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DOCTORAL THESIS

Towards Resilient and Secure Beyond-5G Non-Terrestrial Networks (B5G-NTNs): An End-to-End Cloud-Native Framework

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This thesis entitled "*Towards Resilient and Secure Beyond-5G Non-Terrestrial Networks (B5G-NTNs): An End-to-End Cloud-Native Framework*", by *Henok Berhanu Tsegaye*, Student ID: 228992, Class of 2021 (37th cycle) has been approved for submission to the Department of Information Engineering and Computer Science (DISI), University of Trento, in partial fulfillment of the requirements for the Doctor of Philosophy (PhD) in Information Engineering and Computer Science.

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Declaration

I declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this or any other university. This dissertation is my work and contains nothing that is the outcome of work done in collaboration with others except as specified in the text and Acknowledgements.

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It always seems impossible until it is done!

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Abstract

Integrating Terrestrial and Non-Terrestrial Networks (NTNs) within Beyond-5G (B5G) and future 6G ecosystems represents a transformative advancement in achieving ubiquitous, resilient, and scalable communication services. NTNs, including Low Earth Orbit (LEO) satellites, Unmanned Aerial Vehicles (UAVs), and High Altitude Platform Systems (HAPS), extend traditional terrestrial networks by providing continuous connectivity in remote, underserved, and connection-critical scenarios such as disaster-hit regions and rural areas. This thesis deals with an end-to-end cloud-native framework that leverages cutting-edge technologies, including Multi-Access Edge Computing (MEC), Software-Defined Networking (SDN), Network Function Virtualization (NFV), blockchain, and advanced AI/ML models, to enhance service availability, security, and Quality of Service (QoS) in 3D NTN environments.

The research first explores the deployment of disaggregated Next-Generation Radio Access Networks (NGRANs) across terrestrial and non-terrestrial domains using a Kubernetes-based architecture. A Graph Neural Network (GNN) model is developed to monitor and manage these networks, detecting link failures and optimizing traffic routing paths between terrestrial and satellite components. The GNN model achieves an 85% accuracy in link failure detection and significantly reduces end-to-end delays in NTN deployments, highlighting the potential of AI-driven network management in enhancing overall network resilience.

To address the challenge of dynamic resource management in NTNs, this thesis investigates the implementation of functional splits, such as F1 and E1 interfaces, between terrestrial control units (gNB-CU) and satellite-based distributed units (gNB-DU). The study employs Long Short-Term Memory (LSTM) neural networks to predict resource utilization, specifically CPU, memory, and bandwidth of satellite payloads. These predictive models enable proactive monitoring and resource allocation decisions, ensuring efficient use of limited computational resources and maintaining high levels of network performance.

Security remains a critical concern in NTNs due to decentralized and open 5G satellite communications. A blockchain-based authentication framework is proposed to mitigate these risks, enhancing the security of data exchanges and remote firmware updates in LEO satellite constellations. Blockchain technology provides a decentralized, transparent, and immutable security framework, improving authentication efficiency and protecting against unauthorized

access, though with trade-offs in network performance, such as increased latency and reduced throughput. This approach makes the hybrid B5G NTN network secure, reinforcing the integrity and confidentiality of communication channels, which is essential for emerging services and applications.

Furthermore, this thesis comprehensively evaluates MEC-based experimental testbeds that demonstrate service resiliency in NTNs during terrestrial network outages. The MEC deployments allow seamless transitions to satellite access networks, ensuring service continuity and improving QoS. These testbeds showcase the capability of cloud-native technologies in maintaining service availability, highlighting their critical role in resilient NTN networks.

The findings of this thesis demonstrate that integrating cloud-native architectures, blockchain-based security mechanisms, and advanced AI/ML models significantly enhances the resilience, security, and resource efficiency of NTNs. These innovations pave the way for robust, adaptive, and secure communication systems, supporting the seamless deployment of critical B5G and 6G applications across diverse and challenging environments. This research provides valuable insights into designing and implementing resilient NTNs, setting the foundation for future advancements in global connectivity and intelligent network management.

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AUTHORS LIST OF PUBLICATION

The following peer-reviewed conference papers are accomplished within the time frame of the doctoral program:

1. H. B. Tsegaye and C. Sacchi, "MEC-based Experimental Framework for Service Availability in 3D Non-Terrestrial Networks," 2024 IEEE Aerospace Conference, Big Sky, MT, USA, 2024, pp. 1-10, doi: 10.1109/AERO58975.2024.10521118.
2. H. B. Tsegaye and C. Sacchi, "Graph Neural Network-based C-RAN Monitoring for Beyond 5G Non-Terrestrial Networks," 2024 11th International Workshop on Metrology for AeroSpace (MetroAeroSpace), Lublin, Poland, 2024, pp. 338-343, doi: 10.1109/MetroAeroSpace61015.2024.10591610.
3. Y. M. Worku, Henok B. Tsegaye et al., "Blockchain-Enhanced Security for LEO Satellite Firmware Updates in Beyond-5G NTN Networks," Accepted, in press to IEEE International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD) Conference, Athens, Greece, 2024.
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5. Y. M. Worku, Henok B. Tsegaye et al., "LSTM-A2C Reinforcement Learning for UAV Trajectory Optimization in Dynamic 6G-Enabled IoT Surveillance Networks," Submitted to IEEE Virtual Conference on Communications (VCC) Conference, 2024.
6. L. Valcarenghi, Henok B. Tsegaye et al., "5G New Radio Techniques for 3D Networks in Connection-critical Scenarios," 2024 IEEE Aerospace Conference, Big Sky, MT, USA, 2024, pp. 1-9, doi: 10.1109/AERO58975.2024.10521105.
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Nomenclature

Acronyms

$3GPP$ 3rd Generation Partnership Project

$C-RAN$ Cloud-Radio Access Netwotk

CSP Communication Service Provider

$eMBB$ Enhanced Mobile Broadband

GEO Geostationary Earth Orbiting

$gNB-CU$ gNB Centralized Unit

$gNB-CUCP$ gNB Centralized Unit Control Plane

$gNB-CUUP$ gNB Centralized Unit User Plane

$gNB-DU$ gNB Distributed Unit

GNN Graph Neural Network

$HAPs$ High Altitude Platform Stations

IAB Integrated Access and Backhaul

ISL Internet Service Provider

ITU International Telecommunication Union

KPI Key Performance Indicator

LEO Low Earth Orbit

$LSTM$ Long Short-Term Memory

MEC Multi-Access Edge Computing

MEO Medium Earth Orbiting

$mMTC$ Massive Machine Type Communication

NFV Network Function Virtualization

$NG-RAN$ Next Generation Radio Access Network

$NR-UE$ New Radio User Equipment

NTN Non-Terrestrial Network

$PLMN$ Public Land Mobile Network

RL Reinforcement Learning

SDN Software-Defined Networking

SRI Satellite Radio Interface

UAS Unmanned Aircraft system

UAV Unmanned Aerial Vehicle

$URLLC$ Ultra-Reliable and Low Latency Communications

Chapter 1

Introduction to 5G Non-Terrestrial Networks (5G-NTN)

1.1 Introduction

The continuous demand for enhanced connectivity, increased data rates, and extended coverage areas have marked the evolution of mobile communication systems. While terrestrial 5G networks have made significant strides in delivering ultra-reliable, low-latency communication, their geographic limitations leave remote and underserved regions without access to advanced connectivity solutions. To address these challenges, 5G Non-Terrestrial Networks (5G-NTNs) have emerged as a transformative extension of traditional terrestrial networks, integrating satellite and airborne platforms into the broader 5G ecosystem.

5G-NTNs aim to provide ubiquitous connectivity, bridging the gap between urban centers and remote areas, oceans, and airspaces where terrestrial infrastructure is sparse or nonexistent. This integration extends the reach of 5G. It enhances the overall resilience and flexibility of the network by leveraging the unique capabilities of Low Earth Orbit (LEO) satellites, High Altitude Platform Stations (HAPS), and other airborne technologies. These non-terrestrial platforms operate in regenerative modes, carrying key network functions such as the distributed unit (gNB-DU) and the user plane of the central unit (gNB-CUUP), thus enabling advanced architectures and communication strategies.

Recent advancements in satellite technology, miniaturization, and launch cost reduction have made LEO satellites a viable component of 5G-NTNs. These satellites offer lower latency than traditional geostationary satellites, enabling them to support latency-sensitive applications such as real-time communication, autonomous vehicles, and Industry 4.0 processes. The integration of 5G-NTNs is not merely a technical enhancement but a pivotal step toward realizing a truly connected world, providing seamless coverage and improved quality of service across diverse environments.

In the scope of 5G-NTNs, resource management and optimization are critical challenges due to these networks' dynamic and heterogeneous nature. Deploying key network components as satellite payloads introduces unique bandwidth, latency, and resource utilization constraints. To address these challenges, this research explores advanced predictive approaches using machine learning techniques such as Long Short-Term Memory (LSTM) neural networks to forecast the resource consumption of gNB-DU and gNB-CUUP components deployed in non-terrestrial platforms. By accurately predicting CPU, memory, and bandwidth usage, the proposed approach aims to enhance network resilience through proactive monitoring and resource allocation decisions.

The study evaluates two distinct configurations for disaggregated RAN architectures within 5G-NTNs: one utilizing a split between gNB-CU and gNB-DU over the F1 interface and another incorporating both F1 and E1 splits, with gNB-CUUP deployed as a satellite payload. The findings demonstrate the effectiveness of the LSTM-based approach in predicting resource utilization, highlighting the advantages of combined F1 and E1 split configurations for improved network efficiency and resilience. This novel architecture, characterized by its flexibility and enhanced resource allocation, sets the groundwork for future 5G-NTNs that are robust, scalable, and capable of supporting the ever-growing demands of modern communication networks.

The integration of blockchain technology further enhances the security and reliability of 5G-NTNs by securing communication across satellite components. This approach facilitates seamless and secure traffic flow between terrestrial and non-terrestrial segments, supporting mission-critical applications in various sectors, including intelligent manufacturing, IoT, and beyond.

In conclusion, 5G-NTNs represent a critical evolution in the global communications landscape, promising to extend the benefits of 5G to all corners of the world. The integration of advanced machine learning models for resource prediction and blockchain for security will play a pivotal role in realizing the full potential of these networks, ensuring that they are efficient, resilient, secure, and scalable for future applications.

1.2 Background and Motivation

1.2.1 Overview of 5G and Non-Terrestrial Networks

The evolution of 5G networks and advancements in aerial and space communication technologies have introduced unprecedented opportunities for ubiquitous connectivity, higher capacity, and broader coverage. With its promising capabilities, 5G has the potential to support a wide range of applications across various sectors. This advancement has led to new network architectures incorporating NTN to provide fully automated ubiquitous service. These 3D NTNs offer substantial coverage, capacity, and flexibility advantages over traditional terrestrial networks. These networks encompass diverse communication platforms, including satellites, drones, and deep-sea sensors, enabling communication and data exchange in remote or challenging environments [21], [25].

Integrating NTNs with terrestrial 5G networks supports various applications across diverse sectors, such as autonomous vehicles, remote healthcare, disaster response, and the Internet of Things (IoT). NTNs provide essential links that ensure continuous data exchange and connectivity even when terrestrial networks are compromised [47]. The inclusion of satellites as global interconnection nodes allows NTNs to function as critical infrastructures in 5G and beyond, collecting data from areas with limited or disrupted connectivity [31, 82]. This capability is crucial for achieving the vision of ubiquitous, high-speed communication, a foundational goal of 5G and future 6G networks.

NTNs comprise various communication platforms, including regenerative satellites, transparent satellite access systems, and hybrid configurations seamlessly integrating terrestrial and non-terrestrial components [102, 101]. Regenerative satellites carry network functions, such as gNB-CU and gNB-DU, as payloads, enabling end-to-end connectivity and service continuity even when terrestrial infrastructure fails. On the other hand, transparent satellites act as relays between User Equipment (UE) and ground stations, facilitating communication without processing the signal onboard.

LEO satellites mainly play a transformative role in NTNs. Unlike traditional Geostationary Earth Orbit (GEO) satellites, LEO satellites orbit closer to the Earth, significantly reducing latency and enhancing data throughput. Companies like SpaceX's Starlink and OneWeb are leading this revolution by deploying dense constellations of LEO satellites to provide global high-speed Internet access [11]. These constellations are designed to offer resilient connectivity that supports low-latency, high-bandwidth applications, making them a cornerstone of modern NTNs.

1.3 Cloud-Native Technologies for 5G-NTN Networks

Cloud-native technologies are increasingly central to the deployment and management of 5G Non-Terrestrial Networks (NTNs), which include Low Earth Orbit (LEO) satellites, Unmanned Aerial Vehicles (UAVs), and High Altitude Platform Systems (HAPS). These technologies facilitate the design of scalable, flexible, and resilient network architectures capable of supporting the complex, dynamic, and distributed nature of NTNs. By leveraging principles such as containerization, microservices, orchestration, and virtualization, cloud-native technologies enhance the efficiency and adaptability of 5G-NTNs, enabling them to meet the stringent demands of modern and future communication networks.

Cloud-native technologies are pivotal for developing and deploying 5G Non-Terrestrial Networks (NTN), which integrate satellite and aerial systems with traditional terrestrial networks. This integration aims to enhance connectivity and service delivery across diverse environments, particularly in areas with limited or non-existent terrestrial infrastructure.

1.3.1 Overview of Cloud-Native Technologies

Cloud-native architecture utilizes microservices, containers, and orchestration tools like Kubernetes to build scalable, resilient, and easily deployable applications across cloud environments. This methodology allows for rapid development and deployment of new services, essential for meeting the dynamic demands of 5G networks. The cloud-native 5G core, designed from the ground up for cloud environments, facilitates improved operational efficiency and faster time-to-market for innovative services.

Key Components of Cloud-Native Technologies:

Containerization: Containerization, primarily enabled by platforms like Docker, packages network functions and applications into lightweight, portable units that can run consistently across different environments. For NTNs, containerization ensures network services can be deployed quickly and efficiently on various platforms, including satellite payloads and edge computing nodes, without extensive reconfiguration. This flexibility is crucial in NTNs, where computational resources are often limited and must be utilized optimally.

Microservices Architecture: The microservices approach decomposes traditional monolithic applications into smaller, independent services that can be developed, deployed, and scaled individually. In 5G-NTNs, this modular design allows specific network functions, such as traffic management or security, to be updated or scaled without disrupting the entire network. This adaptability is essential in dynamic NTN environments, where rapid changes in traffic patterns or network conditions require immediate responses.

Orchestration with Kubernetes: Kubernetes is the leading orchestration platform for managing containerized applications at scale. In 5G-NTNs, Kubernetes automates network functions' deployment, scaling, and management across terrestrial and non-terrestrial nodes, ensuring optimal performance and resource allocation. Kubernetes supports self-healing capabilities, automatically detecting and replacing failed services, which enhances network resilience and reliability, especially in NTNs where maintaining service continuity is critical.

Network Function Virtualization (NFV): NFV plays a pivotal role in the cloud-native architecture of 5G-NTNs by virtualizing network functions traditionally implemented in dedicated hardware. This virtualization allows network functions like gateways, firewalls, and load balancers to run on generic hardware across the NTN infrastructure. NFV enhances the flexibility and scalability of NTNs, allowing network operators to deploy and manage services dynamically in response to changing demands.

Multi-Access Edge Computing (MEC): MEC brings cloud computing capabilities closer to end-users by deploying compute resources at the network edge, such as at satellite gateways or terrestrial base stations. In 5G-NTNs, MEC reduces latency by processing data locally, minimizing the need for long-distance transmissions to centralized data centers. This proximity is particularly beneficial for time-sensitive applications, such as remote monitoring, autonomous vehicle coordination, and emergency response, where real-time data processing is essential.

1.3.2 Importance and Challenges of Cloud-Native in 5G-NTN

a) **Flexibility and Scalability**: Cloud-native architectures enable communication service providers (CSPs) to scale services efficiently, adapting quickly to changing market demands and user needs. This is particularly important in NTN scenarios where network conditions can vary significantly due to geographical and environmental factors.

b) **Resilience and Self-Healing**: Cloud-native orchestration tools like Kubernetes enhance the resilience of NTNs by providing self-healing capabilities. In the event of a network failure, such as a disrupted satellite link or malfunctioning network function, Kubernetes can automatically redeploy the affected services on alternative nodes, maintaining service continuity and minimizing downtime.

c) **Resource Efficiency**: Cloud-native platforms' dynamic resource allocation capabilities allow 5G-NTNs to optimize limited computational resources on satellite payloads and edge nodes. By virtualizing and orchestrating network functions, NTNs can adapt to real-time conditions, ensuring that resources are used efficiently and effectively across the entire network.

d) **Improved Network Management**: Cloud-native technologies facilitate centralized control and management of NTNs through tools like SDN controllers, which can dynamically adjust traffic flows, reconfigure network paths, and optimize performance. This centralized management capability is precious in NTNs, where complex interactions between terrestrial and non-terrestrial components require continuous monitoring and adjustment.

e) **Enhanced Security and Isolation**: Containerization and microservices provide enhanced security by isolating individual network functions, reducing the risk of systemic failures from localized threats. This isolation is crucial in NTNs, where the distributed nature of the network makes it vulnerable to various cyber threats. Cloud-native security tools can also be integrated into the orchestration process, providing automated monitoring and rapid response to potential security incidents.

f) **Enhanced Service Delivery**: By leveraging cloud-native technologies, CSPs can implement network slicing, allowing them to customize network performance for specific applications, such as IoT or emergency services, critical in NTN contexts.

g) **Integration of Diverse Networks**: The combination of cloud-native technologies with NTN facilitates the seamless integration of satellite and aerial networks with terrestrial systems. This integration supports a unified service delivery model to enhance global connectivity and service availability, especially in remote or underserved areas.

h) **Automation and Efficiency**: Cloud-native approaches promote automation in network management, reducing operational costs and improving service reliability. This is crucial for managing the complexities introduced by NTNs, which must simultaneously handle various connectivity and service requirements.

Cloud-native technologies are essential for the evolution of 5G NTN networks. They enable greater flexibility, scalability, and efficiency in service delivery while addressing the unique challenges posed by integrating non-terrestrial and terrestrial systems.

While cloud-native technologies offer numerous advantages for 5G-NTNs, they also introduce challenges that must be addressed. The complexity of managing highly distributed, dynamic environments requires advanced orchestration and automation tools that can handle NTNs' unique requirements. Additionally, the integration of AI/ML models to enhance orchestration decisions, optimize resource utilization, and ensure efficient management of network functions is an area of ongoing research.

Future directions in cloud-native technologies for NTNs include the development of lightweight containerization platforms specifically optimized for resource-constrained environments, such as satellite payloads. Additionally, the integration of edge intelligence—embedding AI capabilities directly at the edge nodes—can further enhance the adaptability and resilience of NTNs, enabling real-time decision-making and proactive network management.

In conclusion, cloud-native technologies are foundational to the evolution of 5G-NTNs, providing the scalability, flexibility, and resilience needed to support diverse and complex communication services. By leveraging containerization, microservices, orchestration, and edge computing, NTNs can meet the demands of modern and future networks, offering reliable and efficient connectivity in even the most challenging environments.

1.4 5G-NTN Integration Networks and Standards

An NTN can be deployed in various configurations depending on the type of platform used, as shown in Table 1.1. These platforms are broadly categorized into two main groups: spaceborne and airborne. Spaceborne platforms are usually classified based on three key factors: their altitude, the size of their beam footprint, and their orbital characteristics.

Table 1.1 Types of NTN platforms [5]

Platforms	Altitude Range	Orbit	Beam Footprint Size
GEO satellite	35786 km	Fixed position in terms of elevation/azimuth	200-3500 km
MEO satellite	7000-25000 km	Circular around Earth	100-1000 km
LEO satellite	300-1500 km	Circular around Earth	100-1000 km
UAS platform	8-50 km	Fixed position in terms of elevation/azimuth	2-200 km

Spaceborne platforms can be differentiated as:

Geostationary Earth Orbiting (GEO): has a circular and equatorial orbit around Earth at 35786 km altitude, and the orbital period is equal to the Earth's rotation period. The GEO appears fixed in the sky to the ground observers. GEO beam footprint size ranges from 200 to 3500 km.

Medium Earth Orbiting (MEO): has a circular orbit around Earth, at an altitude varying from 7000 to 25000 km. MEO beam footprint size ranges from 100 to 1000 km.

Low Earth Orbiting (LEO): has a circular orbit around Earth, at an altitude between 300 to 1500 km. LEO beam footprint size ranges from 100 to 1000 km.

LEO and MEO satellites, also known as non-GEO (NGSO) satellites, orbit the Earth in less time than the Earth's rotation period, ranging from 1.5 to 10 hours. The airborne category includes Unmanned Aircraft Systems (UAS), typically operating at altitudes between 8 and 50 km, with High Altitude Platform Systems (HAPS) positioned around 20 km. Like GEO satellites, UAS can maintain a fixed position in the sky relative to a specific ground point, and their beam footprint sizes range from 5 to 200 km. Both spaceborne and airborne platforms can be configured with either transparent or regenerative payloads, depending on the functions carried onboard. The platform handles only radio frequency filtering, conversion, and amplification in a transparent payload configuration. In contrast, the regenerative payload configuration involves implementing all gNB functions directly onboard the satellite or UAS platform.

In addition to space/airborne platforms, the NTN access is featured by the following components:

- **NTN terminal** refers to either the 3GPP User Equipment (UE) or a specific satellite terminal. Tiny aperture terminals operate in the radio frequency of the Ka-band (i.e., 30 GHz in the uplink and 20 GHz in the downlink). In contrast, handheld terminals operate in the radio frequency of S-band (i.e., 2 GHz).
- **NTN gateway** is a logical node connecting the NTN platform with the 5G core network.
- **Service link** is the radio link between the NTN terminal and the NTN platform.
- **Feeder link** is the radio link between the NTN gateway and the NTN platform.

1.4.1 Non-terrestrial Networks in 5G Systems

Until a couple of decades ago, the satellite and terrestrial networks were considered to be independent and were developing separately from each other. These two networks are viewed differently from the current-generation wireless technology (i.e., 5G) onward. The 3GPP standardization has already completed the first 5G NR specifications and progressed on solutions to support the NTN in 5G NR systems [75]. In addition, several projects like SAT5G [77], as part of the H2020 5G PPP initiative [102], targeted to propose cost-effective solutions to provide 5G connectivity everywhere and to create new opportunities in the 5G world market.

Service continuity is one of the key requirements to be ensured when the 5G NTN NG-RAN is integrated with the 5G NR terrestrial RAN or with another 5G NTN NG-RAN [5]. The requirement of service continuity between the two NG-RANs means that the specification support should enable a seamless handover between the systems without a service interruption and a fluent IDLE mode UE operation for optimal network selection.

The NTN segment, when combined with the terrestrial network, plays an essential role in achieving global coverage owing to boosting capacity (as a result of high-frequency reuse and precoding techniques) and ensuring service continuity even when traveling. In [51], architectural and technical issues have been discussed for 5G systems, including the NTN, whereas in [129], the effect of NTN integration into the mobile systems has been assessed through an experimental comparison in terms of the Key Performance Indicators (KPIs).

Integrating terrestrial and non-terrestrial networks is thus considered an attractive solution for 5G technology development. In the past couple of years, multiple research works have investigated a combination of two radio access networks. The authors in [78] were the first to provide a review on Space-Air-Ground Integrated Networks (SAGIN), where the system performance has been improved by exploiting deep learning methods for traffic balancing purposes [64].

In [26], a new perspective on integrated systems has been presented by discussing Software Defined Space-Terrestrial Integrated Networks based on Software Defined Networking (SDN) [102], which separates the control plane from the data plane. In [47], the integration of non-terrestrial and terrestrial networks has been simplified by introducing a new architecture that combines SDN and Network Function Virtualization (NFV), which implements specific hardware functionalities via software.

Security is one of the essential concerns in NTN communications. Several works in the literature tackled this issue in integrated NTN-terrestrial networks, wherein cognitive radio is introduced to improve spectrum utilization when the NTN and the cellular network share the same bandwidth. The authors in [71] investigated the physical layer security and proposed a stochastic beamforming approach. Multi-antenna terrestrial base stations were employed as a source of green interference to enhance the security of NTN communications in [14], [72], and [123].

In [37], a cooperative secure transmission beamforming scheme has been designed to assess the communications security in NTN-terrestrial systems and the secrecy rate has been maximized under the power and transmission quality constraints. In [22], the secrecy performance has been analyzed while considering the connectivity in a multiantenna NTN with terrestrial recipients (i.e., downlink direction) via multiple cooperative relays and in the presence of several eavesdroppers. In [13], different adaptive transmission schemes have been addressed to analytically obtain the expression for the achievable channel capacity in hybrid NTN-terrestrial relay networks.

A joint opportunistic relay selection scheme has been proposed in [52] to enhance the system's protection against attacks. Three typical attack approaches have been described in [56] to illustrate possible threats to NTN security. Unlike previous works where cooperation has been adopted for cognitive NTN-terrestrial networks, in [29], a noncooperative game with limited information exchange was constructed to address the power control problem in the case of spectrum sharing between the NTN and the terrestrial network.

In [16], a standalone GEO satellite NG-RAN has been addressed to deliver multi-layer video services in the forthcoming 5G NR deployments by following a novel RRM strategy for efficient resource allocation that provides several multimedia video flows. Further, in [48], path-based network coding has been proposed for achieving better reliability and time-efficient distribution of traffic in NTN-terrestrial mobile systems. A standalone LEO NG-RAN has been considered for 5G mMTC services in [67], where an uplink scheduling technique has been outlined to make the differential Doppler shift tolerable by the MTC devices.

However, integrating LEO satellites with the 5G technology is not straightforward because of the challenging LEO features, such as the Doppler effect, high-speed mobility around Earth, and a smaller coverage area than the GEO satellite. These factors lead to the construction of LEO constellations for providing global coverage. In [34], an enabling network architecture with dense LEO constellations has been designed to offer enhanced reliability and flexibility in integrated NTN-terrestrial systems.

In a constellation, LEOs are interconnected via ISL, and owing to the onboard processing capabilities of a regenerative payload-based LEO, data transmissions may occur directly between the LEO satellites. In [88], analytical models have been coined for determining the probabilities of call blocking and handover failure in a constellation of regenerative payload-based LEOs. In the case of transparent payload-based LEO, data traffic must be routed to the terrestrial network, thus entailing vertical handover situations.

To ensure connection transfers without harmful interruptions over the heterogeneous wireless access technologies, seamless handover becomes a challenging matter. In [38], a strategy based on positioning has been considered to minimize the delay and to manage the inter-satellite handover in satellite communications (when a handover occurs, the nearest satellite is selected as the access satellite), whereas in [118] stochastic and deterministic optimization problems have been constructed to support handover in heterogeneous aeronautical networks with an SDN controller.

In addition to SDN and NFV [25, 74, 42], 5G supports Network Slicing [93] and Edge Computing (EC) [40]. The former ensures better scalability, higher availability, and overall resource optimization by providing specific network capabilities and characteristics with a logical network customized based on service requirements. The latter shifts computing and storage resources closer to the user, thus supporting lower latency. These two concepts were also adopted for 5G satellite networks in [124], [106], and [15].

In [124], 5GsatEC has been proposed as a 5G satellite edge computing framework, wherein a hardware platform optimizes resources (i.e., computing, storage, network) for different services and users. In contrast, a software framework is built on a 5G satellite edge computing service architecture based on microservices (i.e., system, basic, and user services). In [106], edge computing has been introduced to support space-based cloud-fog satellite network slices. In contrast, edge computing nodes have been added to the computing architecture of a satellite network to reduce the delay in different slices. In [15], the authors studied the integration of CubeSats into multi-tenant scenarios by designing an SDN/NFV IoT platform based on EC that includes CubeSat constellations.

In summary, 5G technology envisions NTN's involvement as a means to extend terrestrial coverage and help provision advanced services whenever and wherever the traditional cellular network is overloaded or unavailable.

1.4.2 5G NTN Use Cases

Currently, 5G networks are being widely deployed, and the seamless integration of terrestrial networks (TN) with non-terrestrial network (NTN) components—including satellite and High-Altitude Platform Station (HAPS)-based networks—will enable truly ubiquitous global coverage. This integration ensures continuous service worldwide, enhancing service reliability and availability. NTNs are anticipated to play a crucial role in 5G and beyond systems by supporting a variety of verticals, such as transport, eHealth, energy, automotive, and public safety, among others 1.1.

5G NTN use cases can be categorized into three main areas: service continuity, which provides NTN access in regions where terrestrial networks are not feasible; service ubiquity, which improves availability during disasters or temporary outages affecting terrestrial networks; and service scalability, which helps to offload traffic from terrestrial networks, especially during peak hours [3].

In the context of 5G and beyond, NTNs support all three usage scenarios defined by the International Telecommunication Union (ITU) [60]: Enhanced Mobile Broadband (eMBB), Massive Machine Type Communications (mMTC), and Ultra-Reliable and Low Latency Communications (URLLC). However, providing URLLC services in NTNs is particularly challenging due to satellite propagation delays and stringent reliability, availability, and latency requirements. Consequently, NTNs primarily focus on eMBB and mMTC as the main enablers of 5G services, which guide the definition of use cases [4].

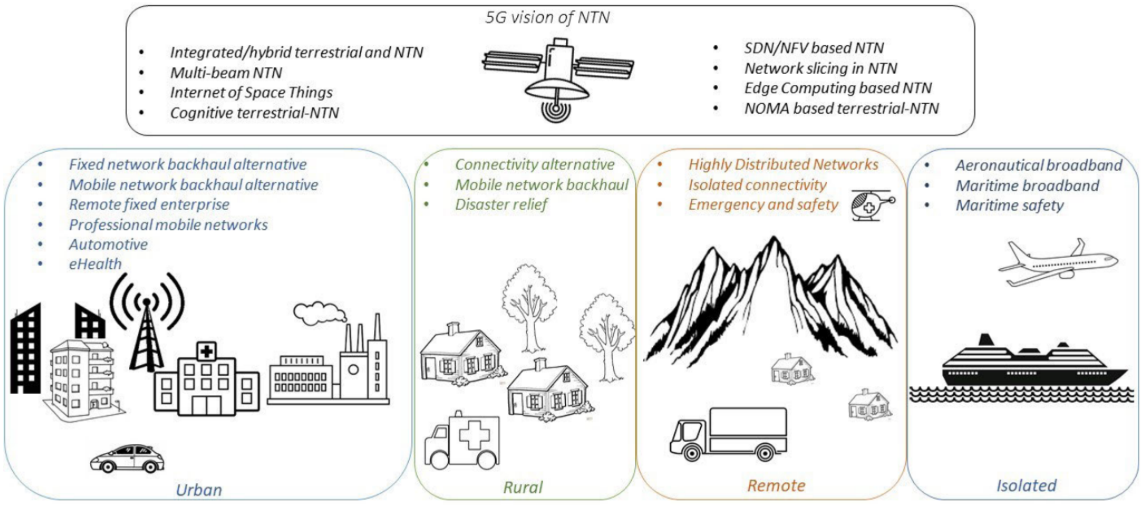


Fig. 1.1 5G NTN Use cases [102]

For Enhanced Mobile Broadband (eMBB) services, Non-Terrestrial Networks (NTNs) aim to provide broadband connectivity in underserved and unserved areas and on moving platforms such as vessels and aircraft. NTNs enhance network resilience by integrating terrestrial and non-terrestrial systems, ensuring continuous service even in challenging environments. Additionally, NTNs can offload terrestrial networks by providing a broadcast channel to deliver broadcast/multicast content or public safety messages to handheld or vehicle-mounted User Equipment (UEs) at home and on moving platforms.

In the context of Massive Machine Type Communications (mMTC), NTNs support IoT services across both wide and local areas. NTNs facilitate connectivity between IoT devices and the network platform for wide-area IoT services. This ensures service continuity via satellites and terrestrial gNBs, particularly for telematics applications in the automotive, road transport, energy, and agriculture sectors. For local area IoT services, NTNs connect the mobile core network to gNBs that serve IoT devices, efficiently gathering data from sensor groups deployed within the coverage of one or more cells.

NTNs are critical to 5G New Radio (NR) systems as they provide significant advantages in urban and rural areas by enhancing targeted performance metrics such as experienced data rate and reliability. They extend connectivity to unserved and underserved areas, benefiting individual users and mMTC devices. Among the key applications, NTNs are particularly valuable in maritime scenarios, where providing coverage through terrestrial networks is cost-prohibitive and capacity-limited. NTNs enable seamless communication in the marine industry, supporting maritime space management and delivering continuous sea traffic services to devices and users in collaboration with seaborne platforms. Furthermore, NTNs can facilitate the transmission of important notifications, such as alerts about vessels in danger and emergency requests during maritime incidents, thereby significantly enhancing maritime safety [102], [7].

1.4.3 5G NTN architecture

New interfaces and protocols are being added to support NTNs in the next-generation radio access network (NG-RAN). An NTN platform may act as a space mirror or gNB in the sky. Consequently, two satellite-based NG-RAN architectures are possible: transparent and regenerative. In the latter case, the NTN platform may implement partial or full gNB functionality depending on whether the gNB functional split (i.e., the gNB comprises central and distributed units [8]) is considered.

Another classification of the NTN architectures can be made based on the type of access [5]. Hence, the NTN platform directly serves the NTN terminal in the satellite access architecture. In contrast, the NTN terminal and the NTN platform communicate via a relay node in the relay-like architecture.

A. Satellite Access Architecture

Figure 1.2 displays the transparent satellite-based architecture where the NTN platform relays the NR signal from the NTN gateway to the NTN terminal and vice versa. The Satellite Radio Interface (SRI) on the feeder link is the same as the radio interface on the service link (i.e., NR-Uu). The NTN gateway can forward the NR signal of the NR-Uu interface to the gNB. One or more transparent satellites may be connected to the same gNB on the ground.

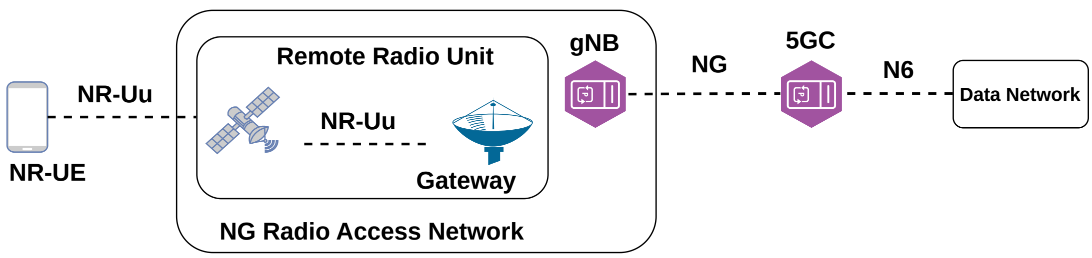


Fig. 1.2 Transparent payload based NTN

Figure 1.3 demonstrates the regenerative satellite-based architecture where the NTN platform has onboard processing capabilities to generate/receive the NR signal to/from the NTN terminal. The NR-Uu interface is on the service link between the NTN terminal and the NTN platform. The radio interface between the NTN platform and the 5G Core Network (5GC) is NG over SRI in the air path between the NTN platform and the NTN gateway. Inter-Satellite Links (ISLs) are transport links between the NTN platforms.

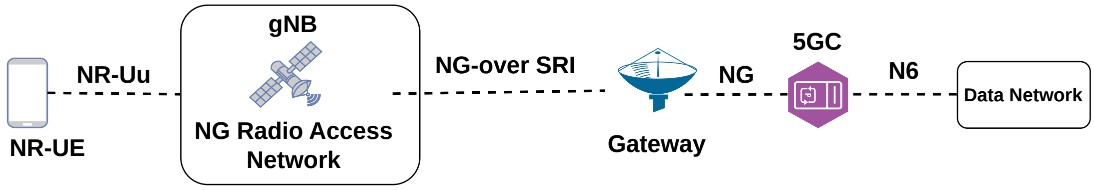


Fig. 1.3 Regenerative payload based NTN

As specified in the NG-RAN [8] architecture description, a gNB consists of a gNB central unit (gNB-CU) and one or more gNB distributed units (gNB-DU). Figure 1.4 shows a "5G NR friendly" NTN architecture based on the regenerative satellite. The gNB-CU on the ground is connected via the F1 interface over SRI to the NTN platform, which acts as a gNB-DU. The NR-Uu is the radio interface between the NTN terminal and the gNB-DU onboard satellite, whereas the NG interface connects the gNB-CU on the ground to the 5GC. gNB-DU on-board different NTN platforms may be connected to the same gNB-CU on the ground.

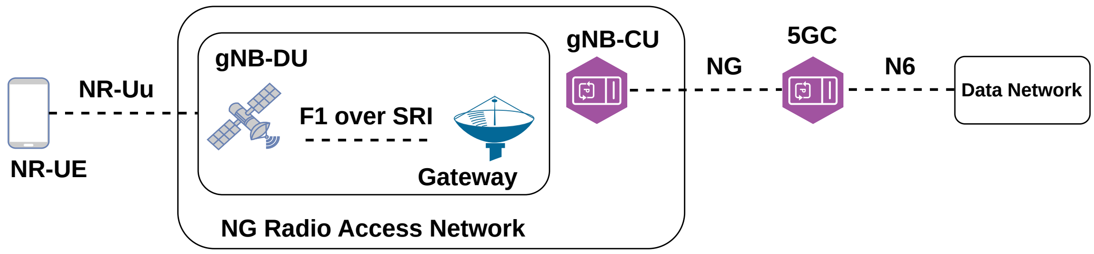
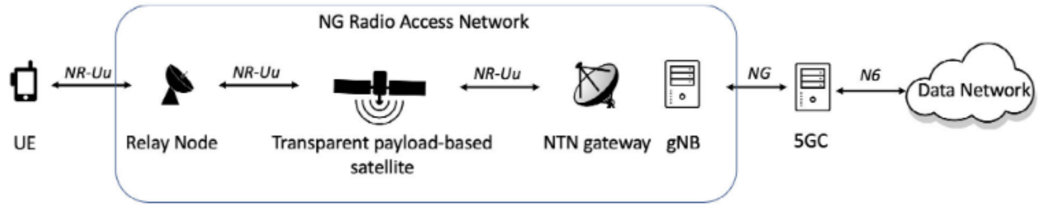


Fig. 1.4 Regenerative NTN based gNB-DU

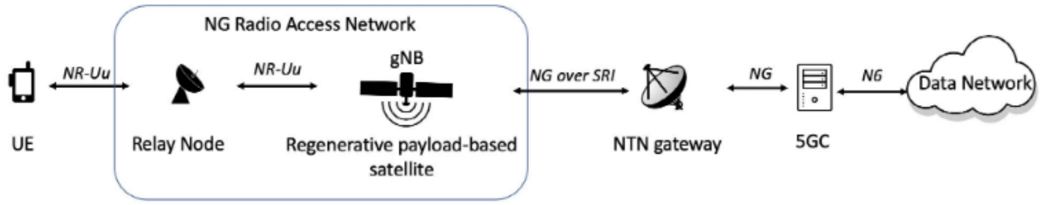
B. Relay-like Architectures

In Figure 1.5(a), the access network forwards the NR signal to the NTN terminal through a relay node, which receives it from the transparent payload-based satellite. In Figure 1.5(b) and Figure 1.5(c), the regenerative payload-based satellite includes the whole and part of the gNB, respectively. The relay node forwards the NR signal from the regenerative payload-based satellite with the gNB functional split to the NTN terminal. For further study, Integrated Access and Backhaul (IAB) architectures are described in [2], which relay the access traffic when both access and backhaul links are considered.

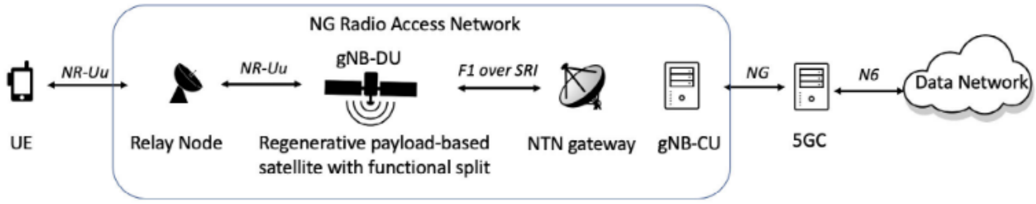
Service Continuity & Multi-connectivity



(a) Transparent payload-based satellite



(b) Regenerative payload-based satellite



(c) Regenerative satellite-based gNB-DU

Fig. 1.5 Relay-like architecture [102]

Integrating NTNs and terrestrial networks is essential to guarantee service continuity and scalability in 5G and beyond systems. An integrated terrestrial-NTN system may offer benefits in urban and rural areas in terms of the 5G performance targets (i.e., experienced data rate and reliability), guarantee connectivity among dense crowds (such as concerts, stadiums, city centers, and shopping malls) and for users traveling in high-speed trains, in airplanes, and onboard of cruises.

However, 5G systems support service continuity between terrestrial NG-RAN and NTN NG-RAN and between two NTN NG-RANs. 3GPP's TR 38.821 [5] studies the multi-connectivity feature to allow simultaneous access to the NTN and terrestrial NG-RANs or two NTN NG-RANs. Therefore, the architectures supporting multiconnectivity are described below.

In Figure 1.6, the ground terminal is connected simultaneously to the 5GC via transparent NTN-based NG-RAN and terrestrial NG-RAN. The NTN gateway is located in the Public Land Mobile Network (PLMN) area of the terrestrial NG-RAN.

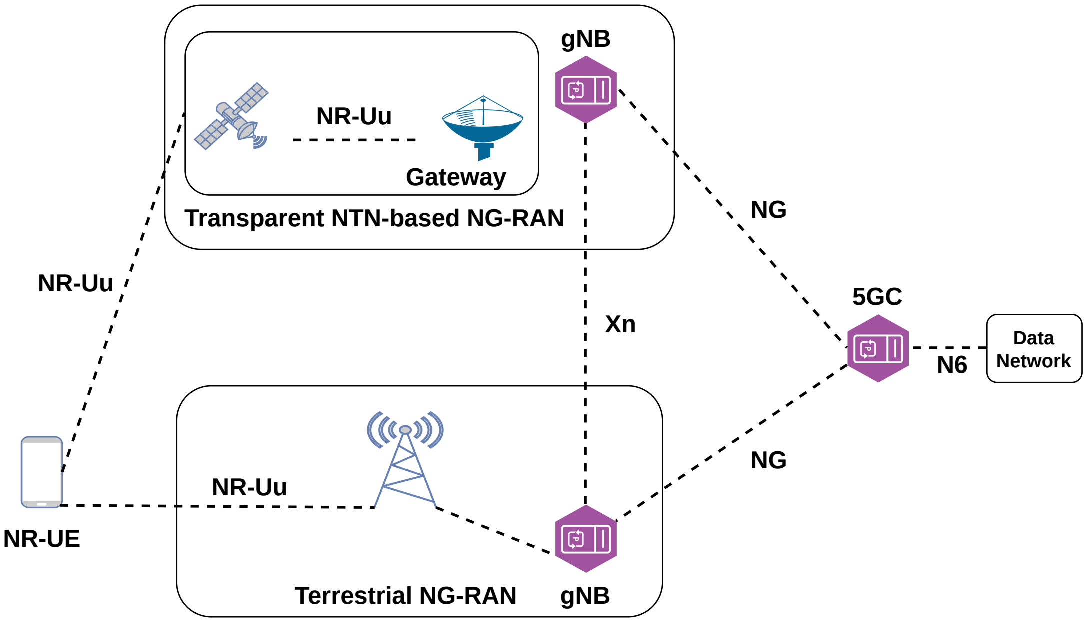


Fig. 1.6 A transparent NTN-based NG-RAN and a terrestrial NG-RAN

Figure 1.7 refers to combining two transparent NTN-based NG-RANs consisting of either GEO or LEO or a combination of both. This scenario may be followed to provide services to the UEs in unserved areas. In particular, LEO is employed to deliver delay-sensitive traffic since it is characterized by lower propagation delay than GEO. The latter provides additional bandwidth and, consequently, higher throughput.

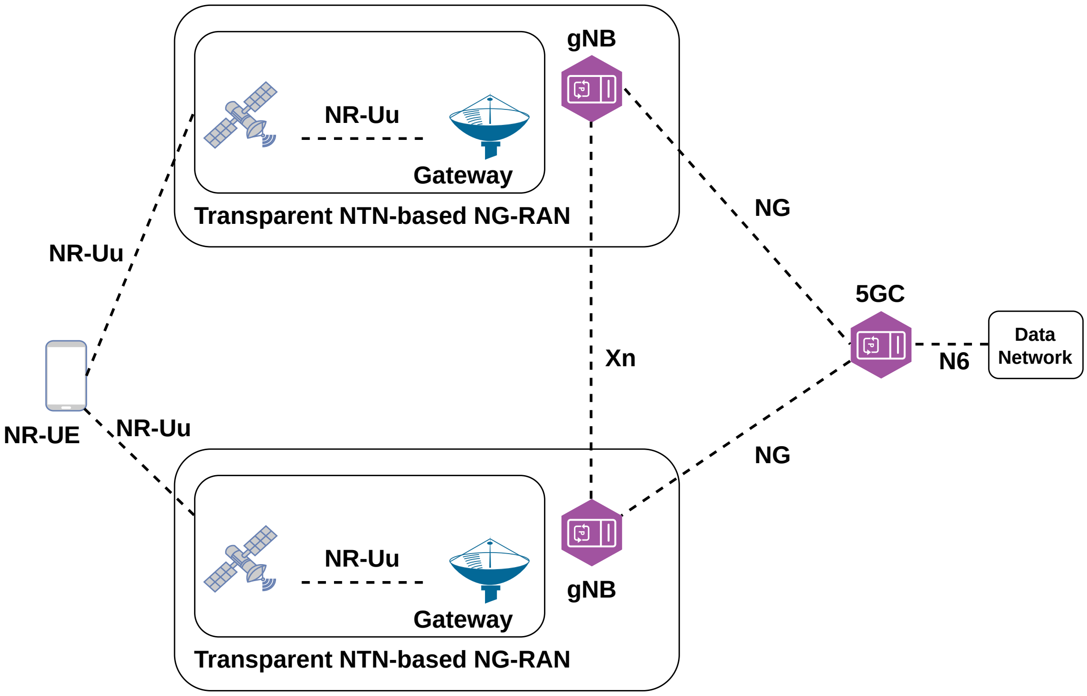


Fig. 1.7 Two transparent NTN-based RAN

Figure 1.8 demonstrates the combination of a regenerative NTN-gNB-DU-based NG-RAN and a terrestrial NG-RAN. The functional split is applied in this type of architecture; hence, the NTN platform represents a distributed unit of the gNB, and the related central unit is on the ground. This scenario may be followed to provide services to the UEs in under-served areas. Multi-connectivity can also involve two regenerative NTN-gNB-DU-based NG-RANs, as shown in figure 1.9.

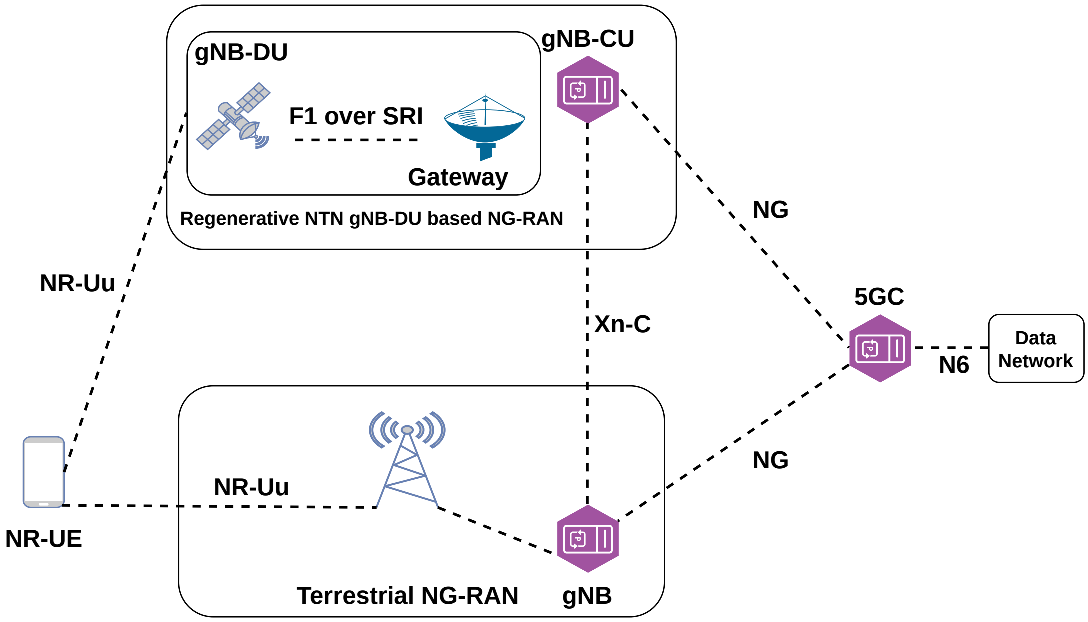


Fig. 1.8 A regenerative NTN gNB-DU based NG-RAN and a terrestrial NG-RAN

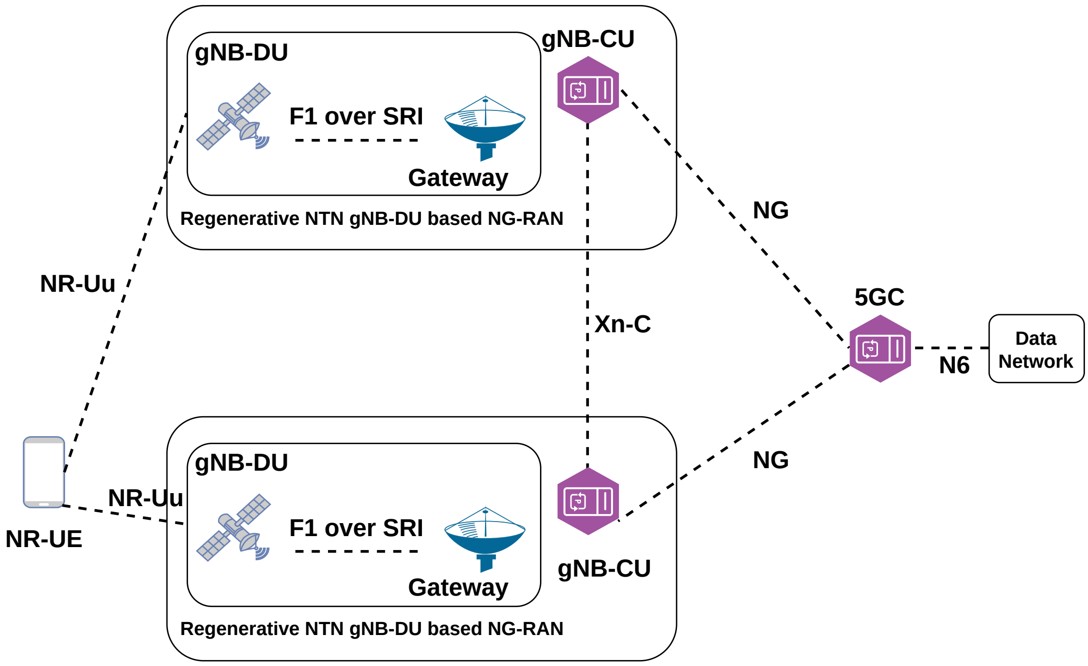


Fig. 1.9 Two regenerative NTN gNB-DU based NG-RAN

Figure 1.11 considers the combination of two regenerative NTN-based NG-RANs consisting of either GEO or LEO or a combination of them interconnected with ISLs. Unlike the previous case, in this type of architecture, the NTN platform performs all the gNB tasks (i.e., the functional split is not applied). Multi-connectivity can also involve regenerative NTN-based NG-RAN and terrestrial NG-RAN, as shown in figure 1.10.

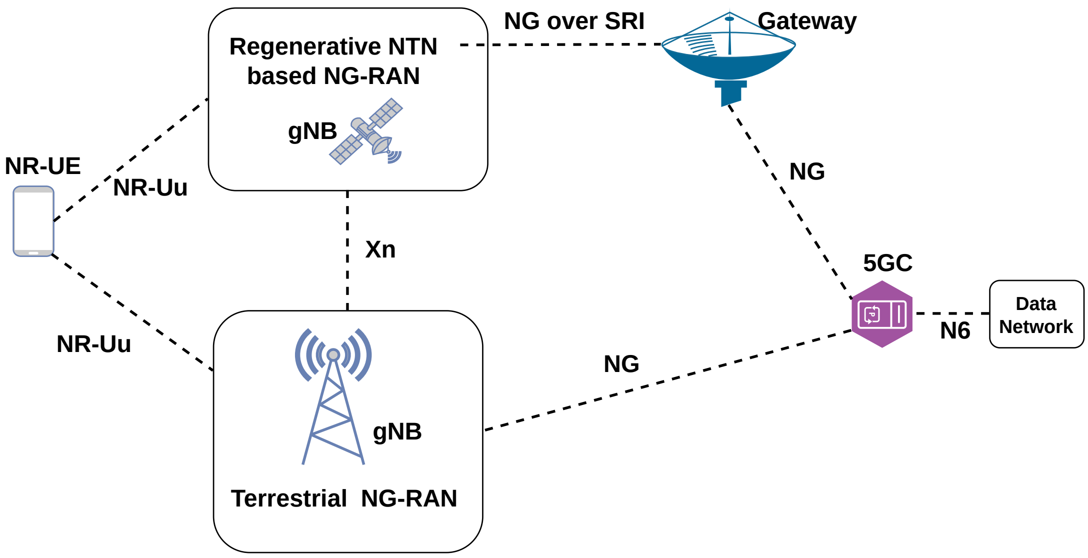


Fig. 1.10 A regenerative NTN-based NG-RAN and a Terrestrial NG-RAN

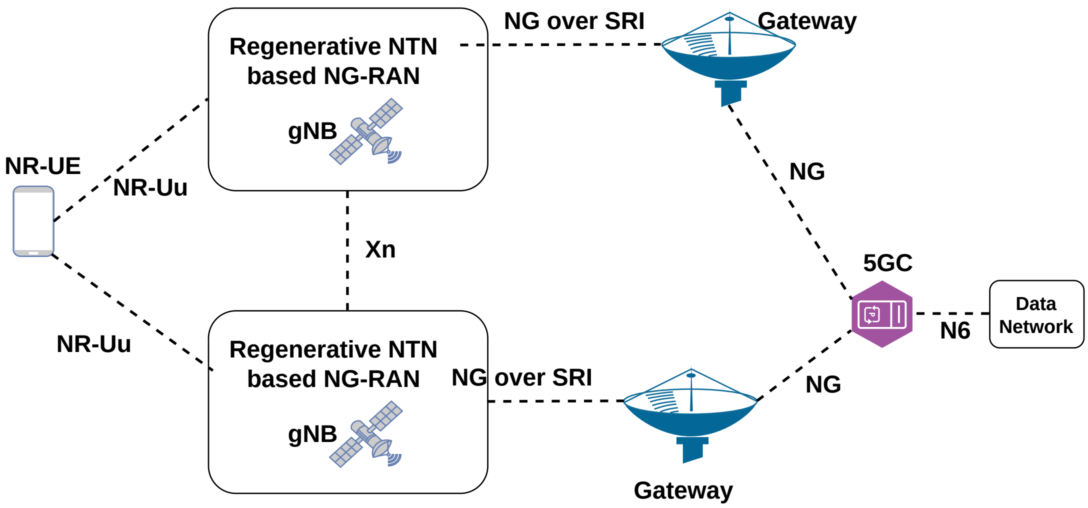


Fig. 1.11 Two regenerative NTN-based RANs

1.5 Technological Enablers for 5G-NTN networks

1.5.1 Network Function Virtualization (NFV) and Software Defined Networking (SDN)

NFV and SDN abstract traditional hardware-specific network functions and decouple the control and data planes, allowing centralized control, programmability, and dynamic reconfiguration of network resources. NFV enables the deployment of virtualized network functions (VNFs) across terrestrial and satellite nodes, enhancing scalability and flexibility by enabling the allocation of resources based on current demand [87, 24]. SDN facilitates efficient traffic management and failure recovery, allowing network operators to dynamically adjust traffic flows and reroute data to maintain optimal performance across diverse network conditions.

1.5.2 Muli-Access Edge Computing (MEC)

MEC brings computational resources closer to the end users, significantly reducing latency and supporting near-real-time processing for time-sensitive applications. MEC nodes can be strategically deployed at satellite gateways or terrestrial edge points, providing localized computing power essential for applications like autonomous driving, remote monitoring, and real-time decision-making [39]. This proximity to the user reduces the dependency on centralized data centers, enhancing overall service quality in NTNs.

1.5.3 Blockchain for secure 5G NTN communication

Blockchain Technology is increasingly integrated into NTNs to address security challenges, such as unauthorized access and data tampering, which are prevalent due to satellite communication links' open and distributed nature. Blockchain provides a decentralized and immutable ledger for securing data exchanges and satellite firmware updates, enhancing the integrity and reliability of NTNs [44, 126]. Blockchain-based authentication mechanisms ensure only authorized entities can interact with the network, reducing vulnerabilities and enhancing the overall security framework. However, these benefits come with trade-offs, including increased latency and computational overhead, which must be carefully managed to balance security with performance [121].

1.5.4 Artificial Intelligence and Machine Learning (AI/ML) Network Management and Automation

Artificial Intelligence (AI) and Machine Learning (ML) techniques are critical in managing the complexities of NTNs. For instance, Graph Neural Networks (GNNs) enable real-time monitoring and optimization of disaggregated NGRANs by analyzing network topology and traffic data [69]. GNNs can detect link failures, predict traffic patterns, and recommend routing adjustments, enhancing network resilience and efficiency.

Long Short-Term Memory (LSTM) models predict resource utilization, enabling proactive management of network functions. These models can forecast CPU, memory, and bandwidth demands, allowing operators to allocate resources dynamically and prevent service degradation. By integrating AI/ML techniques into NTNs, networks can adapt to changing conditions more effectively, ensuring consistent performance across diverse and challenging environments [111, 61].

Network Function Virtualization (NFV), Software-Defined Networking (SDN), Multi-Access Edge Computing (MEC), blockchain, and advanced AI/ML models are pivotal technologies that enhance the capabilities and resilience of Non-Terrestrial Networks (NTNs). These technologies provide the flexibility, security, and efficiency required to manage complex, dynamic network environments involving terrestrial and non-terrestrial components.

AI/ML Models are integral to managing the complexities of NTNs, optimizing resource allocation, enhancing security, and ensuring network resilience. Essential AI/ML techniques used in NTNs include:

Graph Neural Networks (GNNs): GNNs are employed to monitor and manage disaggregated NGRANs by learning from network topology and traffic data. They enable real-time detection of link failures, prediction of network performance, and optimization of routing paths, thus enhancing the overall efficiency and resilience of NTNs [69, 61]. GNNs are particularly effective in environments with dynamic topologies, such as LEO satellite constellations, where they facilitate adaptive network management.

Long Short-Term Memory (LSTM) Networks: LSTM models are used to predict resource utilization, such as CPU, memory, and bandwidth, in disaggregated RAN architectures. By forecasting resource needs, LSTMs enable proactive management of network functions, minimizing service disruptions and improving the operational efficiency of NTNs [19, 113, 114]. These models are advantageous in environments with fluctuating traffic patterns, allowing for dynamic resource allocation that aligns with current demand.

Reinforcement Learning (RL) Techniques: RL models, including LSTM-A2C, optimize the operational parameters of UAVs in NTN deployments, such as trajectory planning and energy consumption. By learning from real-time environmental feedback, RL models dynamically adjust UAV flight paths to maximize coverage while minimizing energy use, enhancing the overall performance of NTN-enabled applications like surveillance and emergency response [80].

Integrating these advanced technologies—NFV, SDN, MEC, blockchain, and AI/ML models—gives NTNs the tools to overcome inherent challenges, such as high mobility, limited computational capacity, and security vulnerabilities. Together, these enablers support the development of robust, adaptive, and secure communication networks that can meet the stringent demands of B5G and future 6G applications.

1.6 Importance and challenges of NTNs in 5G and 6G landscapes

1.6.1 Expanding Coverage and Connectivity

NTNs are essential for expanding the reach of 5G and future 6G networks, providing continuous and reliable connectivity where traditional terrestrial networks fall short. NTNs can quickly restore communication links in disaster-hit areas, enabling rescue and recovery operations to proceed efficiently [9]. In rural and underserved regions, NTNs help bridge the digital divide, providing vital Internet access that supports education, healthcare, and economic development.

NTNs' ability to alleviate congestion on terrestrial networks by offloading traffic during peak periods further enhances overall network performance. By providing alternative communication paths, NTNs reduce the burden on terrestrial infrastructure, enabling a more balanced and efficient use of network resources.

1.6.2 Technical Challenges of Integrating NTNs

Integrating NTNs into existing communication frameworks presents several technical challenges. The high mobility of LEO satellites requires frequent handovers, which can introduce service interruptions if not managed effectively [121, 68]. Propagation delays and Doppler effects further complicate signal synchronization, particularly in applications demanding low latency.

The limited computational capacity of satellite payloads necessitates advanced resource management strategies to optimize available processing power and bandwidth. This is particularly challenging in LEO constellations, where satellites must handle large volumes of data while maintaining stringent QoS requirements. To address these issues, disaggregated Next-

Generation Radio Access Networks (NGRANs) offer a promising approach by separating traditional base station functions into distinct units (CU, DU, RU), allowing for more flexible and efficient resource deployment [110, 65].

1.6.3 Enhancing Resilience in 5G NTNs

Resilience is a fundamental requirement for NTNs, which must maintain reliable service despite disruptions caused by natural disasters, technical failures, or dynamic environmental conditions. Integrating SDN, MEC, and AI-driven monitoring solutions enhances resilience by enabling the network to adapt in real-time [9]. For instance, SDN controllers can reroute traffic from failed terrestrial nodes to satellite links, ensuring uninterrupted communication during emergencies.

The deployment of MEC nodes close to the user further supports resilience by processing critical data locally, reducing dependency on distant data centers, and minimizing the impact of potential network outages. AI-driven monitoring systems continuously assess network performance, detect anomalies, and trigger automatic adjustments to maintain service continuity.

1.6.4 Security Challenges and Solutions

Security is a significant concern in NTNs due to the open nature of satellite communication links, which are susceptible to unauthorized access, data breaches, and other cyber threats. Traditional centralized security models are often inadequate in these decentralized and distributed environments. Blockchain technology offers a promising solution by providing a decentralized, transparent, and immutable framework for securing data exchanges and satellite firmware updates [44, 126].

Blockchain-based authentication mechanisms enhance data integrity and prevent unauthorized modifications, making NTNs more secure. However, these security measures introduce trade-offs, such as increased latency and computational overhead, which can impact overall network performance. Balancing the need for robust security with operational efficiency is critical in designing secure NTNs [121, 68].

1.6.5 Network Management and Orchestration

Network management in 5G Non-Terrestrial Networks (NTNs) involves coordinating and optimizing a highly dynamic and distributed environment comprising satellites, UAVs, and other aerial platforms integrated with terrestrial networks. Unlike traditional terrestrial networks, 5G NTNs must address unique challenges such as high mobility, variable link quality, significant propagation delays, and frequent handovers due to the movement of LEO satellites and UAVs. Effective network management is crucial for ensuring Quality of Service (QoS), optimizing resource allocation, and maintaining seamless connectivity across these heterogeneous components.

Key aspects of network management in 5G NTNs include:

Dynamic Resource Allocation

Efficiently managing the allocation of computational, communication, and energy resources across the various network elements is critical. Techniques such as Network Function Virtualization (NFV) and Software-Defined Networking (SDN) enable flexible and programmable control over network resources, allowing real-time adjustments to changing traffic conditions and network demands.

Traffic Management and Optimization

Advanced AI/ML models such as Long-Short-Term Memory (LSTM) and Graph Neural Networks (GNNs) are employed to handle the dynamic and often unpredictable traffic patterns in NTNs. These models predict traffic loads, detect anomalies, and optimize routing paths, enhancing the network's efficiency and resilience.

Seamless Handover and Mobility Management

Due to the high mobility of LEO satellites and UAVs, NTNs require robust mobility management protocols to ensure seamless handovers between network nodes. SDN controllers play a crucial role in managing these handovers by dynamically rerouting traffic and reconfiguring network paths to maintain connectivity and minimize latency.

Fault Detection and Recovery

In NTNs, network components are susceptible to failures due to the harsh space environment and frequent movement. GNN-based monitoring systems can detect link failures and other network anomalies in real time, allowing for rapid recovery and maintaining service continuity.

Security and Data Integrity

Security is a critical aspect of network management in NTNs due to satellite communication links' decentralized and open nature. Blockchain-based mechanisms and AI-driven threat detection systems are integrated into the network management framework to secure data exchanges and protect against unauthorized access and cyber threats.

Managing NTNs involves addressing the dynamic allocation of resources, optimizing traffic flows, and ensuring seamless handovers between terrestrial and non-terrestrial nodes. ML models, such as LSTM and reinforcement learning (RL) techniques, are instrumental in this process. LSTM models predict resource demands, allowing for proactive adjustments in resource allocation, which helps maintain network performance even under varying conditions [19, 113, 114].

RL techniques, like LSTM-A2C, optimize UAV flight paths and energy consumption, ensuring UAVs can maintain coverage and return safely to their base stations. These models dynamically adjust operational parameters based on real-time feedback, improving the overall efficiency of NTNs and reducing the risk of service interruptions [80].

1.7 Research Objectives and Contributions

Enhancing Network Resilience: This research leverages AI/ML techniques, such as GNN and RL, to monitor and optimize the performance of disaggregated NGRANs in NTNs, ensuring reliable service delivery in dynamic environments. These approaches enable proactive failure detection and adaptive resource management, enhancing the resilience of NTNs.

Improving Security: The study explores the integration of blockchain-based mechanisms to secure NTNs against unauthorized access and data breaches. By balancing robust security with performance trade-offs, this research aims to develop secure communication frameworks that maintain high data integrity and confidentiality.

Optimizing Resource Management: Using LSTM models for resource prediction and RL techniques for trajectory optimization, this research seeks to enhance the efficiency of NTNs in connection-critical scenarios. These models enable dynamic resource allocation and real-time adjustments to operational parameters, supporting efficient network operations.

These contributions aim to provide novel solutions that enhance the deployment and management of NTNs, supporting the development of resilient, secure, and adaptive communication systems for B5G and future 6G applications. The findings of this research are expected to facilitate the seamless integration of NTNs into global communication networks, providing reliable connectivity in even the most challenging environments.

1.8 Thesis Organization

This thesis is organized into five chapters, each focusing on critical aspects of 5G Non-Terrestrial Networks (5G-NTNs), including their architecture, resilience, security, resource management, and optimization techniques. The organization reflects a comprehensive approach to addressing the challenges and opportunities in integrating NTNs within the Beyond-5G (B5G) and future 6G communication ecosystems. Below is an outline of the thesis structure:

Chapter 1: Introduction to 5G Non-Terrestrial Networks (5G-NTN)

The first chapter introduces 5G-NTNs, highlighting their significance in extending connectivity to remote, underserved, and connection-critical areas. It discusses the key enabling technologies, such as Network Function Virtualization (NFV), Software-Defined Networking (SDN), Multi-Access Edge Computing (MEC), and cloud-native architectures, which are fundamental to the design and deployment of NTNs. The chapter also presents an overview of the unique challenges associated with NTNs, including high mobility, resource constraints, and security vulnerabilities, setting the context for the subsequent chapters.

Chapter 2: Multi-Access Edge Computing for Resilient 5G-NTN Networks

This chapter focuses on enhancing the resilience of 5G-NTNs through advanced architectures and technologies. It explores various strategies for maintaining service continuity, particularly when terrestrial networks fail or are unavailable. The chapter discusses the integration of MEC to bring computational resources closer to end users, reducing latency and enhancing the Quality of Service (QoS). It also covers using AI/ML models, such as LSTM and GNN, for predictive maintenance, traffic management, and fault detection, demonstrating how these technologies can dynamically optimize network performance and ensure reliable service delivery.

Chapter 3: Blockchain for 5G Non-Terrestrial Networks

Chapter 3 addresses the security challenges in 5G-NTNs, emphasizing the need for robust mechanisms to protect against unauthorized access, data breaches, and cyberattacks. The chapter introduces a blockchain-based authentication framework designed to enhance the security of data exchanges and satellite firmware updates, providing decentralized and immutable protection for NTN communications. Blockchain integration is evaluated regarding its impact on network performance, offering insights into how security enhancements can be balanced with operational efficiency.

Chapter 4: AI/ML Based Resource Management and Optimization Techniques for 5G-NTNs

This chapter delves into the resource management and optimization techniques essential for 5G-NTNs. It presents advanced AI/ML models, including LSTM-based resource prediction for disaggregated RANs, GNN-based monitoring and optimization of C-RAN, and LSTM-A2C reinforcement learning for UAV trajectory optimization. These models address the challenges of dynamic resource allocation, real-time monitoring, and efficient energy use in NTNs, showcasing their potential to improve network scalability, adaptability, and overall performance.

Chapter 5: Conclusion and Future Directions

The final chapter summarizes the key findings and contributions of the thesis, highlighting the advancements made in enhancing the resilience, security, and resource management of 5G-NTNs. It discusses potential future research directions, including scaling AI/ML models for more complex networks, integrating quantum computing for enhanced optimization, and deploying real-world trials to validate the proposed frameworks. The chapter concludes with a reflection on the broader implications of this research, emphasizing the critical role of NTNs in the evolution of global communication networks and their capacity to support next-generation B5G and 6G applications.

This thesis aims to understand 5G-NTNs and their role in future communication landscapes comprehensively. By integrating advanced technologies and innovative management strategies, the research contributes to developing robust, secure, and adaptive NTN systems that meet the diverse needs of an increasingly connected world.

Chapter 2

Multi Access Edge Computing for Resilient 5G-NTN Networks

2.1 Introduction to Resilient 5G NTN Networks

Resilient 5G Non-Terrestrial Networks (NTN) represent a significant advancement in mobile communication, integrating satellite and aerial platforms with traditional terrestrial networks to enhance global connectivity. This innovative approach addresses the limitations of conventional networks, particularly in remote and underserved areas, where access to reliable communication services is often lacking [111].

One of the standout features of resilient 5G NTN networks is their ability to provide extensive global coverage. By utilizing various satellite systems, such as Low-Earth Orbit (LEO) and Medium-Earth Orbit (MEO) satellites, these networks can reach approximately 80% of land and 95% of marine areas that lack terrestrial network access. This capability is crucial for ensuring connectivity in rural regions and during disasters when terrestrial infrastructure may be compromised [76], [102].

In addition to coverage, 5G NTN networks enhance connectivity for IoT devices and smart city applications [28]. Integrating non-terrestrial elements allows high-speed internet access and reliable communication services, significantly improving real-time data exchange. This enhancement supports various applications, including public services, resource management, and automation, ultimately contributing to smarter and more efficient urban environments.

Another critical aspect of resilient 5G NTN networks is their redundancy and reliability. By providing alternative communication channels, these networks ensure that connectivity remains intact even if terrestrial networks fail. This redundancy is vital for critical applications, such as emergency communications and public safety, where uninterrupted service is essential. Maintaining communication during crises can save lives and facilitate effective disaster response.

The deployment of advanced technologies further enhances the performance of NTN networks. Innovations such as phased array antennas and adaptive beamforming help mitigate common challenges in satellite communications, such as high latency and deep fade. These technologies ensure a more stable and efficient network, allowing seamless communication across diverse environments [111].

Despite the vast potential of 5G NTN networks, several challenges must be addressed to realize their capabilities fully. Regulatory frameworks, spectrum allocation, and effective network management systems are critical areas that require attention. Collaboration among international stakeholders is essential for overcoming these hurdles and optimizing the integration of NTN with existing terrestrial networks.

In summary, resilient 5G NTN networks promise to transform the connectivity landscape by providing reliable, global coverage and enhancing the resilience of communication systems, particularly in challenging environments. Their ability to integrate advanced technologies and maintain connectivity during disruptions positions them as a pivotal component in the future of mobile communication.

2.2 Non-Terrestrial 5G and Beyond Networks

Adopting virtualization technologies and cloud-based approaches within the new 5G Service Architecture (SBA) [6] facilitates unparalleled flexibility in mobile networks, empowering vertical markets. An NTN network utilizes satellite or unmanned aerial system (UAS) platforms to expand the use of existing terrestrial 5G network services. By doing so, NTNs can offer numerous advantages and improve the resilience of 5G network services. This statement can be strengthened by the 3GPP technical specification [5], where NTN networks are pointed out as a complement of the terrestrial network for ubiquitous coverage and service availability.

The diagram in 2.1 illustrates typical regenerative NTN architecture with direct access mode. The terrestrial user with satellite access capability can directly connect to the satellite gNB via the service link to connect to the core network via the feeder link between the satellite and terrestrial gateway.

Integrating non-terrestrial networks with terrestrial 5G networks is a topic of increasing interest, as it promises to enable new use cases and applications that require global coverage and high-speed connectivity. Network operators are exploring emerging technologies such as NFV and SDN to overcome the architectural obstacles facing 5G networks [25] to achieve

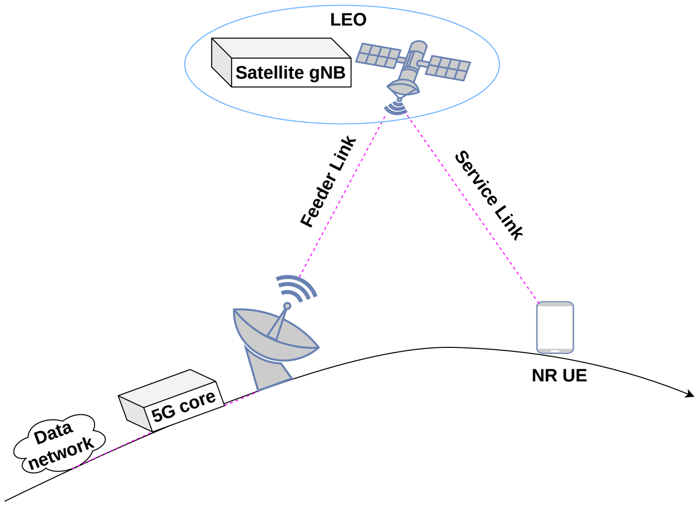


Fig. 2.1 Regenerative NTN architecture with direct access.

this goal. These technologies convert hardware-specific network functions into software-based virtual functions that can be deployed as a virtual machine (VM) or a lightweight containerized environment.

NFV and SDN are expected to play pivotal roles in the digital transformation of network infrastructure. They enable the decoupling of software from hardware and the flexible deployment of various network functions. This allows service providers to spin up new functions automatically whenever a customer requests them, making the network more flexible and agile.

One of the key benefits of NFV and SDN in non-terrestrial 5G networks is the ability to support network slicing, which allows creating multiple virtual networks on top of a single physical network infrastructure. This enables the customization of network resources and services for different use cases, and applications, such as remote sensing, IoT, and smart cities [24].

Integrating NFV and SDN with non-terrestrial networks also presents challenges and future research directions. For example, the dynamic and rapidly changing nature of non-terrestrial networks, such as LEO SatNets, requires the development of intelligent handover algorithms that take into account the specific characteristics of satellite and terrestrial networks, such as latency, bandwidth and coverage [97]. Additionally, integrating NFV and SDN with non-terrestrial networks requires the standardization of interfaces and protocols to ensure interoperability and seamless handover.

The work in [117] delves into the application of 5G New Radio (NR) techniques within three-dimensional (3D) Non-Terrestrial Networks (NTNs) to ensure reliable wireless coverage, particularly in scenarios where connection reliability is paramount. The context of the research emphasizes the critical need for restoring connectivity swiftly in disaster-hit areas, such as rural villages affected by natural disasters, to facilitate emergency rescue operations. The study explores the utilization of Unmanned Aerial Vehicles (UAVs) as integral components of these 3D NTNs. These UAVs function as transparent aerial networks, performing signal amplification and frequency conversion between a satellite-based 5G network and User Equipment (UE). The UAVs operate across various frequency bands, including S-band, C-band, X-band, Ku-band, and Ka-band, ensuring robust and versatile communication capabilities. The performance of the proposed setup is thoroughly evaluated in the paper. Key metrics include achieving throughput rates ranging from 180 Mbps to 4.85 Gbps on the satellite-to-UAV link. Additionally, the research assesses simulated transmission delay and average session time, adhering to a stringent delay budget of 2 ms. These results underscore the efficacy and reliability of the proposed approach in maintaining high-quality connections. The primary applications of this technology are centered around connection-critical scenarios, such as emergency rescue operations and digital divide mitigation. The findings of the paper confirm the viability and effectiveness of using 3D NTNs with UAVs and 5G NR techniques in these contexts. By integrating 5G NR with radio access networks and potentially leveraging FPGA and GPU-based implementations, the proposed topology offers a robust solution for ensuring reliable and high-throughput wireless connectivity in critical situations.

2.3 MEC for NTN Networks

Emerging edge computing solutions are replacing traditional centralized computing due to massive increments of the 5G network users. MEC is an advanced computing technology that provides cloud computing capabilities and an IT service environment close to the network edge [86] [107]. MEC enables ultra-low latency, high bandwidth communication, and data and radio networks for enhanced response time and processing capability.

The expansion of 5G through NTN aims to connect remote regions and busy urban areas while introducing new possibilities for 5G applications. However, satellite networks often struggle with extended delays and limited data capacity, causing connection issues. MEC strives to address these problems by cutting latency, enhancing data capacity, and bolstering security within 5G NTN, ultimately boosting the network's efficiency [10].

MEC can overcome the limitations of cloud computing for applications that require high QoS, computation-intensive, and delay-sensitive requirements because of its proximity to end-users and geographically distributed deployment [92]. This means that MEC hosts are deployed close to end-users, reducing the delay in data transmission and improving service quality. Additionally, MEC can handle computation-intensive applications that require intensive processing power [96].

In the current NTN networks, regenerative architecture is gaining more attraction among the telco industries. This regenerative architecture model raises payload complexity and required computing power; however, incorporating MEC functionalities can substantially reduce the RTT and improve the system QoS.

Integrating MEC with non-terrestrial networks presents opportunities for developing intelligent handover algorithms that consider the specific characteristics of satellite and terrestrial networks, such as latency, bandwidth, and coverage. MEC also enables applications and services to be hosted 'on top' of the mobile network elements, i.e., above the network layer. These applications and services can benefit from proximity to customers and receiving local radio-network contextual information.

Some research works have discussed MEC in the context of non-terrestrial networks. A survey of MEC in 5G and beyond discussed the role of MEC in the 5G network architecture and reviewed related literature published in the last few years [30]. The survey highlighted the potential of MEC to enable a wide variety of applications, such as driverless vehicles. Another survey discussed MEC's security, dependability, and performance in 5G networks [99]. The survey considered the ETSI MEC as a reference but included works on alternative edge computing solutions. The MEC initiative [41] is an Industry Specification Group (ISG) within ETSI that aims to create a standardized, open environment that allows the efficient and seamless integration of applications from vendors, service providers, and third parties across multi-vendor MEC platforms.

2.4 Case Study: MEC-based 5G NTN Experimental Frameworks

2.4.1 Methodology

To demonstrate the resiliency and service availability of the proposed NTN network, an end-to-end experimental testbed that seamlessly integrates satellite and 5G network services was developed. This testbed leverages open-source emulators to mimic various network components, ensuring comprehensive testing and evaluation.

A regenerative LEO-based NG-RAN and terrestrial NG-RAN are considered to deploy a virtualized NTN network as referred to in work [102]. To achieve network resiliency and minimize end-to-end delay, MEC nodes have been utilized to implement the functionality of the 5G core network UPF attached to a satellite terminal in proximity to the user equipment

(UE). MEC can improve network resiliency by providing backup resources and ensuring service continuity even in the case of network failure. It also plays a pivotal role in minimizing RTT after the PDU session is established in a distributed core network deployment. MEC can also help networks withstand and quickly recover from losses or changes in their environment, dynamically adjust to changes in network topology, detect and respond to outages, and route around faults to maintain connectivity and service level agreements (SLAs).

2.4.2 End-to-End Network model

Fig. 2.2 shows the end-to-end deployed network model. As can be seen from the figure, the user equipment is assumed to be capable of connecting to both terrestrial and satellite networks. It has indirect access to the NG-RAN across the satellite terminal to which the MEC node is connected with 5G core network user plane functionalities. The 5G core network is connected to the terrestrial access network and the NTN via the satellite gateway feeder link extending the N2 (satellite gNB with AMF), N3 (satellite gNB with UPF and MEC UPF (UPFMec)), and N4 (UPFMec with SMF) interfaces as shown in Fig. 2.4.

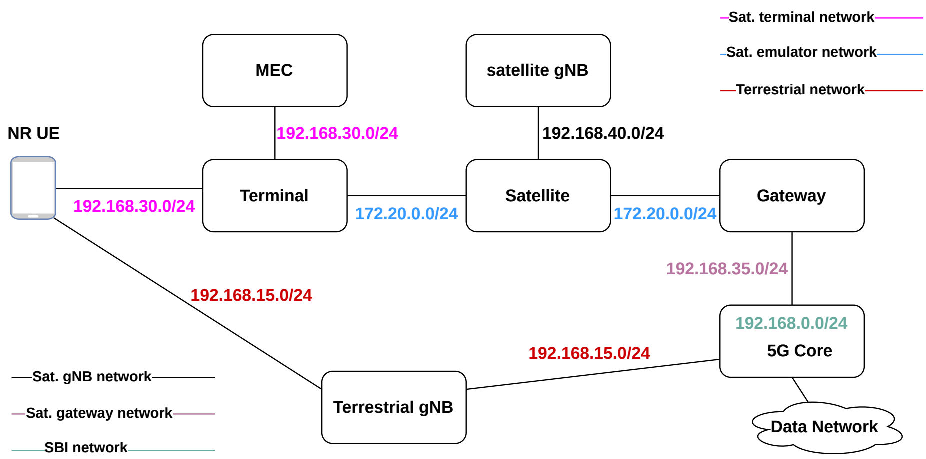


Fig. 2.2 NTN network model.

It is assumed that the UE is capable of connecting to both terrestrial and satellite access networks and an ideal service orchestrator, consisting of a multi-radio access terminal (Multi-RAT) specific SDN, is capable of performing vertical handover from terrestrial to satellite access when the terrestrial access suddenly collapses. The service orchestrator can be considered as one of the 5G core virtual network functions (VNF) or an external network function that integrates into the 5G core network.

Fig. 2.3 depicts the SDN-based NTN model to show how SDN-enabled vertical handover is performed. As also stated in the work [85], when the terrestrial gNB encounters unexpected damage or the received signal strength becomes lower than the threshold value, a new service will be established using the satellite access network. As stated earlier, we simulated the damage of the terrestrial gNB and the vertical handover task using Linux commands such as *tc* and *iptables* to drop traffic across the terrestrial network after the terrestrial PDU session is established. The service orchestrator is ideally implemented in the network to show the availability of a secondary access network with acceptable QoS requirements.

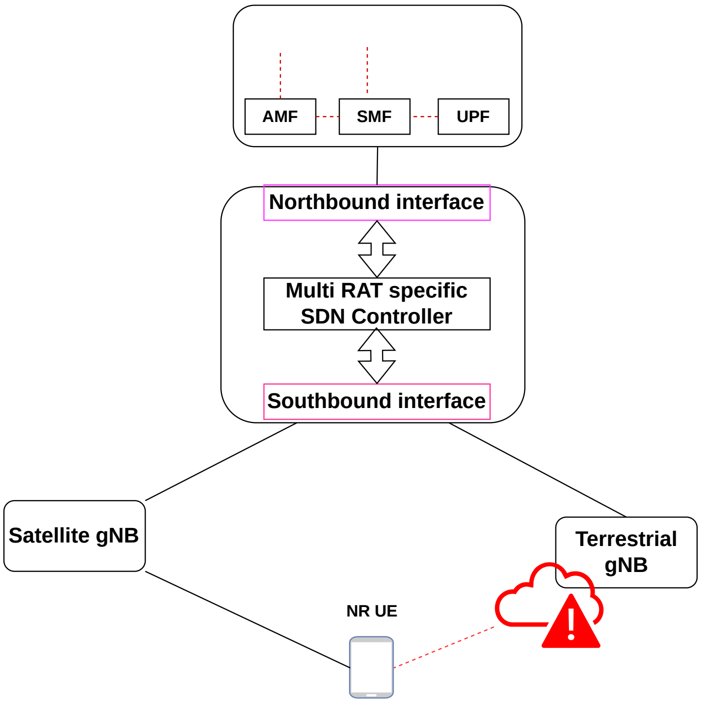


Fig. 2.3 SDN controlled NTN.

2.4.3 Emulated Network Architecture

A comprehensive end-to-end architectural framework is developed to establish a dependable 5G network that seamlessly connects terrestrial and non-terrestrial networks by harnessing the advantages of MEC. This framework is an ideal model for building a network infrastructure that can withstand challenges and provide uninterrupted 5G services. The architecture illustrates how various NTN components are strategically interconnected to provide resilient 5G network service. In essence, this endeavor aims to create a cutting-edge network system that maximizes the potential of 5G technology, combining terrestrial and non-terrestrial capabilities to deliver resilient connectivity and increase service availability.

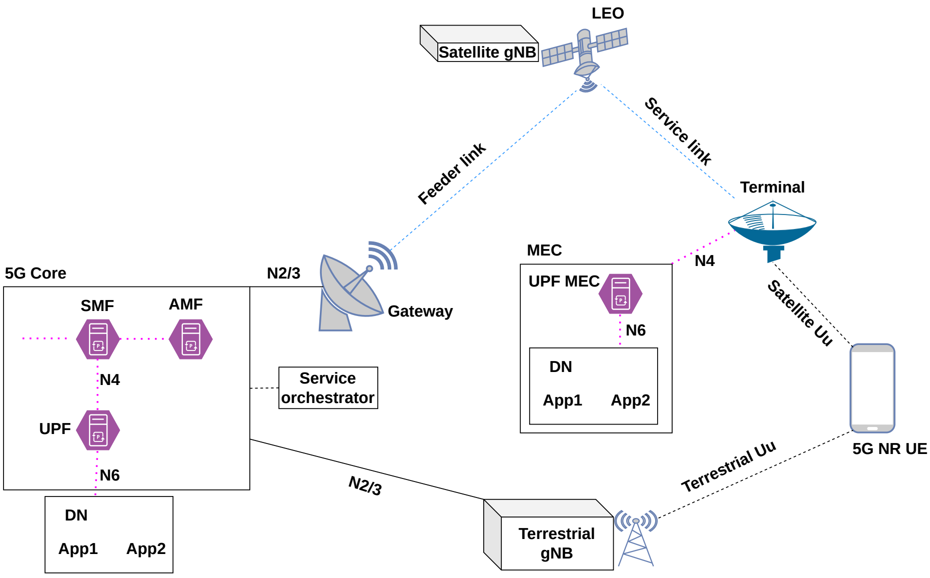


Fig. 2.4 End-to-end network architecture.

As seen from Fig. 2.4, the core network is connected to the satellite gateway and terrestrial access network. Free5GC [43], is used as the 5G core network and Opensand [104] is used as the satellite emulator network to emulate satellite communication scenarios. The emulator is comprised of the gateway, satellite, and terminal. An ideal SDN orchestrator is assumed to be connected to the satellite gateway to control traffic and perform vertical handovers between terrestrial and satellite access. The satellite is considered to operate in regenerative mode with satellite gNB as payload.

The satellite terminal connects the UE and the MEC network. The MEC consists of the UPF of the core network. This intends to place core network functionalities close to the user equipment to reduce latency.

It is assumed that the service orchestrator that performs vertical handover will be triggered following users' mobility information and the quality of received signal strength (RSS) from the terrestrial gNB. The service orchestrator determines the suitable target network for the handover based on factors such as network availability, quality of service, and user requirements. To initiate the handover, the user's device measures the signal strength and mobility information to send a request to the core network. Once the target network (satellite access) is selected, the service orchestrator coordinates the allocation and configuration of resources in the target network to ensure seamless handover.

The vertical handover procedure involves establishing a PDU session with the terrestrial gNB and ensuring its continuity when transitioning to the satellite gNB. Fig. 2.5 shows the procedure of PDU session re-establishment assuming a sudden collapse of the terrestrial access network.

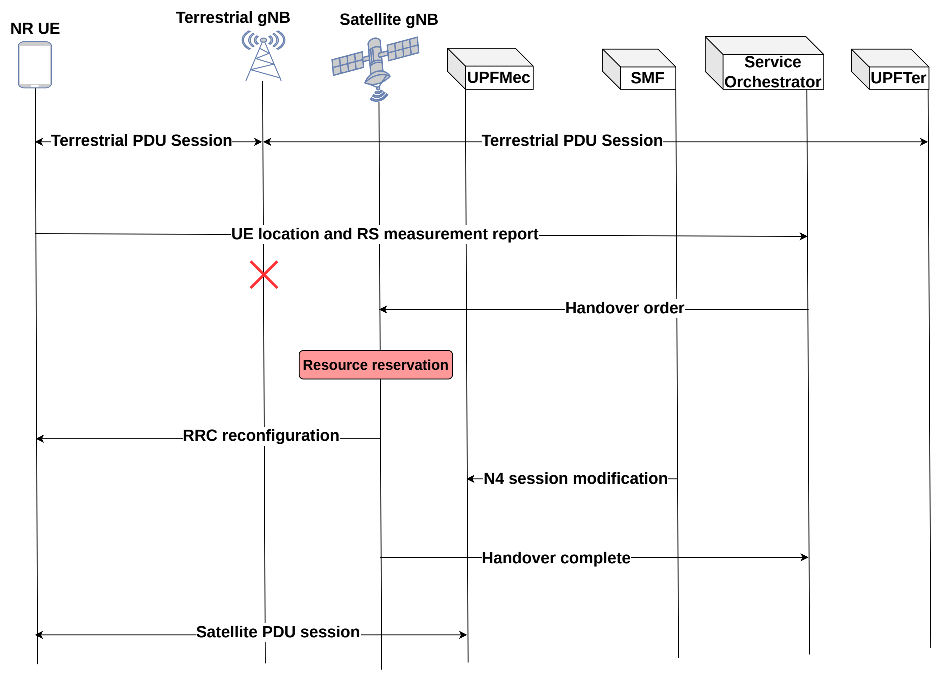


Fig. 2.5 PDU session establishment.

The methodology focuses on implementing NR-NTN to deploy resilient 5G service, assuring service availability during terrestrial access failure. It demonstrates that the PDU session that is initially established with the terrestrial gNB can continue seamlessly with the satellite gNB without service interruptions. Different performance metrics, such as RTT, throughput, and packet loss, are evaluated.

Implementing this methodology, the study aims to validate the feasibility and reliability of terrestrial and satellite-connected gNBs, assuring uninterrupted service for users when terrestrial access is suddenly damaged or unreachable.

2.4.4 5G core and RAN network

Both the core network control plane (CP) and user plane (UP) network functions have been separately deployed in the framework of a container-based application approach, where each 5G core component is implemented as a cloud-native network function (CNF).

The 5G control plane functions are initiated as processes within a designated docker container as a virtual network function (VNF). These VNFs are configured by dynamically using their configuration files and shell scripts as an entry point to forward traffic and properly work with the satellite network. Specifically, the AMFs and SMFs have been configured to work with terrestrial and satellite networks. The 5G user plane functions are also deployed as a separate docker container and configured to handle terrestrial and satellite PDU sessions, creating a separate GPRS tunnel. The 5G core data plane consists of two separate UPFs related to the two network configurations and the data network applications. One of the two UPFs is designated as UPFTer to handle terrestrial connectivity, and the other one UPFMec to handle satellite connectivity. The UPFMec is connected to the satellite-emulated network across the satellite terminal to be in proximity to the user's equipment.

By deploying the control and user plane functions separately and leveraging MEC, our approach aims to achieve a more efficient and flexible 5G core architecture in the non-terrestrial network environment. Such an approach can yield better performance, lower latency, and augmented scalability for non-terrestrial networks.

For the 5G RAN network, UERANSIM [53] is used to simulate the user equipment and the gNB functionality. It is an open-source software framework for simulating UE behavior in 5G networks. This simulator is chosen because of its flexibility and ease of use in a docker-emulated environment. It is a valuable tool for researchers and network professionals to conduct protocol testing, validate designs, and experiment with various 5G network scenarios. This highly customizable tool allows users to configure and control network parameters and is often employed for educational and research purposes. UERANSIM's open nature encourages community contributions and integration with other network simulation tools, ensuring its relevance in the evolving landscape of 5G technology.

In this work, two separate gNBs are used to emulate the satellite and terrestrial connectivity: the former is connected to the satellite (gNBsat), and the latter is connected directly to the core network (gNBter) for terrestrial access as a docker container.

2.4.5 Satellite Network

The Opensand emulator has been used to emulate the satellite network. Opensand [104] is a user-friendly and efficient tool used to emulate satellite communication systems, primarily DVB-RCS (Digital Video Broadcasting - Return Channel via Satellite) and DVB-S2 (Digital Video Broadcasting - Second Generation Satellite). It allows for the configuration and monitoring of the emulated scenarios in real-time, enabling an efficient performance evaluation.

To deploy an Opensand emulator, three hosts are used: the satellite emulator, gateway, and terminal. In this work, the three hosts of the Opensand are deployed as a separate docker container and configured properly to function with the deployed 5G network for non-terrestrial scenarios. The gateway is connected to the main 5G core network, the satellite emulator is connected to the satellite gNB (gNBsat), and the terminal is connected to the MEC emulated network and the user equipment.

2.4.6 The emulated application

The network is deployed using the docker-compose [1] tool, which creates a controlled and replicable testing environment, ensuring flexible evaluation of multi-container services.

For end-to-end evaluation and seamless functioning of the satellite and 5G network, the network elements have been configured. From the 5G core network, the AMF, SMF, and UPF have been configured and rearranged to function in the integrated network. The SMF of the 5G core control plane has been configured to handle both the terrestrial and satellite PDU sessions with UPF reallocation (from terrestrial UPF to satellite UPF). The satellite, terminal, and gateway of the Opensand emulator have also been configured to be connected to the networks.

To test and validate the reliability of the deployed resilient 3D network, we analyzed throughput, jitter, and packet loss of both terrestrial and satellite networks showing the degree of acceptability of the achieved satellite network QoS in the presence of MEC nodes, when the terrestrial access suddenly fails as shown in Fig. 2.5. We have also demonstrated the advantages of using the MEC nodes in reducing the RTT of the LEO constellation.

To replace the function of the service orchestrator, Linux configuration commands, such as '*tc*' and '*iptables*', have been used to simulate the failure of the terrestrial access.

To generate traffic, *iperf3* and *ping* tools are used. VoIP traffic is generated by using *iperf3* with standard bitrate requirements to evaluate throughput, jitter, and packet loss. The *ping* tool has been used to compute the RTT between the core and the NG-RAN network components.

2.4.7 Experimental Results

Scenarios

The emulated network is deployed on a VM environment with an allocated CPU 4 on a standard Linux OS laptop with Intel(R) Core(TM) i7-7500U CPU @ 2.70GHz and 16 GB RAM.

Three scenarios have been considered to test the emulated environment and show service availability. The scenarios are terrestrial access and NTN access with and without the MEC node. UDP VoIP traffic is generated by *iperf3* for end-to-end performance assessment. The collected traffic information is further analyzed to evaluate the typical Key Performance Indicators (KPIs) of networking systems: throughput, Jitter, and packet loss. Since the objective of adding the MEC node is to reduce the RTT by placing core network functionalities near the UE, a *ping* test is performed. The expected outcome is to show that NTN connectivity with the MEC node has a lower end-to-end delay than the NTN without the MEC node.

LEO satellite constellation is considered with an altitude of 1000km, end-to-end target latency of 80ms, and 10ms variable jitter. The LEO is configured to work in regenerative mode having the satellite gNB as a payload which guarantees service availability [4], [2]. We consider a VoIP application scenario with a data rate of 128 Kbps for the test.

Performance assessment

Fig. 2.6, shows the throughput in logarithmic scale vs. simulation time related to the three scenarios of the considered application. The throughput of terrestrial access exhibits better performance with an 8% maximum deviation compared to the NTN access with and without using the MEC node. Starting from 9ms of simulation time the terrestrial access performance abruptly falls to 55 Kbps during a sudden terrestrial gNB damage. In such a case, the NTN access without the MEC node exhibits lower performance since it uses the terrestrial UPF (UPFter) of the core network data plane. Once the SMF reassigns to use UPF of the MEC node (UPFmec) during PDU session recovery, the satellite-connected UE can access the network with an acceptable performance through the NTN access exploiting the MEC node. In any case, NTNs (with and without MEC node) demonstrated their effectiveness in recovering acceptable throughput performance.

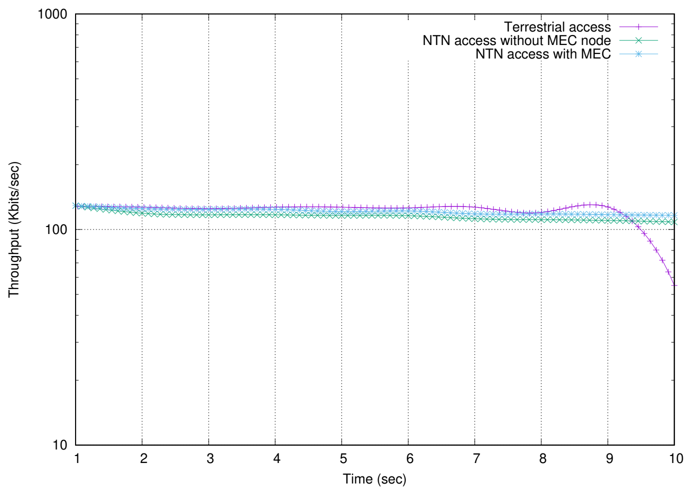


Fig. 2.6 Throughput in log scale (Kbps) Vs time(s).

Fig. 2.7, shows the jitter of the simulated network vs. simulation time. With the same analogy of the throughput plot, the terrestrial access asymptotically overshoots to higher

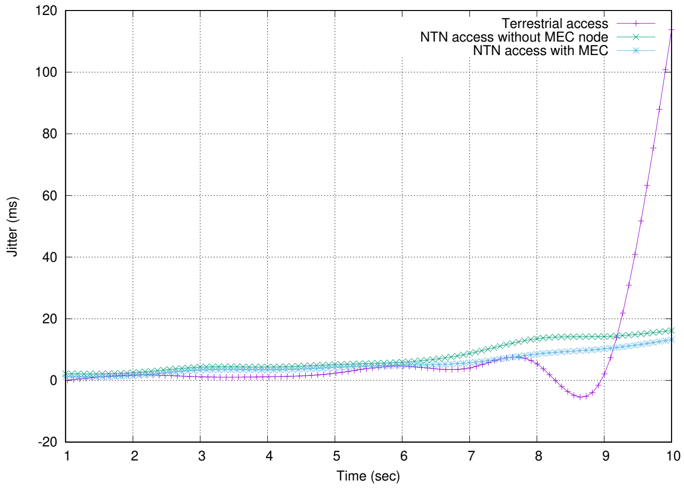


Fig. 2.7 Jitter (ms) Vs time(s).

values when it becomes unavailable. On the other hand, the NTN access with the MEC node, which exhibits around 10% of jitter variation, can assure service continuity.

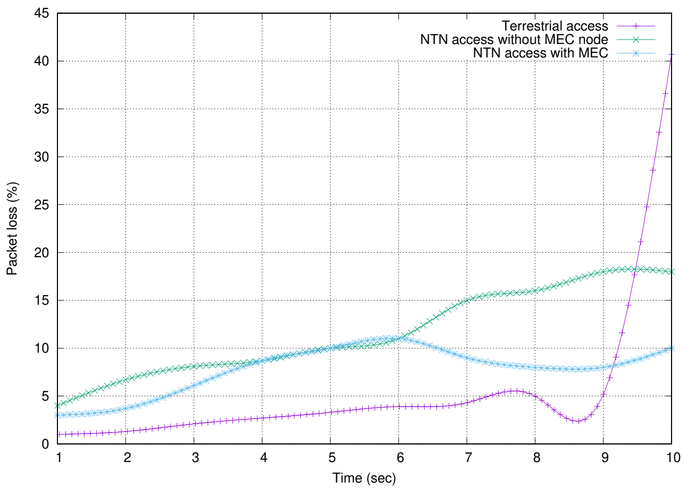


Fig. 2.8 Packet loss (%) Vs time(s).

Fig. 2.8, shows the packet loss vs. simulation time for the tested scenarios. The terrestrial access exhibits less than 5% of packet loss, clearly outperforming NTN access until the collapse event occurs. After the PDU recovery, NTN access with the MEC node shows an acceptable loss of below 10% again outperforming the NTN access without the MEC node.

As shown in Fig. 2.4, the NTN access with the MEC node scenario uses the UPFmec attached to the satellite terminal. This scenario happens when the UE is connected to the satellite gNB and the AMF and SMF from the terrestrial 5G core network must re-assign the GPRS tunnel towards the UPFmec. The reallocation instruction has to route through the gateway and satellite emulator to reach the terminal. Therefore, from 4 to 6 seconds of the simulation time, the NTN access without the MEC node performs similarly to that of the NTN access with the MEC node. However, NTN access with the MEC node tends to perform better with lower packet loss after the UE fully starts using the MEC node during satellite radio access.

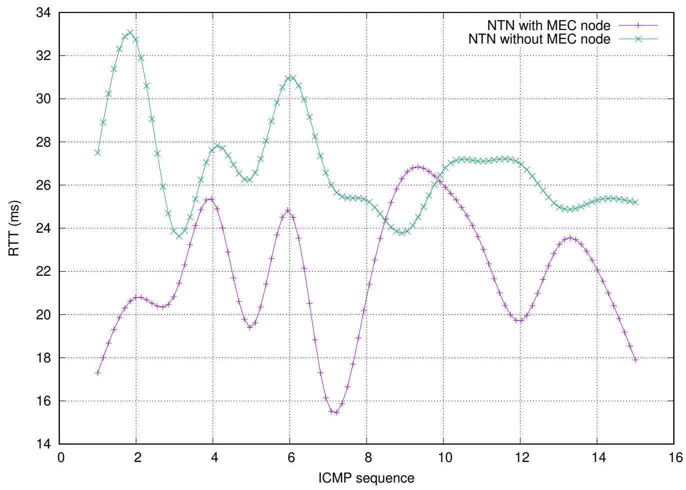


Fig. 2.9 End-to-end delay with and without MEC node.

Fig. 2.9 shows the achieved end-to-end delay between NTN access with and without the MEC node. It is mentioned that the NTN access without the MEC node uses the UPFter located in the terrestrial 5G core network. In contrast, the NTN access with the MEC node utilizes the UPFmec attached to the satellite terminal. Therefore, for the VoIP application case, the ICMP packet sent from the UE has to travel across the satellite and the gateway to reach the data network via the terrestrial 5G core for NTN access without an MEC node scenario. During the NTN access with the MEC node, the ICMP packet has to travel only across the satellite terminal to reach the data network across the UPFmec. Therefore, NTN access with the MEC node can achieve an end-to-end delay ranging between 15ms and 27ms, which is acceptable for the considered application compared to NTN access without the MEC node. Performance improvement when using MEC in the NTN network will reduce the signal travel time needed to reach the destination and increase the network's overall performance.

2.5 Summary

This chapter explored the integration of Multi-Access Edge Computing (MEC) with 5G Non-Terrestrial Networks (NTNs) to enhance network resilience and service availability. The study presented a virtualized end-to-end experimental framework leveraging open-source 5G and satellite emulators to create a robust 3D network model. The proposed setup highlighted how, strategically placed near satellite terminals, MEC nodes improve network performance by reducing latency and ensuring continuity during terrestrial network disruptions.

The framework demonstrated that resilient 5G-NTN networks could provide extensive global coverage, particularly in remote and underserved areas, by utilizing Low Earth Orbit (LEO) satellite constellations operating in regenerative mode with gNB payloads. By integrating MEC with these satellite networks, the study illustrated the advantages of a decentralized architecture that brings computational resources closer to end-users, significantly enhancing response times and maintaining acceptable Quality of Service (QoS) during critical scenarios.

Key findings include the efficacy of MEC in minimizing round-trip time (RTT) and improving throughput, jitter, and packet loss metrics, particularly when terrestrial access becomes compromised. Including MEC nodes in the NTN setup proved instrumental in maintaining service availability, showcasing the potential of MEC to mitigate the inherent limitations of satellite communication, such as high latency and reduced bandwidth.

The experimental results validated the proposed architecture's capability to handle sudden network failures and underscored the importance of integrating advanced computing solutions like MEC in 5G-NTN environments. This chapter highlights the critical role of cloud-native edge computing frameworks in future NTN deployments, emphasizing their capacity to deliver resilient, high-performance communication networks that meet the growing demands of modern digital applications.

Chapter 3

Blockchain for 5G Non-Terrestrial Networks

3.1 Security Challenges in the 5G NTNs

Security challenges in 5G Non-Terrestrial Networks (NTN) are significant due to these systems' complex and interconnected nature. As 5G technology evolves, it introduces new vulnerabilities alongside its advancements, necessitating robust security measures to protect against potential threats. Besides, due to the decentralized, highly dynamic, and open communication environment, the 5G NTN network faces significant security challenges [11]. One of the primary security challenges arises from Network Functions Virtualization (NFV), which is integral to 5G architectures. NFV enables multiple network functions to run on shared servers, increasing the attack surface. This necessitates stringent security protocols to safeguard these virtualized functions from cyber threats, as any vulnerability in one function could compromise the entire network [121], [126].

Key security concerns include:

a) **Unauthorized Access and Data Breaches**: The open nature of satellite communication links makes NTNs vulnerable to unauthorized access, eavesdropping, and data interception, posing risks to data confidentiality and integrity.

b) **Jamming and Spoofing Attacks**: NTNs are susceptible to jamming and spoofing, where adversaries can disrupt communications or impersonate legitimate nodes, leading to service disruptions and compromised network reliability.

c) **Secure Firmware Updates**: Ensuring the integrity of firmware updates in satellite payloads is critical. Without robust authentication mechanisms, NTNs risk being compromised through malicious updates that can introduce vulnerabilities.

d) **Resource Constraints**: Cloud-native approaches promote automation in network management, reducing operational costs and improving service reliability. This is crucial for managing the complexities introduced by NTNs, which must simultaneously handle various connectivity and service requirements.

e) **Decentralized Management**: The distributed nature of NTNs complicates traditional centralized security models, necessitating decentralized approaches like blockchain for secure authentication and data management.

These challenges highlight the need for innovative security frameworks that integrate advanced encryption, blockchain-based authentication, and AI-driven threat detection to safeguard the integrity and reliability of 5G NTNs.

3.2 Blockchain-Enhanced Security Mechanisms

The proliferation of 5G technology promises to change the communication network paradigms thanks to its unparalleled speed, reliability, and connection capabilities. Integrating 5G with Non-Terrestrial Networks (NTN), particularly Low Earth Orbit (LEO) satellites, can considerably extend coverage to remote and underserved regions. LEO satellite constellations have significantly empowered global communication networks, enabling enhanced data exchange and connectivity across various actors. Companies like SpaceX and OneWeb are leading this revolution, launching thousands of satellites to create mega-constellations capable of providing high-speed Internet [11].

Integrating LEO satellites within 5G infrastructures targets ubiquitous coverage and enhanced connectivity. Nonetheless, the dynamic nature of satellite networks and the long distances involved raise significant security concerns, such as unauthorized access and data breaches [127].

Traditional centralized security mechanisms often fail to address these challenges, thus necessitating innovative solutions. With decentralized and immutable characteristics, blockchain technology is viable for enhancing security in 5G NTN. Utilizing blockchain in LEO satellite networks presents its own set of challenges. Issues such as latency, computational overhead, and network throughput require careful consideration. The trade-off between the blockchain security gain and the Quality of Service (QoS) should be evaluated to assess its viability [121], [68].

This chapter discusses the implementation of a blockchain-based authentication mechanism to enhance the security of data exchanges and remote firmware updates in LEO satellite constellations in 5G NTN networks. Firmware updates are crucial for maintaining satellite functionality and performance. Blockchain can provide a trustworthy framework for updating satellite firmware, protecting the network from potential vulnerabilities introduced during the update operations [44], [126].

The proposed setup will demonstrate effective traffic control across the satellite network and ensure secure transactions between the local blockchain network and the 5G NTN. Such a setup relies on the blockchain's immutable nature, which enhances the network's security and integrity.

3.3 State of the artworks on blockchain-based 5G NTN networks

Integrating blockchain technology with 5G and satellite networks has recently received significant attention. Several studies have explored various aspects of this integration, highlighting its potential benefits and challenges. [90] conducted a comprehensive survey on blockchain application in "5G and beyond" networks [113], emphasizing network operations' enhanced security and trust. This work provides a foundational understanding of how blockchain can mitigate security threats in these advanced communication networks.

In the satellite communications context, [109] study outlines challenges and potential solutions for integrating blockchain in the space industry. The paper discusses the role of blockchain in ensuring secure and reliable communication through satellite networks by addressing issues such as data integrity and authentication. Similarly, [120] explores blockchain-empowered space-air-ground integrated networks, presenting solutions for seamless and secure data transmission across different network layers.

The work in [57] proposes a blockchain-based framework for securing over-the-air firmware updates in IoT devices, which can be extended to satellite networks, to enhance security during data transmission and software updates. Another notable paper is [54], which focuses on blockchain-based authentication for 5G networks, regarded as crucial for maintaining secure connections and preventing unauthorized access in satellite communication systems.

In addition to these studies, [90] introduces a new framework, namely MSNET-Blockchain, for securing mobile and satellite networks using blockchain. This framework addresses the unique security requirements of satellite networks and proposes solutions for achieving robust and scalable security mechanisms. Furthermore, [130] examines the mitigation of signaling storms in 5G networks using blockchain, highlighting the technology's potential to enhance network resilience and performance.

Our work builds on these foundational studies by implementing a blockchain-based traffic authentication system for a 5G NTN network in the cloud-native emulated environment. Unlike previous studies that primarily focus on theoretical frameworks and high-level solutions, the approach considered in this work involves the practical deployment and evaluation of blockchain technology in an end-to-end 5G NTN setup. More specifically, the tradeoff between security (inherent to the utilization of blockchain) and achieved QoS is analyzed by providing empirical data on the local blockchain's throughput, latency, and authorization efficiency. This insight will contribute to the existing literature by demonstrating the impact of blockchain integration in 5G NTNs and its viability.

3.4 Case Study: Blockchain-Based Authentication Framework

3.4.1 Overview

The distributed and decentralized nature of 5G and service-based architecture involve different security and privacy challenges. The contrast to security threats is becoming a pivotal research focus in academia and industry. Thanks to its decentralized nature, blockchain is considered a promising technology that is anticipated to be part of the future "5G and beyond" networking standards. 5G NTN networks will be open, virtualized, and scalable, strengthening the necessity of countermeasures to achieve a high level of end-to-end security and prevent inefficient centralized processing and decision. Such security enforcement should pave the way to other network performance enhancement techniques, such as multi-access edge computing (MEC) and federated learning (FL) [90]. Moreover, the decentralized operation mode of blockchain has the advantage of deploying the network with transparent and immutable storage.

Blockchain technology offers several key properties that significantly strengthen its application in enhancing the security and reliability of satellite and 5G networks. The decentralized nature of blockchain eliminates the need for a central authority, thereby reducing single points of failure and enhancing resilience against attacks. The immutability of blockchain ensures that once data is recorded, it cannot be altered or tampered with, which is critical for maintaining data integrity and trust in communication networks. Additionally, blockchain's transparency and traceability enable real-time monitoring and auditing of network activities, ensuring that all transactions are verifiable and accountable. Finally, using smart contracts automates enforcing security policies and protocols, reducing human error and enhancing operational efficiency.

3.4.2 Ethereum-based local blockchain deployment

Ganache is a powerful tool developed by Truffle Suite that provides a local Ethereum blockchain environment for developers to test, develop, and deploy smart contracts and decentralized applications (DApps) without interacting with the live Ethereum network. It simulates the blockchain on a developer's local machine, offering a controlled, secure, and customizable environment that accelerates the development process while eliminating the costs and risks associated with using the main Ethereum network or public testnets. One of Ganache's key features is its ability to customize blockchain parameters, such as block time, gas price, and gas limit, allowing developers to simulate various network conditions and optimize their applications under different scenarios. It also generates personal Ethereum accounts with predefined amounts of Ether, enabling users to test transactions and contract interactions without real financial implications [105], [120].

Ganache offers both a Command Line Interface (CLI) and a Graphical User Interface (GUI), catering to different developer preferences [105]. The CLI version provides a lightweight tool for scripting and automation, while the GUI offers a more visual approach, allowing users to monitor accounts, blocks, transactions, and logs in real time. This detailed logging and debugging capability helps developers inspect transactions, check contract states, and troubleshoot errors effectively. Another standout feature is Ganache's instant mining capability, which provides immediate feedback on transactions and smart contract executions, significantly speeding up the development cycle compared to the live network, where transaction confirmations can be delayed.

The platform supports forking from the main Ethereum network or other testnets, enabling developers to work with the current state of the live blockchain in a local environment. This is particularly useful for testing smart contract interactions with existing contracts and state variables on the mainnet. Ganache's environment is essential for various use cases, including smart contract development, DApp testing, and integration testing of blockchain applications with other software components. It allows developers to experiment in a risk-free environment, optimize contract performance, and ensure seamless operation of the entire application stack before deploying on public networks [54].

Ganache plays a crucial role in education by providing a simple and safe environment for learning blockchain concepts and smart contract development. Its ability to simulate real-world blockchain behavior in a controlled setting makes it an invaluable tool. The platform's

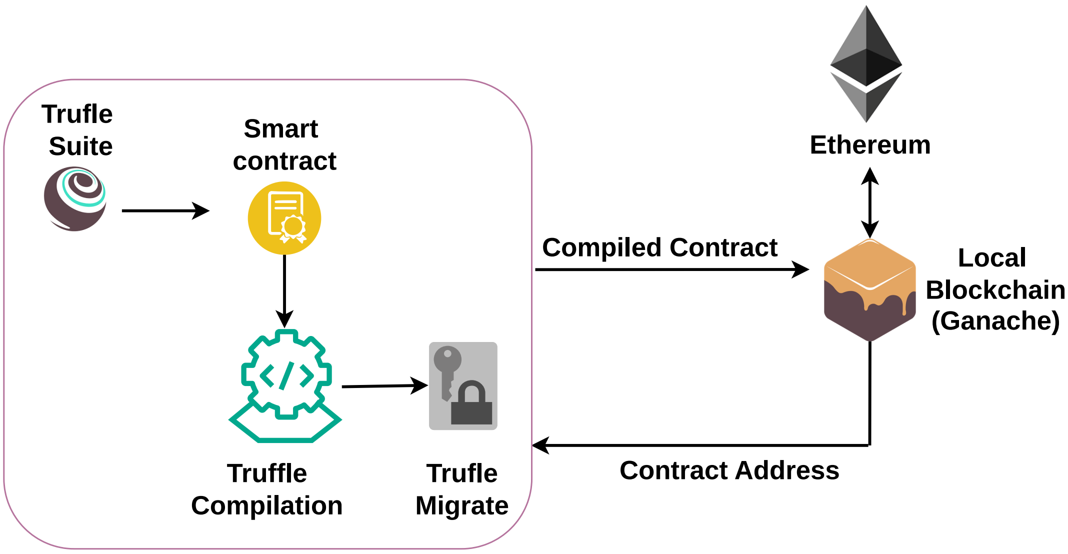


Fig. 3.1 Ethereum-based local blockchain

cost-effectiveness, speed, and extensive debugging capabilities make it an indispensable part of the Ethereum development toolkit, supporting developers in building secure, efficient, and optimized blockchain applications. Ganache empowers developers to confidently create innovative solutions by offering complete control over the blockchain environment, ensuring their applications are robust and ready for deployment in the rapidly evolving world of decentralized technologies [33].

In this research, a private blockchain using Ethereum (Ganache) is implemented, which offers controlled access and higher transaction throughput compared to public blockchains. This choice is particularly suited for the 5G NTN emulation, where the speed and security of transactions are paramount. The inherent properties of blockchain, such as decentralization, immutability, transparency, and automation through smart contracts, provide a robust foundation for securing the communication and authorization processes in our 5G NTN setup.

Fig. 3.1 shows the general working principle of the Ethereum local blockchain during the compilation of smart contracts.

The smart contract is written using Solidity language and compiled using Truffle Suite IDE. After the smart contract is compiled, an Application Binary Interface (ABI) file and the bytecode are generated. The smart contract is then deployed to the Ethereum Virtual Machine (EVM), and a contract address is provided to the interacting applications. The ABI file is then used as an interface between the applications that interact with the blockchain.

3.4.3 Satellite firmware update strategy

Efficient firmware update strategies for Low Earth Orbit (LEO) satellites are essential for maintaining satellite constellations' operational efficiency, reliability, and security. LEO satellites operate in dynamic and often harsh environments, making them susceptible to hardware and software malfunctions that can significantly impact their performance. Regular firmware updates are crucial to address software bugs, enhance functionality, improve performance, and patch security vulnerabilities [127]. However, updating firmware in LEO satellites poses several unique challenges due to their high-speed mobility, limited connectivity, and stringent security requirements, as shown in Figure 4.22.

One prominent strategy for updating LEO satellite firmware is using over-the-air (OTA) updates, similar to the methods used for IoT devices. OTA updates leverage the capabilities of advanced communication networks, such as 5G, to transmit firmware updates directly to the satellites in orbit. The high-speed and low-latency attributes of 5G networks facilitate rapid and efficient deployment of updates, reducing the time and resources needed for maintenance. This method is particularly advantageous as it allows updates to be pushed remotely, eliminating the need for physical access to the satellites, which is impractical in space. However, despite its efficiency, the OTA update approach introduces critical security vulnerabilities that must be carefully managed [57].

One significant security concern with OTA firmware updates is the potential for traffic interception and redirection attacks. As the update data flows from the 5G core network to the satellite, malicious actors can exploit vulnerabilities in the network to redirect the firmware update requests to unauthorized servers. This attack could lead to the satellite receiving corrupted or malicious firmware, compromising its operations or rendering it inoperable. Such security breaches can have severe implications, particularly in critical applications where satellite performance is crucial, such as navigation, communication, or military operations. The threat is exacerbated by satellites often operating autonomously and lacking robust defenses against sophisticated cyberattacks [108].

To mitigate these security challenges, several strategies are employed alongside OTA updates. One approach is the implementation of end-to-end encryption of firmware update data. Encrypting the data transmitted between the ground control and the satellite reduces the risk of interception, as the update packets cannot be easily modified or decoded by unauthorized entities [23]. Additionally, robust authentication mechanisms are used to verify the identity of the sending server and ensure that the firmware updates originate from trusted sources. Techniques such as public-key cryptography and digital signatures play a critical role in confirming the authenticity of the updated files before they are accepted by the satellite.

Another strategy involves using blockchain technology to enhance the security and integrity of firmware updates. Blockchain can provide a decentralized and immutable record of all firmware update transactions, making it nearly impossible for malicious actors to tamper with the update data. Smart contracts within a blockchain framework can automate verification, ensuring only authenticated updates are applied to the satellite. By creating a transparent and tamper-proof update history, blockchain technology can significantly enhance the overall security of satellite firmware updates [131].

In addition to these security enhancements, network segmentation and traffic monitoring are crucial in protecting the update process. Segmenting the network paths used for firmware updates makes it more difficult for attackers to access and manipulate the data flows. Continuous monitoring of the update traffic can also help detect any unusual patterns or anomalies indicating an ongoing attack, allowing immediate countermeasures to be deployed.

Furthermore, developing a robust fallback mechanism is essential in the event of a failed or compromised firmware update. Satellites should be able to revert to a previous stable firmware version if an update fails validation checks or leads to unexpected behavior. This rollback capability can prevent the satellite from being rendered inoperable due to faulty or malicious updates, ensuring continued operation while the issue is resolved.

In summary, while OTA updates provide a rapid and efficient method for updating LEO satellite firmware, the process must be safeguarded against security threats that can compromise satellite operations. A combination of encryption, authentication, blockchain technology, network segmentation, and robust fallback mechanisms is essential to a secure firmware update strategy. These measures protect satellites from cyberattacks and enhance their reliability and operational lifespan, contributing to satellite constellations' overall efficiency and security in the ever-evolving space environment.

3.4.4 Network Architecture and Methodology

The emulated network setup for the secure end-to-end 5G NTN leverages blockchain technology to enhance security across satellite networks. As shown in Figs. 4.22 and 3.3 comprise a 5G core network, radio access network, satellite network, local blockchain node, and middleware. The core network is emulated using Free5GC [43], an open-source, decentralized core network set compliant with 3GPP release 15. The radio access network is simulated using UERANSIM [53], which encompasses the gNB and the user equipment.

The access network (gNB) is considered to be located in the terrestrial segment. This last is connected to the satellite gateway to extend 5G services via the LEO satellite constellation to a remote UE. The satellite is a transparent node connecting the terrestrial gNB with the destination UE.

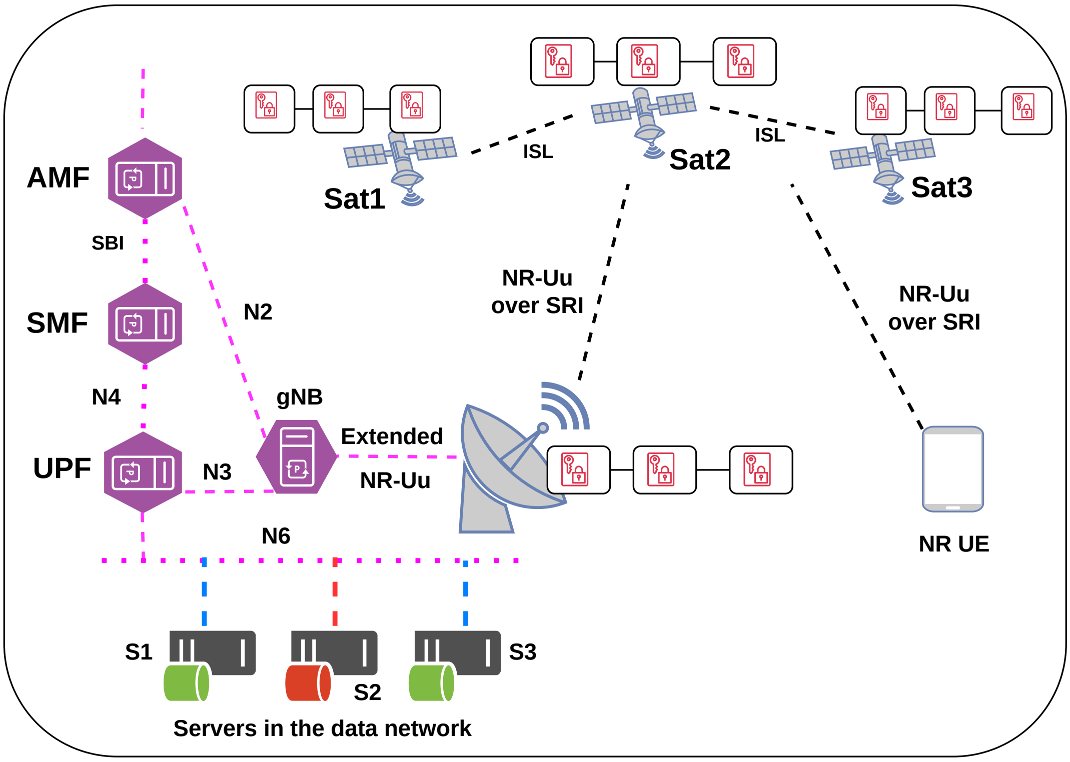


Fig. 3.2 Proposed Blockchain based 5G NTN

The satellite network is emulated using Opensand [104] emulator, and it consists of three separate components: gateway, satellite, and terminal. The gateway is connected to the terrestrial gNB to extend the 5G network services over the satellite radio interface (SRI) [111].

Ethereum's local blockchain environment (Ganache) [105] is used as a local blockchain network to host the smart contact and interact with the 5G NTN network for securing transactions between the 5G data plane network and the satellite network. The interaction between the 5G NTN network and the Ethereum node is realized using the Flask Web micro-framework, which is employed as a middleware.

3.4.5 Experimental Setup

The principle behind integrating the Ganache blockchain into the 5G NTN revolves around leveraging the blockchain's decentralized and immutable nature to enhance satellite network security. Ganache is a local Ethereum blockchain environment used to test and deploy smart contracts that manage and authorize servers from the 5G data network (see Fig. 3.3). The strategy involves using smart contracts to control access to the satellite network by verifying data plane servers and ensuring that only authorized servers can be accessed to generate traffic through the satellite network components. This approach prevents unauthorized access and secures data integrity across the NTN.

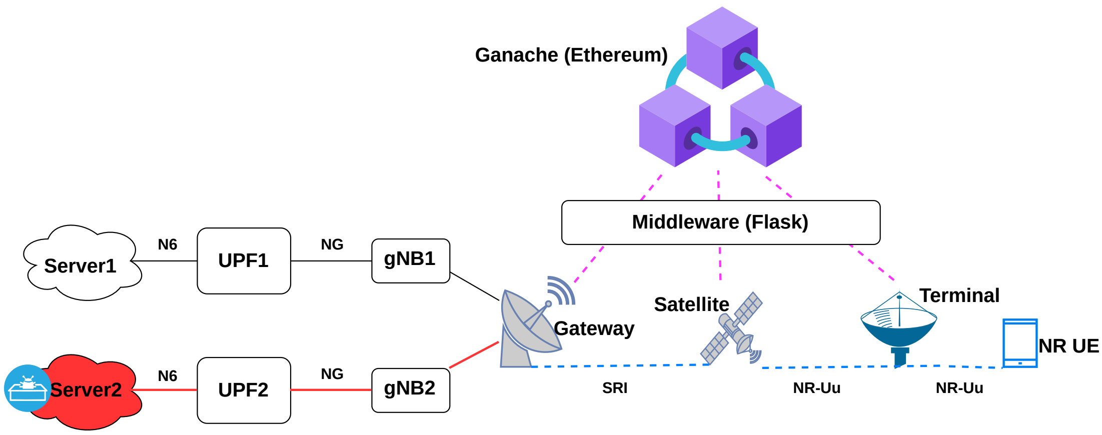


Fig. 3.3 Data plane authorization

All the network components are implemented in a docker-compose environment, properly configured, and sequentially triggered to achieve the proposed objective. The first setup step is to run the Ganache CLI environment as a docker container that listens at port 8545. Next, we develop and compile a smart contract defining the server authorization rules. This smart contract is then deployed to the Ganache using the Truffle suite compiler. An Application Binary Interface (ABI) file is generated when a smart contract is compiled and deployed. The ABI file allows external applications to interact with a deployed smart contract on the local blockchain across the middleware. The Ganache and middleware containers are properly networked to enable seamless communication between the deployed smart contract and the NTN components.

Algorithm 1 Deploy and Interact with Smart Contract

1: **Initialize** Ganache CLI `listens at port 8545`
2: **Compile** Smart contract `Authorization.sol`
3: **Deploy** `smart contract`
4: **Load** `contract ABI` into the middleware
5: **Configure** the contract address and private key to the middleware
6: **Start** middleware container `listens at port 5000`

After the smart contract is deployed, the ABI file, contract address, and private key of the Ganache account address will be provided to the middleware. The middleware, implemented using Flask and Web3, is configured to interact with the smart contract as shown in Algorithm 1. The middleware will be initialized as a docker container and exposed to listen at port 5000 so that the satellite components will interact with it at this port to access the smart contract. It allows for querying the authorization status of data network servers and updating the blockchain with the authorization changes.

Algorithm 2 Authorize Servers

procedure AUTHORIZE_SERVER(server_address)
  Connect to Ganache via Middleware
  Build transaction for `authorizeServer` function
  Sign transaction with private key
  Send transaction to Ganache
  Update blockchain state
end procedure

Once the Ganache and the middleware start their communication, the NTN will be deployed and the satellite components (Gateway, Satellite, and Terminal) will start interacting with the blockchain to check whether the server from which the network is trying to access should be authorized or not as can be seen from Algorithms 2 and 3.

Algorithm 3 Deauthorize Server

procedure DEAUTHORIZE_SERVER(server_address)
  Connect to Ganache via Middleware
  Build transaction for `deauthorizeServer` function
  Sign transaction with private key
  Send transaction to Ganache
  Update blockchain state
end procedure

The gateway, satellite, and terminal configuration files will be updated to enable communication with the middleware to check for authorization. These satellite components will sign transactions using the Ganache network's private key for integrity.

Algorithm 4 Check Authorization Status

procedure IS_AUTHORIZED(server_address)
  Query blockchain for authorization status
  Return authorization status
end procedure

As seen from Algorithm 4, an authorization status will be provided to the satellite network in boolean format, and the satellite network will accept or reject the incoming traffic depending on the provided authorization status.

3.4.6 Result and Discussion

The emulated network setup showcases the integration of blockchain technology into 5G NTN to enhance the security of satellite network communication. Using smart contracts for device authorization provides a robust mechanism to ensure that only legitimate traffic traverses the satellite network. This approach not only secures the communication channels but also demonstrates the potential of blockchain in managing complex 5G NTN architectures.

Fig. 3.4 shows the latency between terrestrial gNB and user equipment located in different locations and connected using an LEO satellite network. VoIP traffic is generated from the 5G data network considering a maximum delay of 50 ms with 5% packet loss to simulate the distance of the LEO constellation. Initially, traffic is collected without utilizing the blockchain authentication setup for comparison. Then, a blockchain middleware service is triggered, so the satellite components must make transactions with the blockchain to check for authorization of incoming VoIP traffic. Considering the situation when the traffic is authorized to pass through the satellite network, a maximum delay of 18 ms is recorded between the terrestrial gNB and UE with a 5 ms deviation from the average NTN traffic delay. This is due to the time required by the transaction of the satellite network to the blockchain to generate the authenticated traffic flow.

Fig. 3.5 shows the computed throughput with and without blockchain authentication. The result shows that the throughput achieved during the traffic authentication process exhibits lower readings than those without blockchain authentication. This is because the traffic forwarding capacity of the NTN network will degrade when the satellite components interact with the local blockchain via the middleware. However, the primary goal of the blockchain approach is to ensure the security of the NTN network for critical tasks, like e.g., the satellite firmware update, rather than improving throughput performance.

Plots of Fig. 3.6 show the tradeoff related to the authorization attempts of multiple traffic flows coming from different servers versus network performance. As the number of traffic flows authorized to traverse across the satellite network increases, the network's performance tends to decrease, such as when the throughput degrades, and the latency between terrestrial gNB and the UE increases. This is due to the overhead imposed by the authentication process of the blockchain node. This suggests that while the network becomes more secure, it becomes less efficient regarding data handling capacity and speed. The authorization attempts can be expressed by the ratio of successful authorizations to the total number of

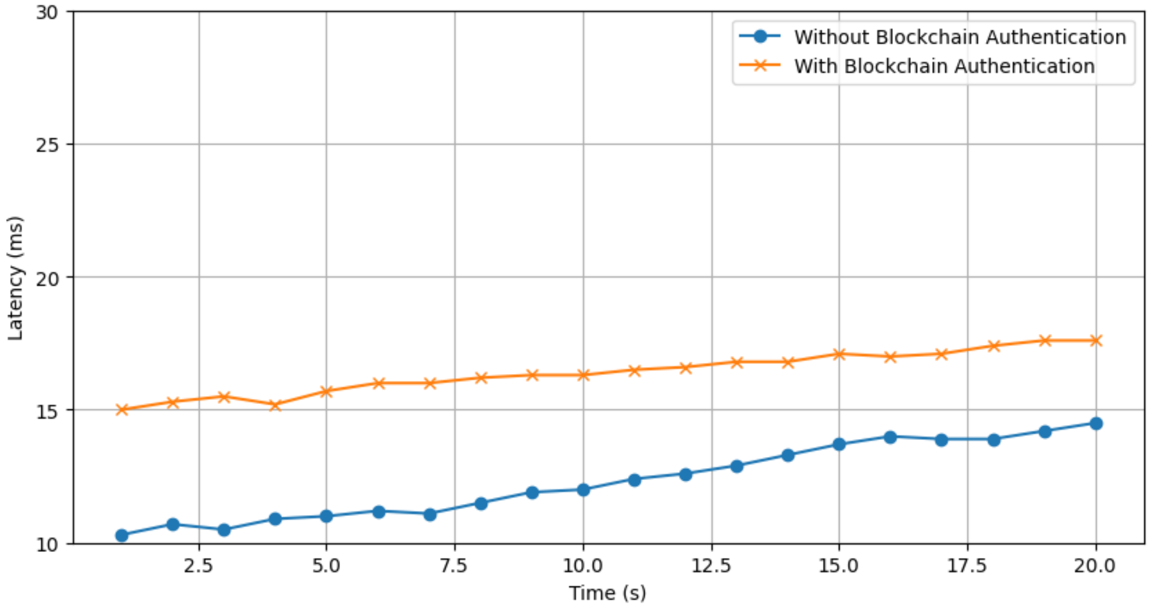


Fig. 3.4 Latency with and without blockchain authentication

authorization attempts $A_{Attempts}(\%)$ (both authorized and unauthorized traffic) as shown in eq. 3.1.

$$A_{Attempts}(\%) = \left(\frac{\text{Successful Authorizations}}{\text{Total Attempts}} \right) \times 100 \tag{3.1}$$

As can be seen from Fig. 3.6, a maximum throughput degradation $T_{Degradation}(\%)$ (see eq. 3.2) of 9.38% is exhibited with a maximum latency increase $L_{Increase}(\%)$ (see eq. 3.3) of 16.5% through the course of increasing the number of authorized traffic flows. For the sake of clarity, T_{baseline} is the baseline VoIP throughput equal to 128 kbps, and T_{current} is the current throughput (measured from the network). Similarly, L_{baseline} is the baseline latency (20 ms), and L_{current} is the current latency measured from the network.

$$T_{Degradation}(\%) = \left(\frac{T_{\text{baseline}} - T_{\text{current}}}{T_{\text{baseline}}} \right) \times 100 \tag{3.2}$$

$$L_{Increase}(\%) = \left(\frac{L_{\text{current}} - L_{\text{baseline}}}{L_{\text{baseline}}} \right) \times 100 \tag{3.3}$$

Fig. 3.7 shows the packet loss measured by launching the *iper3* command between the terrestrial user equipment and the gNB across the satellite network. The higher packet loss is recorded using Linux *tc* and *iptables* commands, which impose a high probability of packet drop to mimic the distance of the LEO satellite from the earth's surface and the loss

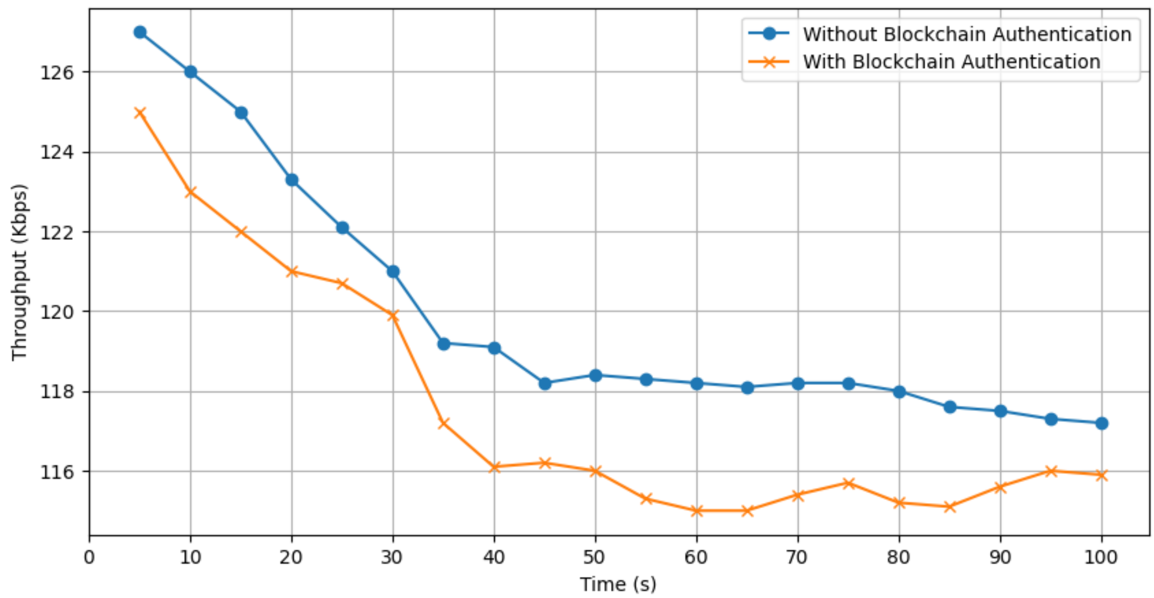


Fig. 3.5 Throughput with and without blockchain authentication

imposed by the satellite component interaction with the Ganache for traffic authorization. The simulation of 5G NTN with blockchain authentication exhibited more than 10% of packet loss as compared to the normal simulation without blockchain.

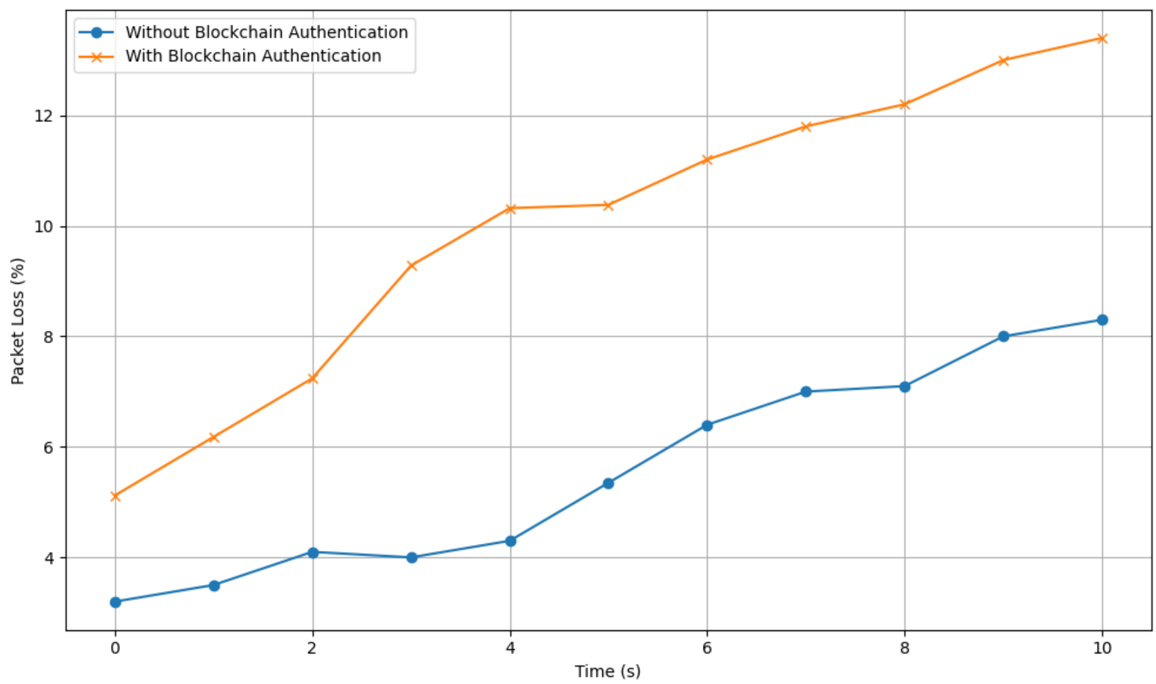


Fig. 3.7 Packet loss with and without blockchain authentication

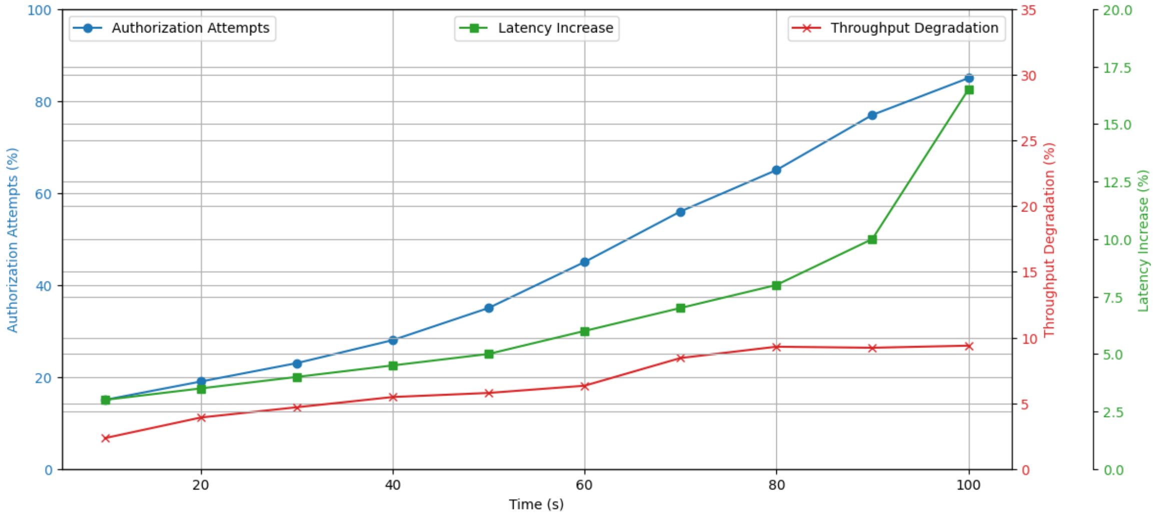


Fig. 3.6 Tradeoff between authorization attempts, throughput, and latency

3.5 Summary

In this chapter, a secure end-to-end 5G Non-Terrestrial Network (NTN) is developed and implemented using blockchain technology to enhance the security of the satellite network segment. By leveraging the capabilities of the Ethereum-based local blockchain (Ganache) and smart contracts, a robust and secure 5G NTN is developed, which ensures that only authorized traffic sources can transmit data across the satellite network, thus significantly enhancing the security and integrity of the satellite communication.

The experimental setup considered a Low Earth Orbit (LEO) satellite network integrated with a 5G core and access network, where blockchain-based authorization mechanisms are deployed to secure inter-satellite communications. The results demonstrated a tangible improvement in the security of the NTN, albeit with a tradeoff in slightly decreased network performance. Indeed, a throughput degradation ranging between 2.34% and 9.38% has been observed, while the measured latency increase ranged from 3% to 16.5%. These results highlight the price to be paid when implementing enhanced security countermeasures. Despite these tradeoffs, the security gain, measured through successful authorization attempts, fully justifies blockchain integration in scenarios (like satellite firmware updating) where security is paramount. The study effectively demonstrates the feasibility of blockchain in enhancing security in 5G NTN environments, setting a foundational basis for future improvement and optimization.

Despite the promising results, there are areas for future research. Enhancements might focus on reducing the latency introduced by the blockchain verification process and improving the system's scalability to handle several network components using the multi-agent concept

[19], [112]. Further research could also explore the integration of advanced security features and investigate the use of alternative platforms to optimize network performance.

Chapter 4

AI/ML Based Resource Management and Optimization Techniques for 5G-NTNs

4.1 Introduction

The rapid advancement and deployment of 5G networks have revolutionized the telecommunications landscape, ushering in an era of ultra-reliable, high-speed, and low-latency communications. This evolution is driven by the increasing demand for high-bandwidth applications such as autonomous driving, smart cities, and the Internet of Things (IoT), which require robust and efficient network infrastructures capable of handling heterogeneous and dynamic traffic loads [46]. As the demand for seamless connectivity grows, integrating Non-Terrestrial Networks (NTNs) with terrestrial 5G networks has emerged as a critical strategy for enhancing global communication capabilities.

NTNs, which include satellite communications, UAVs, and High Altitude Platform Systems (HAPS), complement terrestrial 5G networks by providing extensive coverage, particularly in remote, underserved, and connection-critical areas [111]. By enabling seamless communication across diverse environments, NTNs address key challenges such as the digital divide and the need for resilient network infrastructures in disaster-hit regions [50]. However, integrating NTNs into existing 5G frameworks introduces significant challenges related to resource management and optimization due to factors such as high propagation delays, pronounced Doppler effects, and the need for frequent handovers.

In this context, disaggregated Radio Access Networks (RANs) have emerged as a pivotal innovation in 5G-NTNs. Disaggregated RANs decompose the traditional monolithic base station architecture into distinct components, including the Central Unit (CU), Distributed Unit (DU), and Radio Unit (RU), which can be flexibly deployed across terrestrial and non-terrestrial nodes [110]. This separation facilitates efficient resource management, enhances network performance, and improves scalability by allowing individual components to be optimized independently [65]. However, managing disaggregated RANs in NTNs presents new challenges, particularly in predicting and optimizing resource consumption to maintain Quality of Service (QoS) and minimize Service Level Agreement (SLA) violations.

Accurate network traffic and resource usage prediction is essential for dynamic network slicing, efficient traffic steering, and proactive failure management within NTNs [81]. In this regard, Machine Learning (ML) models have demonstrated significant potential in enhancing resource management through predictive insights and adaptive optimization strategies. Long Short-Term Memory (LSTM) networks, a specific type of recurrent neural network (RNN), have proven particularly effective in time-series prediction, capturing long-term dependencies in data and accurately forecasting network resource needs [19, 113, 114]. LSTM models are well-suited for predicting dynamic and complex traffic patterns, making them valuable tools for optimizing resource allocation in disaggregated RANs within 5G-NTNs [45, 59].

This chapter focuses on developing LSTM-based resource prediction models for disaggregated RAN architectures in 5G-NTNs. By splitting the gNB into gNB-CU and gNB-DU components across the satellite network, these models enable the extension of interfaces like F1 and E1 over satellite radio interfaces (SRI), facilitating efficient management of computational resources such as CPU, memory, and bandwidth. Proactive resource allocation driven by LSTM-based predictions helps maintain network performance and prevent SLA violations in highly dynamic NTN environments.

Additionally, this chapter explores the use of Graph Neural Networks (GNNs) for monitoring and managing disaggregated Centralized RAN (C-RAN) architectures within NTNs. GNNs are leveraged to capture complex relationships between network nodes, enabling real-time detection of link failures, prediction of network performance, and optimization of traffic routing paths [69]. These capabilities are crucial for NTNs, where high mobility and frequent topology changes demand continuous monitoring and rapid adaptation to evolving conditions. The deployment of a cloud-native GNN-based monitoring framework enhances network observability and resilience, providing valuable insights into resource utilization and overall network health.

Resource optimization in NTNs extends beyond the core network to aerial components such as UAVs, which are increasingly used to enhance coverage and connectivity in dynamic and challenging environments. UAVs offer rapid deployment, flexible positioning, and cost-effective coverage solutions, but optimizing their operational parameters, such as energy consumption and flight trajectories, remains a complex challenge [94]. Reinforcement Learning (RL) techniques, particularly the LSTM-A2C (Advantage Actor-Critic) approach, have shown great promise in addressing these challenges by dynamically adjusting UAV paths based on real-time feedback [80]. By optimizing UAV trajectories, these models minimize energy consumption while maximizing coverage, enhancing the overall efficiency of NTNs in applications like 6G-enabled IoT surveillance networks.

This chapter's contributions highlight the critical role of AI/ML models in transforming resource management and optimization in 5G-NTNs. By integrating predictive and adaptive techniques such as LSTM-based resource forecasting, GNN-based network monitoring, and RL-driven UAV optimization, this research addresses the unique challenges of NTNs. It sets the foundation for resilient, scalable, and efficient network architectures. These advanced methodologies pave the way for future B5G and 6G networks, supporting the deployment of critical communication services across diverse and often unpredictable environments.

4.2 LSTM-based Resource Prediction for Disaggregated RAN in 5G-NTNs

4.2.1 Background and Motivation

Non-terrestrial networks (NTNs), including satellite communications, complement terrestrial 5G networks by providing extensive coverage, particularly in remote and underserved areas [111]. Integrating NTNs with terrestrial networks promises to enhance global connectivity, enabling seamless communication across diverse environments [50].

In this context, disaggregated radio access networks (RANs) have emerged as a pivotal innovation. Disaggregated RANs separate the traditional monolithic base station architecture into distinct components such as the Central Unit (CU), Distributed Unit (DU), and Radio Unit (RU) [110]. This separation facilitates flexible deployment and efficient management of network resources, thereby enhancing network performance and scalability [65].

One of the primary challenges in managing 5G NTNs with disaggregated RAN architectures is predicting and optimizing resource consumption to maintain Quality of Service (QoS) and minimize Service Level Agreement (SLA) violations. Accurate network traffic and resource usage prediction is essential for dynamic network slicing, efficient traffic steering, and proactive failure management [81]. In such a framework, Machine Learning can offer valuable solutions. In particular, LSTM networks - a specific typology of recurrent neural network (RNN) - have demonstrated remarkable success in time-series prediction due to their ability to capture long-term dependencies in data [19, 113, 114]. LSTM models are particularly well-suited for predicting network traffic and resource consumption in 5G networks, where traffic patterns are dynamic and complex [45], [59].

This section focuses on developing an LSTM-based resource prediction model for disaggregated RAN in 5G NTNs. We propose two architectures: the first involves splitting the gNB into gNB-CU and gNB-DU across the satellite network, extending the F1 interface over the satellite radio interface (SRI). The second architecture implements the F1 and E1 splits, with the gNB-CUUP as a satellite payload. These architectures are evaluated for their resource consumption (CPU, memory, and bandwidth) and prediction accuracy using the LSTM model.

By leveraging LSTM-based predictions, our approach aims to enhance network management by providing insights into future resource requirements, facilitating proactive resource allocation, and improving overall network performance. This research contributes to the broader goal of developing resilient and efficient 5G NTNs capable of meeting the stringent demands of modern communication applications.

Our research work uniquely addresses the prediction of resource consumption for split NGRAN components across 5G NTN networks so that the prediction output will be used by the network management section to decide which network function of the disaggregated NG-RAN component can be considered as a satellite payload based on their previous resource consumption. By considering both F1 and E1 splits and deploying gNB-DU and gNB-CUUP as satellite payloads, our work aims to improve network resilience and readiness for future network management decisions. This approach extends the existing LSTM-based prediction methodologies to NTNs and provides a comprehensive solution for managing the complex resource requirements of disaggregated RAN architectures in 5G NTN environments.

4.2.2 Disaggregated RAN Architecture

In the evolving landscape of 5G networks, the Next Generation Radio Access Network (NGRAN) disaggregation has emerged as a key architectural innovation to modularize and simplify network complexity and convert the centralized NGRAN functionality into a disaggregated function. This will benefit network service providers and operators by simplifying network monitoring tasks to maintain the required Quality of Service (QoS). The 3GPP TS 38.401 specification [8] discusses how the NGRAN can be functionally split into distinct units, namely the Central Unit (CU) and Distributed Unit (DU), which can be further divided into the CU-Control Plane (CU-CP) and CU-User Plane (CU-UP).

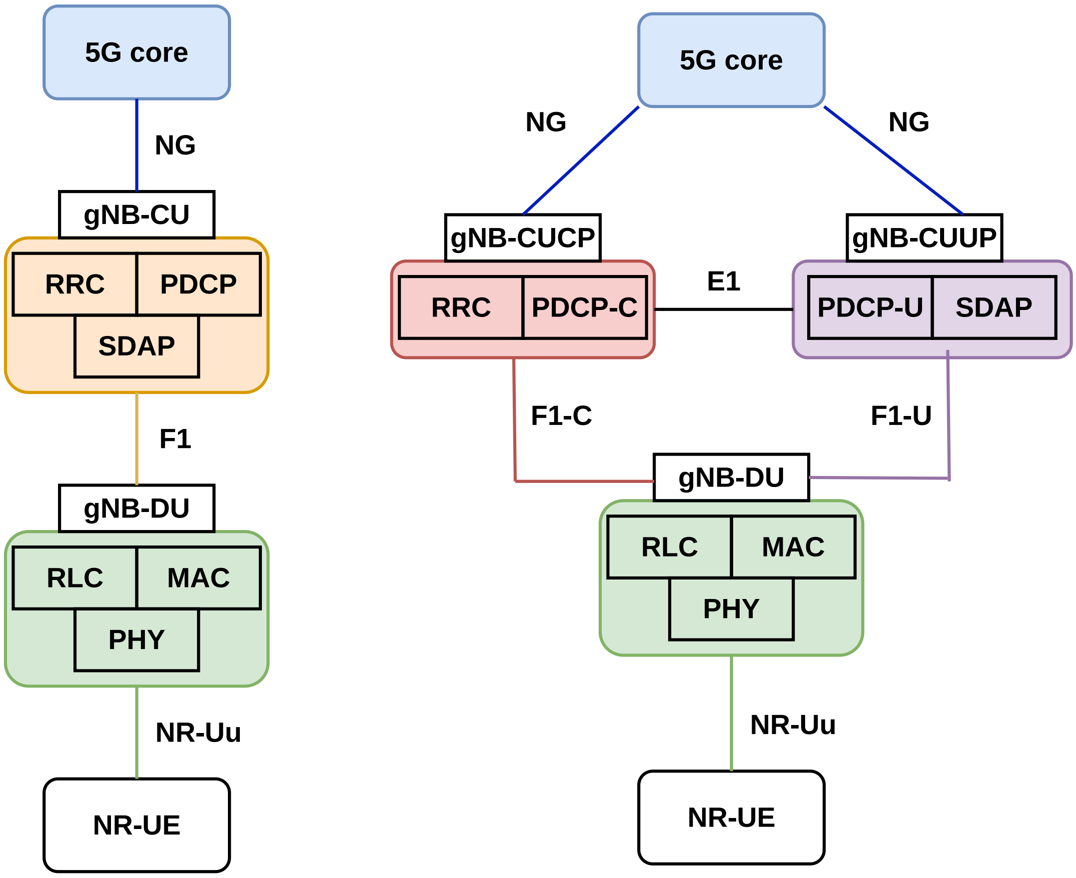


Fig. 4.1 NGRAN Functional splitting architecture

This disaggregated approach enables operators to deploy network functions in a cloud-native environment, optimizing resource allocation and reducing latency by strategically positioning these components in the network. The disaggregated RAN supports more efficient network traffic management by separating control and user plane functions. It facilitates the integration of new technologies and services, making it a cornerstone of next-generation 5G NTN networks.

As referenced in [8], [84], and [17], the gNB-CU and gNB-DU are connected via the F1 interface. The gNB-CU consists of three layers: the packet data convergence protocol (PDCP), radio resource control (RRC), and service data adaptation protocol (SDAP). The RRC manages connection, mobility, security, and QoS between user equipment (UE) and the network. PDCP handles data compression, security, sequencing, and reliable transfer, while SDAP maps QoS flows to data radio bearers (DRBs) to prioritize traffic based on QoS requirements. The gNB-DU hosts the radio link control (RLC), medium access control (MAC), and physical layers. The RLC manages the segmentation, reassembly, and retransmission of data; the MAC layer handles scheduling, error correction, and multiplexing; and the physical layer is responsible for transmitting and receiving data over the radio interface.

Figure 4.1 also shows a further split of the gNB-CU into gNB-CUCP and gNB-CUUP, where the gNB-CUCP handles the RRC and the control plane tasks of PDCP (PDCP-C) and the gNB-CUUP handles the SDAP and PDCP user plane (PDCP-U) tasks [66], [100]. The PDCP-C handles control plane tasks such as managing signaling messages, while the PDCP-U is responsible for user plane data functions like header compression, encryption, and integrity protection. This split allows for flexible network deployment and efficient resource management to maintain QOS and efficient service level agreements (SLAs).

4.2.3 Proposed Network Architecture and Methodology

The payload capability of a typical LEO satellite in terms of available CPU and memory capacity varies significantly based on the specific design and the intended application. This work considers a typical LEO satellite working in a 5G NTN environment. Two network architectures are considered in this work. The first architecture in Figure 4.2 shows the 5G NTN network with gNB F1 interface over satellite radio interface (F1 over SRI) where the gNB-DU is moved to the satellite payload.

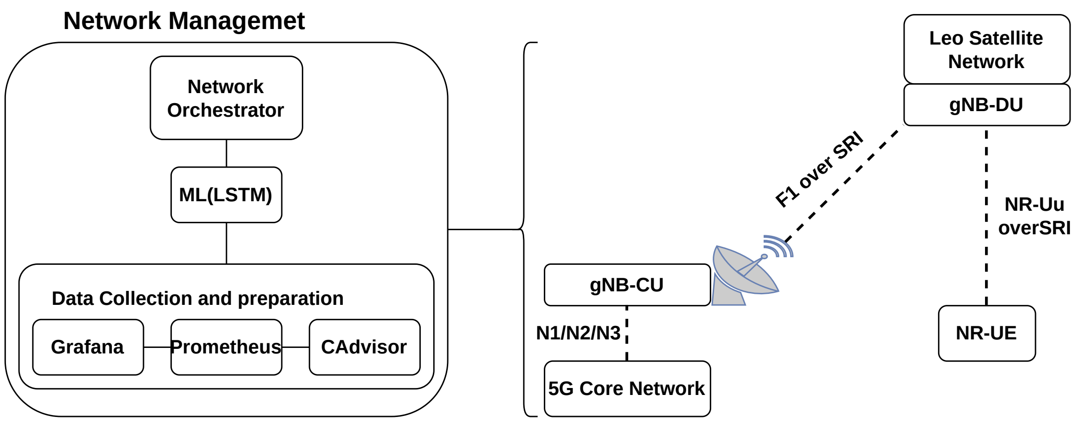


Fig. 4.2 5G NTN with F1 split

Figure 4.3 shows the second 5G NTN network architecture with gNB F1-E1 over SRI (F1-E1 over SRI), where both the F1 and E1 splitting of gNB are deployed across the satellite network. In this scenario, the gNB-CUUP will embark on the payload of the LEO satellite, and the other network components will be placed in the terrestrial network.

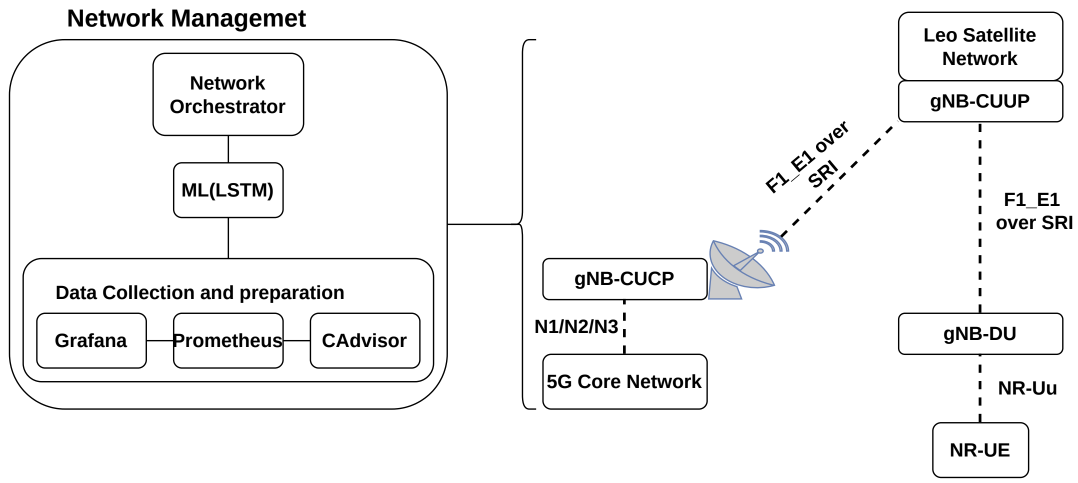


Fig. 4.3 5G NTN with F1_E1 split

The network management section in both scenarios above relies on components like data collection and preparation, LSTM-based prediction model, and network orchestrator. The data collection section consists of open-source tools that can be used together to monitor docker container-based networks. These components are used to collect and visualize the resource consumption of the target network function. The first component of this section is CAdvisor [49], which is used to collect, aggregate, and export information about containers running on a host computer. It can collect metrics like CPU usage, memory usage, and bandwidth utilization. The second component is Prometheus [36], which collects and stores metrics as time series data that can be used for visualization. The third component is Grafana [35], which queries and visualizes metrics from Prometheus.

The management section's network orchestrator is assumed to decide on the network functions based on the related historical resource utilization outputs provided by the LSTM prediction model. A real orchestrator has not been implemented in our emulations. We assumed an ideal orchestrator making ideal decisions driven by the prediction outcomes.

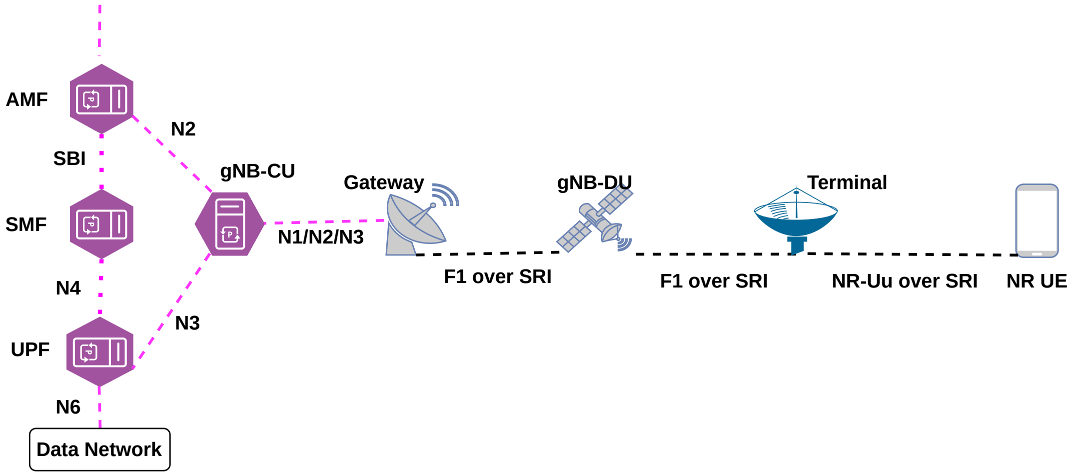


Fig. 4.4 Emulated 5G NTN with F1 split

The emulated network as shown in Figure 4.4 and Figure 4.5 depicts the two architectures with only F1 split considering gNB-DU as the satellite payload and with both F1 and E1 split considering gNB-CUUP as the satellite payload.

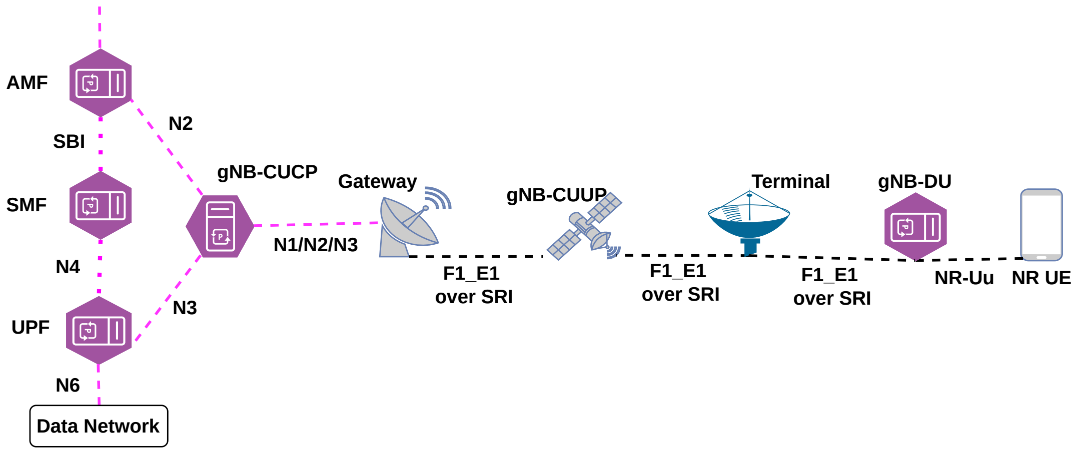


Fig. 4.5 Emulated 5G NTN with F1_E1 split

Algorithm 5 below describes the resource utilization prediction of the LSTM model used in this work.

4.2.4 Results and Analysis

Data on CPU usage, memory usage, and bandwidth utilization for the gNB-DU and gNB-CUUP components were collected over 10 hours of simulation from Figures 4.2 and 4.3

Algorithm 5 LSTM for Resource Consumption Prediction

Input: Data (CPU, Mem), seq_length, epochs
for each epoch **do**
    Load data
    data.columns ← strip names
    data(Bandwidth) ← $\frac{data[CPU] \cdot data[Mem]}{10^6}$
    Initialize: MinMaxScaler
    scaled_data ← scaler.fit(data)
    x, y ← create_sequences(seq_length)
    x_train, x_test, y_train, y_test ← split(scaled_data, 0.2)
    Initialize: Sequential(LSTM, Dropout, Dense)
    Initialize Adam
    model.compile(loss='mse', optimizer=Adam)
    early_stopping, reduce_lr ← set callbacks
    model.fit(x_train, y_train, callbacks=[early_stopping, reduce_lr])
    test_loss, test_mae ← model.evaluate(x_test, y_test)
    Predictions ← model.predict(x_test)
    y_test_original ← inverse_transform(y_test)
end for
Output: Trained model with metrics (test_loss, test_mae) and reconstructed labels (y_test_original)

using Prometheus and Cadvisor. This data was normalized with a MinMaxScaler to scale features between 0 and 1, essential for LSTM model performance. The normalized data was transformed into sequences of 10 consecutive time steps, facilitating the learning of temporal dependencies. The dataset was split 80-20 into training and testing sets, with the training set further divided to include a validation subset to prevent overfitting.

An enhanced LSTM model, incorporating layers such as LSTM, BatchNormalization, Dropout, and Dense, was trained for 300 epochs, employing early stopping and learning rate reduction for optimization. Model performance was assessed on the test set using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2).

This section presents simulation results, focusing on the resource utilization of the LEO satellite payload components gNB-CUUP and gNB-DU within the disaggregated NG-RAN 5G NTN network. The network simulation uses OpenAirInterface for the disaggregated NG-RAN and free5GC as the 5G core, while OpenSAND emulates the satellite network's gateway, satellite, and terminal components. The entire network is emulated in a Docker Compose environment, equipped with data collection and visualization monitoring tools integral to the LSTM model. The experiment is conducted on a Linux OS laptop with an Intel(R) Core(TM) i7-7500U CPU @ 2.70GHz, four allocated CPUs, and 16 GB of RAM. The complete code for the experiment is available at https://github.com/HenokBerhanu/disag_vcc.

Analysis on the resource consumption of gNB-DU on F1 split

This subsection considers the architecture shown in Figure 4.4, where the gNB-DU is the payload of the LEO satellite, and its resource consumption will be analyzed. Video traffic of 4 Mbits/s is generated across the network using *iperf3* to collect data.

Figure 4.6 compares the actual and predicted CPU usage of the gNB-DU component over a specific time window. This plot demonstrates how the LSTM model can effectively capture the temporal patterns in CPU usage, with a mean absolute percentage error (MAPE) of 12.24% showing acceptable prediction accuracy. An average predicted value of 0.5% CPU utilization is recorded.

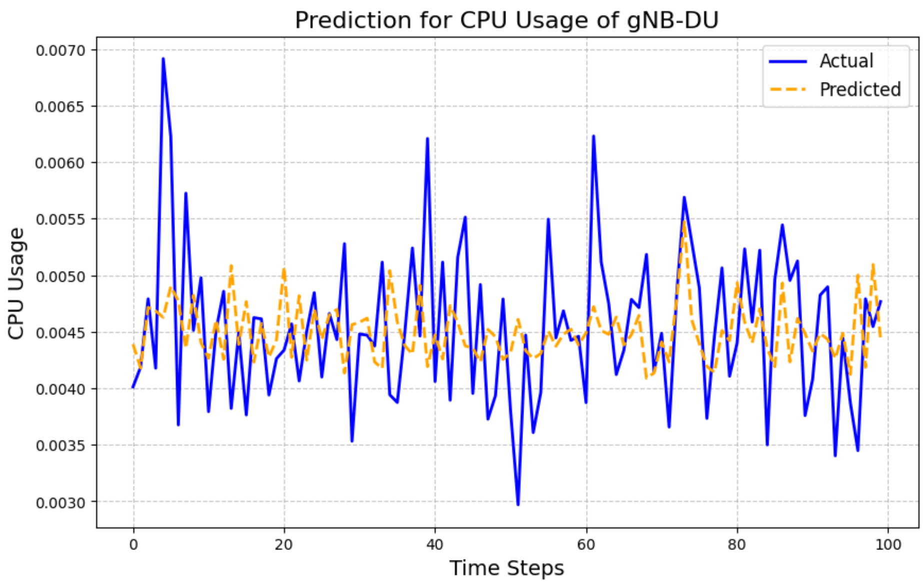


Fig. 4.6 CPU Usage for gNB-DU F1 split

Figure 4.7 illustrates the memory usage of the gNB-DU, following the same format as the CPU usage plot. It compares the actual memory usage to the related predicted values, with a MAPE of 0.72% with a highly reliable prediction performance. The average predicted memory usage by the LSTM model is around 20 MiB.

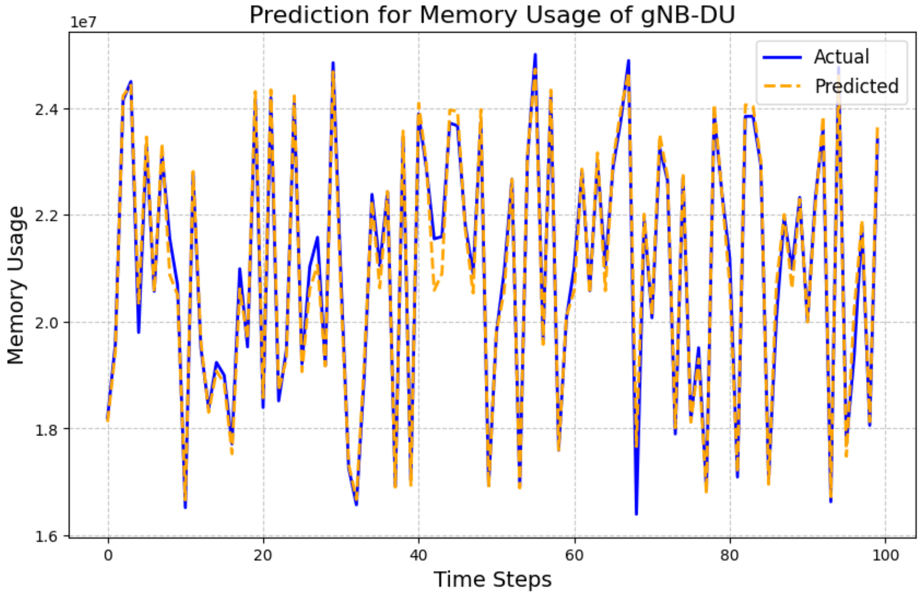


Fig. 4.7 Memory Usage in byte for gNB-DU F1 split

Figure 4.8 shows the bandwidth utilization, comparing actual versus predicted values with a MAPE of 11.96%, an MSE of 0.0002, MAE of 0.0111, and an R-squared value of 0.3743 showing acceptable prediction accuracy of satellite gNB-DU.

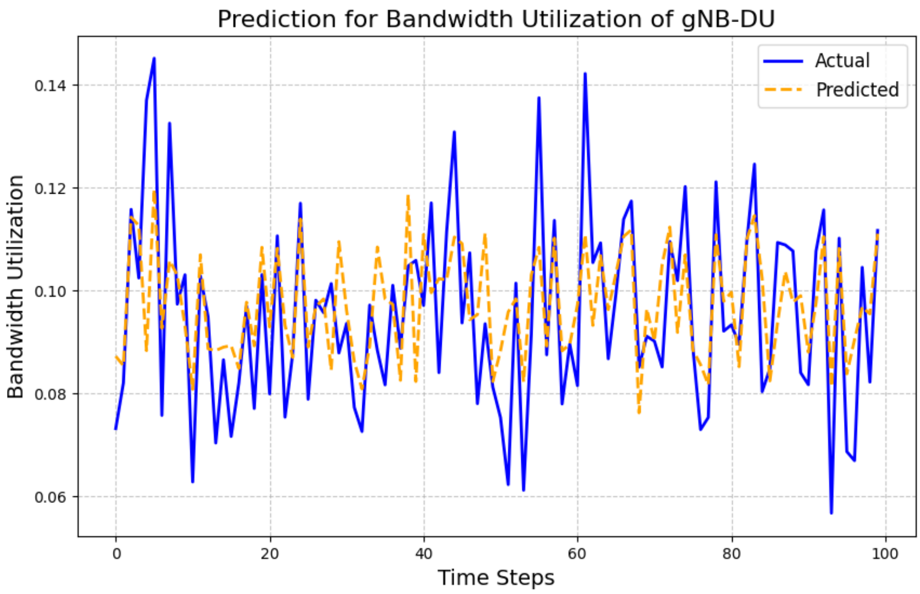


Fig. 4.8 Bandwidth utilization for gNB-DU F1 split

The error distribution plots in figure 4.9 provide a detailed view of the discrepancies between each feature's predicted and actual values. By visualizing these errors through histograms and the ML model loss as shown in figure 4.10, we can assess the accuracy of our predictions and identify any patterns or anomalies in the prediction errors.

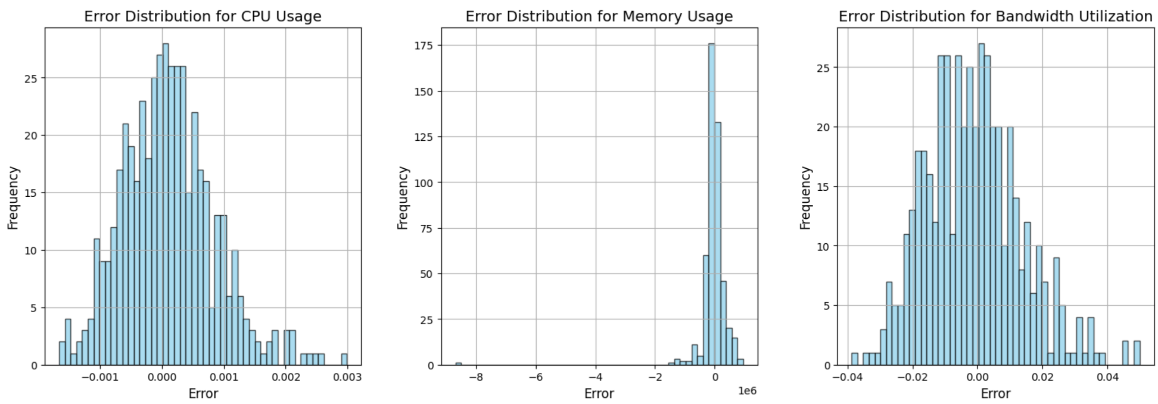


Fig. 4.9 Error Distribution for CPU, Memory, and Bandwidth usages for gNB-DU F1 split

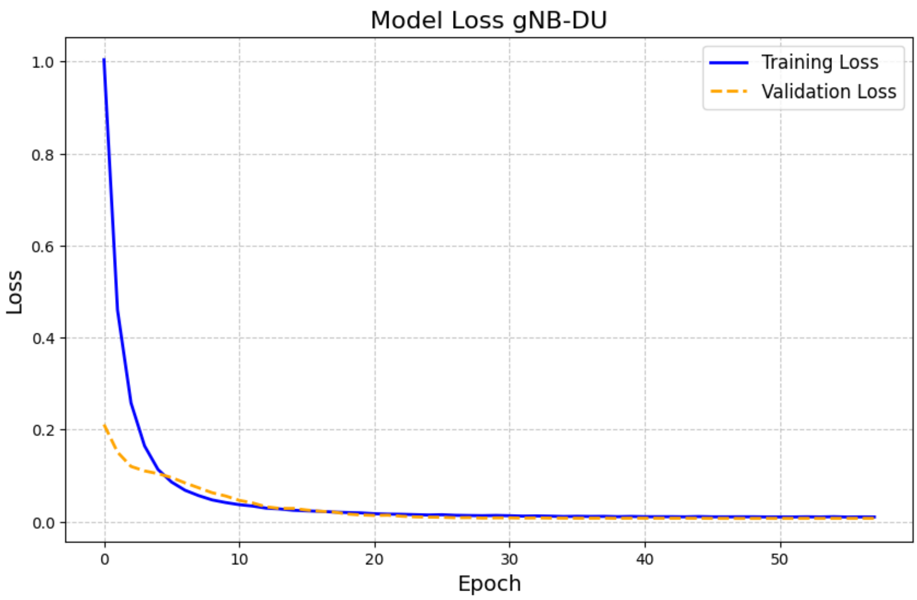


Fig. 4.10 Model Loss gNB-DU F1 split

The training vs. validation Mean Absolute Error (MAE) plot in Figure 4.11 compares the model performance on the training and validation sets across different epochs. The training MAE indicates how the model error decreases on the training data as it learns over epochs.

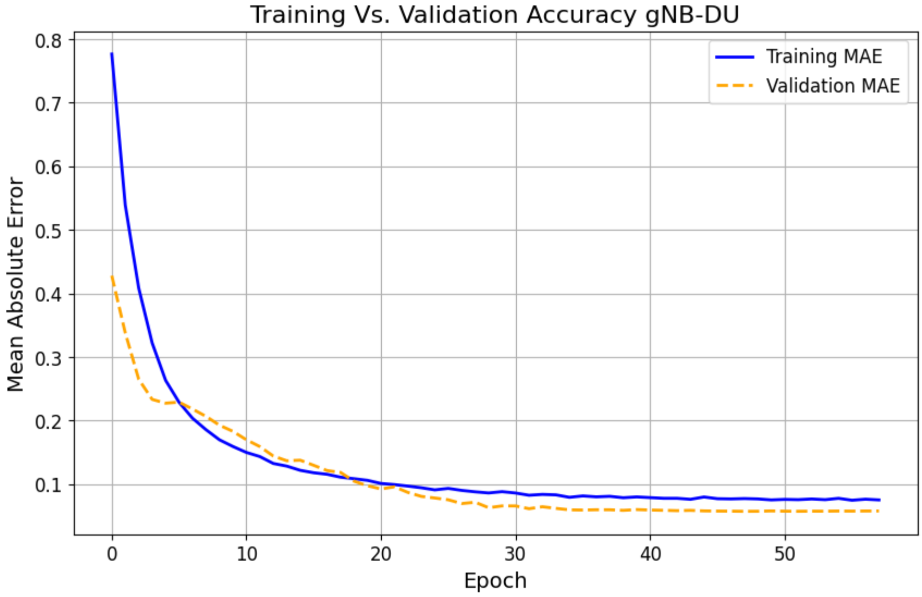


Fig. 4.11 Training vs Validation Accuracy for gNB-DU F1 split

Analysis on the resource consumption of gNB-CUUP on F1-E1 split

Figure 4.12 compares the actual and predicted CPU usage of the gNB-CUUP component over a specific time window. The model has moderate predictive accuracy with an ideal MSE of 0, MSE of 0.0004, and an R-squared value of 0.0126, indicating that the model has efficiently learned the provided data pattern.

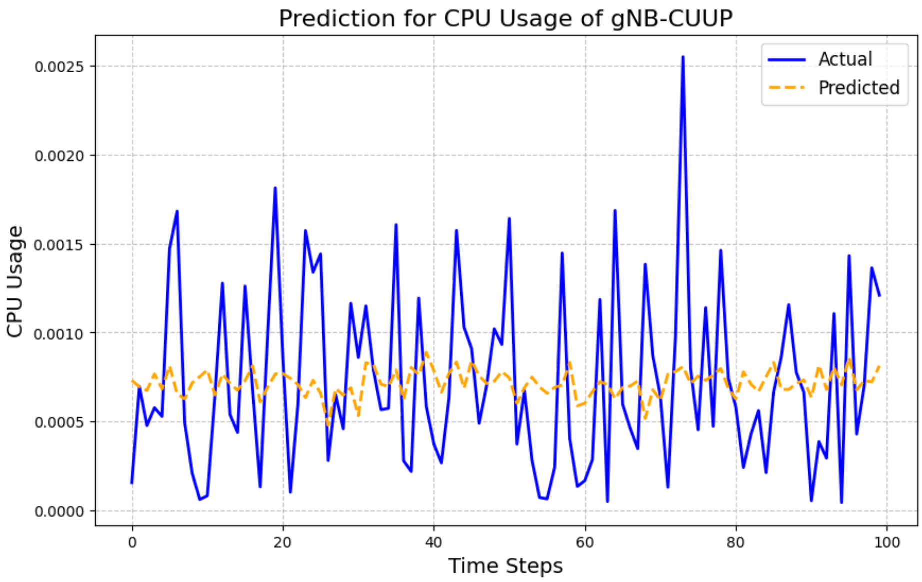


Fig. 4.12 CPU Usage of gNB-CUUP for F1-E1 split

As can be seen from Figure 4.6 and Figure 4.12, there is a higher CPU demand for the gNB-DU, as compared to the CPU demand of gNB-CUUP of the F1-E1 split. This indicates that it is technically better to consider the gNB-CUUP of the disaggregated NG-RAN as moved to the LEO satellite payload.

Figure 4.13 shows the memory usage of the gNB-CUUP of the LEO satellite payload. With a MAPE of 0.9% and an R-squared value of 0.9985, the prediction accuracy of the proposed model exhibits better performance in memory prediction.

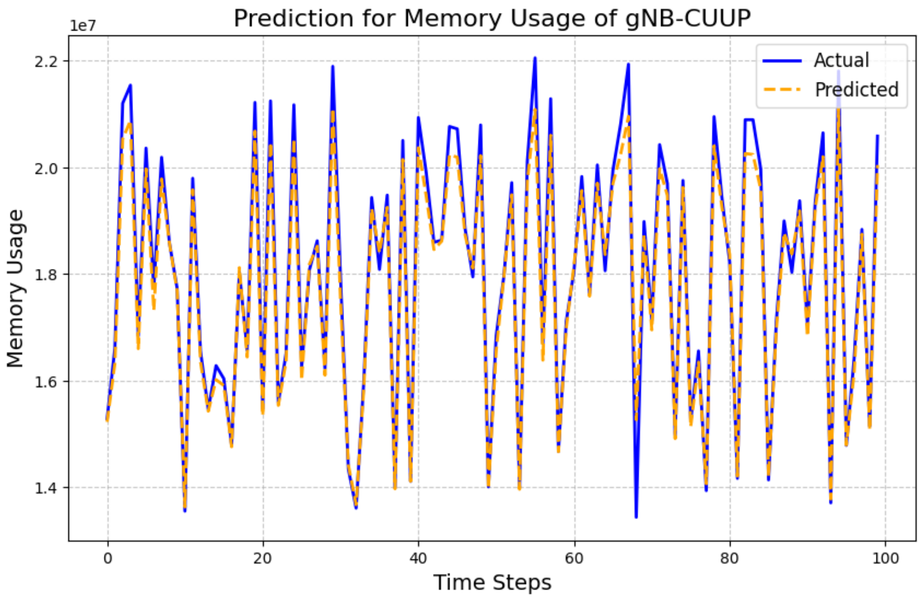


Fig. 4.13 Memory Usage for gNB-CUUP F1-E1 split

Figure 4.14 shows bandwidth utilization, comparing actual versus predicted values. The MAPE is 13%, showing acceptable prediction accuracy with an MSE of 0.0007, MAE of 0.0214, and R-squared error of 0.5428.

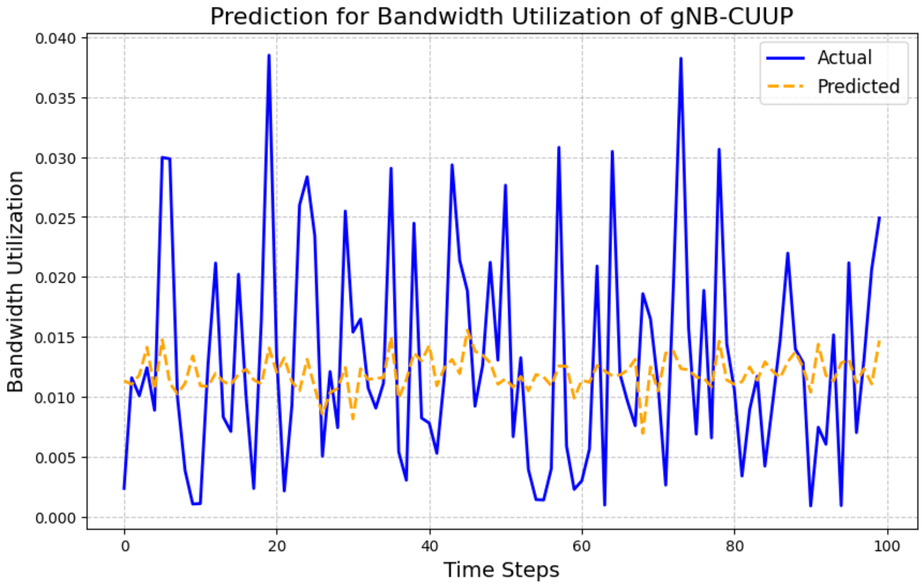


Fig. 4.14 Bandwidth utilization for gNB-CUUP F1-E1 split

The training vs. validation Mean Absolute Error (MAE) plot in Figure 4.15 compares the model's performance on the training and validation sets across different epochs. This visualization helps us understand how well the model generalizes unseen data.

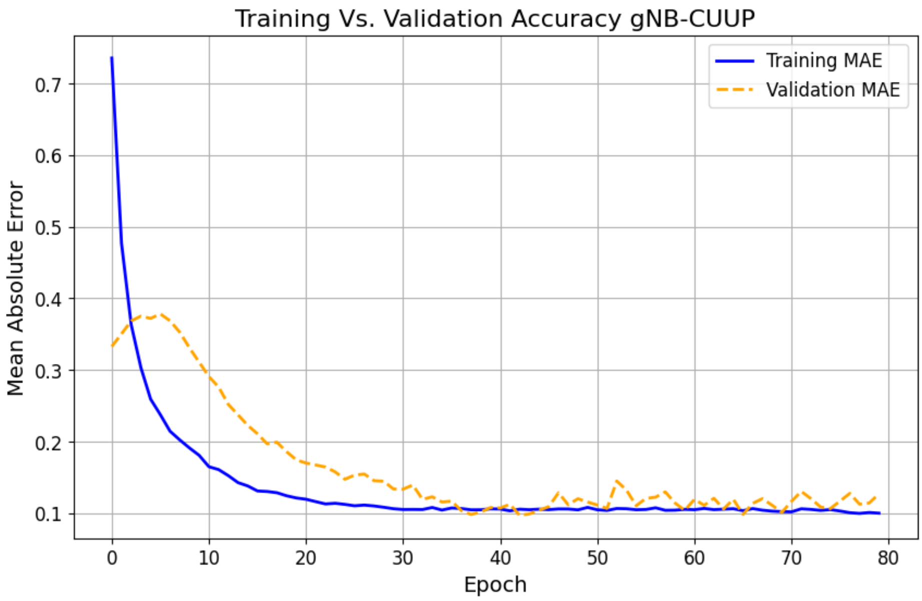


Fig. 4.15 Training vs. Validation Accuracy for gNB-CUUP F1-E1 split

The training MAE indicates how the model's error decreases on the training data as it learns over epochs. The validation MAE reflects the model's performance on validation data and can reveal if the model is overfitting or underfitting.

4.3 Graph Neural Network-based C-RAN Monitoring for Beyond 5G-NTNs

4.3.1 Introduction

Non-terrestrial networks (NTN) are instrumental in shaping the development of ubiquitous, reliable, and scalable B5G networks. It extends beyond traditional terrestrial communication systems by providing connectivity to remote and isolated regions that are otherwise challenging to access due to geographical constraints. Additionally, it helps alleviate congestion on primary links during periods of high traffic demand. However, integrating NTN into existing communication frameworks presents some peculiar challenges, including significant propagation delays, pronounced Doppler effects, resource allocation complexity, and the need for rapid and frequent handovers. These obstacles pose significant challenges to the effective deployment of NTN.

The discussion on challenges and potential solutions in 5G satellite networks is complemented by utilizing Artificial Intelligence/Machine Learning (AI/ML) and edge computing technologies to efficiently monitor and manage future cloud-native beyond 5G (B5G)/6G networks. Within the context of Software-Defined Networking (SDN) and Network Function Virtualization (NFV) in 5G NTN, the network orchestrator of the satellite and terrestrial network can benefit from the utilization of efficient AI/ML mechanisms to minimize the data processing and traffic routing overhead on the satellite thereby automating the NTN network.

The work by [111] presents a virtualized end-to-end experimental testbed employing Multi-Access Edge Computing (MEC) functionalities for a 5G NTN network. Considering Low Earth Orbit (LEO) small satellites, the deployment utilizes open-source 5G and satellite emulators with network functions distributed as Docker containers and orchestrated using Docker Compose. Optimization of the routing path in the LEO satellite constellation can be achieved by considering various Key Performance Indicators (KPIs) such as routing re-computation time, satellite altitude, distance from user equipment, inter-satellite links, and input/output packet rates.

Advancing towards inclusive 6G systems involves leveraging AI/ML for network management, routing, resource allocation, and integrating cloud services into NTN networks [32]. A comprehensive survey of AI-powered satellite-based NTN for 6G network services is extensively discussed in [83]. Furthermore, [20] compares satellite emulators for experimental setups, evaluating Mininet and Opensand for a VoIP scenario.

OpenAirInterface (OAI), a widely adopted open-source 3GPP-compliant protocol stack based on software-defined radio (SDR), plays a crucial role within the research community for conducting experiments and testing within 5G networks [83]. The work in [91] discusses the development of a virtualized Cloud Radio Access Network (C-RAN) orchestration using a Kubernetes cluster using OAI, deploying an LTE RAN stack component and allocating resources based on the proposed network scenario. The work in [63] outlines the OAI 5G New Radio (NR) project roadmap to achieve a fully standard-compliant implementation of 5G NR.

This work focuses on monitoring disaggregated NGRAN between terrestrial and LEO satellite constellations using a graph convolution network (GCN) based cloud-native 5G network deployed in a four-node Kubernetes cluster. An end-to-end 5G network is deployed using OAI and Opensand satellite emulator with the NGRAN split among centralized (gNB-CU) and distributed units (gNB-DU). The gNB-CU is deployed in the terrestrial network, while the gNB-DU is incorporated as a payload of LEO satellite constellations. The GCN module can generalize any topology once trained offline with an arbitrary topology. GCN gathers network information from the core network data plane components and the disaggregated NGRAN across the FlexRAN controller. Mosaic5G operator and flexible software-defined RAN controller (FlexRAN) will automate the network.

4.3.2 Motivation and Challenges

Radio access deployment based on disaggregated NGRAN is becoming a significant trend in the integrated NTN architecture. Considering an LEO satellite constellation that works in regenerative mode, the satellite payload faces substantial challenges due to the limited resources available for data processing and traffic routing capability.

This work considers the distributed unit of the radio access network (gNB-DU) to be carried on the satellite board with multiple LEO constellations [102], while the centralized radio access units (gNB-CU) are to be deployed on the terrestrial network in different geographical locations. Therefore, it is believed that a Machine-Learning-based approach should be employed in the NTN network to identify faulty nodes and links across the disaggregated NGRAN and find the shortest traffic routing path from the terrestrial core network to the user equipment via the satellite network. The high mobility of LEO satellites and the limited processing capability will be optimized by adding GNN for resilient and monitored service.

GCN can learn a condensed representation of each node in the network that contains information about the node, its neighbors, and their interconnecting topology [61]. Here, the nodes are assumed to be container network functions or pods deployed in a four-node Kubernetes cluster. The GCN module can generalize on any topology once it's trained offline with an arbitrary topology, which benefits the frequently changing topology of the LEO satellite network. Graph-based terrestrial and satellite network information such as the location, distance from the user equipment, link information between network components, and received signal strength can be used to train the proposed GCN model to optimize the NTN network performance. For instance, the GCN can identify which radio unit of the LEO constellation failed and which satellite node is closest to the user equipment to route traffic by identifying the shortest path for delay-sensitive services.

Considering the shortcomings of the NTN network mentioned above, a four-node Kubernetes cluster is deployed to implement NTN network services utilizing a software-defined service orchestrator and ML techniques to monitor the network. The deployed network is fully cloud-native, utilizing a Mosaic5G operator to automate the end-to-end service by configuring the network and instantiating a new network function into the NTN network service.

The F1 interface over the satellite radio link failure detection and automatic traffic routing strategies are implemented in the end-to-end NTN-based 5G network utilizing a graph convolution network-based monitoring solution. This strategy effectively compensates for LEO satellites' limited computational resources and payload capacity.

4.3.3 Background Work

The present work is in a state-of-the-art framework dealing with innovative NTN architectures and related non-conventional monitoring and management techniques.

In [102], Rinaldi *et. al* target at surveying NTNs and their potential role in 5G and beyond New Radio (NR) systems. This article reviews the 3GPP NTN features and assesses their capability to meet user expectations in 5G and beyond networks. A detailed analysis of service availability, continuity, and scalability within integrated T-NTN networks is provided. In particular, NTNs play a crucial role in ensuring uninterrupted service to mission-critical applications with minimal tolerance for failure. An architectural view of an integrated T-NTN network is computed for various use cases applying a functional splitting of gNB into a distributed unit (gNB-DU) and central unit (gNB-CU), which provides service for user equipment (UEs) located in under-served areas involving multi-connectivity between multiple regenerative gNB-DU based NGRANs.

Similarly, a cloud-native 5G disaggregated network using Openairinterface [95] and FlexRIC controller is considered in [115]. FlexRIC, a flexible software-defined RAN (SD-RAN) controller for network programmability, enforces slice decisions issued by an ML model built into the network. The primary objective of the work is to develop a service-aware dynamic slice allocation scheme supported by supervised learning. The decision of slice allocation is enforced on the network through the FlexRAN controller in a Kubernetes environment. The work in [122] deploys an end-to-end 5G network service using a Kubernetes cluster. The authors demonstrate the implementation of the Mosaic5G operator using OpenairInterface-based 5G services supporting network slicing.

The concept of leveraging cloud-native technologies and automation to manage and optimize 5G networks is addressed in [18]. A two-node Kubernetes cluster is implemented to deploy the Openairinterface core and disaggregated NGRAN with the Mosaic5G operator as an automation tool. The major task planned for this work is to switch dynamically between monolithic and disaggregated RAN with auto-configuration. However, the specific usage scenario of the Mosaic5G platform is not explicitly discussed.

A tutorial [110] presents the emerging challenges and possible applications of AI/ML techniques in NTN networks. Densification of satellites may involve high-complexity problems, such as resource allocation and routing path selection. AI/ML methods are expected to automatically solve such problems in a near-optimal fashion without causing service interruption. In the same framework, [12] discusses the possible ML models that can serve as a 6G enabler.

The work in [79] presents a near-optimal onboard routing for a large constellation of LEO satellites by using a graph neural network (GNN). GNN can learn the graph structure of satellites and find a shorter path for routing traffic. The dynamic topology and limited processing resources onboard make the routing challenging to manage. The GNN model learns offline data, minimizing the on-board decision-making tasks and saving processing resources.

4.3.4 System Architecture

To deploy the emulated cloud-native 5G NTN network to test the graph convolution network (GCN)-based C-RAN monitoring, a four-node Kubernetes cluster is developed on virtual machines using the vagrant tool. The cluster consists of three worker nodes and one master node. One of the worker nodes is with the OAI 5G core, namely Mosaic5G, and the ML section. The second worker node is for gNB-CU deployment, and the third worker node is dedicated to deploying the satellite emulator (Opensand) with a gNB-DU as a payload. The implementation embarks a cloud-native containerized 5G disaggregated network, using

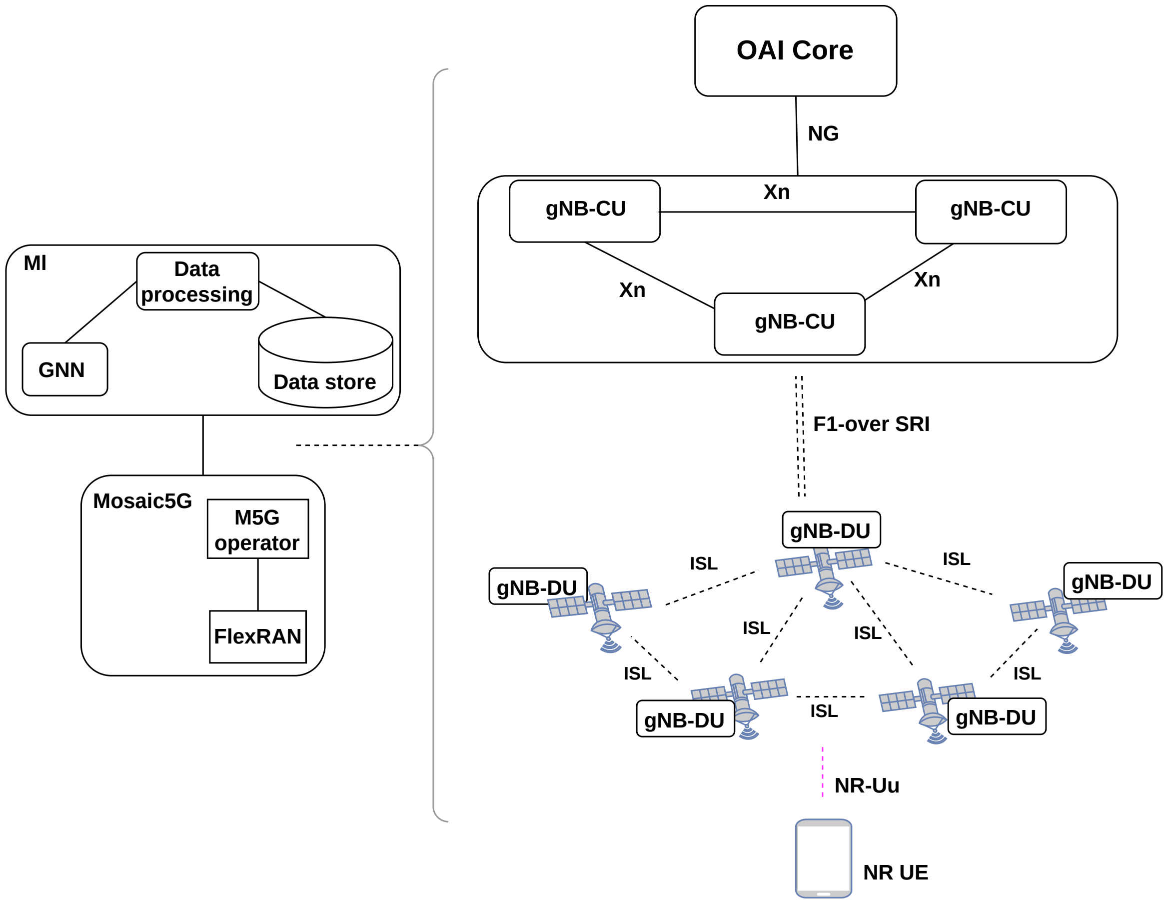


Fig. 4.16 C-RAN monitoring topology.

open-source 5G and satellite emulators. A network of geographically distributed terrestrial gNB-CU and satellite gNB-DU is realized using the GCN model to identify the faulty NGRAN component based on link delay and the shortest traffic routing path. Figure 4.16 and 4.17 illustrate the system architecture, highlighting the comprehensive structure of the containerized 5G network. It includes the applications, the integrated machine learning unit featuring the proposed GCN model, and the interactions among all the components involved. This architecture is implemented at the target facility, which supports the development, deployment, and testing of the containerized 5G network equipped with GCN capabilities.

For the ML section, traffic data is collected using Wireshark from the 5G core user plane function (UPF) and the decentralized access network of both terrestrial and satellite sections using the FlexRAN controller. The collected data is processed, while a training and test dataset is prepared to train the GCN module to detect failure based on link delay in the access

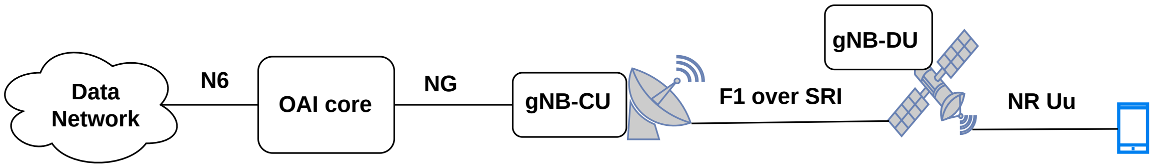


Fig. 4.17 End-to-end service with regenerative satellite-based gNB-DU.

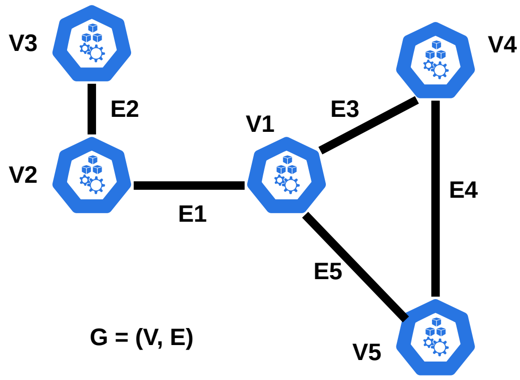


Fig. 4.18 Graph data representation.

network. NetworkX generates graph-based datasets containing delay metrics on the edges, representing links between nodes.

These datasets are used for both training and testing. NetworkX is used to convert the dataset into graph data for model training. The training data is labeled as normal and anomalous based on the threshold delay metrics of the graph edge attribute. The GCN model in the ML section of figure 4.16 will be trained offline, and the related failure detection probability will be computed. Here, the mosaic5G operator will be imposed to reroute the traffic to a path where the delay is not compromised, thus fulfilling the QoS requirements.

4.3.5 Graph Convolution Network Representation

A Graph Convolution Network (GCN) is a typology of deep learning graph neural network specifically designed for handling data represented in graph structures. It excels at performing fault detection tasks of the network of nodes. Graph data can be represented by two fundamental elements: nodes/vertices and edges/links. A graph can be denoted as $G = (V, E)$, where **V** represents the set of nodes, **E** represents the link connecting the nodes as shown in the figure 4.18.

GCNs are well-suited for anomaly detection in networks modeled as graph-structured data. In these applications, the disaggregated C-RAN of the NTN network is represented as a graph, with the nodes representing the terrestrial gNB-CU and satellite gNB-DU and the edges featuring the connections between them. The key advantage of using GCNs for this task is their ability to effectively capture the local neighborhood information around each node and identify faulty edges based on the training data.

The mathematical expression that relates the gNB-CU and gNB-DU as node entities of the graph data and the link between them as edges with their feature elements in a GCN is formulated in the equation below:

$$x_v^{(l+1)} = \sigma\left(\sum_{w \in \mathcal{N}(v)} \frac{1}{\sqrt{|\mathcal{N}(v)|}\sqrt{|\mathcal{N}(w)|}} \mathbf{W}^{(l)} \mathbf{x}_w^{(l)} + \mathbf{W}_e^{(l)} \mathbf{e}_{vw}^{(l)} + \mathbf{b}^{(l)}\right) \tag{4.1}$$

Where:

- $x_v^{(l+1)}$ is the output feature vector of node v in the $(l+1)$th layer
- $\mathcal{N}(v)$ is the set of neighbors of node v including v itself
- $\mathbf{W}^{(l)}$ is the layer-specific trainable weight matrix for node features
- $\mathbf{x}_w^{(l)}$ is the input feature vector of node w in the lth layer
- $\mathbf{e}_{vw}^{(l)}$ is the edge feature vector between nodes v and w in the lth layer
- $\mathbf{W}_e^{(l)}$ is the trainable weight matrix for the edge features
- $\mathbf{b}^{(l)}$ is the layer-specific trainable bias vector
- σ is a nonlinear activation function

.

4.3.6 Methodology

Different open-source software is utilized for the testbed; Openairinterface [95] is used as a 5G core and disaggregated gNB with splitting functionality into centralized and distributed units inside the Kubernetes cluster. The satellite network is emulated using Opensand [104]

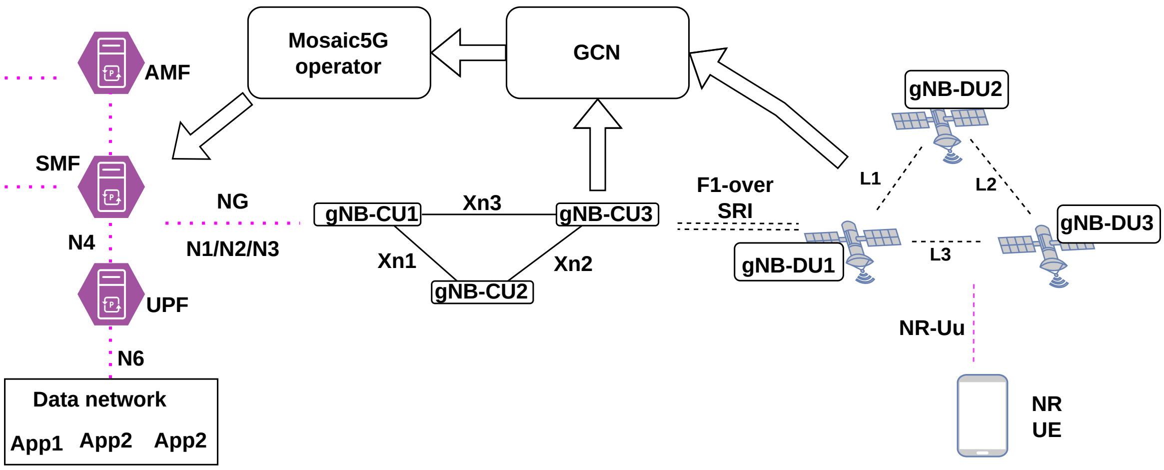


Fig. 4.19 GCN-based NTN network

satellite emulator with three pods (Gateway, Satellite, and Terminal). The satellite emulators work in regenerative mode with gNB-DU as a payload. Mosaic5G is used as a network operator to configure, deploy, and instantiate the network components together with a flexible software-defined RAN (FlexRAN) controller, which is used to manage the disaggregated access network as shown in the figure 4.19.

For what concerns the Kubernetes cluster, Flannel and Multus are used as the container network interface (CNI) plugin, and Contained is used as the container runtime interface (CRI) compliant with the OAI core and radio access network requirements. The OAI core, NGRAN, Mosaic5G operator, and FlexRAN controller network functions are configured to function with the Opensand satellite emulator.

The OAI core will be deployed on worker node 1, while the Mosaic5G operator and the FlexRAN will be deployed on worker node 2. At the same time, the Opensand satellite emulator and the disaggregated NGRAN will be deployed on worker node 3. Then, an end-to-end NTN network will be set up in the cluster as shown in figure 4.19. The network's connectivity is tested by generating traffic using *iperf3*, which is also used for collecting data traffic to train the GCN model.

To prepare the dataset for training and evaluating the GCN model, we first represented the network as a graph $G(V,E)$ using NetworkX, where V represents the nodes (gNB-CU and gNB-DU) and E represents the edges (links) between them. Then, we loaded the delay metrics collected from the emulated network into the generated graph as edge attributes. This allows the link features to be incorporated into the model. Next, we used NetworkX's built-in functions as node degree to show the number of links a node acquires and edges to describe link attributes to analyze the graph structure and extract relevant features for the GCN. Then the dataset is split into training, validation, and test sets. To prepare the target labels for training, we labeled the training data as normal or anomalous based on thresholds on the delay metrics of edge attributes collected from the emulated network. We then exported the training and test data in the format required by the GCN library, such as adjacency matrix and feature matrix. After that, we created the GCN layers and data generator using StellarGraph's FullBatchNodeGenerator.

Finally, we built and trained the GCN model using TensorFlow Keras, compiling it with the appropriate optimizer, loss function, and metrics.

4.3.7 Result and Discussions

Network failure detection is based on link delay metrics collected from the deployed network to generate and train the ML model. The GCN model is trained offline using the network data. The training data is prepared by collecting topological and traffic information on the NTN network from both the distributed gNB-CU of the terrestrial network and the satellite-connected gNB-DU.

Figure 4.20 shows the end-to-end delay plot of the emulated network using two scenarios. The first is the default scenario, where a link delay is imposed across the F1 link between the terrestrial and satellite gNBs. The second one is computed assuming the Mosaic5G operator receives an order from the ML section to re-route the traffic across nodes closer to the user equipment. The traffic data is collected using Wireshark and plotted using the Gnuplot tool.

As shown in figure 4.21, the overall jitter decreases across the simulation time to show the user experience of jitter during the extended F1 link delay and after the delay is reduced from the detection of faulty link and the Mosai5G operator routes the traffic using a shorter routing path.

Traffic data collected from the emulated network environment uses a delay scenario where the F-1 over satellite radio interface link between the terrestrial gNB-CU and satellite gNB-DU has different delay metrics simulated using Linux *tc* command. The Mosaic5G operator will be instructed to re-route the traffic across other nodes to deliver the traffic to the destination to fulfill the QoS requirements of user equipment. This strategy is crucial in achieving service continuity and network resiliency, ensuring service level agreements (SLAs).

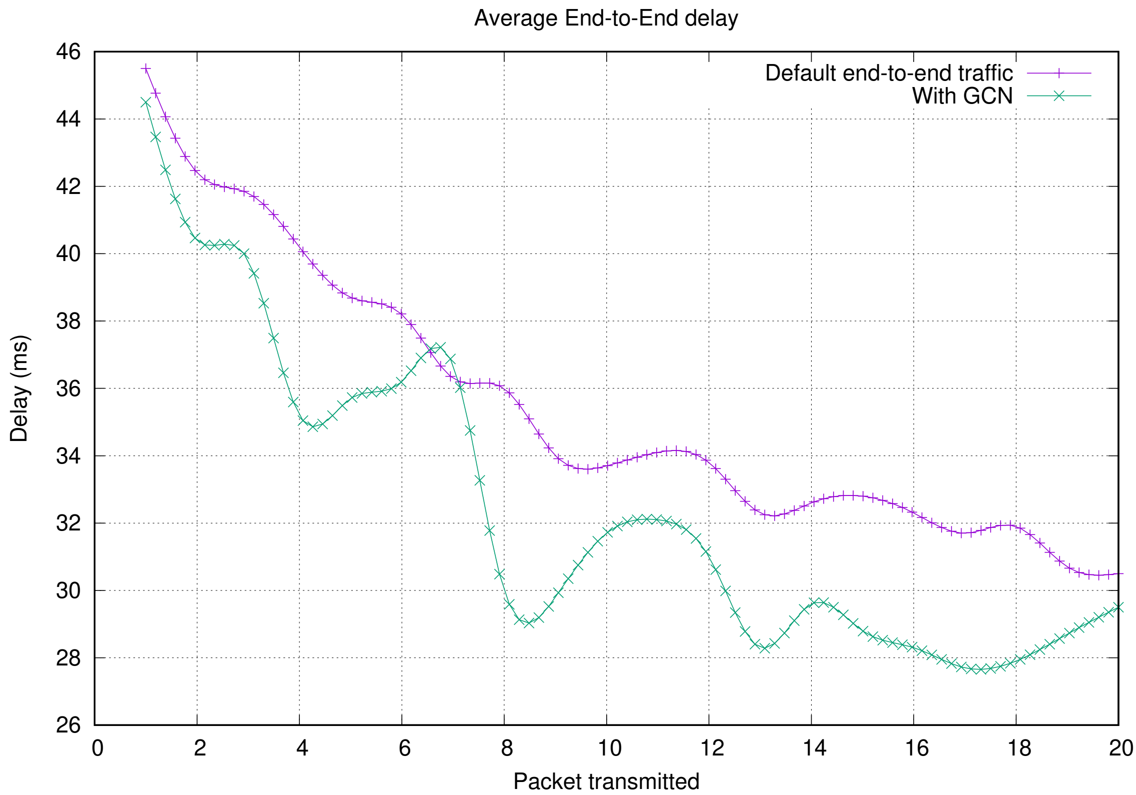


Fig. 4.20 End-to-end delay computed with default traffic and after utilizing GCN to detect failed link and impose traffic routing instruction to Mosaic5G operator.

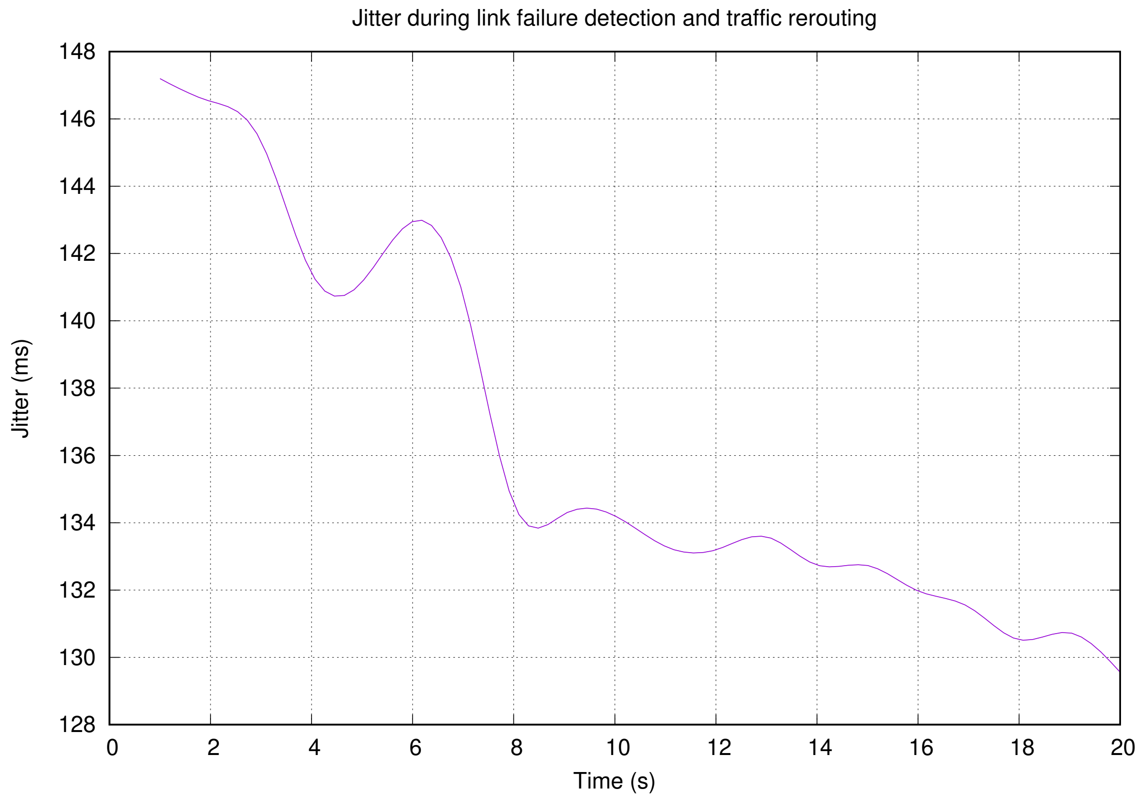


Fig. 4.21 The overall Jitter experienced by the user equipment during a larger delay in the *F1* interface and traffic rerouting by Mosaic5G operator as identified by the GCN model.

4.4 UAV Trajectory Optimization for Resilient 3D NTN networks

The proliferation of wireless communication technologies has driven the need for innovative solutions to enhance network coverage and efficiency. Unmanned Aerial Vehicles (UAVs) have emerged as a versatile tool in wireless networks, offering rapid deployment, flexible positioning, and cost-effective coverage solutions. However, optimizing the operational parameters of UAVs, particularly their energy consumption and user coverage, poses significant challenges, especially in dynamic and unpredictable environments [94].

Energy efficiency is critical for UAV operations, given their limited battery capacity. Balancing the need to maximize coverage of mobile users while ensuring that the UAVs can return to their landing sites before battery depletion requires sophisticated planning and optimization techniques [55]. Traditional approaches often fail to address the complexity and variability of real-world scenarios [62].

Reinforcement Learning (RL) has shown great promise in tackling complex optimization problems through its ability to learn optimal policies from interaction with the environment [80]. UAVs can dynamically adjust their flight paths and operational parameters using RL techniques to achieve desired outcomes. In this study, we explore the application of advanced RL methods, including Q-learning, Double Deep Q-Network (DDQN), and Actor-Critic approaches, to optimize the energy consumption and coverage of UAVs in dynamic wireless networks [58].

Our research investigates the performance of these RL techniques under various conditions, such as different starting positions and environmental factors like wind. We aim to develop a robust framework that enables UAVs to cover as many users as possible while conserving energy efficiently. Through extensive simulations, we demonstrate the potential of these RL approaches to achieve convergence and optimize UAV performance [125]. However, we also identify and analyze inconsistencies in reproducing optimal results, suggesting areas for further improvement in reward structures and hyper-parameter tuning [103].

The key contributions of this paper are as follows: (1) We develop and implement a novel LSTM-A2C reinforcement learning approach for UAV trajectory optimization in dynamic 6G-enabled IoT environments. (2) In various challenging scenarios, We conduct a comprehensive comparative analysis of our LSTM-A2C method against state-of-the-art RL techniques, including Q-learning, DDQN, and traditional Actor-Critic methods. (3) We demonstrate the superior performance of our approach in terms of coverage optimization, energy efficiency, and adaptability to dynamic user distributions and adverse environmental conditions. Our findings significantly advance UAV-based surveillance capabilities in next-generation wireless networks, paving the way for more efficient and resilient communication systems in complex, real-world environments.

4.4.1 Literature Overview

Optimizing UAV operations, especially energy consumption and coverage, is extensively studied in wireless communication and IoT networks. However, the dynamic nature of 6G-based IoT environments demands more adaptive solutions. Energy efficiency is crucial for UAVs, particularly during long flights for data collection. Early research focused on optimizing UAV trajectories to reduce energy use. Zeng et al. [128] created a framework that optimizes propulsion and communication energy, balancing mission goals with energy efficiency. Adaptive strategies for UAVs have advanced to handle real-time environmental changes. For instance, Mozaffari et al. [89] investigated UAV deployment strategies that adjust dynamically to user distribution and demand fluctuations. However, these methods often rely on static models and may struggle with real-world unpredictabilities, such as sudden wind or unexpected obstacles. Effective surveillance and data collection depend on maximizing coverage. Traditional optimization techniques use geometric models or heuristics to ensure UAVs cover the area efficiently. Gupta et al. [27] proposed a path-planning algorithm that segments the area to guarantee full coverage. Reinforcement Learning (RL) has recently been increasingly applied to UAV systems for autonomous decision-making in complex environments. RL enables UAVs to learn optimal strategies through interaction, aiding energy management and coverage optimization tasks.

Q-Learning is a core RL algorithm for UAV path planning and obstacle avoidance. Chen et al. [116] demonstrated its effectiveness in learning navigation policies without prior environment knowledge. However, more advanced methods have been developed due to its slow convergence and inefficiency in high-dimensional spaces.

The Double Deep Q-Network (DDQN) improves upon Q-Learning by reducing over-estimation bias through separate action selection and evaluation, resulting in more stable learning. Wang et al. [119] applied DDQN to multi-UAV coordination, showing it outperforms traditional Q-Learning in complex scenarios.

Recent advances in deep reinforcement learning (DRL) have enhanced UAV path planning and collision avoidance. Ramezani et al. [98] proposed an LSTM-MPC method integrated with the Deep Deterministic Policy Gradient (DDPG) algorithm, which stores future states and actions in a predicting pool. This method improves learning robustness, efficiency, and convergence rates compared to traditional RL approaches.

While the LSTM-MPC-DDPG approach enhances prediction and control in path planning, our research employs LSTM-Advantage Actor-Critic (LSTM-A2C) to optimize UAV energy consumption and coverage in dynamic 6G-based IoT networks. Unlike LSTM-MPC's deterministic policy, LSTM-A2C balances exploration and exploitation to find optimal trajectories for maximizing user coverage and energy efficiency. This shows LSTM-based RL methods' adaptability to various UAV objectives, from path planning to mission-critical tasks.

Lee et al. [70] introduced SACHER, a Soft Actor-Critic (SAC) algorithm with Hindsight Experience Replay (HER) for UAV path planning and collision avoidance. SACHER improves exploration and robustness over earlier DRL methods but may compromise learning optimality due to SAC's entropy-augmented objective.

In contrast, our study uses an LSTM-Actor Critic approach to capture sequential dependencies in dynamic 6G-based IoT environments. Unlike SACHER, which focuses on immediate path planning and collision avoidance, our method prioritizes long-term energy efficiency and coverage by modeling the problem as an episodic, un-discounted RL task.

The LSTM-Advantage Actor-Critic (LSTM-A2C) method has shown its robustness in sequential decision-making across various dynamic systems. For instance, Wang et al. [73] applied LSTM-A2C to network slicing with user mobility, demonstrating its effectiveness in adapting to changing demands and conditions for real-time resource optimization.

Despite its success in network settings, LSTM-A2C's application to UAV energy and coverage optimization has been explored less. Our research addresses this gap by applying LSTM-A2C to UAV trajectory optimization in 6G-based IoT networks, aiming to improve energy efficiency and coverage in dynamic environments through the sequential learning capabilities of LSTM.

While Q-Learning and DDQN have advanced UAV energy and coverage optimization, they often face scalability and adaptability issues in real-world scenarios, especially with the sequential dependencies of complex UAV operations in 6G-based IoT networks.

Our research introduces a novel LSTM-Actor Critic approach to address gaps in UAV operations. LSTM networks, known for capturing temporal dependencies, are ideal for sequential decision-making in dynamic settings [19, 113, 114]. Integrating LSTM with the Actor-Critic framework aims to improve UAV efficiency in 6G and Non-Terrestrial Networks (NTN).

We use Q-Learning and DDQN as benchmarks to evaluate our LSTM-Actor Critic model. Extensive simulations show that our approach enhances convergence speed, stability, and energy efficiency, especially in uncertain and variable environments.

4.4.2 Optimization Formulation

This study optimizes a UAV's trajectory for surveillance over a 20×20 meter grid. The UAV's task is to capture images of individuals while managing constraints such as limited energy, upward winds, and no-fly zones, as shown in Figure 4.22.

To simplify control dynamics, the UAV flies at a fixed altitude and speed, reducing the problem to a 2D plane and lowering computational complexity. Starting from a designated point, the UAV must land within a specified area before its battery depletes. It can make up to 25 discrete movements in four directions: up, down, left, or right.

The main goal is to maximize the number of unique individuals captured while adhering to energy limits and avoiding restricted zones.

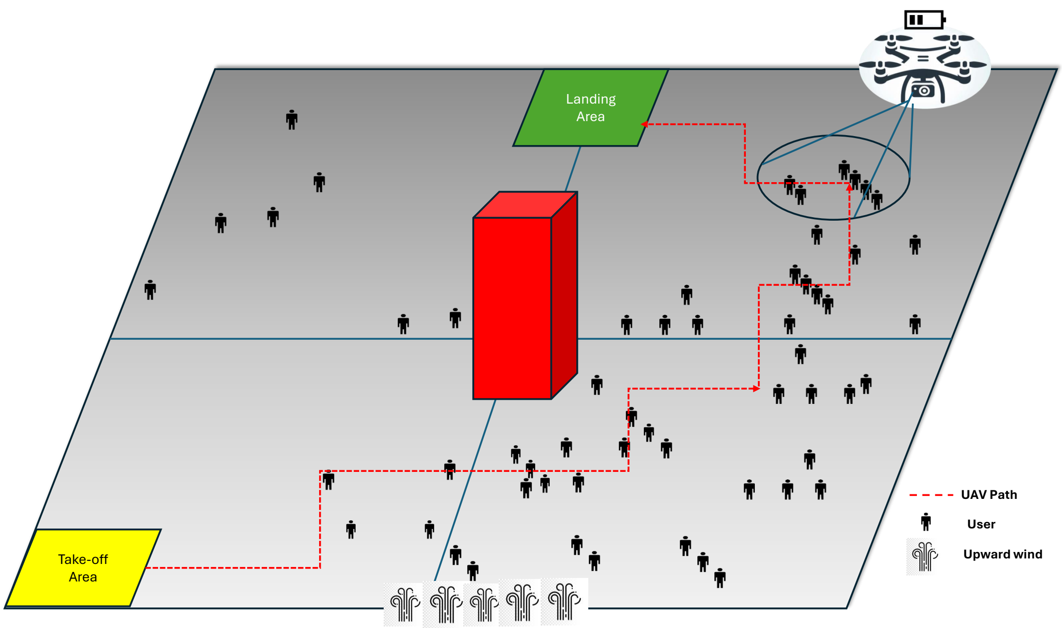


Fig. 4.22 System Model

The surveillance area features a high-rise building within a 20x20 meter grid that the UAV must avoid. Additionally, upward wind in certain regions pushes the UAV's movement one unit up, complicating path planning.

People's locations are distributed according to 2D Gaussian distributions, redrawn each episode, introducing stochasticity into trajectory planning.

This path planning problem is a combinatorial optimization challenge with constraints and dual objectives: maximizing observed people and ensuring the UAV lands within the target area before battery depletion. Due to its constraints and dynamic environment, the problem is NP-hard. Its complexity grows with grid size and battery capacity, resulting in a state-space complexity of $O(400 \times 4^{20})$, where 400 is the number of grid locations and 4^{20} represents the action sequences in 25 steps.

The UAV's trajectory optimization problem can be formulated as a multi-objective optimization problem with the following objective function and constraints, as illustrated in Equation 4.2.

$$\begin{aligned}
\textbf{Objective:} \quad & \max \sum_{t=1}^{T} N_t \\
\textbf{Subject to:} \quad & (x_{t+1}, y_{t+1}) = (x_t, y_t) + \text{action}(A_t) + \\
\text{wind}(x_t, y_t), \quad & \\
& 1 \leq x_t, y_t \leq 20, \quad \forall t, \\
& (x_T, y_T) \in SL, \\
& (x_t, y_t) \notin SB, \quad \forall t, \\
& \sum_{t=1}^{T} e_t \leq 25.
\end{aligned} \tag{4.2}$$

Where:

- (x_t, y_t) represents the UAV's position at time step t.
- A_t is the action taken at time step t, with $A_t \in \{\text{up}, \text{down}, \text{left}, \text{right}\}$.
- N_t is the number of new individuals observed in the image taken at time step t.
- $SL = \{(x, y) \mid 7 \leq x \leq 9, 18 \leq y \leq 20\}$ is the designated landing area.
- $SB = \{(x, y) \mid 8 \leq x \leq 14, 10 \leq y \leq 13\}$ is the no-fly zone corresponding to the high-rise building.
- wind_shift(x_t, y_t) adjusts the UAV's movement in regions affected by wind, defined for specific x, y coordinates.
- T is the total number of steps the UAV can take, limited by its battery.

This optimization problem involves searching through a large state space with dynamic constraints, making it challenging to solve using brute-force methods.

4.4.3 Advanced RL Based Approach

Given the UAV surveillance problem's complexity and dynamic nature, we propose a new Reinforcement Learning (RL) framework for optimal or near-optimal solutions. RL efficiently handles large state spaces and dynamic environments, making it suitable for UAV path planning. This approach aims to maximize surveillance effectiveness while meeting constraints on energy, landing, and obstacle avoidance.

RL utilizes Markov Decision Processes (MDPs) to model the environment and optimize actions. MDPs formalize sequential decision-making, where the UAV learns a policy, π, to maximize cumulative rewards by interacting with its environment.

In our UAV surveillance problem, the RL agent learns a policy to maximize unique observations while managing energy and ensuring a safe landing. Reformulated in RL terms, this involves maximizing the expected cumulative reward, which represents the number of new people observed, while adhering to constraints (see Equation 4.3 and Equation 4.4).

$$\text{Objective:} \quad \max_{\pi} \mathbb{E}_{\pi} \left[\sum_{t=1}^{T} R_t \right] \tag{4.3}$$

$$\text{Subject to:} \quad \text{(C1), (C2), (C3), (C4), (C5)} \tag{4.4}$$

Where:

- π is the policy that maps states to actions, $\pi : S_t \to A_t$.
- R_t is the reward obtained at time step t, which corresponds to the number of new individuals observed in the image taken at time step t (N_t).

To effectively model the UAV surveillance problem using the RL framework, we define the key components of the Markov Decision Process (MDP).

we define the state space S_t to encapsulate all relevant information needed for decision-making as in Equation 4.5

$$S_t = (x_t, y_t, b_t) \tag{4.5}$$

At any given location, The UAV has four available actions action A_t at time step t corresponding to the possible directions of movement: up, down, left, right. Each action consumes one energy unit.

The reward function is designed to reflect the multi-objective nature of the problem (Equation 4.6):

$$R_t = N_t(S_t, A_t) - \lambda_1 E(A_t) - \lambda_2 \mathbb{I}[S_{t+1} \notin S_L \text{ and } t = T] \tag{4.6}$$

Where:

- λ_1 is a penalty factor for energy usage, encouraging energy-efficient paths.
- λ_2 is a penalty for failing to land in the designated area at the end of the episode.
- $\mathbb{I}[\cdot]$ is an indicator function that adds a penalty if the UAV does not land in the landing zone SL at the end of the episode.

Further, it can be modified, as in Equation 4.7:

$$R_t = \begin{cases} -5 - \lambda_1 E(A_t) & \text{if } (x_t, y_t) \text{ is out of bounds} \\ & \text{or in a no-fly zone,} \\ 20 - \lambda_1 E(A_t) - \lambda_2 \mathbb{I}[t = T] & \text{if } (x_t, y_t) \text{ is in the landing} \\ & \text{ zone,} \\ N_t(S_t, A_t) - \lambda_1 E(A_t) - 1 & \text{if new people are observed,} \\ -10 - \lambda_1 E(A_t) & \text{if } (x_t, y_t) \text{ is revisited.} \end{cases} \tag{4.7}$$

This model's reward function combines penalties for invalid actions and energy use with rewards for key achievements. It promotes efficiency by minimizing unnecessary movements, managing energy well, and rewarding successful observations and strategic landings.

4.4.4 LSTM-A2C

The Advantage Actor-Critic (A2C) is a key RL algorithm for optimizing UAV surveillance policies. It combines policy-based and value-based methods to balance exploration and exploitation in complex environments. A2C employs two neural networks (see Equation 4.8):

- **Actor:** Updates the policy π_θ to maximize expected cumulative rewards by adjusting θ based on the critic's feedback. It increases the probability of actions that lead to higher rewards, guided by the advantage estimate from the critic.
- **Critic:** Evaluates the value function V_ϕ to estimate expected returns for given states and actions. It calculates action advantages by comparing predicted and actual returns, updating ϕ to minimize temporal difference (TD) error and stabilize learning.

$$\begin{aligned} \delta_t &= R_t + \gamma V_\phi(S_{t+1}) - V_\phi(S_t) \\ \theta &\leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(A_t \mid S_t) \delta_t \\ \phi &\leftarrow \phi + \beta \delta_t \nabla_\phi V_\phi(S_t) \end{aligned} \tag{4.8}$$

To improve UAV path planning and surveillance, we integrate Long Short-Term Memory (LSTM) networks with the A2C framework (see Figure 4.23). LSTMs, a recurrent neural network (RNN), excel in capturing temporal dependencies and long-term patterns, making them ideal for dynamic environments. They mitigate vanishing gradient issues using memory cells and gating mechanisms to retain relevant information over extended periods.

- **State Representation:** In the integrated model, at each time step t, the LSTM receives an input that represents the current state of the UAV, such as $s_t = [x_t, y_t, b_t]$. This sequence can be represented as in Equation 4.9:

$$S_t = \{s_{t-n}, \ldots, s_{t-1}, s_t\} \tag{4.9}$$

  where s_{t-n} to s_t represent the sequence of states up to the current time step t, and n the sequence of length. This sequence provides the LSTM context on the UAV's historical behavior, allowing it to make informed decisions based on past observations.

- **Hidden State:** The LSTM retains a hidden state h_t and a cell state c_t at each time step. The hidden state h_t incorporates information from previous steps, while the cell state c_t maintains long-term dependencies for informed decision-making.

- **Feedback Mechanism:** Both actor and critic networks use the LSTM's hidden state h_t. The actor refines the policy π_θ based on this state, enhancing responsiveness to temporal patterns. The critic uses it to improve the accuracy and stability of its value function V_ϕ.

Algorithm 6 demonstrates how integrating LSTM networks with the A2C algorithm enhances UAV adaptability in complex environments, leading to improved surveillance and path planning. This integration boosts performance by better managing temporal sequences and dependencies, optimizing both operations and planning.

4.4.5 Simulation Scenario

To evaluate our DRL approach, we created a simulation environment representing urban surveillance scenarios within a 20x20 meter area, with 100 individuals distributed across five clusters:

The distribution of individuals is as follows:

- **Cluster 1:** 40 users are distributed randomly around (17, 4) with a standard deviation of 5.

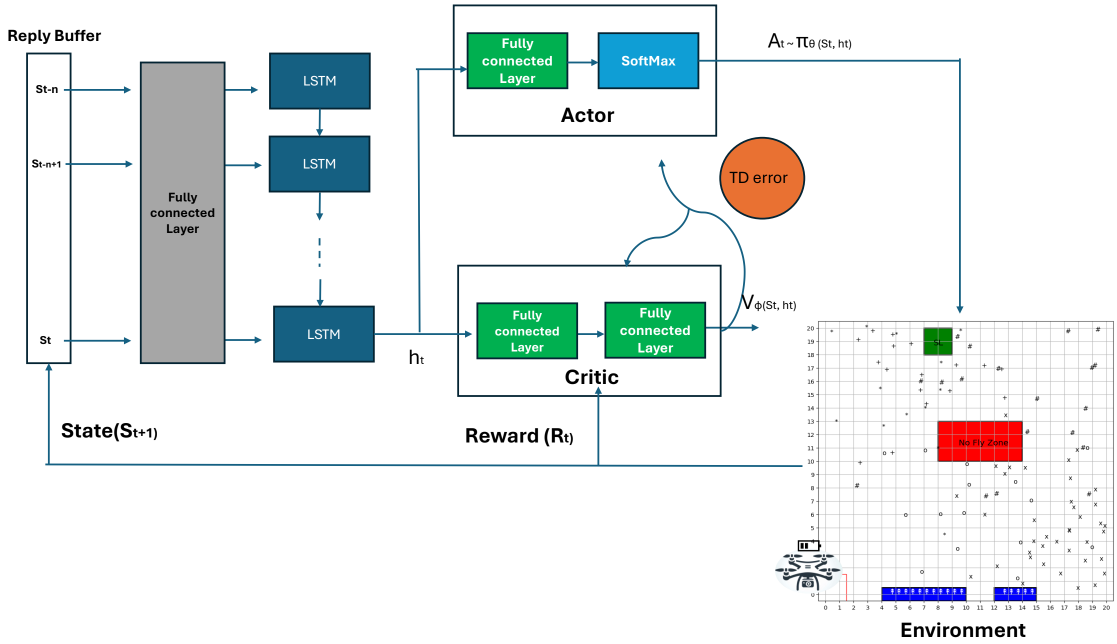


Fig. 4.23 LSTM-Actor Critic Network Architecture

Algorithm 6 LSTM-A2C for UAV Surveillance

Initialize: LSTM-A2C model with parameters θ (actor), ϕ (critic), LSTM state (h_0, c_0), replay buffer D
for each episode **do**
    Initialize UAV position in Take-off Area
    Randomize people locations
    for each step t until battery depletion or Landing Area **do**
        Update LSTM state (h_t, c_t)
        Select action $A_t \sim \pi_\theta(\cdot \mid S_t, h_t)$
        Compute value $V_\phi(S_t, h_t)$
        Execute A_t, observe R_t, S_{t+1}
        if $|D| < n$ **then**
            $D \leftarrow D \cup (S_t, h_t, A_t, R_t, S_{t+1})$
        else
            Remove oldest entry from D
            $D \leftarrow D \cup (S_t, h_t, A_t, R_t, S_{t+1})$
        end if
        Compute TD error: $\delta_t = R_t + \gamma V_\phi(S_{t+1}, h_{t+1}) - V_\phi(S_t, h_t)$
        Update actor: $\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(A_t \mid S_t, h_t)\delta_t$
        Update critic: $\phi \leftarrow \phi + \beta \delta_t \nabla_\phi V_\phi(S_t, h_t)$
    end for
end for

- **Cluster 2:** 15 users are distributed randomly around (12, 6) with a standard deviation of 4.
- **Cluster 3:** 15 users, similar to Cluster 2, are distributed around the same parameters.
- **Cluster 4:** 20 users are distributed randomly around (15, 15) with a standard deviation of 5.
- **Cluster 5:** 10 users are distributed randomly around (7, 16) with a standard deviation of 3.

The UAV's trajectory and coverage were optimized using an actor-critic network with an LSTM architecture. The model's fully connected layers, featuring 256 units and ReLU activation, effectively handle complex features and time-dependent sequences.

In training, the key parameters include a learning rate of 0.01 and a discount factor (γ) of 0.99, totaling 1000 episodes. The Adam Optimizer is utilized, also with a learning rate of 0.01. The loss function used is Huber Loss. Penalty factors are set with λ_1 at 0.1 for energy consumption and λ_2 at 10 for failing to reach the landing area by the end of the episode.

4.4.6 Discussion

Our experiments demonstrate that the LSTM-based Advantage Actor-Critic (A2C) method optimizes UAV operations in a 6G IoT network. The goal was to maximize coverage, defined by the number of unique individuals captured, while ensuring a safe landing before battery depletion. We compared our approach with Q-learning, DDQN, and traditional Actor-Critic methods. The results are presented in Figures 4.24, 4.25, and 4.26.

We assessed key performance metrics, including coverage, which refers to the number of unique individuals detected; energy consumption, the total energy used during flight; and completion rate, representing the percentage of successful landings within the target area. Adaptability measures the ability to adjust to changing conditions, such as wind and user distribution. Convergence indicates the speed and stability of reaching an optimal policy, while computational performance evaluates the training time required for each algorithm.

As depicted in Figure 4.26, the LSTM-A2C algorithm effectively navigates the UAV through the dynamic environment. The LSTM-A2C method consistently outperformed Q-learning, DDQN, and traditional Actor-Critic in coverage. It detected 15-20% more unique individuals in dynamic conditions due to its ability to model temporal dependencies and adapt to environmental changes as seen in Figure 4.24.

Figure 4.24 also shows that the LSTM-A2C method achieved faster and more stable convergence to an optimal policy than the baseline methods. It reached a steady state

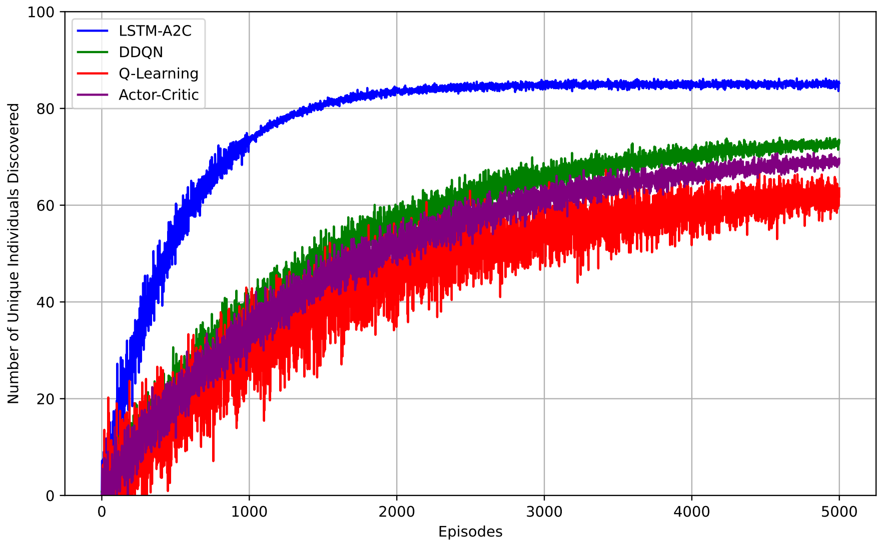


Fig. 4.24 Coverage Evaluation

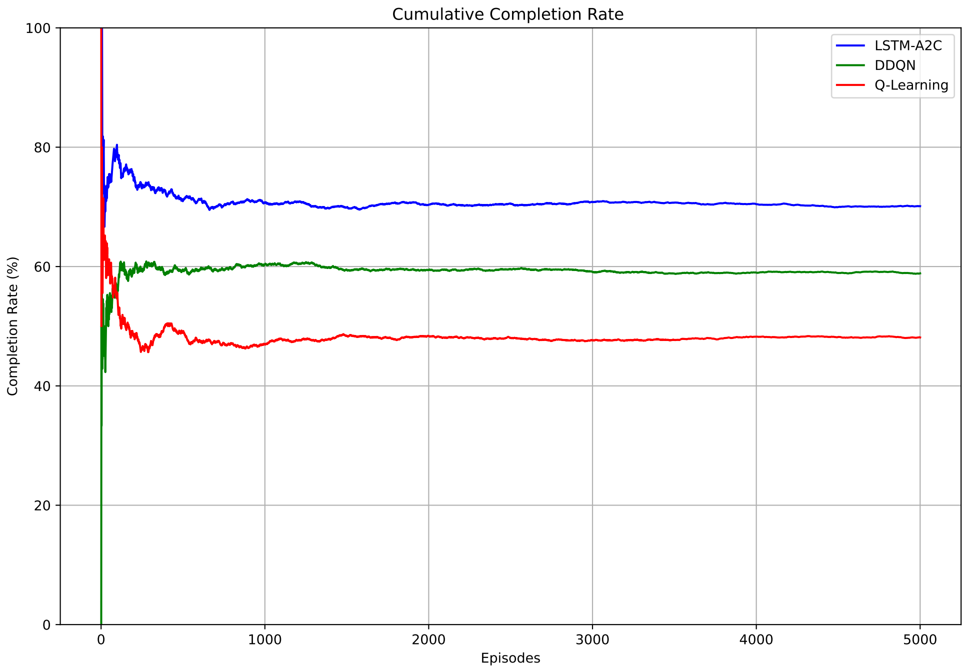


Fig. 4.25 Completion Rate

with fewer episodes and demonstrated less reward variance during training. In complex environments, LSTM-A2C outperformed other methods, which converged more slowly and

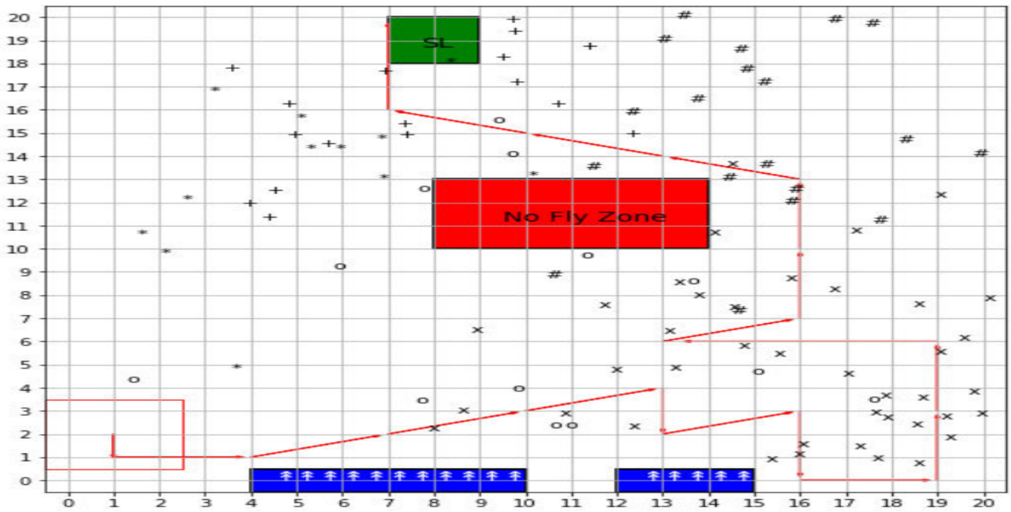


Fig. 4.26 Optimal UAV Path snapshot at one of the episodes

with greater performance fluctuations, thanks to its ability to capture temporal correlations for improved decision-making.

In Figure 4.25, the LSTM-A2C method achieved an approximately 80% completion rate, outperforming Q-learning and DDQN, highlighting its effectiveness in balancing exploration and exploitation for UAV landing. While some methods initially focused on reaching the landing quickly, this often led to fewer users being discovered. Our reward mechanism penalized such behavior, encouraging broader exploration. LSTM-A2C quickly adapted, maintaining a high completion rate while increasing user discovery and effectively balancing multiple objectives.

We evaluate energy efficiency by the number of individuals discovered per 25-unit battery. The LSTM-A2C method maximizes coverage within this limited battery, uncovering more people than other methods. Its adept balance of exploration and efficiency enhances discovery and ensures the UAV reaches the landing station effectively before battery depletion.

The LSTM-A2C method had comparable training times to DDQN and traditional Actor-Critic methods. The additional computational cost of LSTM layers was outweighed by the improvements in coverage and energy efficiency, making it practical for real-world UAV applications.

Our experiments show that the LSTM-A2C method significantly outperforms traditional RL algorithms in optimizing UAV operations in dynamic environments. By modeling sequential decision-making effectively, LSTM-A2C excels in coverage, energy efficiency, convergence, and mission success. This highlights its potential for advancing UAV surveillance in 6G-enabled IoT networks with variable conditions and dynamic user distributions. Future work will focus on extending this research to 3D contexts and multi-UAV scenarios, aiming to improve scalability and robustness for complex surveillance tasks. We will also explore integrating advanced neural network architectures, such as Transformers, to enhance performance in large-scale, dynamic environments.

4.5 Summary

This chapter presents an LSTM-based approach for predicting resource utilization in disaggregated RAN architectures within 5G Non-Terrestrial Networks (NTNs). By comparing two configurations—one with a gNB-CU and gNB-DU split over the F1 interface and another adding F1 and E1 splits with gNB-CUUP as a satellite payload—we demonstrate LSTM's effectiveness in predicting CPU, memory, and bandwidth usage. These predictions enable proactive resource management, ensuring efficient network utilization and high QoS. The combined F1 and E1 split configuration offers greater flexibility and resource efficiency while integrating critical network functions into satellite payloads, which enhances network resilience, particularly in remote areas. This work underscores LSTM's potential in improving 5G NTN management, especially in handling dynamic traffic patterns. Future work will scale these models for larger networks and incorporate additional ML techniques for fault detection and energy efficiency.

The primary objective of the Beyond 5G (B5G)/6G network is to ensure ubiquitous service availability by leveraging non-terrestrial networks (NTN). Efficient detection of network function failures and automatic traffic routing strategies are essential to compensate for LEO satellites' limited computational resources and payload capacity. This work monitors disaggregated NGRAN between terrestrial and LEO satellite constellations using a GCN-based cloud-native 5G network deployed on a Kubernetes cluster. The testbed utilizes OpenairInterface and Opensand satellite emulators with the NGRAN split functionality. GCN gathers network information from the core network user plane function (UPF) and disaggregates NGRAN components across the FlexRAN controller. The preliminary results discussed in the paper show that the GCN module can learn the graph data representation of disaggregated NGRAN and detect the F1 link failure over the NTN network to optimize the QoS requirements and impose service level agreements (SLAs). Once the GCN is trained offline with the generated graph dataset, it can be generalized over new topology, making it a promising solution for the frequently changing topology of the LEO satellite constellation. As the future extension of this work, A physical testbed of the emulated environment will be implemented for a cloud-native 5G NTN network employing software-defined radio (SDR) applications.

Chapter 5

Conclusion and Future Directions

5.1 Conclusion

This thesis has explored the integration of Non-Terrestrial Networks (NTNs) within Beyond-5G (B5G) and future 6G ecosystems, focusing on enhancing their performance, efficiency, and security. NTNs, including Low Earth Orbit (LEO) satellites, Unmanned Aerial Vehicles (UAVs), and High Altitude Platform Systems (HAPS), expand the reach of terrestrial networks by providing connectivity in remote, underserved, and connection-critical scenarios. However, integrating NTNs into existing communication infrastructures presents unique challenges, such as high mobility, propagation delays, resource constraints, and security vulnerabilities. This research has addressed these challenges through innovative approaches leveraging cloud-native technologies, AI/ML models, and blockchain-based security mechanisms.

The research work significantly focused on resource management and optimization techniques for NTNs. The research developed Long Short-Term Memory (LSTM) models for predicting resource utilization in disaggregated Radio Access Network (RAN) architectures, enabling proactive allocation of CPU, memory, and bandwidth resources to maintain Quality of Service (QoS) and prevent Service Level Agreement (SLA) violations. Additionally, Graph Neural Networks (GNNs) were employed to monitor and manage disaggregated Centralized RAN (C-RAN) components, enhancing network observability and adaptability by detecting link failures and optimizing traffic routing in real-time. The thesis also explored reinforcement learning, specifically the LSTM-A2C model, for optimizing UAV trajectories, which improved coverage and energy efficiency in dynamic 6G-enabled IoT surveillance networks.

Security remains a critical concern in NTNs due to open and decentralized satellite communications. To address these vulnerabilities, this work proposed a blockchain-based authentication framework that secures data exchanges and satellite firmware updates, ensuring data integrity and protection against unauthorized access. The integration of blockchain technology demonstrated robust security benefits, albeit with trade-offs in terms of increased latency and computational overhead. These findings underscore the importance of balancing security enhancements with network performance.

Furthermore, this thesis demonstrated the importance of Multi-Access Edge Computing (MEC) in enhancing NTNs by bringing computational resources closer to end users, reducing latency, and improving the Quality of Service (QoS). Experimental testbeds showed that MEC-based deployments effectively maintained service availability during terrestrial network outages, supporting seamless transitions to satellite access networks. This approach significantly improved network resilience, particularly in critical emergency response and remote healthcare applications.

Overall, the proposed research highlights the transformative role of advanced technologies in optimizing the performance and security of NTNs. By integrating predictive and adaptive AI/ML models, cloud-native architectures, and decentralized security mechanisms, this thesis provides a comprehensive framework for managing the complex dynamics of 5G-NTNs. The findings demonstrate that NTNs, when effectively managed and optimized, can significantly enhance global connectivity and support the deployment of critical communication services across diverse and challenging environments.

Looking forward, several areas warrant further investigation to fully leverage the potential of NTNs in future 6G networks. Scaling AI/ML models to handle more prominent and complex networks, integrating quantum computing for enhanced optimization and security, and exploring advanced blockchain mechanisms are promising avenues for future research. Additionally, developing edge intelligence capabilities, enhancing UAV optimization techniques through multi-agent and federated learning, and focusing on sustainability and energy efficiency will be crucial for the next generation of NTNs. Real-world deployment and validation of the proposed models will also be essential to assess their practical performance further and refine these approaches. By addressing these future directions, NTNs can evolve into highly resilient, secure, and adaptive communication systems, paving the way for an increasingly connected world.

5.2 Future Directions

While this thesis provides substantial advancements in the field of 5G-NTNs, several areas warrant further investigation to fully realize the potential of NTNs in future 6G networks.

5.2.1 Scalability of AI/ML Models

Future work should focus on scaling the AI/ML models developed in this thesis to handle more prominent and complex 5G NTN environments. This includes enhancing the models' ability to learn from more extensive datasets, incorporating additional variables, and adapting to the rapidly changing conditions characteristic of NTNs.

5.2.2 Integration of Quantum Computing

Integrating quantum computing with NTNs could provide new avenues for optimizing resource management and security. Quantum algorithms could enhance the speed and accuracy of predictive models, offering more robust solutions for network optimization and data encryption.

5.2.3 Advanced Blockchain Mechanisms

While blockchain has enhanced security in NTNs, future research should explore advanced blockchain mechanisms, such as sharding and off-chain solutions, to reduce latency and computational overhead. These approaches could provide more efficient security frameworks that better balance performance and protection.

5.2.4 Enhanced UAV Optimization Techniques

Further investigation into advanced reinforcement learning algorithms, such as multi-agent reinforcement learning (MARL) and federated learning, could improve the efficiency and adaptability of UAVs in NTNs. These approaches could enable UAVs to collaborate more effectively, enhancing overall network performance.

5.2.5 Edge Intelligence for NTNs

Edge Intelligence for Non-Terrestrial Networks (NTNs) refers to the integration of Artificial Intelligence (AI) and Machine Learning (ML) algorithms directly at the edge of the network, such as at satellite payloads, Unmanned Aerial Vehicles (UAVs), or Multi-Access Edge Computing (MEC) nodes. By processing data closer to the source, edge intelligence reduces the need for extensive back-and-forth communication with centralized data centers, significantly lowering latency and improving real-time decision-making. This is particularly crucial for NTNs, which often operate in remote or connection-critical environments where rapid response times are essential for maintaining Quality of Service (QoS) and ensuring network efficiency. Edge intelligence empowers these edge nodes to autonomously manage network traffic, optimize resource allocation, and predict network conditions, thereby enhancing the overall performance and resilience of NTNs.

One of the significant benefits of deploying AI/ML algorithms at the network edge is the ability to handle complex, real-time applications in dynamic environments. For instance, edge intelligence can detect network anomalies and adjust parameters to reroute traffic through satellite or aerial platforms in disaster recovery scenarios or remote healthcare, where connectivity must be maintained despite disruptions. Additionally, edge nodes equipped with intelligence can predict traffic patterns and proactively allocate resources, ensuring efficient bandwidth usage and reducing the risk of congestion. This is especially beneficial in Non-Terrestrial Networks, where communication links are prone to delays and fluctuations in connectivity due to the movement of satellites or UAVs.

However, integrating edge intelligence into NTNs presents several challenges. Edge nodes, such as satellite payloads, typically have limited computational power and energy resources, making it challenging to run resource-intensive AI algorithms. This necessitates the development of lightweight AI models that can function efficiently within these constraints while maintaining high levels of accuracy. Furthermore, given the decentralized nature of NTNs, edge intelligence must be designed to operate in a distributed manner, allowing multiple edge nodes to collaborate and share insights without overwhelming the network. Future research in this area could focus on optimizing AI algorithms for edge environments, enhancing energy efficiency, and ensuring that edge intelligence is seamlessly integrated with the broader network infrastructure.

5.2.6 Standardization and Interoperability

As NTNs evolve, standardization and interoperability between terrestrial and non-terrestrial components will be crucial. Future research should explore frameworks facilitating seamless integration and communication between diverse network elements, ensuring consistent performance across various technologies and platforms.

5.2.7 Sustainability and Energy Efficiency

With sustainability's growing importance, future work should prioritize energy-efficient designs for NTNs, focusing on reducing the carbon footprint of satellite constellations and UAV operations. Exploring green AI techniques and energy-aware routing algorithms could contribute to more sustainable NTN deployments.

5.2.8 Real-World Deployment and Validation

Finally, the proposed models and frameworks must be deployed and validated in the real world. Field trials and pilot projects could provide valuable insights into NTNs' practical challenges and performance, inform future refinements, and guide the development of industry standards.

We have built a physical testbed for the work "Graph Neural Network-based C-RAN Monitoring for Beyond 5G Non-Terrestrial Networks." using our laptop and USRPs. The 5G emulated network using a four-node Kubernetes cluster was connected to USRPs for further analysis and experimentation.

The findings and contributions of this thesis lay a strong foundation for advancing NTNs as a core component of future communication networks. By addressing the outlined future directions, researchers and industry stakeholders can further enhance NTNs' capabilities, paving the way for resilient, secure, and adaptive communication systems that meet the needs of an increasingly connected world.

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