub-6 GHz spectrum. Variations in RSS over time indicate potential HOs.
- **SNR:** SNR compares the strength of the desired signal to unwanted noise, determining signal quality and reliability. Higher SNR values indicate better performance, while lower SNR values can lead to connectivity issues.

4.4.4.2 QoS Parameters

Two QoS parameters are analyzed to assess the proposed HO algorithm's impact on the communication link:

- **Throughput:** This measures the data transfer rate over a wireless network, a critical factor for network performance.
- **Latency:** Latency measures the delay in data transmission, with lower latency being desirable for faster data transfer.

Additionally, the number of ping-pong HOs is measured. Ping-pong HOs refer to situations where a UAV repeatedly switches its connection between two or more BSs.

The performance of decision parameters is depicted in Figure 4.10, which shows RSS plotted against time for three methods: the proposed GM, hysteresis method, and threshold method.

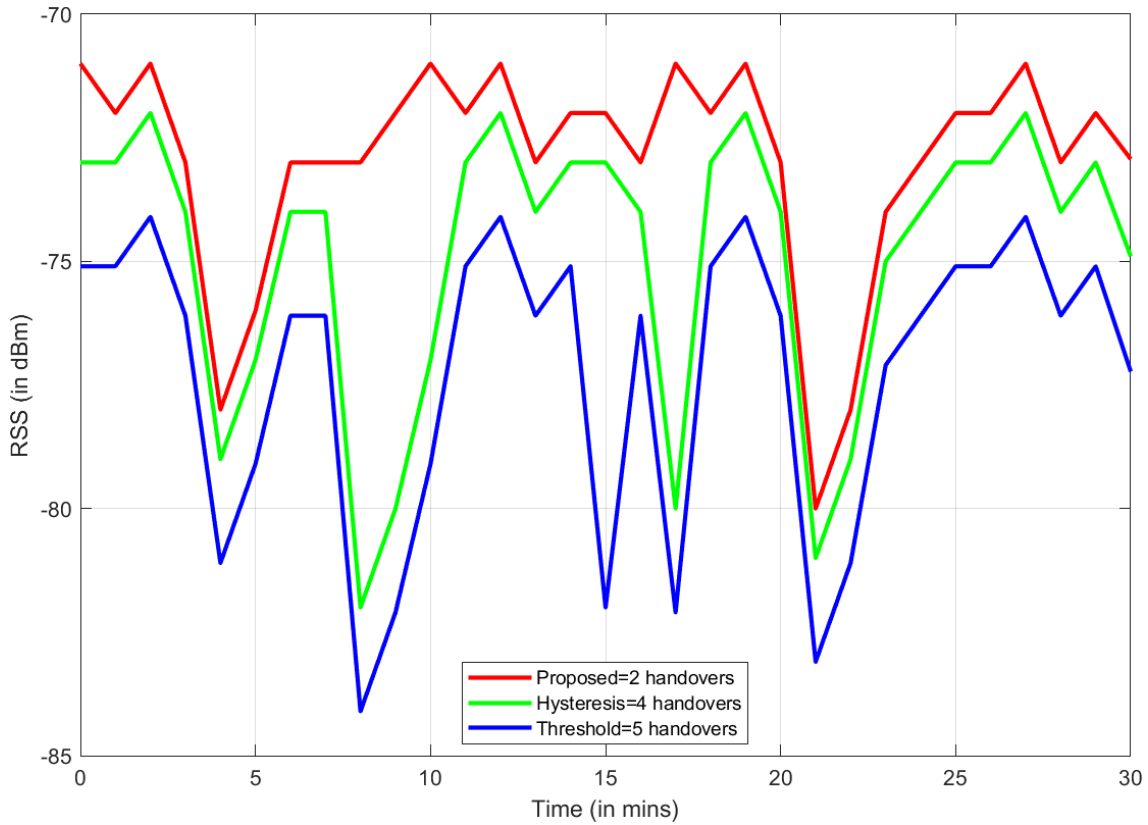


Figure 4.10: RSS vs Time

The GM shows an average RSS of -72.933 dB with only 2 HOs, outperforming the other methods. The hysteresis method has an average RSS of -74.9 dB with 4 HOs, while the threshold method performs the poorest, with over 5 HOs and an average RSS of -77.23 dB.

SNR performance is evident in Figure 4.11, where the GM excels with the fewest HOs. The hysteresis method and the threshold method under-perform in both SNR and frequency of HOs. The higher number of HOs is partly due to ping-pong HOs, as indicated in the plot.

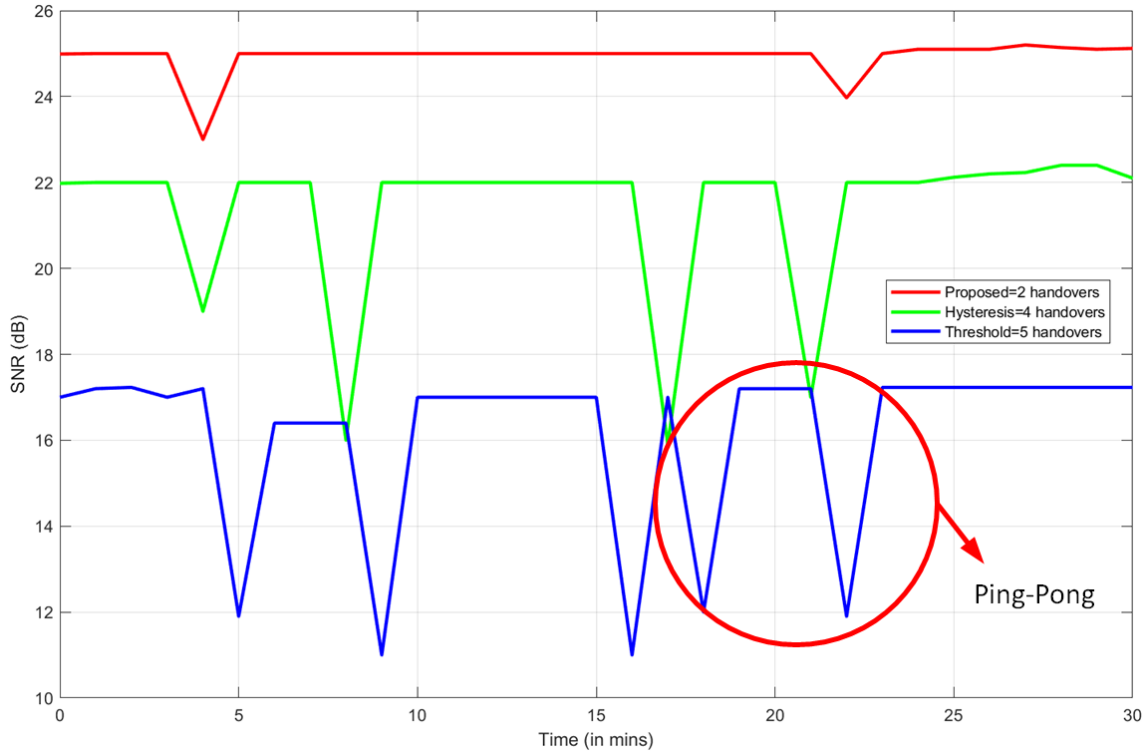


Figure 4.11: SNR vs time

QoS parameter analysis is presented in Figure 4.12, where the implementation of the GM improves throughput values compared to the other methods. This is attributed to efficient HOs' positive impact on communication system performance. The hysteresis and threshold methods are affected by their drawbacks and the occurrence of ping-pong HOs.

Figure 4.13 illustrates latency, showing that the implementation of the GM reduces latency compared to the other methods. Efficient HOs play a crucial role in enhancing communication system performance, while the hysteresis and

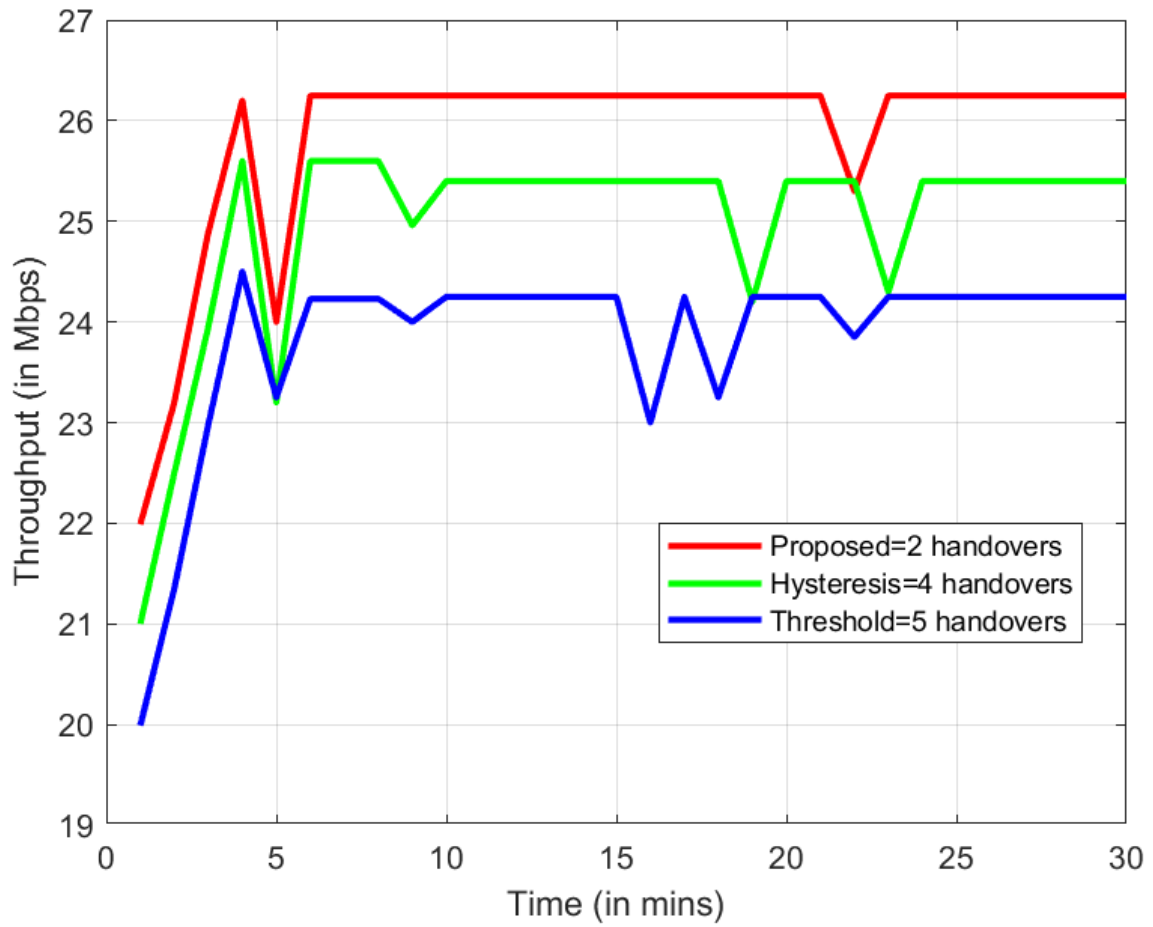


Figure 4.12: Throughput vs Time

threshold methods suffer from their drawbacks and the occurrence of ping-pong HOs.

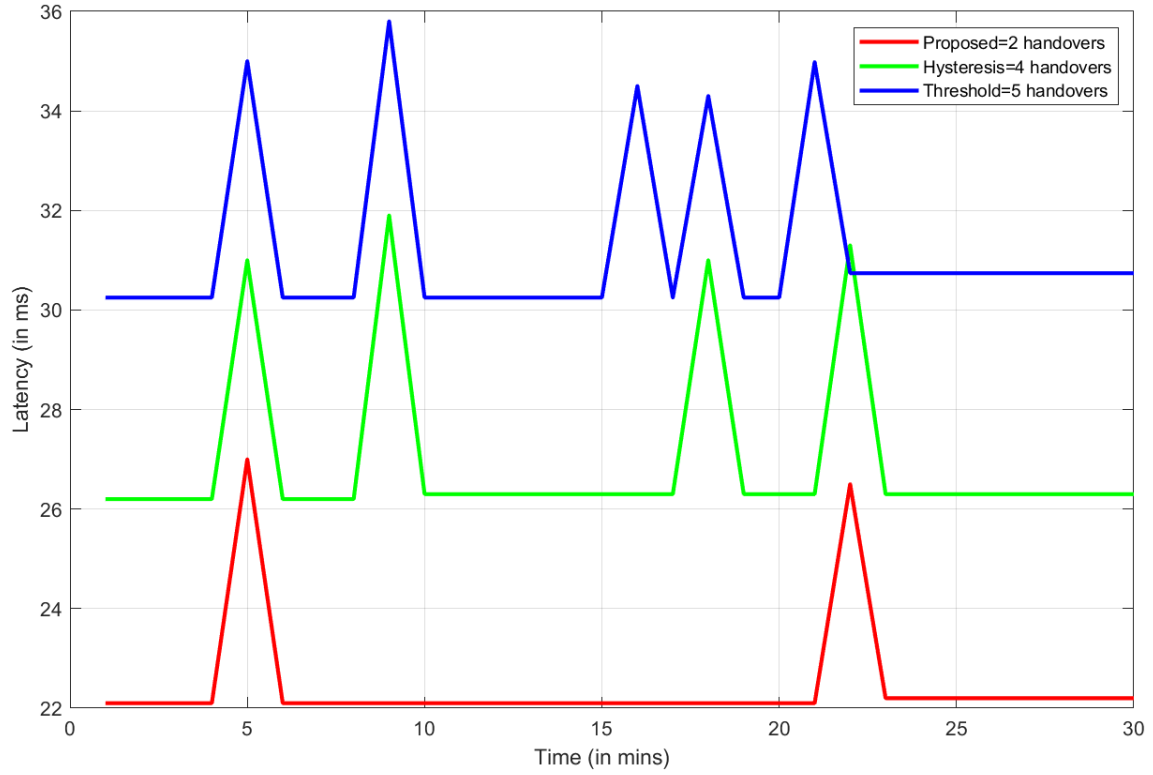


Figure 4.13: Latency vs Time

To visualize the HO process better, network status plots are provided for each of the three methods. Figure 4.14 displays the UAV's network status, indicating connections to the satellite or the 5G network at different time instances. Similar to the decision parameter plots, HOs occur at 300 s and 1320 s.

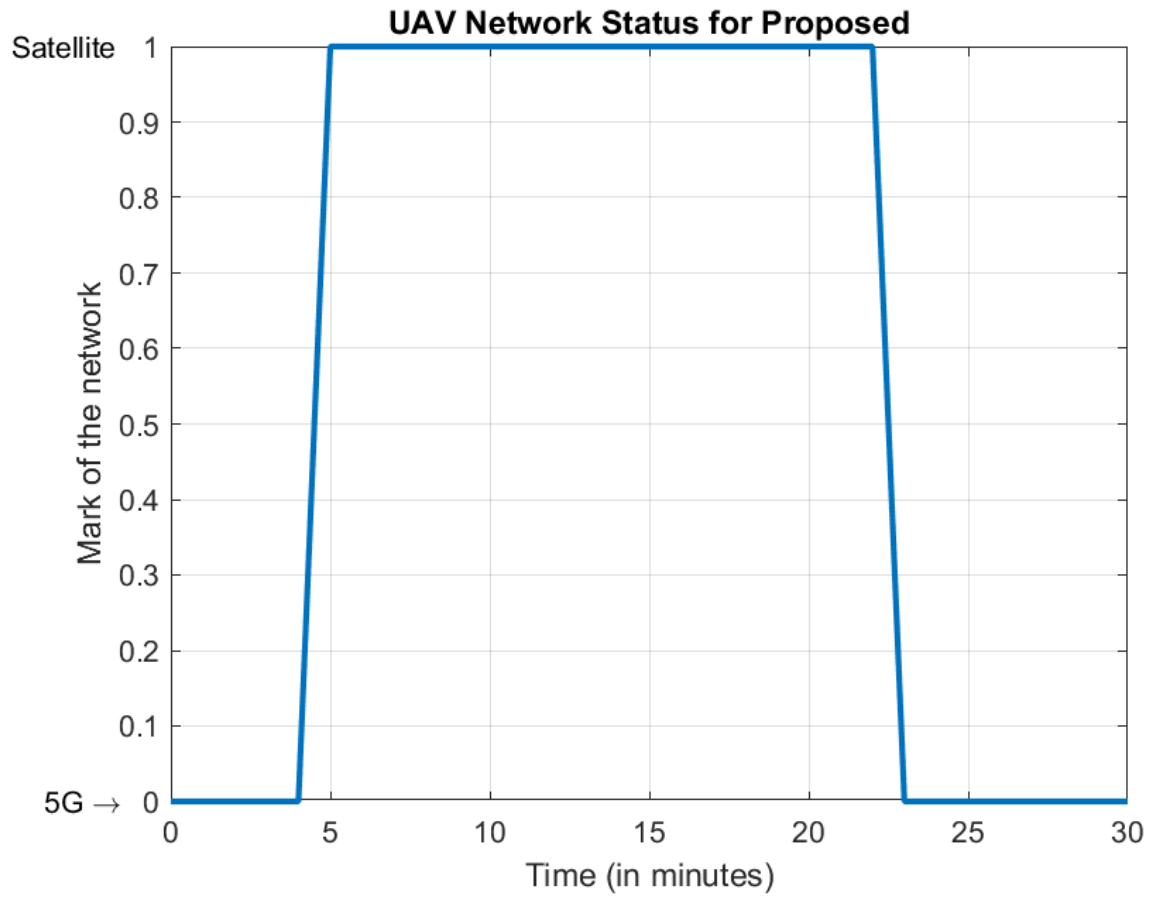


Figure 4.14: Network status for proposed GM

In Figure 4.15, the network status for the hysteresis method is shown, revealing 4 HOs at 300 s, 480 s, 1020 s, and 1320 s.

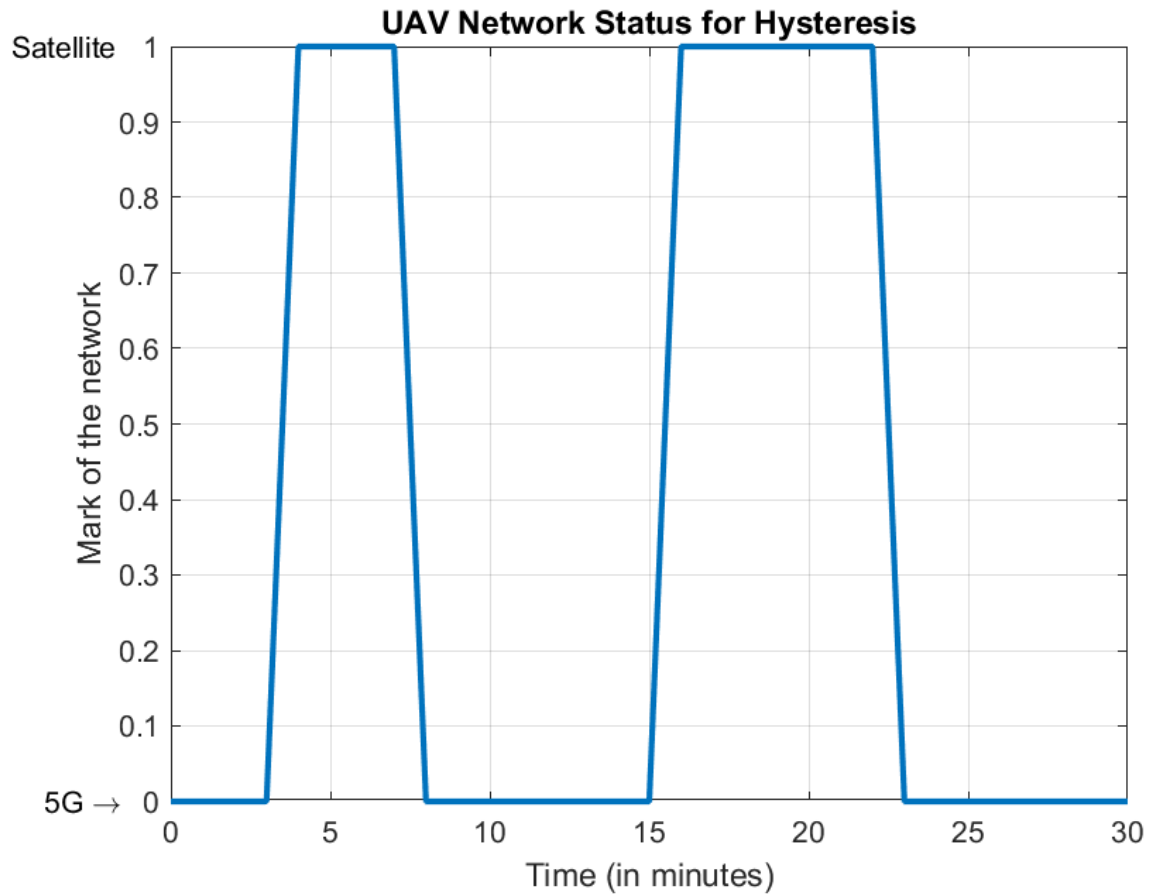


Figure 4.15: Network status for Hysteresis method

Lastly, Figure 4.16 depicts the network status for the UAV using the threshold method, with 5 HOs and one ping-pong HO, occurring at 1020 s and 1260 s.

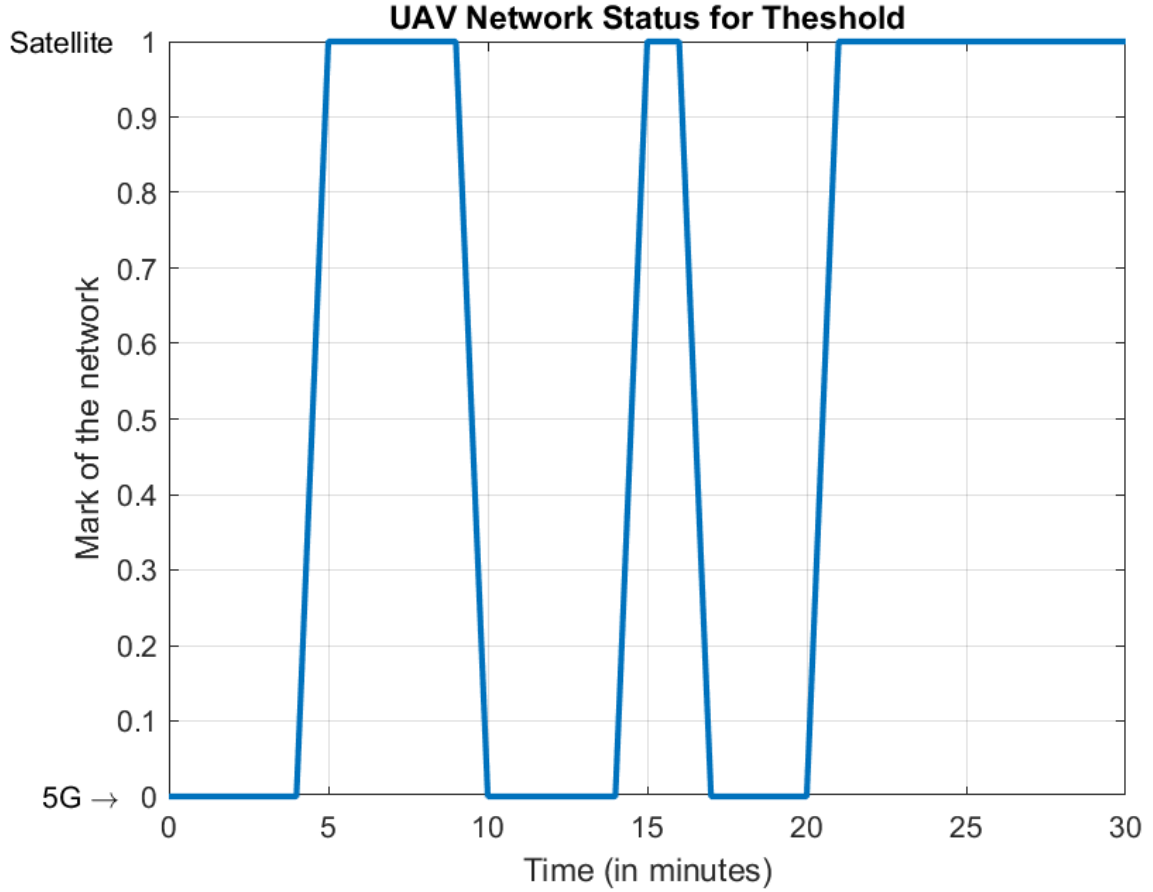


Figure 4.16: Network status for threshold method

These results are obtained with a relaxation period set to 240 s. However, altering this value impacts link performance.

When the relaxation period is set to $\delta = 300$ s, throughput improves by 7.94%, averaging 27.98 Mbps, but an additional HO occurs at 1560 s as shown in Figure 4.17. This is due to Algorithm 1 exploring more nodes in the graph, potentially finding better solutions but also leading to more HOs.

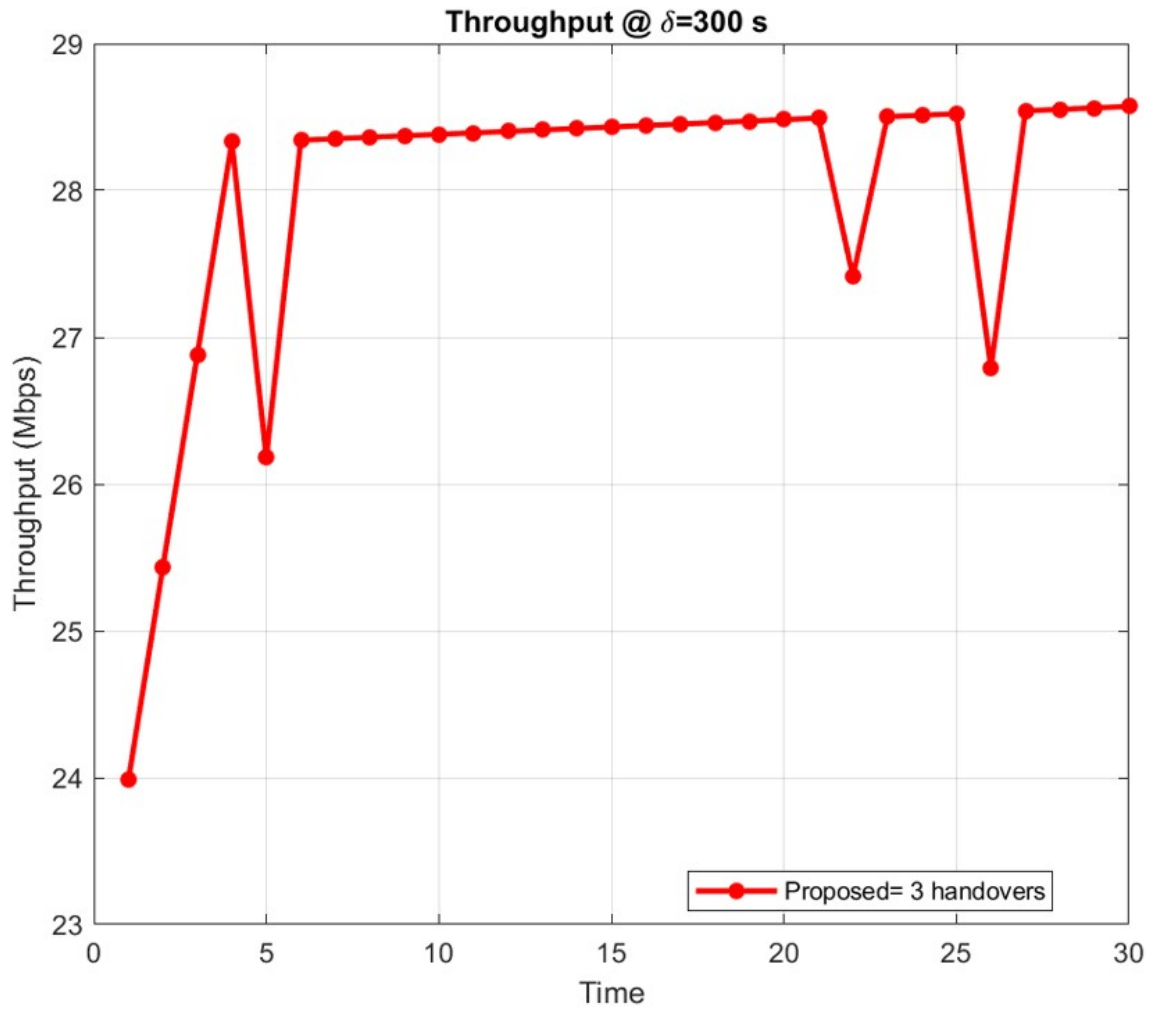
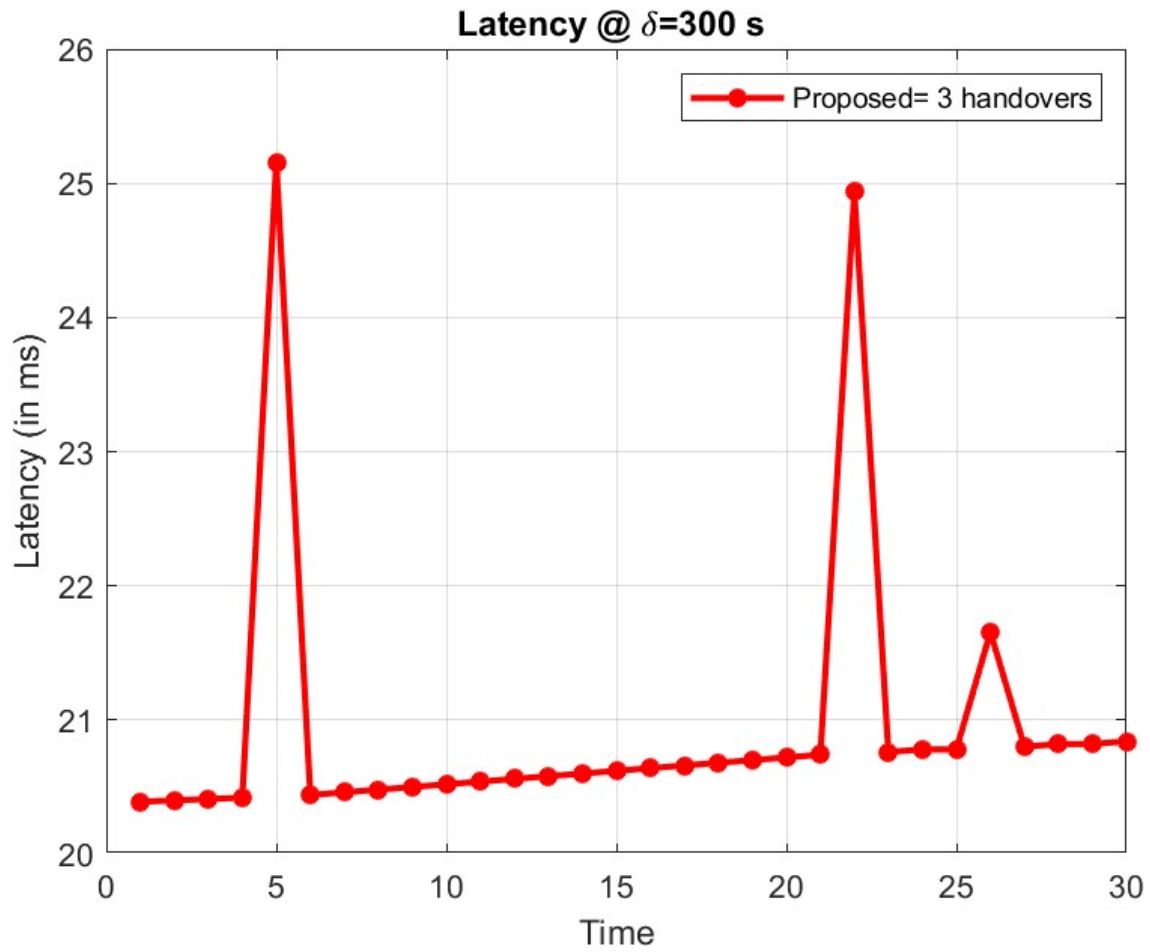
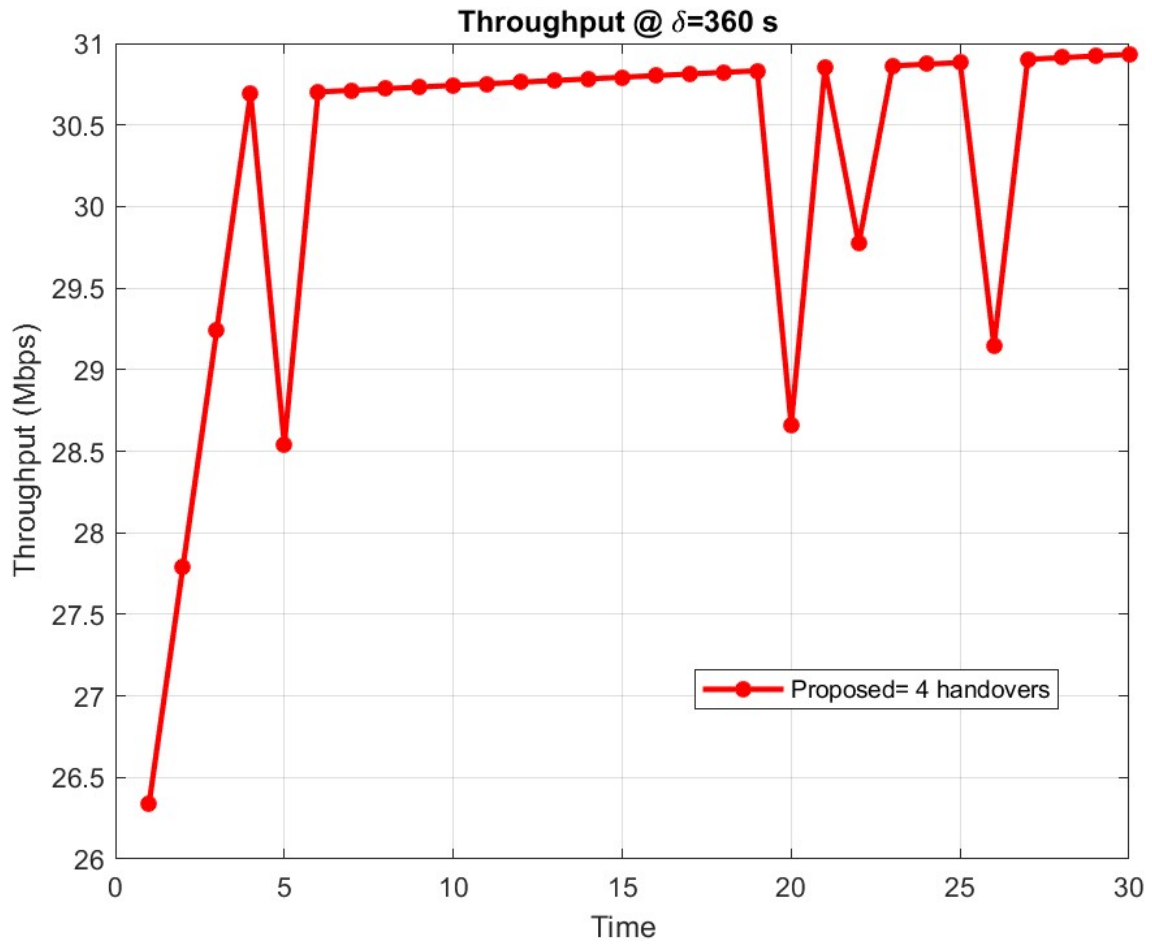
Figure 4.17: Throughput vs time at $\delta = 300$ s

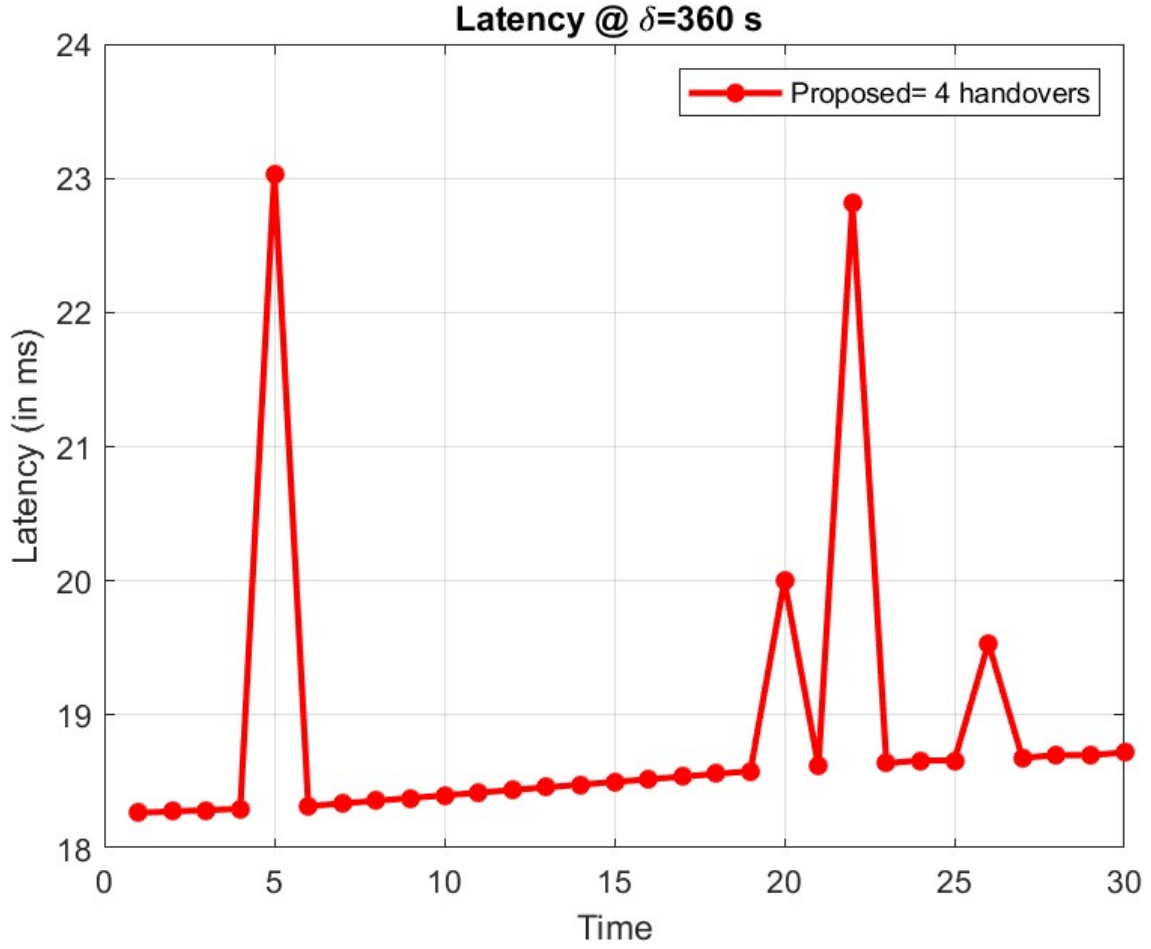
Figure 4.18 illustrates the latency plot for $\delta = 300$, reflecting nearly an 8% improvement in values. However, an additional HO is observed, as previously explained.

Figure 4.18: Latency vs time at $\delta = 300$ s

Increasing the relaxation period to $\delta = 360$ s, as shown in Figure 4.19, leads to a notable throughput enhancement, with a 16.74% increase compared to $\delta = 240$ s and an 8.14% increase compared to $\delta = 300$ s. HOs occur at 300 s, 1320 s, and 1560 s, similar to the $\delta = 300$ s scenario, with an additional HO at 1200 s.

Figure 4.19: Throughput vs time at $\delta = 360$ s

In Figure 4.20, the latency plot for $\delta = 360$ reflects an approximate 9.88% improvement in values, similarly accompanied by an additional HO, as previously discussed.

Figure 4.20: Latency vs time at $\delta = 360$ s

Hence, the choice of relaxation period should consider the UAV's application requirements, as it affects link performance and the frequency of HOs.

To analyze the performance of the algorithms, the number of ping-pongs is measured. In Figure 4.21, it is seen that proposed GM has no ping-pongs while the the threshold method has maximum ping pong HOs.

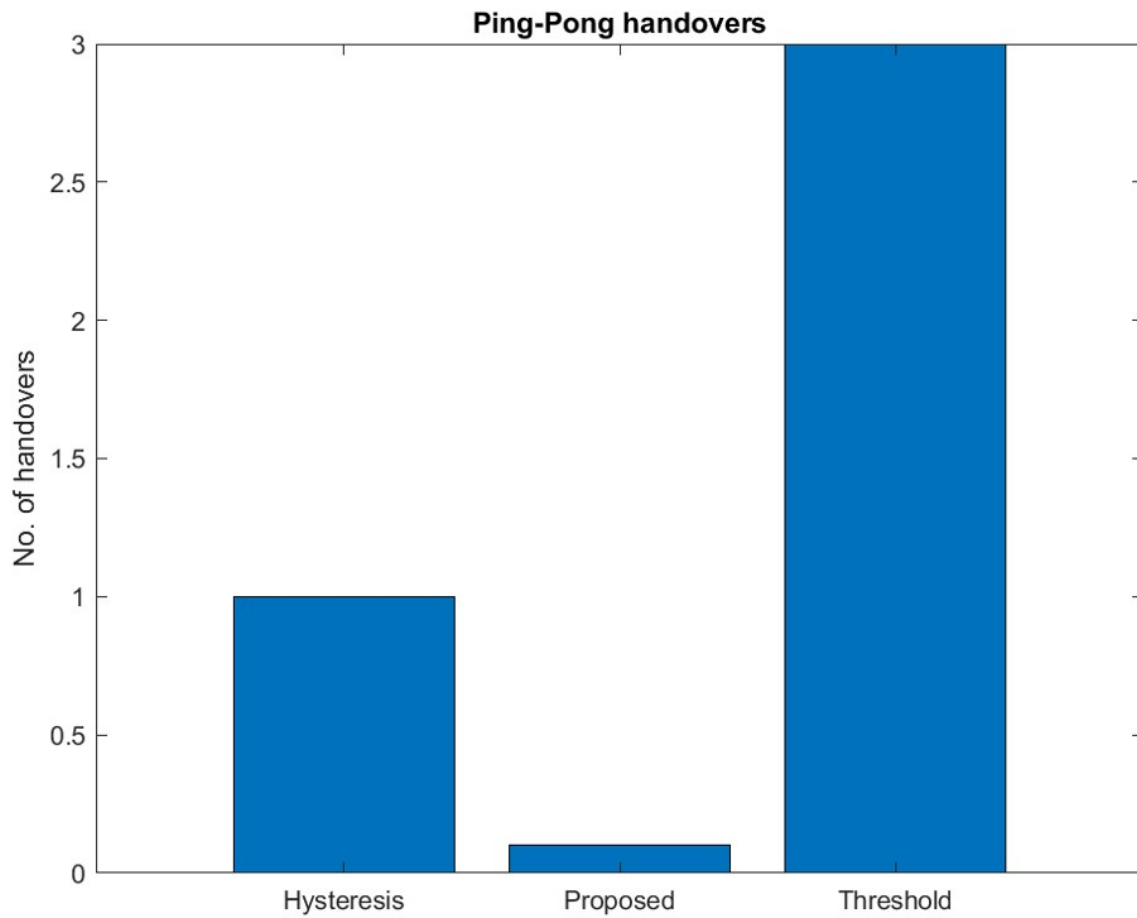


Figure 4.21: No. of Ping-Pongs

Finally, the probability of which decision parameters is chosen by the WSM model is presented in Figure 4.22

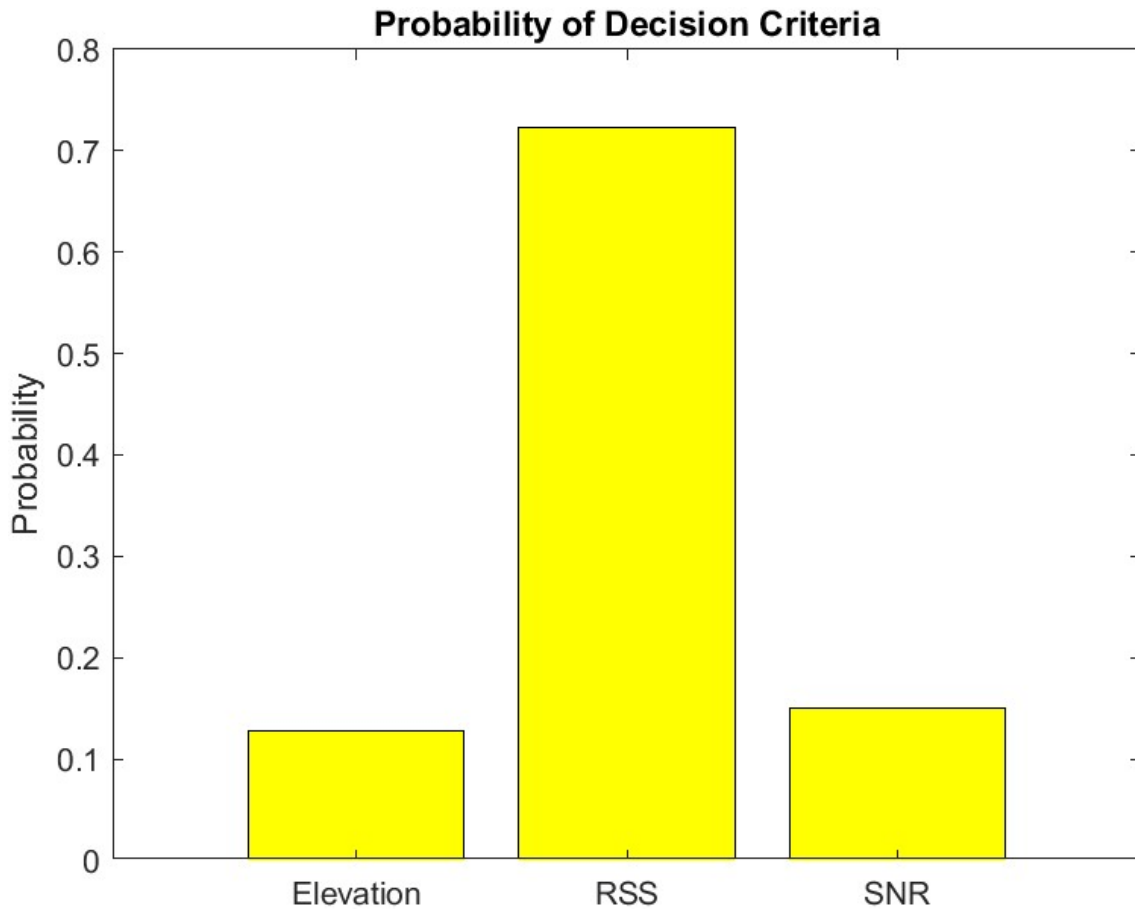


Figure 4.22: Probability of decision parameters

RSS is given the highest weight in the simulation, therefore it is selected with the highest probability as a decision parameter.

As evident from the aforementioned findings, the devised approach demonstrates superior performance compared to certain prevailing industry benchmarks. Nevertheless, the graph theory algorithm proposed herein is not without its constraints. Notably, in the context of exceptionally extensive networks, the application of the graph method necessitates augmented storage capacities, posing a potential challenge in deployment scenarios involving UAVs. It is anticipated that forthcoming advancements in storage hardware will offer a viable resolution to this issue. Additionally, this chapter does not delve into the satellite visibility

problem, working under the assumption that the UAV sees the satellite all the time. However, LEO satellite have a short visibility times ranging from 240 s to 1200 s necessitating satellite to satellite HO, (not part of the scenario considered for this chapter) which would be a potential next step from this to fully integrate the space based satellite network including GEO satellites

4.5 Chapter Summary

The integration of UAVs into future networks will open up new possibilities for applications ranging from surveillance to communication infrastructure maintenance, precision agriculture, and surveying. However, ensuring uninterrupted connectivity for UAVs operating in remote or dynamic environments remains a significant challenge. This chapter presents a novel approach to achieving seamless HO for UAVs when transitioning between terrestrial and satellite communication networks. The proposed method in this chapter, leverages graph theory and develop a decision-making algorithm to optimise HO decisions, minimizing latency, improving performance, and reducing service disruption. Graph-theory based handover decision approaches, leverage mathematical models to minimize service disruption during the transition between communication links in mobile networks. In this approach, the network is represented as a graph, where nodes represent different communication links or access points, and edges represent possible handover paths between them. Each node can have attributes such as signal strength, bandwidth availability, latency, and quality of service (QoS). Graph-theory algorithms evaluate potential handover paths based on cri-

teria such as RSS, SNR and elevation angle. These algorithms analyse the graph structure to determine the optimal path for handover that minimizes service disruption and maintains or improves service quality. Dijkstra's algorithm is used for finding the shortest path which optimizes path selection. The graph-theory based approach allows for real-time decision-making during handover events. As a mobile device or UAV moves through the network, the algorithm continuously evaluates the network conditions and dynamically adjusts handover decisions to ensure seamless connectivity. It is also scalable to large and complex networks, ensuring that the handover decision-making process remains efficient even in networks with numerous nodes and dynamic traffic patterns. It establishes a comprehensive graph model that represents the dynamic topology of available network nodes, including terrestrial BSs and LEO satellites, which adapts in real-time to changes in UAV position and network conditions. The approach incorporates a decision-making algorithm that takes into account various factors, such as RSS, SNR, and elevation angle, to determine the optimal time and location for a HO between terrestrial BSs and satellite links. This ensures a seamless transition between communication links, minimizing service disruption. The performance of this method is evaluated through extensive simulations and comparison with existing solutions demonstrating significant improvements in RSS, SNR, throughput, latency, ping-pongs and enhanced overall UAV connectivity. The proposed GM based seamless HO solution represents a crucial advancement in enabling reliable and uninterrupted communication for UAVs operating in remote and challenging environments. By managing HOs between terrestrial and

satellite networks, this research contributes to the realisation of the full potential of UAVs in emerging applications, thereby advancing the state-of-the-art in UAV technology.

Chapter 5

Mobility Interference in 5G-Connected UAVs

Mobility of UAVs presents challenges in developing effective HO schemes, which were addressed and solutions proposed in chapters 3 and 4. However, owing to mobility and altitude, UAVs also face an interference problem that requires efficient mitigation techniques. This chapter presents a deep learning framework that implements power control to effectively manage interference for UAV-5G networks. It links to the third and fifth objective.

5.1 Introduction

The issue of communication with cellular-connected UAVs has gained significant attention in recent times [119]. Existing cellular networks have not been specifically optimized to support UAVs and are primarily focused on providing high-quality service to terrestrial users. Given the stringent regulatory requirements,

the need for extensive research and standardization efforts to ensure the reliable operation of UAVs in a range of deployment scenarios is evident. These factors highlight the importance of optimizing current cellular networks to facilitate seamless communication with UAVs.

Novel guidelines and programs like the Federal Aviation Authority's (FAA) "Drone Integration Pilot Program" are expected to accelerate the growth of the UAV industry globally. Thus, UAVs are seen as an interesting opportunity for businesses in the next decade.

One of the prominent technologies to enable UAV communications is the 5G cellular technology. 5G technology will ultimately replace 4G networks as the new standard cellular networks. Currently, it provides connectivity to most cell phones. 5G is beneficial because it is expected to provide higher download speeds and greater bandwidth. The future infrastructure of 5G networks can therefore link seamlessly and ubiquitously with everything. For instance, one attractive and growing technology is the IoT, which has generated a tremendous increase in data traffic, thus leading to the requirement of advanced networks to cope with reliability and traffic requirements.

The realization of 5G and beyond 5G (B5G) wireless networks is crucial to meet the requirements of connected UAVs. These networks offer low latency, high speed, massive capacity, and edge computing, which can enable UAVs to operate virtually in real-time. This translates to fewer incidents of loss of control and mid-air collisions, making 5G networks a critical component for the safe and efficient operation of UAVs. Therefore, there is an urgent need to accelerate the

development and deployment of 5G networks to support the growth of the UAV industry. [144]

Although 5G networks can provide high data rates and low latency, they may not be fully optimized for UAVs and may face challenges such as signal blockage and limited coverage. Therefore, using 6G networks, which are expected to provide advanced features such as intelligent networking, enhanced sensing and perception and autonomous decision-making to resolve current challenges in communication with UAVs may need to be considered. However, it should be noted that the scope of our project does not include the development of 6G networks. [145] [95].

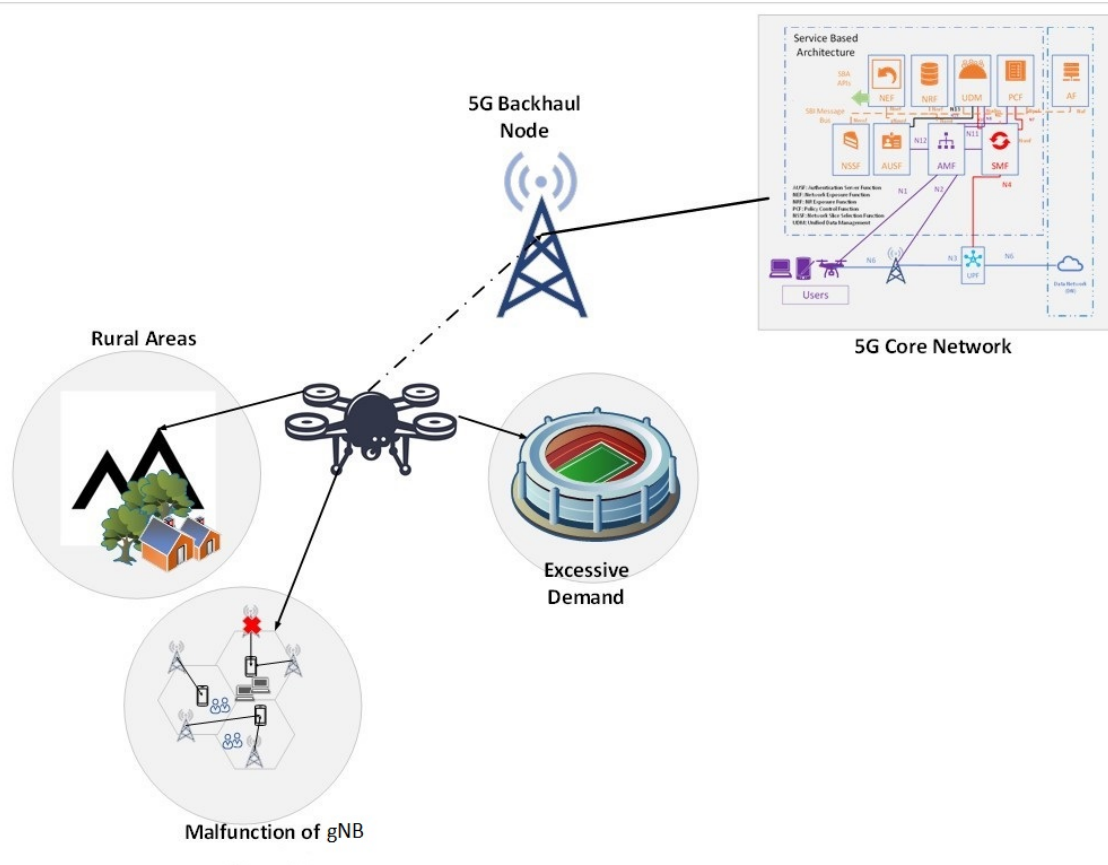


Figure 5.1: 5G-Connected UAVs

The utilization of UAVs in communication confers various promising advantages, including the ability for ad-hoc deployment, adaptable network reconfiguration, and a higher probability of achieving LoS links. UAVs that function as 5G BSs, referred to as gNBs, represent one of the most remarkable examples and are anticipated to perform a critical role in forthcoming generations of wireless networks, as stated by [146]. The benefits provided by UAV-gNBs, like swift deployment, mobility, increased likelihood of unimpeded propagation, and flexibility, have gained extensive interest and are being widely investigated.

Figure 5.1 demonstrates several use cases for 5G, including (i) serving as a backup in areas where a gNB malfunction occurs (ii) providing coverage in rural areas with limited or no gNB infrastructure, and (iii) enhancing Quality of Service (QoS) in areas with unexpected surges in demand, such as densely populated sports events, by establishing a network connected to the 5G core network via a backhaul node. Further details on the Software-based Architecture (SBA) of 5G will be presented in the following sections.

At present, communication between UAVs and the ground is restricted to Visual Line of Sight (VLoS) range, which limits reliability, coverage, security and performance. To overcome these limitations, it is crucial to connect drones to cellular networks to enable BVLoS capabilities. While integrating drones with 5G offers several advantages, it also poses certain challenges [147], [63], [148], [149], [150].

5.2 Interference Mitigation Challenges

When comparing UAVs to traditional ground UEs, it is important to note that UAVs typically operate at higher altitudes. This presents a unique challenge for gNBs, as they must provide 3D communication coverage instead of the usual 2D coverage for ground UEs. While conventional gNBs are angled downward to serve ground users and minimize inter-cell interference, UAVs must be integrated into this 3D communication network. This introduces new challenges that must be addressed in order to achieve effective and seamless communications. One of the most critical challenges in UAV communication within a cellular network is interference management. Interference in aerial users is exacerbated by LoS dominated UAV-gNB channels, which is largely due to the high altitude of UAVs. As a result, this phenomenon represents a significant obstacle to the proper functioning of UAVs in the network. In summary, the integration of UAVs into cellular networks requires careful consideration of 3D coverage, interference management, and other challenges unique to aerial communication.

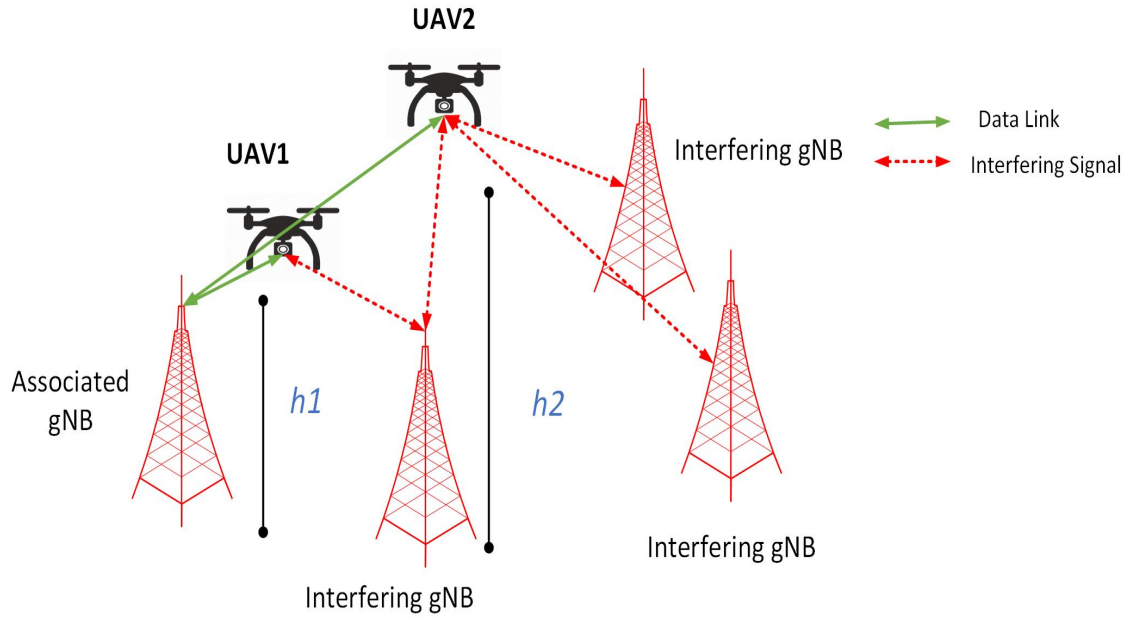


Figure 5.2: Interference in UAV networks

Figure 5.2 illustrates aerial interference in a 5G network. Specifically, it highlights the impact of height on interference for two UAVs, namely UAV1 and UAV2, which fly at altitudes h_1 and h_2 respectively. UAV1 experiences severe interference from a neighboring gNB, whereas UAV2, flying at a greater altitude ($h_2 > h_1$), faces interference from three neighboring gNBs due to the presence of favorable LoS links. This observation suggests that higher altitude leads to interference from all neighboring gNBs due to the existence of favorable LoS links. During downlink communication, each UAV experiences interference from multiple neighboring gNBs that are not associated with it due to strong LoS channels, resulting in poor downlink performance. In uplink communication, the UAV creates significant interference for several adjacent non-associated gNBs, thereby causing a new gNB interference problem. Although Resource Block (RB) allocation is a common approach for addressing this issue, it is ineffective for

severe air-ground interference. This is because of the limited number of RBs available to UAVs and the high frequency reuse for terrestrial UEs in cellular networks. Thus, developing an interference mitigation technique that accounts for the unique channel and interference characteristics of cellular-connected UAVs is critical. Although current terrestrial mitigation strategies can partially mitigate air-ground interference, severe interference cannot be entirely eliminated. This chapter presents an interference mitigation algorithm that is designed exclusively for downlink scenarios involving 5G-connected UAVs.

The objective of this chapter is to devise a new approach to power control that can mitigate interference in 5G networks, specifically addressing the challenges associated with the use of UAVs. To accomplish this, the utilisation of DQL algorithm as a means of mitigating interference in power control is put forward.

5.2.1 Contributions

The purpose of this chapter is to develop a technique for performing power control to mitigate interference in UAVs operating within 5G networks. To achieve this goal, a novel method of power control is proposed, deviating from conventional approaches. Specifically, this method regulates transmit power not only at the serving gNB but also controls transmit powers of interfering gNBs from a central location. This approach introduces a race condition where the serving gNB for one UAV can act as an interfering gNB for another user. To address this challenge, deep reinforcement learning is employed due to its proven effectiveness in resolving similar problems.

The DQL algorithm is considered a promising solution to the interference problem, as it eliminates the need for reporting Channel State Information (CSI), thereby reducing overhead and resulting in a low-complexity system design. Under the DQL approach, UAVs report only their received SINR and coordinates, while the gNB, supported by a cloud-based architecture, performs power control to mitigate interference. This approach involves both associated and interfering gNBs issuing power control commands, diverging from industry standards where only the associated gNB is involved. Building upon our previous work [77], this chapter presents the following significant contributions:

- Develops a power control optimization problem for the downlink direction to maximize the SINR experienced by the UAV.
- Develops a framework based on Deep Reinforcement Learning (DRL) that enables the concurrent execution of multiple actions and dynamically adjusts power levels to achieve optimal SINR by utilizing data from a given dataset.

5.3 5G, UAV and gNB Functionality

5.3.1 5G Functionality

The utilization of 5G networks is regarded as advantageous for UAVs owing to their capacity to offer consistent connectivity while concurrently lowering cost and resource requisites. The 5G framework incorporates sophisticated Radio Access Networks (RANs) and employs a plethora of technology enablers such as

beamforming, edge computing, network slicing, and others, to cater to an extensive array of wireless services. These advancements have a considerable influence on UAV communication, enabling greater flexibility and efficiency in operation.

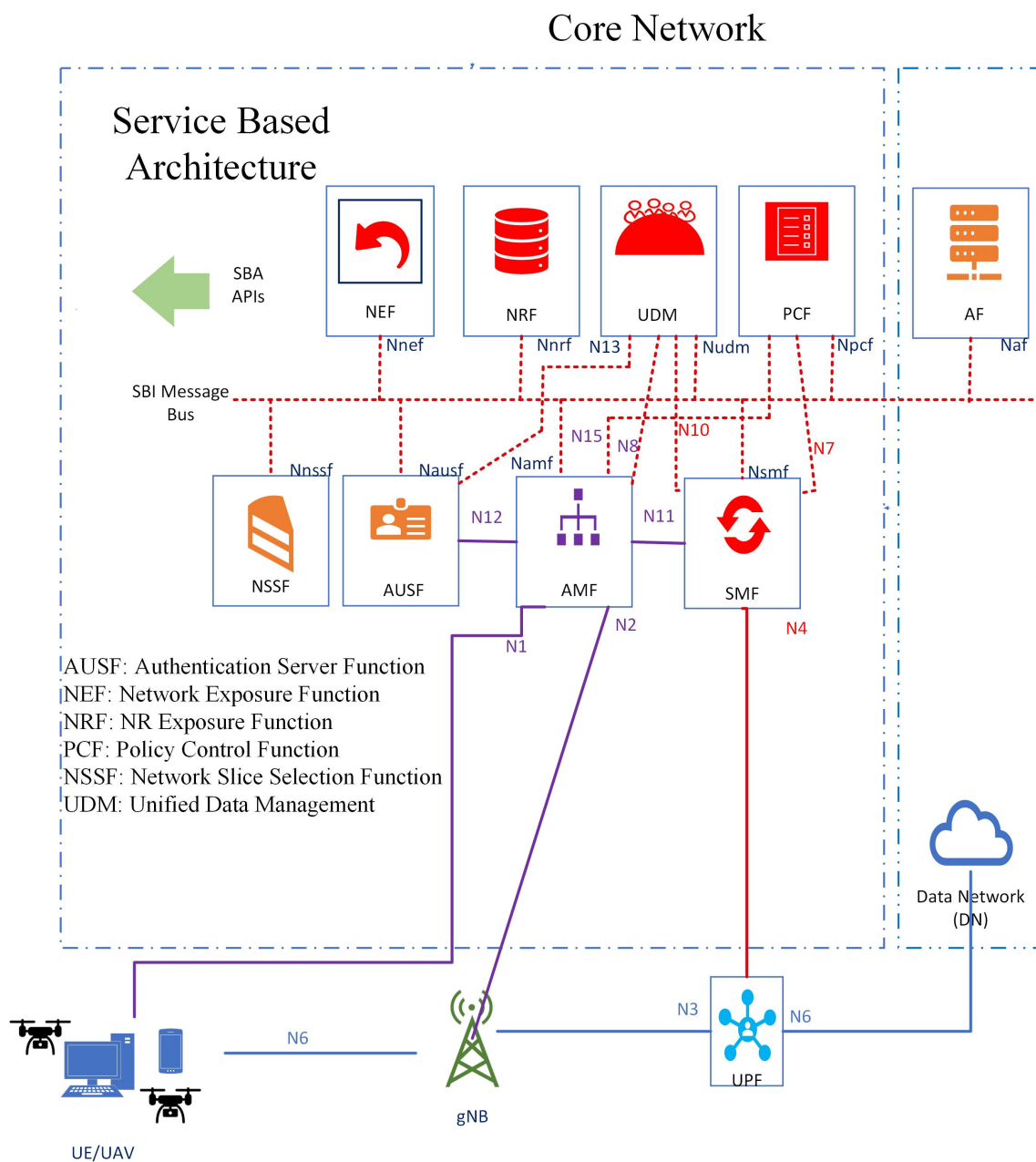


Figure 5.3: 5G Software Based Architecture

The recently introduced 5G Network Core is outlined in the 3GPP standard [151] and is depicted in Figure 5.3, utilising a cloud SBA. This updated system encompasses all 5G related functions and interactions, including session management, authentication, protection, and end-user traffic aggregation, which are briefly described below as defined in:

1. Network Exposure Function (NEF): A network component known as the Network Exposure Function (NEF) serves as a bridge between 3GPP core network functionalities and external entities, including third parties and non-3GPP environments. NEF plays a vital role in ensuring the security of interactions when services or Application Functions (AFs) connect to 5G Core nodes. It can be likened to a versatile intermediary, an Application Programming Interface (API) aggregation hub, or a translator that facilitates seamless integration into the 5G Core Network.
2. Network Function Repository Function (NRF): The 5G Network Function Repository Function (NRF) is a critical component of the 5G network architecture that acts as a central registry for all the network functions available in a 5G network. The NRF maintains a database of all the network functions that are available in a 5G network, including core network functions, service functions, and network slice functions. It also provides information about the location and availability of these functions, allowing other network functions to locate and access them when needed. Some of the key functions of the NRF including registering and storing information about

all network functions available in the network. The NRF is an essential component of the 5G network, enabling the dynamic and flexible allocation of network resources to support a wide range of use cases and services. By providing a centralised repository for network functions, the NRF simplifies the process of locating and accessing network resources, making it easier for network operators to deploy and manage their networks.

3. Network Slice Selection Function (NSSF): The 5G Network Slice Selection Function (NSSF) is a key component of the 5G network architecture that is responsible for selecting and assigning network slices to users based on their specific requirements and the availability of network resources. A network slice is a logical partition of the 5G network that is created to provide a specific set of services and capabilities tailored to the needs of a particular user or group of users. Network slices can be created for a wide range of use cases, including mobile broadband, and mission-critical services. The NSSF plays a crucial role in enabling the dynamic and flexible allocation of network slices by performing user and device authentication and authorisation, network slice selection, and network slice management. Also, the NSSF allocates network resources to support the delivery of network slices, including RAN resources, core network resources, and transport network resources.

4. The Access and Mobility Management Function (AMF): is a network func-

tion that is responsible for managing access and mobility for devices or users. It authenticates and authorises the device or user, manages access to the network, and ensures seamless mobility as the device or user moves between different network locations or coverage areas. The AMF also manages ongoing sessions for the device or user, monitoring QoS and ensuring that appropriate resources are allocated for the session. As a critical component of the 5G core network architecture, the AMF plays a crucial role in enabling seamless connectivity and mobility for 5G devices and users.

5. The Unified Data Management (UDM): is a key component of the 5G network architecture that is responsible for managing user-related information, such as authentication and authorisation data, user preferences, and service subscriptions. The UDM is a centralised function that stores and manages all the user-related information that is needed by the 5G network, including information about the user's device, SIM card, and subscription. The UDM provides a unified view of user data to other network functions, allowing them to access the data they need to deliver services and manage network resources. The key functions of the UDM including authenticates users and authorises access to network resources based on their credentials and service subscriptions. The UDM provides policy control functions to manage network access, traffic routing, and other network resources based on user profiles and service requirements. The UDM manages subscriber data, including SIM card information, service subscriptions, and billing in-

formation. The UDM is a critical component of the 5G network architecture, providing a centralised repository for user-related information that enables other network functions to deliver customised and optimised services to users.

6. The Policy Control Function (PCF): The Policy Control Function (PCF) is a key component of the 5G network architecture that is responsible for managing policy decisions and enforcement in the network. The PCF acts as a centralised policy controller, defining and enforcing policies for network access, traffic routing, and other network resources. The PCF uses information from the UDM function to make policy decisions based on user profiles and service requirements. The PCF is an essential component of the 5G network architecture, providing a centralised function for policy control that enables operators to manage network resources and deliver customised services to users. By defining and enforcing policies for network access, traffic routing, and resource allocation, the PCF ensures that network resources are used efficiently and effectively, enabling operators to deliver high-quality services to their customers.

Thus, the SBA places a strong emphasis on the deployment of virtualized functions using the MEC infrastructure as a fundamental architectural tenet. MEC is an essential element of 5G infrastructure, which seeks to enhance cloud computing by relocating applications from centralised data centres to the edge net-

work in closer proximity to end-users. This strategy offers numerous benefits, including reduced latency, increased bandwidth, and real-time access to RAN data. The implementation of MEC is particularly important for the Command and Control (C2) link, which requires extremely low latency communication. The proposed algorithm is implemented in a cloud-based architecture as part of the SBA infrastructure discussed above.

5.3.2 gNB functionality

The primary component of the 5G-RAN architecture is the gNB. The gNB provides the air interface for user devices to connect to the 5G network and manages the radio resources used for wireless communication. The flight controller unit reports SINR values, while the GPS module reports coordinates. Ground controls primarily perform tasks such as controlling the UAV's attitude, displaying and manipulating payload data, planning missions, tracking the UAV's position, displaying routes on maps, positioning navigational targets, and maintaining communication links with other subsystems. According to the DQL algorithm proposed in this chapter, the gNB receives coordinates and received SINR values from the UAV to reduce interference. Figure 5.4 represents the system model used in this chapter, which shows the RAN network linked to the MEC architecture and core network

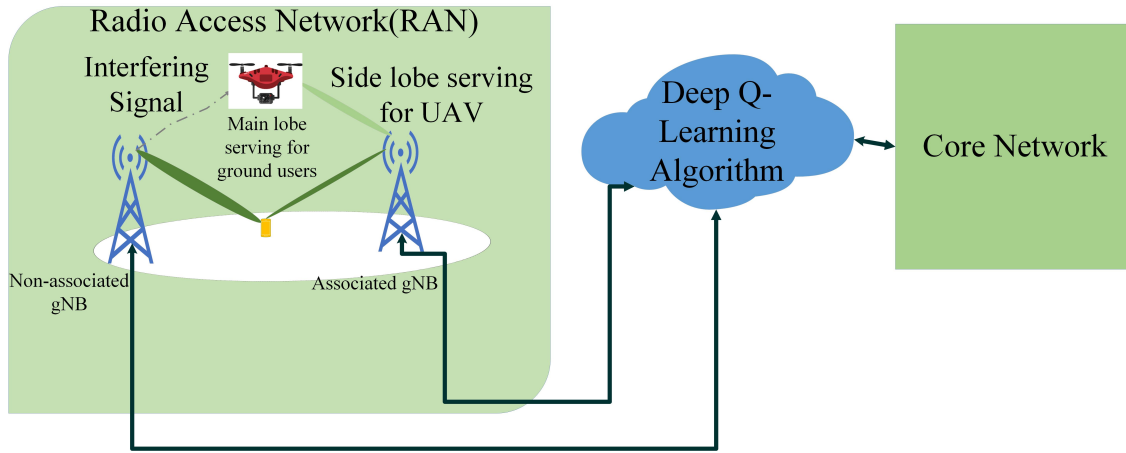


Figure 5.4: Interference Mitigation System Model

MEC is a key technology in the 5G network architecture that enables the computation of traffic, processes, and services to be moved from centralized data centers to the edge of the network, closer to the end-users. By processing data and running applications closer to the RAN, MEC can significantly reduce latency, improve network performance, and enable new high-bandwidth, low-latency applications that were not possible with earlier mobile network technologies. Figure 5.5 depicts the MEC architecture as per the 3GPP standard [152]. It consists of a MEC orchestrator and MEC host. The MEC orchestrator interacts with the NEF, while the MEC host is deployed in the data network of the 5G system. The NEF can also be deployed at the edge to enable low latency and high throughput service access. The proposed DQL algorithm is implemented in the MEC host along with other applications on the application platform.

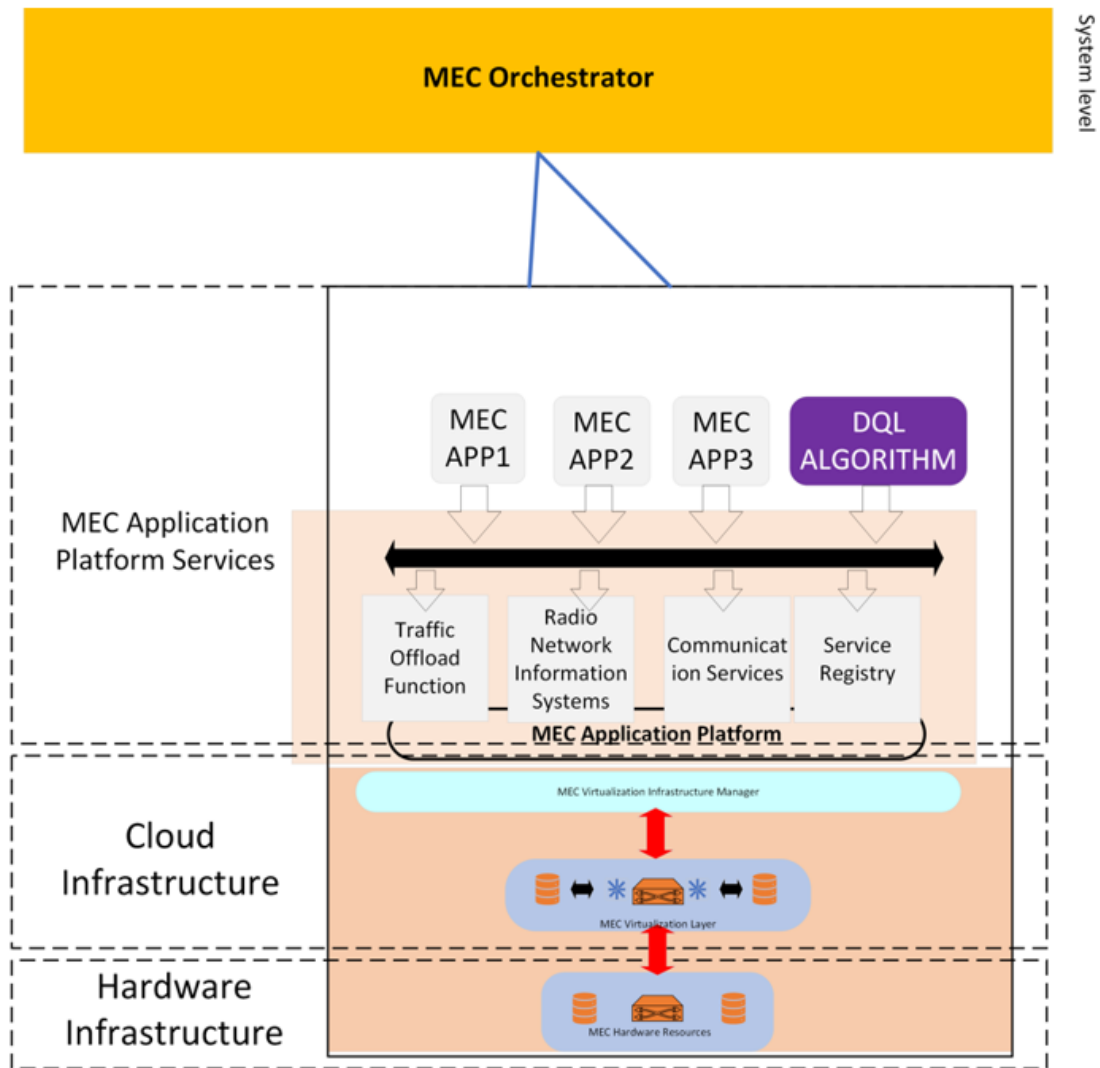


Figure 5.5: MEC Cloud Architecture

Figure 5.6 shows the functional blocks of the system model from Figure 5.4. This is divided into 3 sections, (i) RAN: Within the RAN, a UAV is being served by 1 gNB and receives an interfering signal from a non-associated gNB. The UAVs are primarily served by the side lobes of gNB antennas as the main lobes are down-tilted for optimal support to mobile devices. This also shows the structure of the gNB and its different components. (ii) cloud location: the gNBs in RAN are linked to the cloud architecture, where the proposed DQL is deployed. The MEC

architecture block was shown in Figure 5.5. It receives the SINR and location parameters from the gNB and computes the optimal power control commands and sends them back to the gNB. The gNB in turn, sends these to the UAVs and thus interference is mitigated. Further, the cloud is linked to the core network. (iii) Core network: the core network is linked to the RAN via the cloud architecture and provides support through the virtualized functions as discussed in 5.3.1

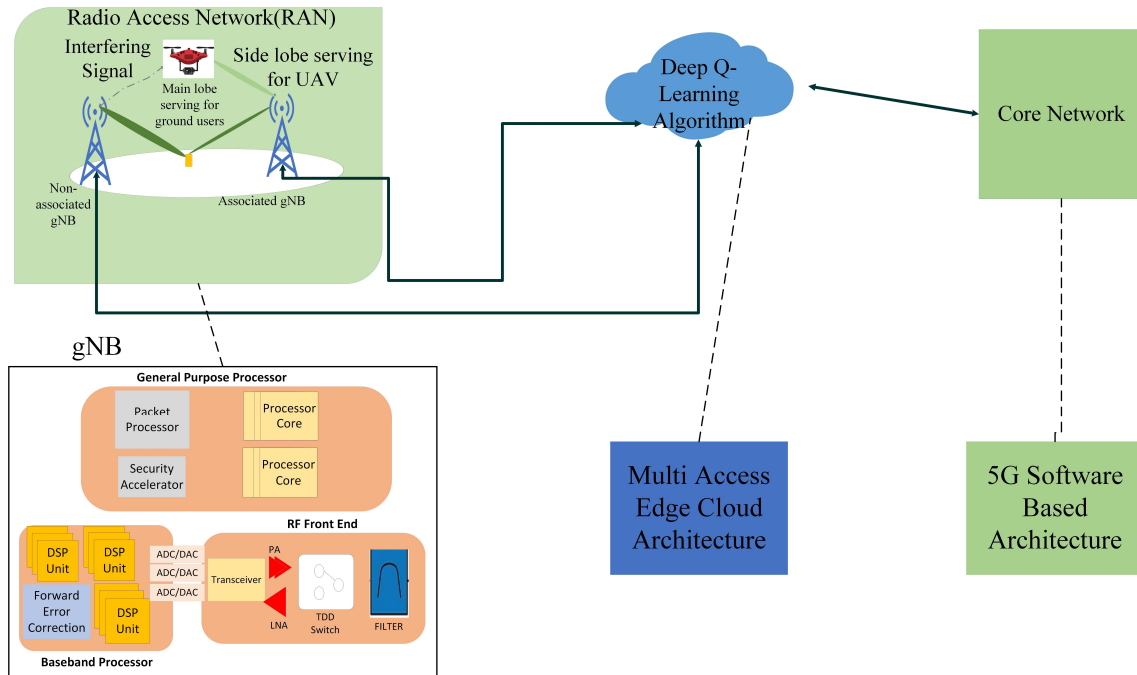


Figure 5.6: Interference Mitigation System Functional blocks

This chapter proposes a solution to the issue of interference in 5G networks caused by non-associated gNB for UAVs. The solution involves the implementation of a DQL algorithm within a cloud architecture. The algorithm is designed to enhance the SINR of UAVs and reduce interference by modifying the functions

of the gNB. The decision-making process takes place at a central location, where data from UAVs is transmitted over the backhaul to the central hub, which is then connected to the 5G core network.

5.4 Reinforcement Learning

Reinforcement Learning (RL) is a specialized area within the realm of ML that concerns itself with determining appropriate actions to be taken by an intelligent agent in a given environment. The objective of this methodology is to maximize the cumulative reward obtained by the agent by selecting the most optimal action. It places emphasis on finding a balance between exploration and exploitation, thereby continually refining the agent's decision-making capabilities. The agent must actively gather information about possible states, actions, transitions, and rewards. Unlike supervised learning where evaluation is separate, in RL, the agent is evaluated while learning. The agent interacts with the environment through perception and action. The agent receives input in the form of the current state of the environment and selects an action to alter the environment's state. The agent then receives a scalar reinforcement signal or reward based on the value of the state transition. The agent's goal is to maximize the long-run sum of the reinforcement signal's values by selecting actions that tend to increase the reward.

Table 5.1 provides definitions for various elements involved in the training phase that determine interaction between the agent and states and give expected discounted reward value. Figure 5.7a illustrates inter-element interaction. The

agent changes its state from s to s' by taking an action a in an environment and receives reward w for it.

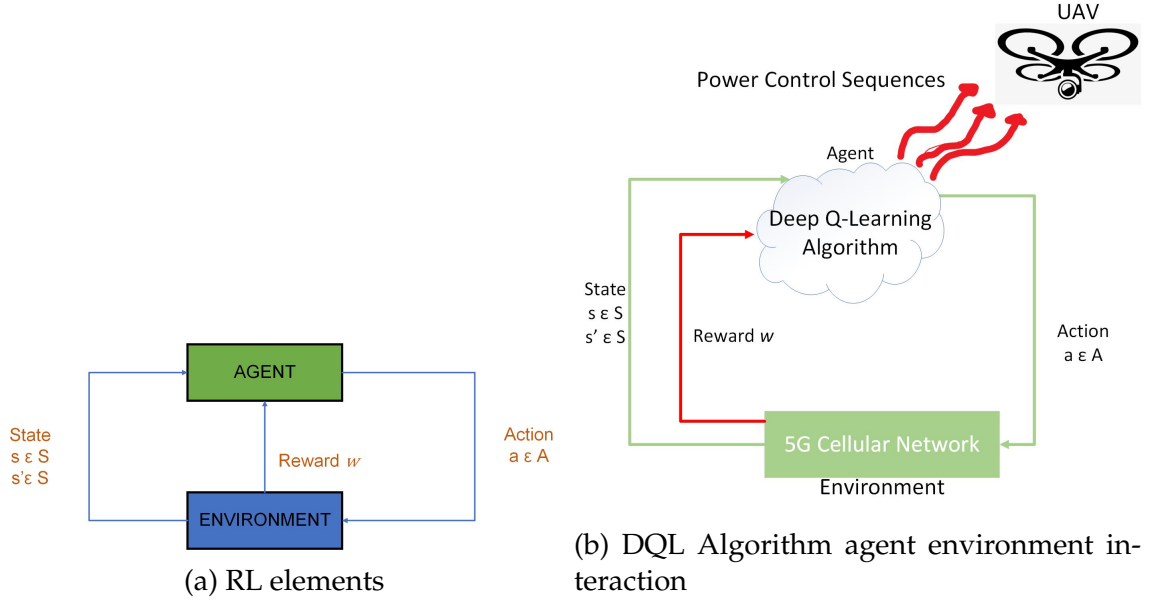


Figure 5.7: Agent-Environment Interaction

In this chapter, the agent is the DQL algorithm which exists in a given state s i.e., a specific power value. It takes a suitable action i.e., increase or decrease the power value to optimise SINR value. This interaction takes place in 5G cellular environment. Finally, these commands are sent to the UAV. This is depicted on Figure 5.7b

Table 5.1: Elements of Reinforcement Learning

Elements	Definition
Observations	Observations are measurements of characteristics of the environment. They are expressed as $\mathcal{O} \in \mathbb{R}^p$, where p is the no. of characteristics
States	A state is defined as the discretized form of the observations at time step t , and is denoted as, $s_t \in S$, where s_t represents the current state.
Actions	An action is a valid choice that can be made at a given time step t . It changes the state from s to the target state s' . It is denoted by $a_t \in \mathcal{A}$.
Policy	The relationship between the state and the action is governed by a policy, denoted as $\pi(\cdot)$. The policy determines how the agent selects a new state by taking an action.
Rewards	After the agent takes ' a ' when it is in ' s ' at t and moves to s' , it receives a reward. The reward signal obtained is represented as $w_{s,s',a}[t; q]$

5.4.1 Q-Learning

Q-learning is a commonly used reinforcement learning algorithm for making optimal decisions in Markov Decision Processes (MDPs). In Q-learning, the agent learns a Q-function that maps a state-action pair to a value representing the ex-

pected cumulative reward obtained by taking that action from that state and following an optimal policy thereafter. Thus, the Q-table is the mapping of state-action pairs with a Q-value relating to the reward. Table 5.2 illustrates a Q-table.

Table 5.2: Example of Q-table with state action pairs mapped to Q-values

State-Action	Q-value
(S1,A0)	4
(S3, A4)	2
(S5, A1)	1

The Q value is not calculated in a fixed manner, instead, it is implemented in the Q-table an iterative approach. This is known as the training phase.

The Q-table is a fundamental component in the Q-Learning algorithm, serving as a means of storing and updating information regarding the states, actions, and their associated expected rewards. It is implemented as a mapping between state-action pairs and their corresponding Q-values, which represent the estimated optimal future rewards of taking a particular action from a specific state.

The Q-Learning algorithm works through the following steps:

Initialise Q-table: At the initiation of the Q-Learning process, the Q-table is initialised to an array of zeros, indicating a lack of prior knowledge about the environment. As the agent interacts with the environment through trial and error, it updates its understanding of the state-action pairs and their corresponding Q-values, which it uses to optimise its future actions and maximise its expected reward.

Choose an action: To choose an action in Q-learning, the agent can use an

exploration-exploitation strategy. During the exploration phase, the agent randomly chooses actions to gain information about the environment. During the exploitation phase, the agent chooses actions based on its current estimate of the optimal action-value function. One common exploration-exploitation strategy is the epsilon-greedy strategy. The agent chooses a random action with probability ϵ , and the optimal action (i.e., the action with the highest Q-value) with probability $1 - \epsilon$. As the agent gains more experience, it can gradually decrease the value of ϵ , which allows it to explore less and exploit more.

Update Q-table: The Bellman Equation is a mathematical expression that facilitates the determination of updates to the Q-table following each step taken by the agent. The equation effectively integrates the current perception of value with the anticipated optimal reward, which is premised on the selection of the optimal action as known at that moment. In a practical implementation, the agent assesses all feasible actions for a given state and chooses the state-action pair with the maximum Q-value. The Bellman Equation [68] is formulated as in (5.1).

$$Q_{\pi}^*(s_t, a_t) := E_{s', t} \left[w_{s, s', a} + \gamma \max_{a'} Q_{\pi}^*(s', a') \middle| s_t, a_t \right] \quad (5.1)$$

Here, $\gamma : 0 < \gamma < 1$. s' is the next state a' is the next action. These steps are repeated until the optimal solution is converged. This is also represented in Figure 5.8

In this chapter, Q-learning for interference mitigation is considered the baseline method, against which the proposed algorithm is compared.

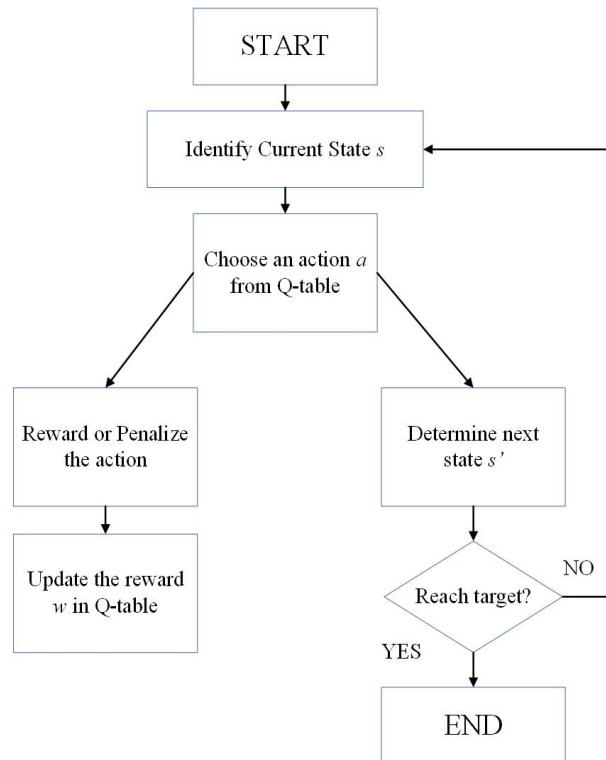


Figure 5.8: Representation of Q-table working

5.4.2 Deep Learning

Deep learning algorithms use gradient descent optimisation and back propagation to iteratively adjust the weights of the network and improve its predictions, with the goal of minimising the prediction error on the training data. The hierarchical representation learning in deep learning enables the model to learn increasingly complex features and representations, leading to its widespread use in numerous applications, including natural language processing, computer vision and speech recognition. The depth and number of layers in deep learning models can vary, ranging from simple feed forward networks to complex recurrent NNs and convolutional NNs [153].

NN is an AI model composed of interconnected neurons or activations arranged in multiple layers. The NN transforms input data into output data based

on a pre-established training dataset. This mapping is accomplished through the distribution of adjustable parameters known as weights across the various layers. The weights are refined through the use of the back-propagation algorithm, which minimises a loss function that gauges the deviation between the network's predictions and actual values. To reduce the loss function (or to optimise the back-propagation algorithm), gradient descent is used. In the mathematical theory of NNs, universal approximation theory establishes the density of an algorithmically generated class of functions. Therefore, if $(f(x))$ is an arbitrarily complex function, then the NN can approximately approach the solution of the function irrespective of its type. This implies that NNs are capable of representing a wide variety of functions when given appropriate weights [154]. Activation functions help NNs differentiate between useful and irrelevant data points

5.4.3 Neural Network-based function approximator

If the initial state-action value function $Q_{\pi}(s, a)$, is modified for every time instant 't', then it will converge to $Q_{\pi}^*(s, a)$ as $t \rightarrow \infty$. However, this is not easy to achieve. The primary cause for this due to its implementation in a non-stationary environment. Real-world environments such as the 5G-UAV integrated network considered in this chapter, are often dynamic and may change over time. In such environments, the optimal policy itself may change, making it difficult for the algorithm to converge. Frequent updates of the state-action values can exacerbate this issue, as the learning process might not be able to keep up with the changes in the environment. To counteract this, a function approximator is used.

At a given time, a NN with its weights is defined as $\varphi_t \in \mathbb{R}^{uv}$. Also, if $\varphi_t := \text{vec}(\varphi_t) \in \mathbb{R}^{uv}$ is defined, a function approximator $Q_\pi(s, a; \varphi_t) \approx Q_\pi^*(s, a)$ is constructed.

This NN-based function approximator forms the DQN. An important component of NNs is activation functions. The sigmoid function, as shown in (5.2), is a popular choice [68] for the activation function. The sigmoid function is a mathematical function that maps any real-valued number to a value between 0 and 1. It is defined as:

$$\sigma : x \mapsto 1/(1 + e^{-x}) \quad (5.2)$$

The deep network is trained by modifying φ at for every t to reduce the MSE loss represented by $K_t(\varphi_t)$:

$$\underset{\varphi_t}{\text{minimize}} K_t(\varphi_t) := E_{s,a} \left[(m_t - Q_\pi(s, a; \varphi_t))^2 \right] \quad (5.3)$$

where,

$m_t := E_{s',a'} [w_{s,s',a} + \delta \max_{a'} (Q_\pi(s', a'; \varphi_{t-1}) | s_t, a_t)]$ is the approximate value of the function at t , when the current state is s and action a . Interacting with the environment in this manner and making a prediction, comparing it against the correct response, and suffering a loss $K_t(\cdot)$, is termed online training. The associated gNB relays the UAVs' feedback data to a central location for DQN training in online learning [68].

The dimension of the input layer is the no. of states $|S|$, while the output layer is set to the no. of actions $|A|$. A small depth is chosen for the hidden layer as it has a direct impact on the computational complexity. This is shown in Figure 5.9

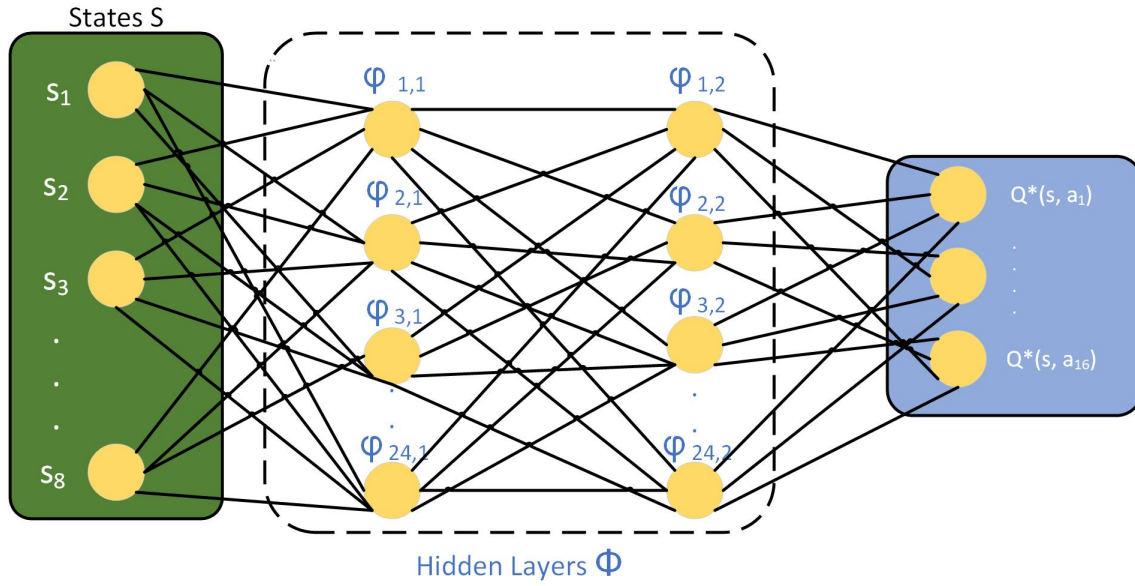


Figure 5.9: Structure of the DQN, with 2 hidden layers of dimension H

5.4.4 Deep Reinforcement Training Phase

5.4.4.1 Stochastic Gradient Descent

During the training phase, the weights are subject to iterative modifications employing the Stochastic Gradient Descent (SGD) technique. SGD represents a variant of the gradient descent method, wherein a differentiable (or sub-differential) function is optimized through stochastic approximation. This is achieved by substituting the actual gradient, computed from the complete dataset, with an estimated gradient derived from a randomly selected minibatch of the dataset. By

adopting this approach, particularly in optimization problems characterized by a high dimensionality, the computational burden is mitigated, resulting in accelerated iterations.

During the training phase, the weights φ_t are subject to modification following each iteration of time, achieved through the utilisation of the SGD method on a selected minibatch of data. It starts with an initial value of φ , that is chosen at random, and iterates and updates this value using an $\eta > 0$ step size as follows:

$$\varphi_{t+1} := \varphi_t - \eta \nabla L_t(\varphi_t) \quad (5.4)$$

The training is supported by replaying the experience from a replay buffer $\mathcal{D}$. $\mathcal{D}$ stores the different experiences i_t from different episodes at each time step. i_t is defined in (5.5)

$$i_t := (s_t, a_t, w_{s,s',a}[t; q], s'_t) \quad (5.5)$$

Subsequently, random samples were drawn from the dataset $\mathcal{D}$ and organized into minibatches. The training process is then conducted on these minibatches of data. This approach offers stability and mitigates the risk of convergence to local minima. As a result, the parameters used to generate the sample from $\mathcal{D}$ differ from the current parameters of the deep NN.

The state-action value function $Q_\pi^*(s, a)$ estimated by the Deep Q-Network (DQN) is defined by equation (5.1).

5.4.5 Policy Selection

Q-learning is a type of off-policy reinforcement learning algorithm, which allows for the creation of a nearly optimal policy even if actions are selected based on a random exploratory policy. As a result, a nearly greedy action selection policy is adopted, consisting of two modes.

- exploration: In the beginning, when the agent is unaware of the most effective action, it tries different actions randomly to determine an effective action a_t
- exploitation: Once the agent learns the various actions, it then chooses an action based on this knowledge to maximise the state-action value function $Q_\pi(s, a; \varphi t)$.

According to this policy, where $\epsilon : 0 < \epsilon < 1$ is a hyperparameter the trade-off between exploration and exploitation:

- (i) the agent carries out exploration with a probability ϵ .
- (ii) $1 - \epsilon$ probability is used for exploitation

The trade-off results in this policy being referred to as ϵ -greedy action selection policy. This policy has a linear regret in t .

In the system model adopted in this chapter, it is assumed that UAVs move at

speed v and the agent selects a_t from its s_t and receives $w_{s,s',a}[t;q]$ and finally moves to $s' := s_{t+1}$. An episode is the time period in which the agent and environment interact. If the target is achieved within the episode, then it is said to have converged.

In the proposed DQN implementation, the UAV coordinates are particularly kept track of. These coordinates are reported to the network, and used for decision-making, to improve the network performance. Thus, UAV coordinates are part of the DRL framework.

5.4.6 Hyperparameter Tuning using Random Search

Hyperparameter tuning is required for the proposed DQL algorithm to achieve better performance and stability during the training process. In this section, the random search technique is used to effectively tune the hyperparameters.

Random search is a simple and intuitive hyperparameter tuning technique widely used in ML and deep learning. Its primary goal is to find optimal hyperparameter configurations that maximize the performance of a model in a given task. Random search samples hyperparameter values randomly from predefined ranges. The process of random search involves defining a search space for each hyperparameter, typically specified by minimum and maximum values. During each iteration, the algorithm selects random values for each hyperparameter from their respective search spaces. These randomly sampled hyperparameter configurations are then used to train the model. The random search method is

implemented similar to [68], as the environments used in their chapter is similar to ours. Random search entails the following steps:

1. Define search space: This is range of possible values to sample from, for each hyperparameter, i.e., learning rate (α), discount factor (γ) and exploration rate (ϵ).
2. Initialize optimal hyperparameters: Before the random search begins, the hyperparameters are set to an initial value. In the proposed algorithm, a maximization problem is considered, therefore the initial values are set to a very low value. After, this random search is performed.
3. Train the DQL agent with sampled hyperparameters: Using the sampled values obtained after the random search, the DQL agent is trained within the environment until convergence.
4. Evaluate the performance: Evaluate the agent's performance by running the agent in the environment for a fixed no. of episodes. Compute the average reward as given by expression in Table 5.1 as a performance metric.
5. Update the optimal hyperparameters: If the values of hyperparameters after random search is better than initial optimal values, then the optimal values are updated to current values.

The optimal hyperparameter values obtained from this method is given in Table 5.4

5.5 Existing Methods and Proposed Solution

5.5.1 Fixed Power Control (FPA)

FPA is a standard industry technique for interference mitigation and is, therefore, used as a baseline algorithm. It assigns a specific value for the transmit signal power. FPA does not use interference coordination. The total transmission power is uniformly allocated across all Physical Resource Blocks (PRBs), resulting in a constant power level. The gNB retains its power level and adjusts the code schemes and modulation techniques. This is termed link adaptation. The link is adapted based on the measurements reported by the UAV back to gNB. The link is adapted either based on periodic or aperiodic measurements because the transmit power is fixed resulting in a higher effective SINR. There are no measurement reports sent to the interfering gNB [155]. The total power is simply divided among the PRBs:

$$P_{TX,b}[t] := P_{gNB}^{\max} - 10\log N_{PRB} + 10\log N_{PRB,b}[t] \quad (\text{dBm}) \quad (5.6)$$

5.5.2 Tabular RL

The tabular Q-learning is a solution used for interference mitigation. In this method, the state-action value function is denoted by: $Q_{\pi}(s_t, a_t)$. The Q-learning update process is defined by the learning rate. This is due to the fact that in the tabular setting, the Q-table must store the Q-values for every possible state-action pair. In practical applications, the state and action spaces can be very large, re-

sulting in a large and possibly infinite size of the Q-table. To ensure convergence, the Q-table must be updated continuously with new experiences, and all state-action pairs must be visited and updated an infinite number of times. However, in practice, this is not feasible, and convergence may be slow or never reached. This is why the tabular setting of Q-learning is more suited to problems with smaller state spaces. Additionally, it also requires a non-trivial initialisation of the $Q \in \mathbb{R}^{|S| \times |A|}$ table to avoid longer convergence times. Therefore, computationally, it suits problems with smaller state spaces. Q-learning has no NN involvement. The Q-learning update analog of 5.1 is defined as:

$$Q_{\pi}(s_t, a_t) := (1 - \alpha)Q_{\pi}(s_t, a_t) + \alpha \left(w_{s,s',a} + \delta \max_{a'} Q_{\pi}(s', a') \right) \quad (5.7)$$

In this context, $Q_{\pi}(s_t, a_t) := [Q]_{s_t, a_t}$. The learning rate, $\alpha > 0$ determines the level of aggressiveness of the Q-learning update and sets how much weight is given to prior experience. The table-based approach is suitable for problems with small state spaces, allowing for the storage of the table Q.

5.5.3 Proposed Solution

The primary objective of the optimization problem is to maximize the sum of $\delta^i[t]$ for all i in the set $\{1, 2, \dots, L\}$, that represents the gNBs. In mathematical terms, the objective function is:

$$\begin{aligned}
& \underset{P_{TX,i}[t], \forall i}{\text{maximize}} \quad \sum_{i \in \{1,2,\dots,L\}} \delta^i[t], \\
& \text{if } P_{TX,i}[t] \in \mathcal{P}, \quad \forall i,
\end{aligned} \tag{5.8}$$

$$\delta^i[t] \geq \delta_{\text{target}}$$

Here, $P_{TX,i}[t]$ represents the transmission power for the i^{th} gNB at time t . The objective is to find the values of $P_{TX,i}[t]$ that maximize the sum of $\delta^i[t]$.

The optimization variables are $P_{TX,i}[t]$ for all i gNBs. These variables represent the transmission power levels for different gNBs at a given time t . The goal is to find the optimal values for these transmission power levels. To ensure that the optimization remains feasible and practical, there is a constraint on the transmission power levels. The transmission power $P_{TX,i}[t]$ for each gNB i must be chosen from a predefined set $\mathcal{P}$. The second constraint is imposed on the values $\delta^i[t]$. Each $\delta^i[t]$ must be greater than or equal to a predefined minimum threshold value δ_{target} . The δ values at each gNB i) comes from the UAV measurement reports.

The i -th gNB tries to solve this problem and, as a result, finds the optimal value for $P_{TX,i}$. The proposed DQL algorithm solves (5.8) at a central cloud location. Algorithm 1 is proposed that is based on the DQL approach. It enables power control without the need for the UAV to transmit explicit power control commands, leading to lower computational overhead compared to tabular Q-learning for a given number of states and network depth of the DQN network [68].

The flow diagram for the proposed Algorithm 1 is shown in Figure 5.10. The main steps can be summarised as follows:

1. Choose an optimising action.
2. Choose a power control action.
3. Evaluate the impact on effective SINR $\delta_{\text{eff}}^l[t]$.
4. The action is rewarded based on the distance from δ_{target} or δ_{min} , for instance, a higher reward could be given to an agent that is in closer proximity to the δ_{target} , while a lower reward would be given to an agent that is closer to the δ_{min} .
5. The DQN is trained by utilising the produced outcomes.

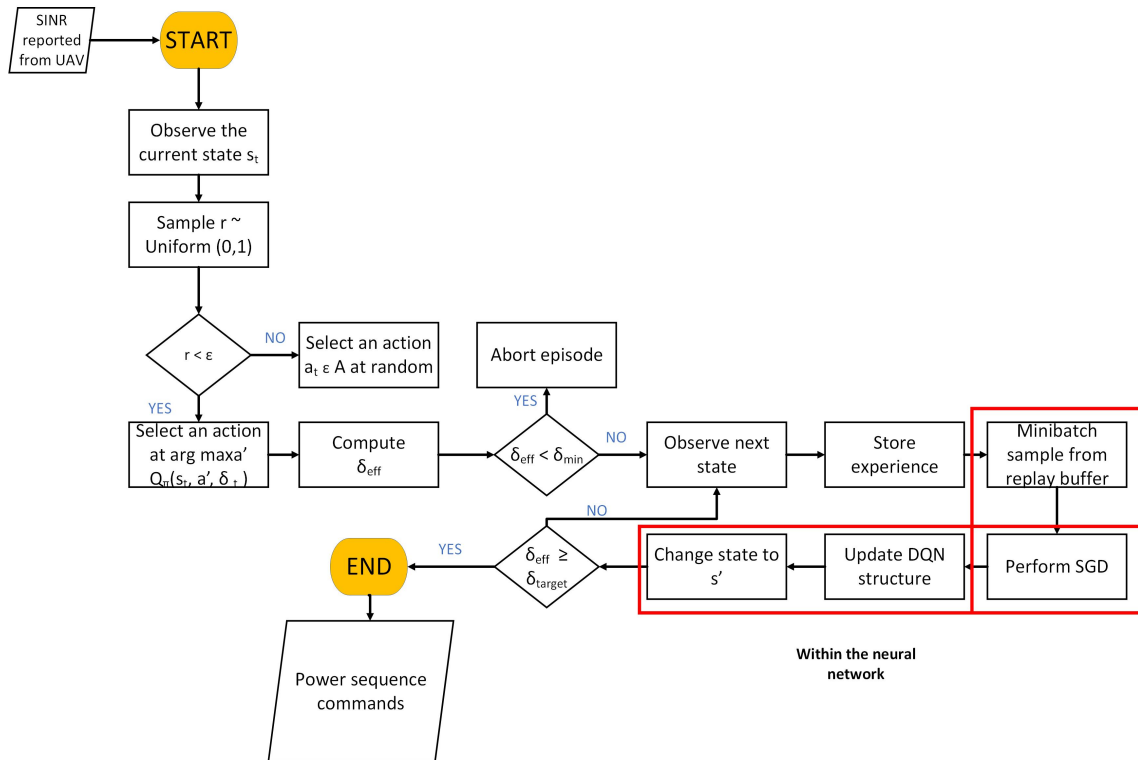


Figure 5.10: Deep Q learning for interference mitigation flow diagram

The reported SINR from the UAVs is fed as input to the DQL algorithm. Firstly, the current states are observed. The algorithm starts with a higher value of ϵ , where the system selects random actions and learns about the best rewards. As it progresses the ϵ value decays and the system keeps choosing the action, with the highest reward. After a reward is received, the effective SINR δ_{eff} is calculated and checked against the minimum SINR δ_{min} . If $\delta_{\text{eff}} < \delta_{\text{min}}$ then the episode is aborted, otherwise the next state is observed and stored in the experience buffer $\mathcal{D}$. From $\mathcal{D}$, the data is minibatched and SGD is performed on it. The results are used to update the DQN and the states are updated to s' . The mini batching and the consequent updating of states via back-propagation occurs within the NN as shown earlier in Figure 5.9. Finally, it is checked if $\delta_{\text{eff}} \geq \delta_{\text{target}}$ where δ_{target} is the target SINR. If it is, then the power control sequence commands are generated else the algorithm repeats until the target SINR is achieved. The pseudo code is shown in Algorithm 1 below:

Algorithm 3 Deep Q-Learning Algorithm for UAV interference mitigation**I/P: Downlink δ_{eff} reported by the UAVs****O/P: Power Control Commands to optimise received δ**

```

1: Initialise states, time, replay buffer  $\mathcal{D}$  and actions
2: repeat until convergence or termination
3:   repeat
4:     Increment  $t$ 
5:     Current state observed is  $s_t$ 
6:      $\epsilon := \max(\epsilon \cdot d, \epsilon_{\min})$ 
7:     Sample  $r$ 
8:     if  $r \leq \epsilon$  then
9:        $a_t \in \mathcal{A}$  is randomly selected
10:    else
11:       $a_t = \arg \max_{a'} Q_{\pi}(s_t, a'; \varphi_t)$ 
12:    end if
13:    Calculate  $\delta_{\text{eff}}^l[t]$  and  $w_{s,s',a}[t;q]$ 
14:    if  $\delta_{\text{eff}}^l[t] < \delta_{\min}$  then
15:       $w_{s,s',a}[t;q] := w_{\min}$ 
16:      Terminate episode
17:    end if
18:    Next state  $s'$  is observed
19:    Save  $i[t] \triangleq (s_t, a_t, w_{s,s',a}, s')$  in  $\mathcal{D}$ 
20:    Mini batch experience sample from  $\mathcal{D}$ :  $i_j \triangleq (s_t, a_t, w_j, s_{j+1})$ 
21:     $\gamma_i := w_j + y_{\max_a}, Q_{\pi}(s_{j+1}, a'; \varphi_t)$  is set
22:    Stochastic Gradient Descent is performed on  $(y_i - Q_{\pi}(s_j, a_j; \varphi_t)^2)$ , and
    determine  $\varphi^*$ 
23:    Update  $\varphi_t := \varphi^*$  in the DQN and calculate loss  $L_t$ 
24:     $s_t := s'$ 
25:    if  $\delta_{\text{eff}}^l[t] \geq \delta_{\text{target}}$  then
26:       $w_{s,s',a}[t;q] := w_{s,s',a}[t;q] + w_{\max}$ 
27:    end if
28:  until  $t \geq T$ 
29: until convergence or termination
30: end

```

DQL is an efficient solution to the problem of interference, as it doesn't require channel CSI (unlike traditional link adaptation techniques) to calculate SINR. Additionally, it also reduces the requirement for UAVs to provide feedback to the gNB. Moreover, DQL also decreases the need for UAVs to send feedback to the gNB. Currently, as per methods documented in existing works, UAVs need to re-

port their CSI, leading to an increase in overhead and complexity due to the large amount of information (in the form of CSI) being transmitted in systems. The proposed DQL algorithm offers a more streamlined communication mechanism between UAVs and gNBs. The UAVs are only required to transmit their SINR and coordinates, leaving the agent in charge of power control. This stands in contrast to conventional practices in the industry, which usually necessitate the transmission of specific commands for power control to both the associated and interfering gNBs. The associated gNB need only transmit power control commands to the UAV, thus reducing the amount of transmitted information and simplifying the overall communication process. Table 5.3 summarises the symbols used.

Table 5.3: List of notations

Notation	Description
t	Time
s_t	States
ϵ	Exploration rate
d	Exploration rate decay
a_t	Actions
r	Data Sample
L	No. of associated gNBs
B	No. of interfering gNBs
i	Total no. of gNBs
h	No. of UAVs
Q_π	State-Action Value Function
φ_t	Neural network weights
$i[t]$	experience
δ	SINR
δ_{eff}	Effective SINR
δ_{target}	Target SINR
δ_{min}	Minimum SINR
δ_{thresh}	Threshold SINR
SGD	Stochastic Gradient Descent
P_{TX}	Transmit Power
$\mathcal{P}$	Set of transmit powers

$\mathcal{D}$	Experience Replay buffer
y_l	Received signal
$\mathbb{E}$	Estimated function
H	Neural Network Width

5.6 Network, System and Channel Model

5.6.1 Network Model

In this scenario, a cellular network with $\mathcal{L}$ gNBs is analysed. Each network consists of one associated gNB and at least one interfering gNB, and the UAVs' association with their associated gNB is based on their distance. A UAV can only be served by one gNB at a time, so the cell radius can be expressed as $r > R/2$.

5.6.2 System Model

Under the given network model and considering a multi-antenna setup, with each gNB equipped with M antennas and each UAV having a single antenna, the signal received at the UAV from the $\mathcal{L}$ -th gNB can be expressed as:

$$y_l = c_{l,l}^* h_l x_l + \sum_{b \neq l} c_{l,b}^* h_b x_b + n_l \quad (5.9)$$

here $x_l, x_b \in \mathbb{X}$ are transmitted signals from the $\mathcal{L}$ th and $\mathcal{B}$ th gNBs, and it meets the power constraint

$$\mathbb{E}[|x_l|^2] = P_{TX,l} \quad (5.10)$$

The vectors $c_{l,l}, c_{l,b}$ are the $M \times 1$ are channel vectors representing the connection between the UAV and the $\mathcal{L}$ -th gNB, and the connection between the UAV and the $\mathcal{B}$ -th gNB, respectively. Finally, n_l is drawn from a complex normal distribution with zero mean and variance of σ_n^2 , representing the noise received by the UAV.

The first term in equation (5.9) represents the desired signal received by the UAV, while the second term represents the interference received from non-associated gNBs.

Each gNB $\mathcal{L}$ transmits power $P_{TX,l} \in \mathcal{P}$ from the set of all possible power values, denoted by $\mathcal{P}$. This set is defined such that the possible transmit power is a power offset.

5.6.3 Channel Model

In order to delineate the conditions of signal propagation, the concept of LoS probability is introduced to quantify the likelihood of the LoS component's presence. The 3GPP channel model [156] provides specific LoS probability models, with antenna heights of 3 m for indoor scenarios, 10 m for Urban Micro (UMi) environments, and 25 m for Urban Macro (UMa) settings. With respect to this chapter, the UMa scenario is chosen. This can be written as:

$$P_{rLOS} = \begin{cases} 1, & d_{3D-out} \leq 18m, \\ \left[\frac{18}{d_{3D-out}} + \exp\left(\frac{-d_{3D-out}}{63}\right) \left(1 - \frac{18}{d_{3D-out}}\right) \right], & 18m < d_{3D-out} \\ \left[1 + C'(h_{UT})^{\frac{5}{4}} \left(\frac{d_{3D-out}}{100}\right)^3 \exp\left(\frac{d_{3D-out}}{150}\right) \right] \end{cases} \quad (5.11)$$

where,

$$C'(h_{UT}) = \begin{cases} 0, & h_{UT} \leq 13m \\ \left(\frac{h_{UT}-13}{10}\right)^{1.5}, & 13m < h_{UT} \leq 23m \end{cases} \quad (5.12)$$

Pathloss presents a strong correlation with the channel modelling and is influenced by distance. Since, UAVs operate in 3D environment, the pathloss is given by:

$$PL_1 = 28 + 22 \log_{10}(d_{3D}) + 20 \log_{10}(f_c) \quad (5.13)$$

where, d_{3D} is the location of the UAVs 3D distances and f_c is the operating frequency.

This algorithm adopts a narrow-band geometric channel model, as described in [77]. With this model, the downlink channel from gNB $\mathcal{B}$ to the UAV in gNB $\mathcal{L}$ can be expressed as:

$$c_{l,b} = \frac{\sqrt{M}}{\rho_{l,b}} \sum_{p=1}^{N_{l,b}^p} \alpha_{l,b}^p a^*(\varphi_{l,b}^p) \quad (5.14)$$

where,

$\alpha_{l,b}^p$: path gain of the p -th path,

$\varphi_{l,b}^p$: angle of departure(AoD),

$a(\varphi_{l,b}^p)$: array response vector associated with AoD,

$N_{l,b}^p$: no. of channel paths.

This model accounts for both LoS and NLoS scenarios. For the LoS case, $N_{l,b}^p = 1$ is assumed

The received power at the UAV is measured over a set of PRBs at a given time t and is given by:

$$P_{UAV}^{l,b}[t] = P_{TX,b}[t] \left| c_{l,b}^*[t] h_b[t] \right|^2 \quad (5.15)$$

where, $P_{UAV}^{l,b}[t]$ is received downlink power $P_{TX,b}[t]$ is power from gNB $\mathcal{B}$.

Some additional losses are also suffered due to penetration and oxygen absorption.

5.7 Simulation Set-up and Results

In the system model considered in this paper, a UAV is operating within the range of 2 gNBs in 5G-RAN network. One gNB is the associated with the UAV and the other one is the interfering gNB. The UAV sends its measured SINR to the gNB, which is then served as the input to the DQL algorithm. The SINR received by the UAV served in gNB $\mathcal{L}$ at time t is computed as follows,

$$\delta^\ell[t] = \frac{P_{TX,\ell}[t] |c_{\ell,\ell}^*[t] h_\ell[t]|^2}{\sigma_n^2 + \sum_{b \neq \ell} P_{TX,b}[t] |c_{\ell,b}^*[t] h_b[t]|^2} \quad (5.16)$$

This is the received SINR that will be optimised by the proposed DQL, which is located in the cloud, linked to the RAN. The output of the DQL is then fed back to the gNB. The gNB then sends these commands back to the UAV, which optimises the SINR and mitigates interference.

5.7.1 Simulation Setup

The network, system, and channel models have been detailed in prior descriptions. The UAVs are in motion at a velocity of ' v ' and are subject to the impact of log-normal shadow fading and small-scale fading on their movement. The radius of the cell is denoted as ' r ', and the inter-site distance is established as $R=1.5r$. The channel conditions of the UAVs are influenced by a probability of LoS denoted as p_{LOS} . The remaining parameters are presented in Table 5.4. The target effective

SINRs for the objective are specified as:

$$\begin{aligned}\delta_{\text{target}} &:= 3\text{dB}, \\ \delta_{\text{target}}^{\text{thresh}} &:= \delta_0^{\text{thresh}} + 10\log M \text{ dB}\end{aligned}\tag{5.17}$$

where δ_0^{thresh} is the established SINR. If the δ_0^{thresh} drops below a minimum of -3 dB, the episode is considered to have concluded and the session cannot proceed any further.

The hyperparameters used to tune the RL-based model are shown in Table 5.4. Table 5.5 summarises the radio parameters.

Table 5.4: RL Parameters

Parameter	Value
Discount Factor γ	0.995
Initial exploration rate ϵ	1.000
Number of States $\mathcal{S}$	8
Deep Q-Network width H	24
Exploration rate	0.995
Minimum exploration rate $\epsilon_{\min}, \epsilon_{\min}^{\text{thresh}}$	(0.15,0.10)
No.of actions $\mathcal{A}$	16
DQN Depth	2

The simulated states $\mathcal{S}$ are setup as:

$$\begin{aligned}
 (s_t^0, s_t^1) &:= \text{UAV}_\ell(x[t], y[t]), \\
 (s_t^2, s_t^3) &:= \text{UAV}_b(x[t], y[t]), \\
 s_t^4 &:= P_{\text{TX},\ell}[t], \quad s_t^5 := P_{\text{TX},b}[t], \\
 s_t^6 &:= h_n^\ell[t], \quad s_t^7 := h_n^b[t],
 \end{aligned} \tag{5.18}$$

where (x,y) are the Cartesian coordinates (i.e longitude and latitude) of the given UAV.

Table 5.5: Radio Environment Parameters

Parameter	Value
gNB power $P_{\text{gNB}}^{\max}$	46 dBm
Cellular Geometry	Hexagonal
Antenna Gain(TX,thresh)	(11,3) dBi
Probability of LoS ($P_{\text{LOS}}, P_{\text{LOS}}^{\text{thresh}}$)	(0.9,0.8) [156]
Downlink Frequency	4.7 GHz
Cell Radius r	150m
UAV Antenna Gain	0 dBi
Inter-site distance R	225m
Number of Multipaths N_p	15
Average UAV Speed v	(10,20,20) m/s
Frame Duration	20ms

By leveraging the cardinality of $\mathcal{P}$, which scales in the order of 2, the set of actions $\mathcal{A}$ can be derived. Specifically, a register a is utilised to facilitate a binary encoding of the available actions. With the aid of masks, bitwise-AND operations, and shifting, the power control commands can be obtained. The ensuing code segment as shown in Table 5.6 is adopted:

When $q=0$:

Table 5.6: Code for Power Control

Code	Description
a[0,1]= 00	power is reduced by 3 dB for gNB b
a[0,1]= 01	power is reduced by 1 dB for gNB b
a[0,1]= 10	power is increased by 1 dB for gNB b
a[0,1]= 11	power is increased by 3 dB for gNB b
a[2,3]= 00	power is reduced by 3 dB for gNB l
a[2,3]= 01	power is reduced by 1 dB for gNB l
a[2,3]= 10	power is increased by 1 dB for gNB l

It can be inferred from above that $\mathcal{P} = (\pm 1, \pm 3)$ dB offset from the transmitter power. The following factors affected the choice of these offset values:

1. It conforms to the standards [157] that selects integers for power value increments
2. It maintains the non-convexity of the in (5.8) because it keeps the constraints discrete. Actions that increase or reduce gNB transmit powers are implemented as in [67].

A function $p(\cdot)$ is defined that returns an element from $\mathcal{P}$ depending on the selected code. In this chapter it is considered that $p(00) = -3$, $p(01) = -1$, $p(10) = 1$, $p(11) = 3$. The received SINR resulting from the above actions can be therefore written as:

$$\delta_{a[0],a[3]}^b \text{ for gNB b} \quad (5.19)$$

$$\delta_{a_{[1]},a_{[2]}}^l \text{ for gNB } l \quad (5.20)$$

The reward is thus written as:

$$\begin{aligned} w_{s,s',a}[t;q] &:= \left(p(a_{[0,1]}[t]) - p(a_{[2,3]}[t]) \right) \\ &\quad (1 - q) + \left(\delta_{a_{[0]}[t],a_{[3]}[t]}^b + \delta_{a_{[1]}[t],a_{[2]}[t]}^\ell \right) q \end{aligned} \quad (5.21)$$

where $q=0$.

The agent is rewarded the most when it triggers a power control command. The episode is aborted when the constraint imposed on (5.8) becomes inactive. In this scenario the agent receives a reward $w_{s,s',a}[t;q] := w_{\min}$ along with one of the following:

- A penalty is imposed by awarding the agent with the minimum possible reward $w_{\min}$. This occurs when the SINR falls below $\delta_{\min}$.
- A maximum reward $w_{\max}$ is imposed when δ_{target} is achieved.

In the simulations, the following steps are taken:

- Minibatching is performed with a sample size of $N_{\text{mb}} = 32$ training samples.
- The width of the DQN can be found using as per [158]. Thus, (5.22) is written as:

$$H = \sqrt{|A| + 2} N_{\text{mb}} \quad (5.22)$$

Substituting for $|A|=16$ and N_{mb} and $H=24$.

The following performance measures are used to benchmark our algorithms:

1. *Convergence (ζ):* is defined as the episode at which the δ_{target} is satisfied over the duration T for all UAVs. It is expected that as the no. of UAVs h increases, ζ will increase. For several random seeds, an aggregated percentile convergence episode is taken
2. *Run Time:* Determining the run-time complexity of the proposed DQL algorithm is difficult due to the absence of guarantees for convergence and stability. Therefore, run times from simulation per UAV is considered
3. *Coverage:* A complement cumulative distribution function (CCDF) of δ_{eff}^l is built by changing the random seed and performing the simulation in iterations, effectively modifying the way the UAVs drop from the network

The proposed DQL overcomes the shortcomings of FPA, by implementing an adaptive power control scheme, that can accommodate the changing interfering conditions. Tabular Q-learning, relies on the initialised state-action value function which is fixed. This results, in the size of Q-table becoming quite large and therefore taking longer times to find the optimal solutions, thus resulting longer

convergence time. However, in the proposed DQL, the NN implementation eliminates the need for a Q-table instead updating the optimal actions in real time.

5.7.2 Results

Considering the episode with the highest possible reward, Figure 5.11 shows the plot of the CCDF of δ_{eff} is shown for the three algorithms: FPA, tabular Q-Learning and the proposed DQL.

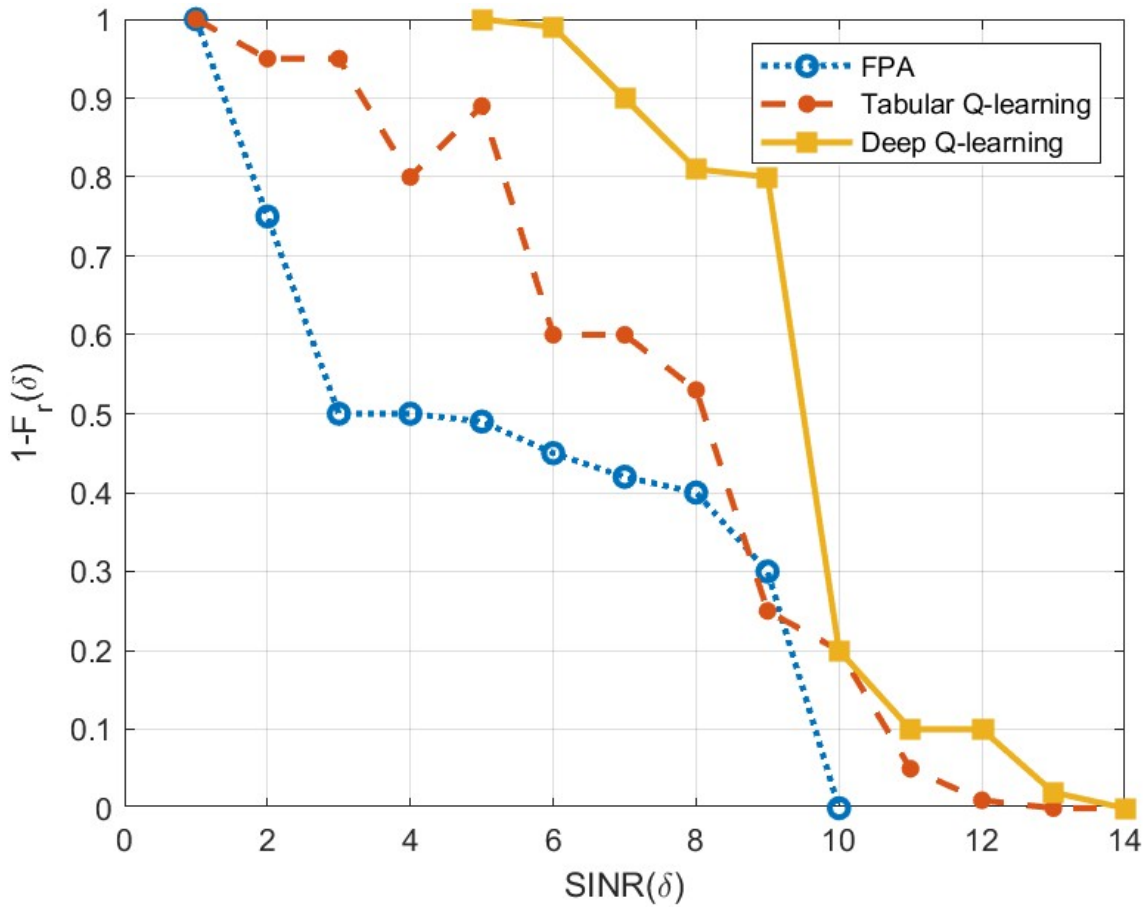


Figure 5.11: CCDF vs δ_{eff} for FPA, tabular Q-learning and DQL

As anticipated, the FPA strategy produces the least optimal performance due to its lack of power control or interference coordination. Tabular Q-learning exhibits slightly improved results over FPA, yet it still falls short when compared to

the addition of power control mechanisms to the gNBs, under performing FPA at approximately $\delta_{\text{eff}} = 9$ dB. On the other hand, the proposed DQL algorithm outperforms the other two algorithms, achieving better convergence to a solution. Unlike the tabular implementation, the convergence of DQL is not affected by the initial state-action value function. As δ_{eff} approaches 13 dB, UAVs are situated in closer proximity to the gNB, resulting in comparable performance among all power control algorithms.

The link performance is analysed for each of the algorithms at different heights of the UAV. As explained in the previous sections, when the altitude increases the interference also increases.

The simulation is run for a duration of 120 s, with the UAVs flying at three different altitudes viz. 50 m, 100 m, 120 m. To analyse, the link performance, SINR and latency is compared for the different heights and the three different interference mitigation schemes.

5.7.2.1 UAV @ 50 m

In this section the results are discussed, when the UAV is flying at a height of 50 m. This is a relatively lower altitude therefore the number of interfering elements is relatively lower.

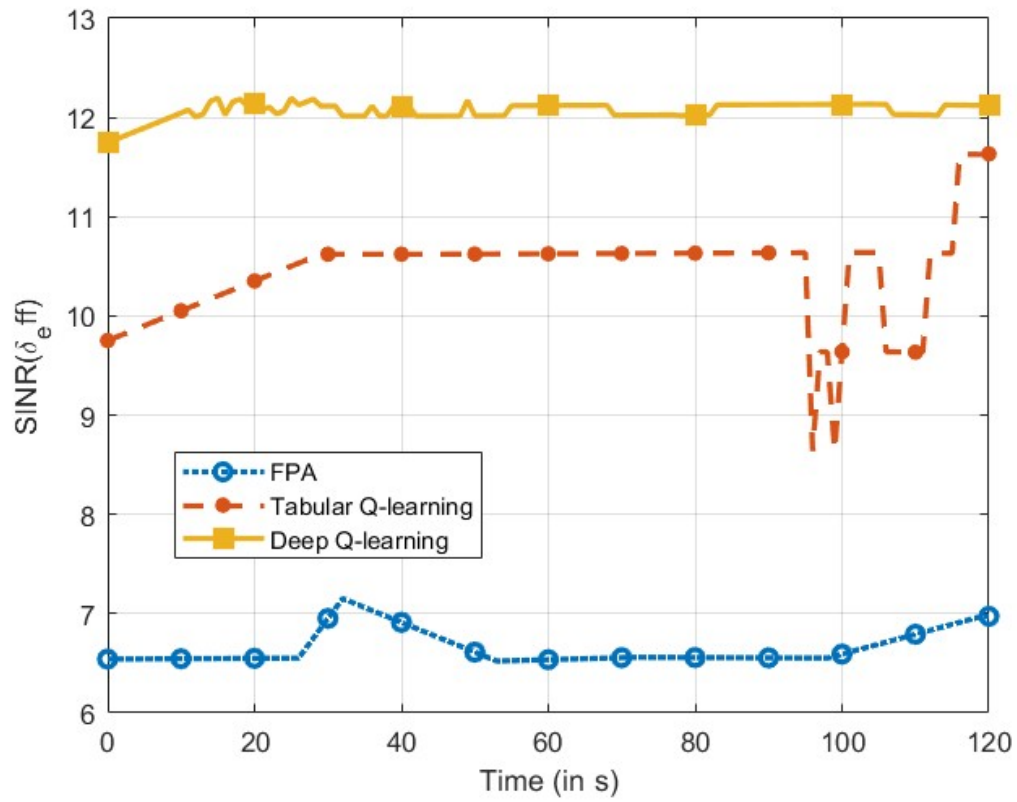


Figure 5.12: SINR vs time @ 50 m

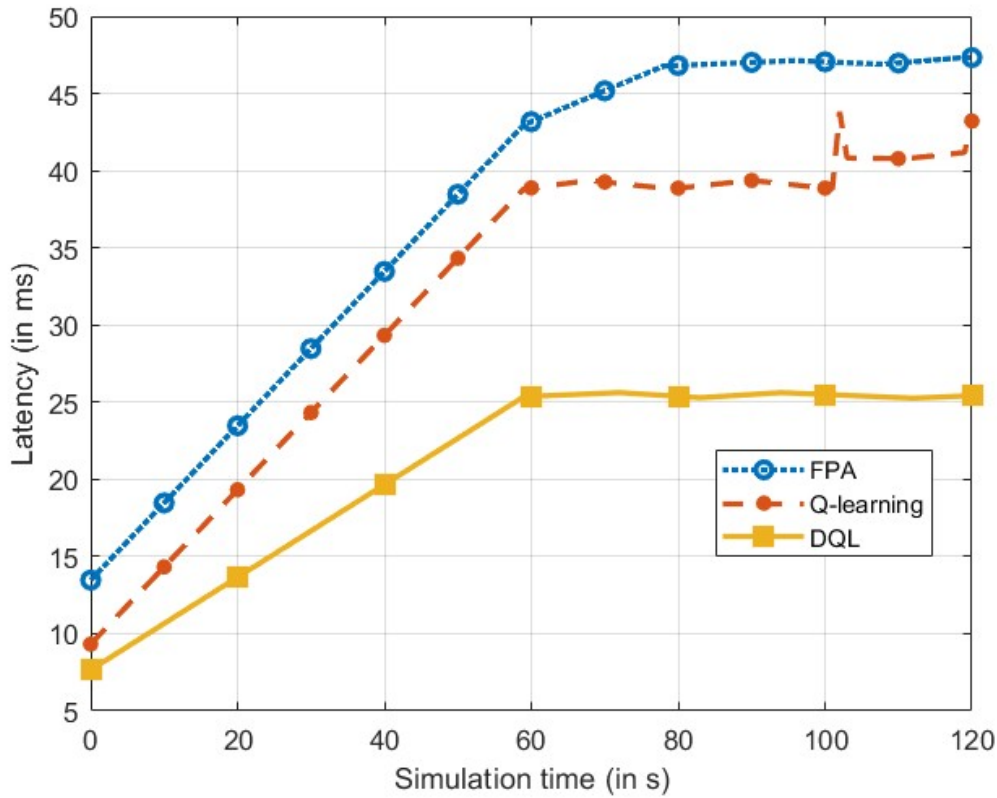


Figure 5.13: Latency at 50 m

Figure 5.12 shows SINR values for UAV @ 50 m. When no link adaptation is employed, i.e. when the FPA method is used, the values vary from very 6.52dB to 7.15dB. This is relatively a steady performance, however the SINR values are the lowest compared to Q-learning and DQL. This is expected as it is a lower altitude and the interference conditions do not change drastically, except for a brief 27 s peak between the 26 s and 53 s marks. Q-learning starts with a higher value of 9.7 dB and even goes up to 11.6 dB with an average value of 10.45 dB. This is indicative of good performance for the link, however, after about 95 s it suffers a drastic dip in performance in addition to presenting erratic patterns till the end of the simulation. This can be seen in Figure 5.12 as the annotated text in the red circle. When the simulation progresses, the Q-table becomes large and achieving

the optimal solution becomes difficult. This is also reflected in the link latency as shown in Figure 5.13.

Finally DQL performs the best with an average, minimum and maximum values of 12.06 dB, 11.74 and 12.19 db respectively, which is indicative of steady performance with high SINR values. It also shows really low latency values of 25.61 ms. Consequently interference is best mitigated by DQL amongst the three methods.

5.7.2.2 UAV @ 100m

In this section the results are discussed, when the UAV is flying at a height of 100 m. This is a higher altitude therefore the number of interfering elements is relatively higher.

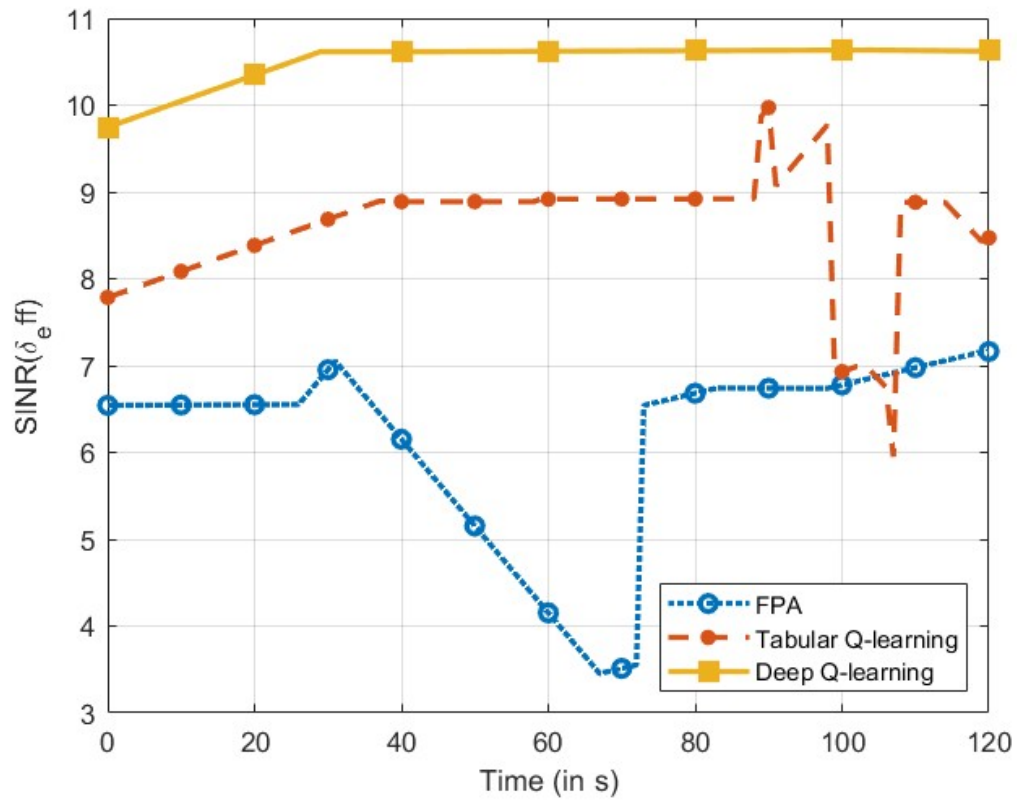


Figure 5.14: SINR vs time @ 100 m

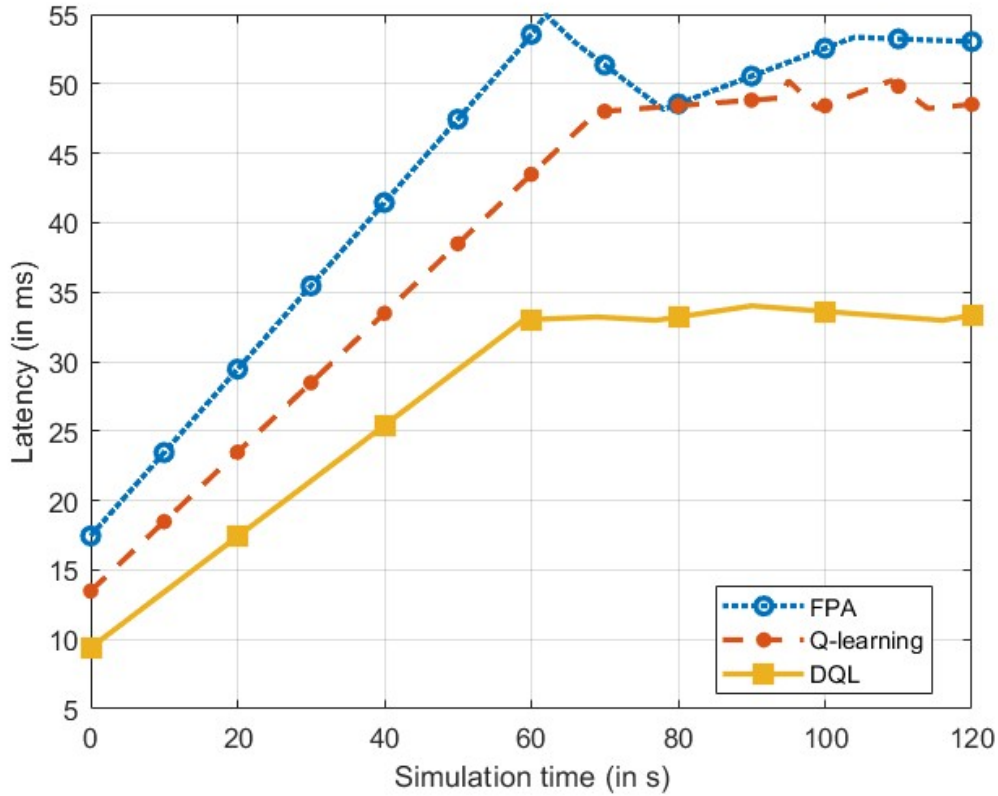


Figure 5.15: Latency at 100 m

Figure 5.14 shows SINR values for UAV @ 100 m. When no link adaptation is employed, i.e. when the FPA method is used, the values vary from very 3.45 dB to 7.16 dB. This represents an unstable link, as the SINR values vary drastically. For. e.g, at about the 32 s mark , there is an increase to 6.95 dB from 6.5 dB, but from thereon , it drops sharply to reach its minimum possible value. It increases again and does not stay constant. As mentioned above, this is primarily because the FPA algorithm cannot take into account the changing interference conditions and at a higher altitude of 100 m, the increase of interfering elements leads to a change in the interference conditions. This also coincides with the latency values, that see delays of up to 55 ms as shown in Figure 5.15

Q-learning starts with a lower value of 7.74 dB as compared to its 50 m per-

formance. It maintain steady performance value of close to 8.8 dB till about 88 s. This is indicative of good performance for the link, however, after about 89 s it suffers a drastic dip in performance and undergoes a series of peaks and troughs till the end of simulation. At one point, specifically at the 104 s mark it falls even below the FPA values. This can be seen in 5.14 as the annotated text in the red circle. When the simulation progresses, the Q-table becomes large and achieving the optimal solution becomes difficult. This is also reflected in the link latency as shown in Figure 5.15.

Finally DQL performs the best with an average, minimum and maximum values of 10.51 dB, 9.74 dB and 10.633 dB respectively, which is indicative of steady performance with high SINR values. It also shows really low latency values of 34.01 ms. Even though it shows a 12.58 % decrease in SINR values and 32.6 % increase in latency values as compared to 50 m, it is still the best performing algorithm. It implements link adaptation absent from FPA and eliminates the need for Q-tables by the use of NNs.

It is to be noted that the overall performance of the UAV at 100 m deteriorates as compared to 50 m. The main cause for this is the fact that due to the higher altitude the number of interfering elements, i.e., gNBs that UAV has LoS with increases.

5.7.2.3 UAV @ 120 m

In this section the results are discussed, when the UAV is flying at a height of 120 m. This is a highest altitude under consideration therefore the number of interfering elements is the maximum amongst the considered scenarios.

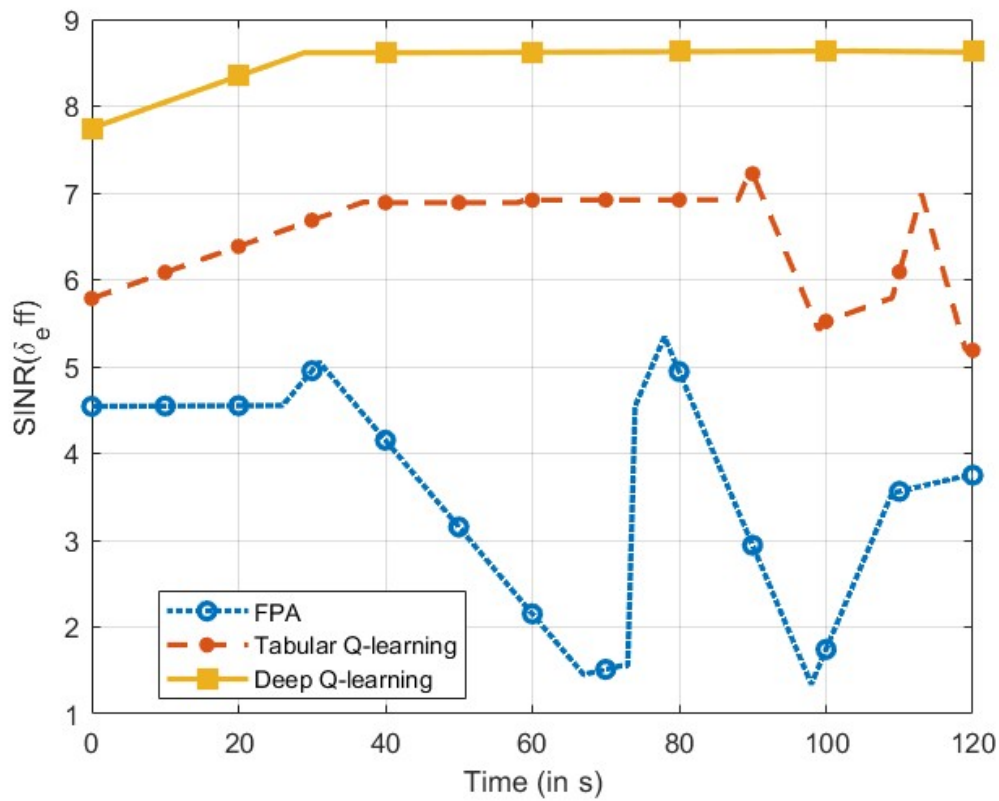


Figure 5.16: SINR vs time @ 120 m

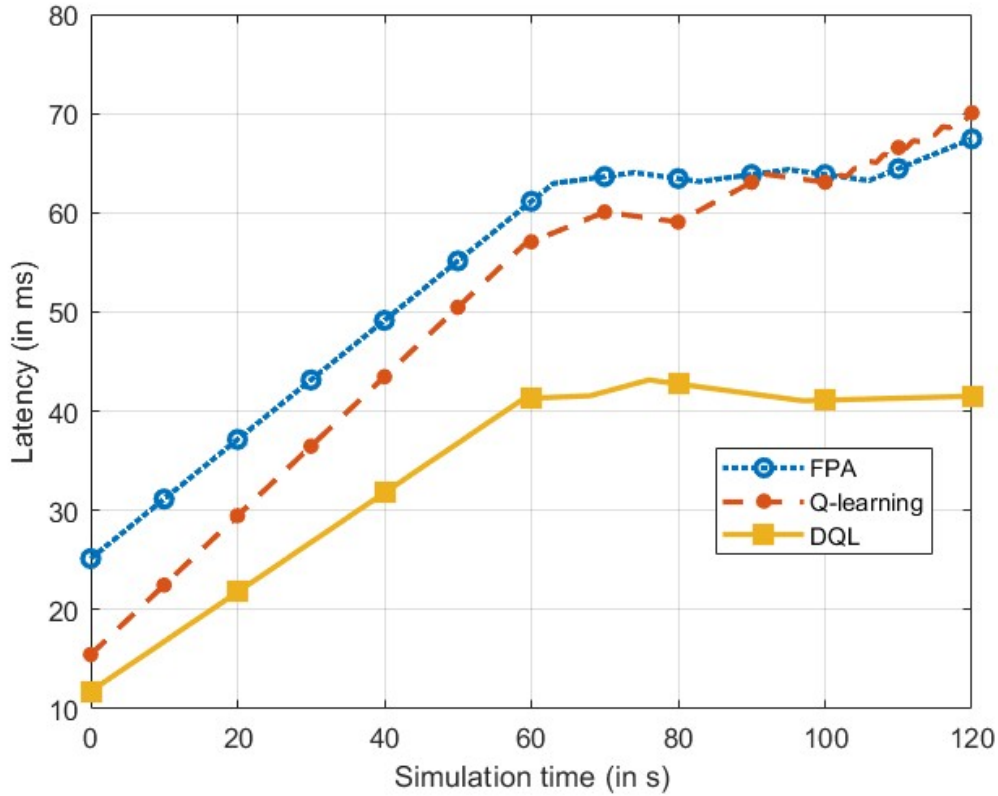


Figure 5.17: Latency at 120 m

Figure 5.16 shows SINR values for UAV @ 120 m. When no link adaptation is employed, i.e. when the FPA method is used. The values vary from very 1.34 dB to 5.36 dB. This represents an unstable link, as the SINR values vary drastically. For. e.g, at about the 31 s mark , there is a sharp drop to 1.45 dB from 5.05 dB for about 30 s. But at the 73 s mark it increases till 5.38 dB sharply in a 6 s duration before falling back to 41.38 ms, by the end of 100 s. After which, it increases again and does not stay constant. The periods of steady and stable values are lesser as compared to when the UAVs are at a lower height, for. e.g, between 0 and 26 s, and between 67 s and 73 s. As mentioned above, this is primarily because the FPA algorithm cannot take into account the changing interference conditions and at a higher altitude of 100 m, the increase of interfering elements leads to a change in

the number of interfering elements. This also coincides with the latency values, that see delays of up to 67.447 ms as shown in Figure 5.17

Q-learning starts with a lower value of 5.78 dB as compared to its 100 m performance. It maintain steady performance value of close to 6.8 dB till about 88 s. This is indicative of good performance for the link, however, after about 89 s it suffers a drastic dip in performance and undergoes a series of peaks and troughs till the end of simulation. When the simulation progresses, the Q-table becomes large and achieving the optimal solution becomes difficult. This is also reflected in the link latency as shown in Figure 5.17.

Finally DQL performs the best with an average, minimum and maximum values of 8.51 dB, 7.72 dB and 8.6354 dB respectively, which is indicative of steady performance with high SINR values. It also shows really low latency values of 43.15 ms. Even though it shows a 15.58 % decrease in SINR values and 26.87 % increase in latency values as compared to 100 m, it is still the best performing algorithm. It implements link adaptation absent from FPA and eliminates the need for Q-tables by the use of NNs.

It is to be noted that the overall performance of the UAV at 120 m is the worst as compared to 50 m and 100 m. The main cause for this is the fact that due to the higher altitude the number of interfering elements, i.e., gNBs that UAV has LoS with increases.

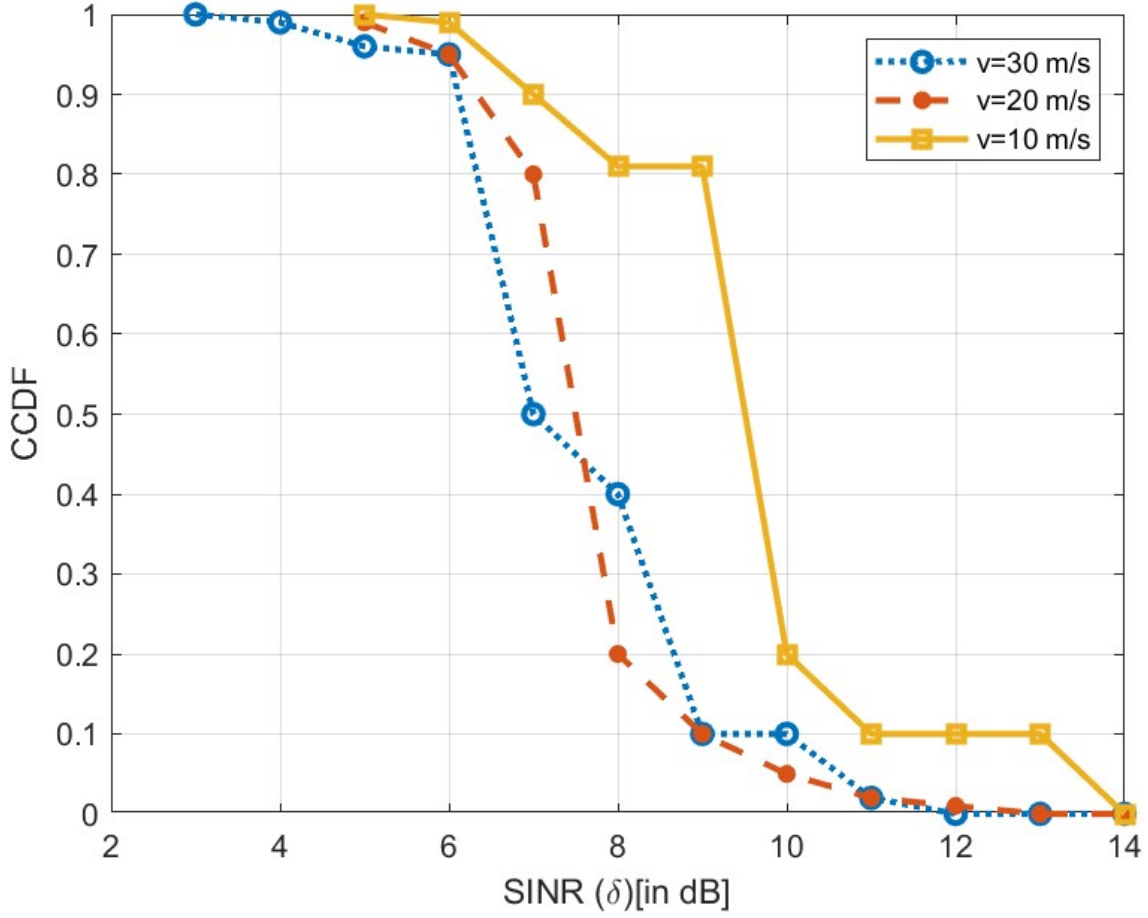
Figure 5.18: δ at different speeds of UAV

Figure 5.18 shows the SINR values for three different speeds of the UAV. It is seen that, with increasing speeds of the UAV, does not see any drastic changes in SINR values. The average δ value falls from about 9.5 dB at 10 m/s to 8.5 dB at 30 m/s. This is a clear indication that the DQL algorithm deals well with high speeds of the UAV. Table 5.7 summarises the results with different speeds. DQL learns ideal state-action pairs through online learning, this means that as the speed changes for the UAV, the agent learns that a new pair of state-actions will be the ideal, instead of the previous one. This means that even with varying speeds, the agent is able to compute appropriate actions. With speed being one of the unique properties of UAVs and a cause of interference in 5G connected UAVs,

adapting to this is a key enabler is solving the interference problem.

Table 5.7: δ at different speeds of UAV

UAV Speed	Average SINR
10 m/s	9.5 dB
20 m/s	9.5 dB
30 m/s	8.5 dB

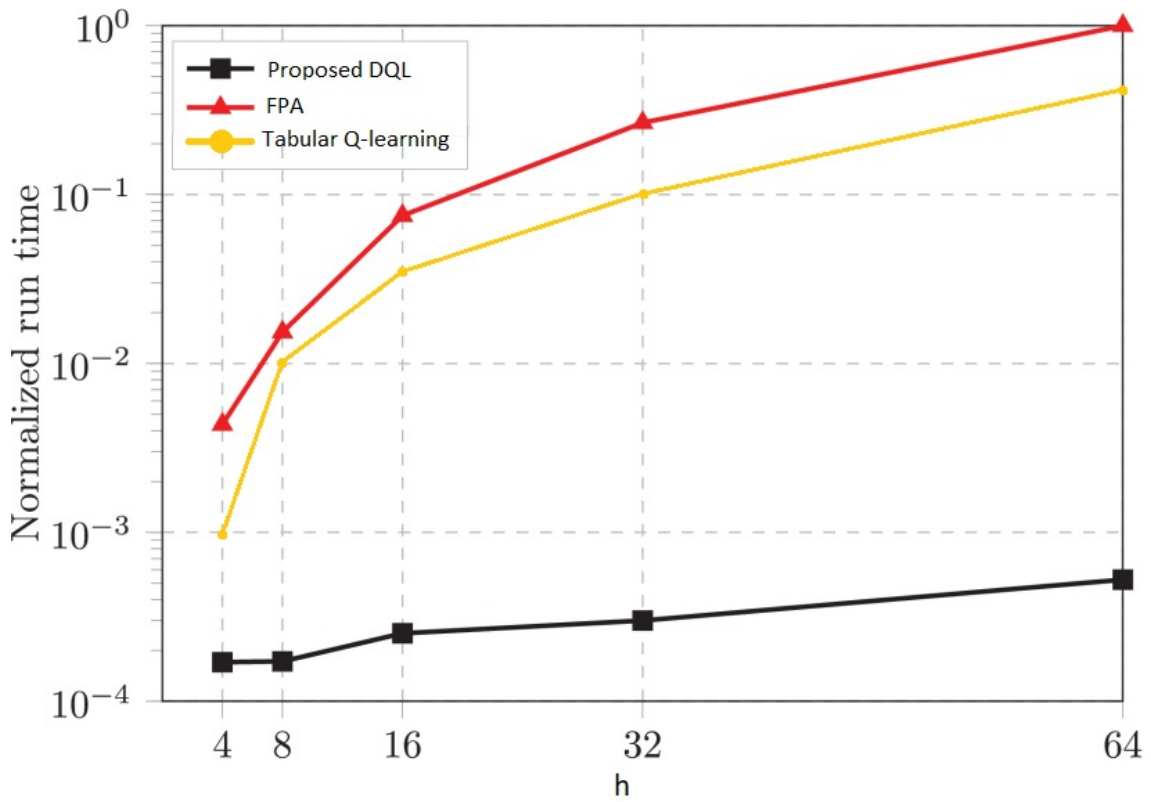


Figure 5.19: Normalised run times as a function of the no. of UAVs h

Figure 5.19 shows the observed normalised run time. Compared to FPA and tabular Q-learning, the proposed DQL algorithm has a shorter run time and performs better in terms of convergence and capacity. As the no. of UAVs h increases, run time complexity of FPA and tabular Q-learning increases rapidly, but the run time of DQL remains relatively low. At $h=4$, the DQL algorithm only took 4% of

the run time of the other two algorithms. This behaviour is observed, because the increase in h means that the number of interfering elements increase. FPA and tabular Q-learning are not able to accommodate these changing interfering conditions effectively, but the proposed DQL performs better than them.

Another way to visualise and evaluate an agent's performance during its training process is the reward plot. Figure 5.20 shows the reward plot for the proposed DQL method. As expected, the rewards are low in the beginning as the agent is learning to find the best solution, but it increases as the episodes progress, as the agent learns the best solution and keeps leveraging that knowledge as the proposed model employs a epsilon greedy policy.

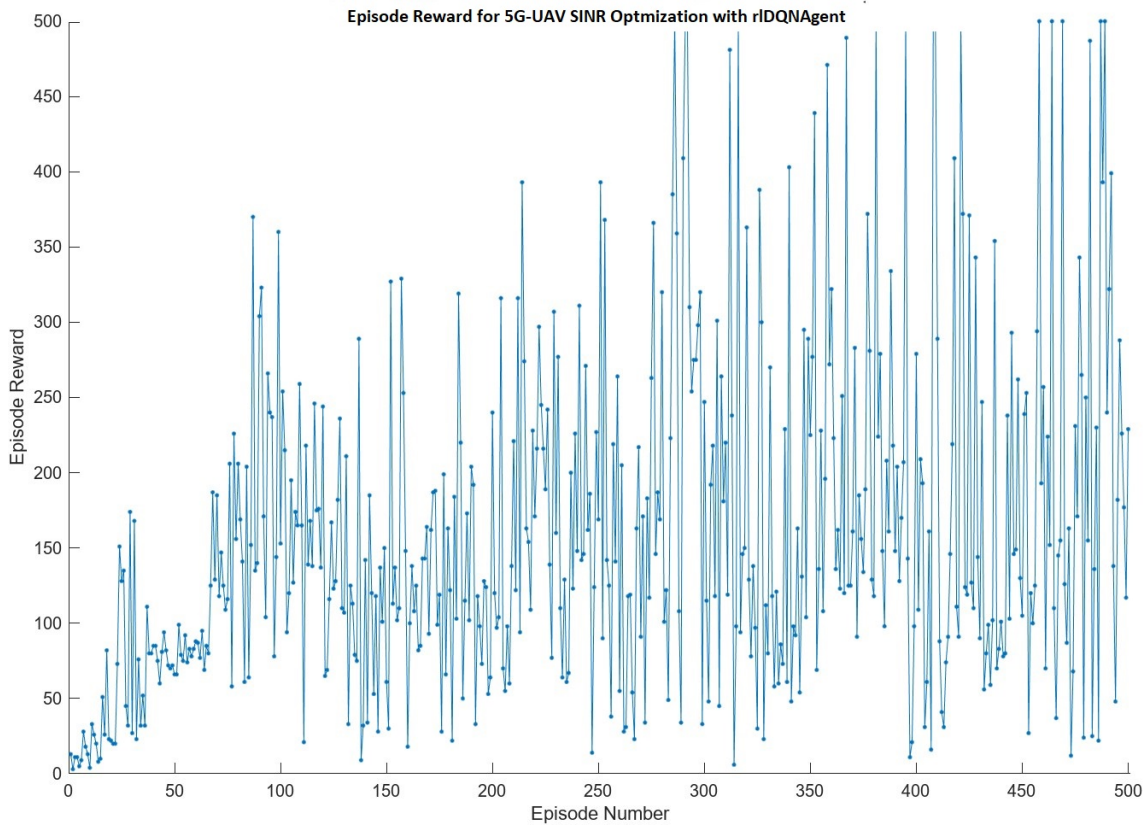


Figure 5.20: No. of episodes vs Rewards

5.7.3 Outcomes

In this section the outcomes of the performance measures are presented:

1. *Convergence*: It is observed that normalised convergence under (5.17) where, $\delta_0^{\text{thresh}} = 5$ dB. Each time step is equal to one radio sub-frame, with a duration of 1 ms. With an increase in the number of "h," the number of episodes necessary to achieve convergence also increases, with little to no impact on the threshold. δ_0^{thresh} since $h \gg \delta_0^{\text{thresh}}$
2. *Run time*: The normalised run time is observed. As h increases, the complexity of run-time complexity also increases for the proposed algorithm. This is justified because an increased number of interfering elements.
3. *Coverage*: Coverage is defined by $1 - F_r(\delta)$, which evidently improves everywhere. Coverage improves where δ increases monotonically.

Additionally, the proposed solution is compared against some of the state-of-art methods implemented in the environment used in our chapter. The following Table 5.8 summarises the results from, It is observed that the proposed DQL is considerably better than other method. SINR sees a 41.66 % increase while using DQL as compared to mean field game theory, the next best algorithm.

Table 5.8: Comparison of Results with State of Art

Reference	Algorithm	Average SINR Value
[66]	CNN	6 dB
[74]	Q-learning	6.5 dB
[75]	Mean-Field Game Theory	6.42 dB
[159]	Mean field Q learning	0.30 dB
[160]	PSO based Power Allocation	4 dB
<i>Proposed</i>	<i>Proposed</i>	9.095 dB

In Figure 5.21 the average SINR values of different methods as well as the proposed methods are plotted and observed that the proposed method performs better than existing methods in effectively mitigating interference. This can be explained by the following reasons: CNN often require large memory spaces to store the weights and activations of the convolutional layers, this results in large overhead and complex design as opposed to the proposed DQL. Mean field Q-learning has scalability limitations, unable to cope with a large number of agents and the consequent large growth of the action space. Particle swarm optimization can also be used for power allocation to mitigate interference. But this method is designed to exploit the best solutions in the search spaces to a global optimum, which may not be the best trade-off between exploration-exploitation. Mean field game-theory for interference mitigation is also one of the methods amongst existing works. However, this method is computationally complex, expensive and

challenging.

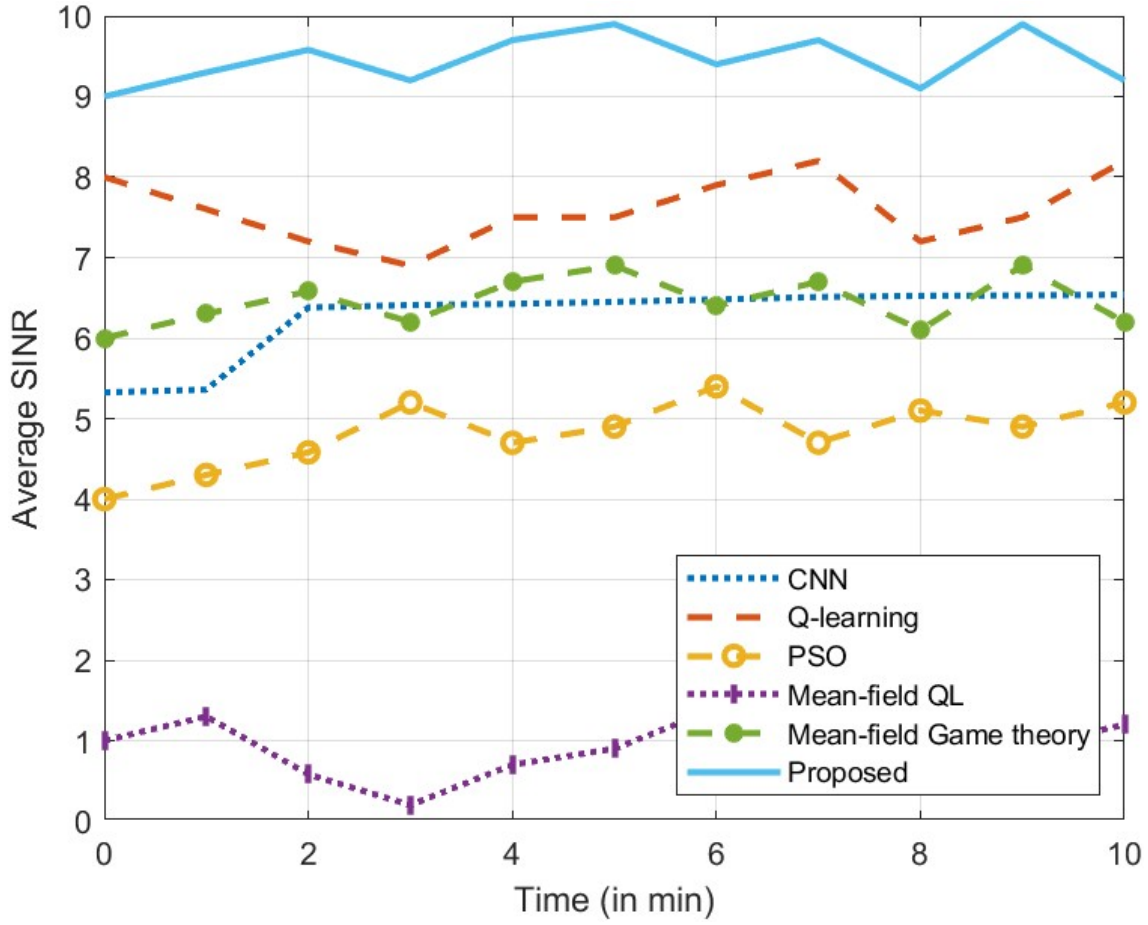


Figure 5.21: Comparison of Results with state-of-art

The proposed algorithm maximises the SINR of UAVs in a 5G network by using DRL for power control and interference mitigation. It overcomes the unique challenges posed by the 3D motion of UAVs and the resulting air-to-ground interference by leveraging the cloud-based architecture of 5G systems. The algorithm outperforms traditional algorithms like Q-learning and FPA. The proposed DQL requires the UAV to send its position coordinates and receive the SINR at each step of the way to the gNB. However, it has no previous information about the CSI, which effectively means that channel estimates and associated training sequences are not needed. Thus, overall UAV feedback is reduced when the UAV

sends its coordinates. Therefore, the interference mitigation proposed in this chapter surpasses existing methods, outperforming the next best algorithm by 41.66% and offers a solution to one of the major obstacles in the implementation of 5G-connected UAVs, namely air-to-ground interference.

5.8 Chapter Summary

Integrating autonomous Unmanned Aerial Vehicles (UAVs) with 5G networks presents a significant challenge due to network interference. UAVs' high altitude and propagation conditions, increases vulnerability to interference from neighboring 5G base stations (gNBs) in the downlink direction. This chapter proposes a novel Deep Reinforcement Learning Algorithm, powered by AI, to address interference through power control. By formulating and solving a SINR optimization problem using the DQL algorithm, interference is effectively mitigated, and link performance is improved. Performance comparison with existing interference mitigation schemes, such as FPA, tabular Q-learning, particle swarm optimization and game theory demonstrates the superiority of the DQL algorithm, where it outperforms by the next best method by 41.66 % and converges to an optimal solution faster. It also observed that, at higher speeds the UAV sees only a 10.52 % decrease in performance, which means the algorithm is able to perform effectively at high speeds. The proposed solution effectively integrates UAVs with 5G networks, mitigates interference, and enhances link performance, offering a significant advancement in this field.

Chapter 6

Conclusion and Future Work

The future of UAV-5G integration holds significant promise and is poised to revolutionize various industries and sectors. UAV-5G integration will provide enhanced connectivity, enabling UAVs to operate more effectively and reliably in diverse environments, including remote and urban areas. This improved connectivity will facilitate real-time data transmission, enabling applications such as surveillance, monitoring, delivery services, and disaster response.

6.1 Conclusion

UAVs necessitate continuous communication with ground stations to ensure uninterrupted data flow. Among the critical parameters influencing the implementation of the UAV-5G integrated architecture, the mobility model holds significant importance. The work done in this thesis, specifically Chapter 3, develops a mobility architecture that integrates UAVs with 5G communication systems. Specifically, it focuses on urban environments and devises an entropy-weighted

decision algorithm to facilitate seamless handover. Through simulation, the efficacy of this algorithm is demonstrated in achieving seamless HO between 5G and LTE networks. The methodology incorporates RSS-based selection, employing the EWM for decision-making. Graphical representations of the results illustrate orderly switching, with three scenarios evaluating varying UAV speeds and their corresponding effects. The findings attest to the algorithm's capability to address the high-speed and mobility challenges inherent to UAV operations. Ensuring uninterrupted connectivity for UAVs in remote and dynamic settings poses a formidable challenge. Chapter 4 of this thesis presents a pioneering approach to this issue, leveraging graph theory to develop a decision-making algorithm for optimizing HOs between terrestrial and satellite communication networks. Through a dynamic network node model and considering factors like RSS, SNR, and elevation angle, the research demonstrates seamless transition between communication links. Extensive simulations and comparisons with existing solutions underscore significant improvements in key metrics such as RSS, SNR throughput, latency, and ping-pongs, ultimately enhancing UAV connectivity. This graph-based seamless HO solution represents a crucial advancement in facilitating reliable communication for UAVs operating in challenging environments, thereby pushing the boundaries of UAV technology. In Chapter 5 of this thesis, an interference mitigation algorithm is proposed that aims to maximize SINR for UAVs within a 5G network, employing DQL for power control and interference mitigation. Addressing challenges posed by the 3D motion of UAVs and resultant air-to-ground interference, it leverages the cloud-based ar-

chitecture of 5G systems. Outperforming traditional algorithms like Q-learning and FPA, the proposed DQL requires UAVs to transmit their position coordinates and receive SINR feedback at each step toward the gNB. Despite lacking previous information about CSI, the algorithm eliminates the need for channel estimates and associated training sequences. Consequently, UAV feedback is reduced when transmitting coordinates.

6.2 Future Work

However, there are some limitations with the EWM. As noted in the results, above 400 ft., the UAV drops the session. It typically assumes static weights for input parameters throughout the decision-making process. However, in highly dynamic environments where the importance of certain factors changes over time, this lack of adaptability can limit the method's effectiveness in accurately reflecting evolving decision contexts. Further research directions must focus on improving this method. The graph theory algorithm proposed is not without its constraints. Notably, in the context of exceptionally extensive networks, the application of the GM necessitates augmented storage capacities, posing a potential challenge in deployment scenarios involving UAVs. It is anticipated that forthcoming advancements in storage hardware will offer a viable resolution to this issue. Additionally, this work does not delve into the satellite visibility problem, working under the assumption that the UAV sees the satellite all the time. However, LEO satellites have a short visibility time ranging from 240 s to 1200 s necessitating satellite-to-satellite HO (not part of the scenario considered for this work), which

would be a potential next step from this to fully integrate the space-based satellite network, including GEO satellites. DQL presents some challenges, especially as they are prone to overestimation or underestimation of Q-values, particularly when using function approximation with deep NNs. This can lead to suboptimal policies and reduced learning efficiency, especially in environments with sparse rewards or complex dynamics. Balancing exploration (trying new actions to discover optimal policies) and exploitation (leveraging known information to maximize rewards) is crucial in reinforcement learning. DQL algorithms often struggle to find the right balance, leading to either excessive exploration, which can be inefficient, or premature convergence to sub optimal solutions due to excessive exploitation. Future research must focus on optimizing such ML algorithms, to implement optimal policies for power control and thus, mitigate interference effectively.

The future of UAV-5G integration is promising, with the potential to revolutionize various industries and sectors by enabling autonomous, connected, and intelligent UAV operations at scale. As technology continues to advance and regulatory frameworks evolve, UAVs integrated with 5G networks will play an increasingly important role in shaping the future of transportation, communication, and data-driven decision-making. With the advent of 6G technology on the horizon, further exploration and integration of UAVs with even more advanced communication networks hold the promise of unlocking new frontiers in aerial connectivity and autonomy, thereby further advancing the capabilities and applications of UAV technology.

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