UNICO I+D Project 6G-INTEGRATION-3 (TSI-063000-2021-127)

6G-INTEGRATION-3

Final innovations design for NTN integration with 3GPP networks

Abstract

This document presents key innovations for integrating High Altitude Platform Systems (HAPS) into non-terrestrial networks (NTN) aligned with 3GPP and 6G standards. It highlights the application of advanced AI and machine learning algorithms, such as reinforcement learning, to optimize resource allocation, routing, network slicing, and mobility management in highly dynamic NTN environments. The work introduces efficient frame transmission strategies for LEO satellites and HAPS, including "withhold scheduling," which balances data loads across ground stations to improve throughput and latency. Deep reinforcement learning agents are developed for optimal routing, adapting to real-time changes in network topology and congestion. A modular drone platform equipped with edge computing and 5G connectivity is designed and deployed to validate these innovations in real-world NTN scenarios. The document also analyzes the stringent bandwidth, latency, and reliability requirements of emerging AR/VR applications, informing the design of MEC-enabled HAPS nodes for distributed caching and processing. A convergent NTN-6G architecture is proposed, integrating MEC at HAPS nodes to support seamless handovers and ultra-low latency. Conclusions emphasize

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the need for holistic co-design of algorithms, hardware, and standards, and identify future research directions in scalable AI, open interfaces, post-quantum security, and advanced materials for HAPS platforms. These contributions form a comprehensive roadmap for scalable, reliable, and high-performance NTN integration towards 6G.

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Resumen Ejecutivo

La integración de plataformas de gran altitud (HAPS) en redes no terrestres (NTN) hacia 6G representa un desafío y una oportunidad para la evolución de las telecomunicaciones globales. Este documento sintetiza los principales avances e innovaciones desarrolladas durante el proyecto 6G-INTEGRATION-3 que ayudarán en la integración y convergencia entre infraestructuras terrestres y no terrestres, abordando tanto retos técnicos como soluciones prácticas para la próxima generación de redes móviles 6G.

En primer lugar, se destaca el uso de algoritmos avanzados de inteligencia artificial y aprendizaje automático, en particular el aprendizaje por refuerzo (Reinforcement Learning, RL), para la optimización dinámica de la búsqueda de rutas ópticas de las NTNs. Estos algoritmos permiten modelar y resolver problemas complejos de enrutamiento, gestión de movilidad y segmentación de red en entornos altamente variables, como los que presentan las constelaciones de satélites LEO y las plataformas HAPS en movimiento.

Uno de los principales aportes es la propuesta e implementación de estrategias de transmisión eficiente de tramas en enlaces HAPS-satélite-tierra. Se introduce el concepto de "withhold scheduling", que permite balancear las colas de datos entre estaciones terrestres y reducir la latencia general del sistema, superando así los enfoques tradicionales de transmisión inmediata y maximizando el throughput global de la red.

El documento también aborda la importancia de la sincronización distribuida y la gestión de los efectos Doppler, fundamentales en escenarios donde los nodos de la red (satélites, HAPS, UAVs) presentan movilidad a gran velocidad. Se proponen técnicas específicas para mantener la fiabilidad del canal y minimizar los errores de transmisión, esenciales para aplicaciones críticas y comunicaciones ultra fiables de baja latencia (URLLC).

En el ámbito experimental, se detalla el diseño y despliegue de una plataforma dron modular, equipada con edge computing (Jetson Orin), router 5G y sensores Lidar, que permite validar en campo los algoritmos y arquitecturas propuestos. Esta plataforma facilita la experimentación realista en escenarios NTN.

El documento profundiza en el análisis de los requisitos de aplicaciones avanzadas, como la realidad aumentada y virtual (AR/VR), que serán determinantes en la demanda de capacidad y latencia en las redes 6G. Se presentan resultados experimentales con dispositivos VR/AR Meta Quest 3, evidenciando necesidades de hasta 1 Tbps para aplicaciones holográficas y latencias inferiores a 2 ms para feedback háptico, junto con exigencias de fiabilidad extrema en los enlaces HAPS-terrestres.

Como elemento innovador, se propone una arquitectura convergente que integra capacidades de Multi-access Edge Computing (MEC) en los nodos HAPS, permitiendo el cacheado distribuido de contenidos, procesamiento local de flujos AR/VR y una gestión inteligente de handovers entre segmentos satelitales, HAPS y terrestres. Esta aproximación reduce la latencia y mejora la experiencia de usuario en aplicaciones de nueva generación.

Finalmente, el documento subraya la necesidad de una coordinación estrecha entre el diseño algorítmico, la innovación en hardware y la validación experimental para afrontar los retos de movilidad 3D, variabilidad de canal y coexistencia espectral en NTNs. Las contribuciones recogidas sientan las bases técnicas para el despliegue masivo y eficiente de HAPS en el ecosistema 6G, posicionando estas plataformas como un pilar esencial de la conectividad global futura.

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Executive Summary

The integration of high altitude platforms (HAPS) into non-terrestrial networks (NTN) towards 6G represents both a challenge and an opportunity for the evolution of global telecommunications. This paper synthesizes the main advances and innovations developed during the 6G-INTEGRATION-3 project that will aid in the integration and convergence between terrestrial and non-terrestrial infrastructures, addressing both technical challenges and practical solutions for the next generation of 6G mobile networks.

First, the use of advanced artificial intelligence and machine learning algorithms, in particular Reinforcement Learning (RL), for the dynamic optimization of NTN optical path finding is highlighted. These algorithms allow modeling and solving complex routing, mobility management and network segmentation problems in highly variable environments, such as those presented by LEO satellite constellations and moving HAPS platforms.

One of the main contributions is the proposal and implementation of efficient frame transmission strategies in HAPS-satellite-ground links. The concept of "withhold scheduling" is introduced, which allows balancing data queues between ground stations and reducing the overall system latency, thus overcoming traditional immediate transmission approaches and maximizing the overall network throughput.

The paper also addresses the importance of distributed synchronization and Doppler effects management, which are fundamental in scenarios where network nodes (satellites, HAPS, UAVs) exhibit high-speed mobility. Specific techniques are proposed to maintain channel reliability and minimize transmission errors, essential for critical applications and ultra-reliable low latency communications (URLLC).

In the experimental field, the design and deployment of a modular drone platform, equipped with edge computing (Jetson Orin), 5G router and Lidar sensors, is detailed, allowing field validation of the proposed algorithms and architectures. This platform facilitates realistic experimentation in NTN scenarios.

The paper delves into the analysis of the requirements of advanced applications, such as augmented and virtual reality (AR/VR), which will be determinant in the demand for capacity and latency in 6G networks. Experimental results with VR/AR Meta Quest 3 devices are presented, evidencing needs of up to 1 Tbps for holographic applications and latencies below 2 ms for haptic feedback, together with extreme reliability requirements on HAPS-terrestrial links.

As an innovative element, a converged architecture is proposed that integrates Multi-access Edge Computing (MEC) capabilities in the HAPS nodes, enabling distributed content caching, local processing of AR/VR streams and intelligent management of handovers between satellite, HAPS and terrestrial segments. This approach reduces latency and improves the user experience in next-generation applications.

Finally, the paper highlights the need for close coordination between algorithmic design, hardware innovation and experimental validation to address the challenges of 3D mobility, channel variability and spectral coexistence in NTNs. The collected contributions lay the technical foundation for the massive and efficient deployment of HAPS in the 6G ecosystem, positioning these platforms as an essential pillar of future global connectivity.

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1. Introduction

Non-Terrestrial Networks (NTNs) represent a pivotal evolution in modern telecommunications, offering the potential to connect remote regions, enhance network resilience, and enable a new generation of applications requiring seamless global connectivity. By integrating satellite systems, high-altitude platforms, and drone-based networks with terrestrial infrastructures, NTNs aim to overcome traditional limitations such as geographical barriers, network congestion, and scalability constraints. However, the realization of NTNs at scale poses several technological challenges, requiring innovation across multiple domains, from algorithms and hardware to application-specific optimizations.

This document presents a structured exploration of these challenges, and the technological advancements required to address them. Each section builds upon the preceding one, creating a cohesive narrative that highlights the interconnected nature of NTN development.

The journey begins in Section 2, which focuses on the fundamental issue of efficient frame transmission within NTNs. Unlike terrestrial networks, NTNs operate in highly dynamic environments characterized by longer propagation delays, higher levels of signal degradation, and intermittent connectivity. These factors demand specialized algorithms to optimize data transmission while ensuring minimal latency and maximum reliability. This section examines the complexities of data transmission in NTNs and introduces novel approaches to achieve efficient frame delivery, paving the way for robust communication in scenarios where traditional networks struggle.

Building on the challenges outlined in Section 2, Section 3 introduces reinforcement learning (RL) as a promising approach to optimize routing within NTNs. Optimal routing is crucial in NTNs, where the network topology constantly changes due to the movement of satellites, drones, or high-altitude platforms. RL algorithms offer the ability to learn and adapt to these dynamic conditions, ensuring efficient data routing even in the face of unpredictable changes. This section not only provides an overview of RL concepts but also delves into the practical implications of applying RL to NTNs. It addresses the critical gap between simulation-based algorithm development and real-world deployment, highlighting the need for validation in operational environments. Additionally, it explores a cutting-edge application of machine learning for privacy firewalling and telemetry, illustrating how NTN-specific innovations can enhance network security and monitoring capabilities.

While the theoretical foundation of RL is compelling, the practical deployment of such algorithms in NTNs requires robust and versatile hardware platforms. Section 4 takes a closer look at this aspect by presenting the design and capabilities of a research-oriented drone tailored for NTN environments. This drone serves as a testing bed for RL algorithms and other innovative networking solutions. Equipped with advanced sensors, communication modules, and computational resources, it facilitates the real-world validation of NTN technologies. By bridging the gap between theoretical research and field experimentation, this section underscores the importance of hardware innovation in the development lifecycle of NTNs.

The final section, Section 5, shifts the focus toward the end-user perspective, examining the implications of NTNs for bandwidth-intensive and latency-sensitive applications such as virtual reality (VR). VR applications are increasingly seen as a benchmark for network performance due to their stringent requirements for ultra-low latency, high bandwidth, and consistent reliability. This section evaluates the bandwidth and latency demands of VR scenarios using experimental setups with MetaQuest3 headsets. It also explores the broader implications of integrating VR and other emerging technologies into existing telecommunications networks, highlighting the adjustments needed to ensure a seamless and immersive user experience.

The overarching narrative of this document connects these diverse elements into a unified vision for advancing NTNs. The interplay between algorithmic innovation, hardware design, and application evaluation is at the heart of NTN development. Efficient frame transmission algorithms lay the groundwork for reliable communication, while RL-based routing introduces adaptability and intelligence to the network. Real-world validation through specialized hardware ensures that these advancements are practical and scalable. Finally, a focus on cutting-edge applications like VR underscores the transformative potential of NTNs, serving as both a driver and a beneficiary of these technological advancements.

Through this holistic exploration, we aim to illuminate the critical challenges and opportunities in the development of NTNs. By addressing these challenges, this document seeks to contribute to the realization of NTNs as a cornerstone of future global connectivity, enabling a wide array of applications that will shape the technological landscape for years to come.

2. Efficient algorithms for frame transmission

2.1 Challenges for data transmission in LEO satellites

Frame transmission in Non-Terrestrial Networks (NTNs), particularly those involving Low Earth Orbit (LEO) satellites and High Altitude Platforms (HAPs), faces several significant challenges that can affect the overall efficiency and reliability of communication systems. In particular:

- Latency is a critical concern, particularly for applications requiring ultra-reliable low-latency communications (URLLC). While LEO satellites offer the advantage of low-latency communications due to their proximity to Earth, traditional Geostationary Earth Orbit (GEO) satellites present significant delays that can adversely affect signal transmission. Additionally, scenarios involving store-and-forward communications can introduce further latency, as signals may need to be queued for transmission when satellites gain visibility to ground stations.

- Signal instability is also a major concern and is exacerbated by the high-speed motion of satellites in LEO. This rapid movement can lead to pronounced Doppler effects, resulting in significant frequency shifts that complicate frequency offset estimation. As satellites traverse their orbits at high speeds, maintaining synchronization becomes increasingly difficult due to these frequency offsets, thereby affecting the accuracy of frame detection methods employed at the receiver end.

- Frame size: The necessity for bursty communication, common in satellite environments, further complicates frame transmission. Unlike traditional long-frame structures, short-frame structures are often adopted to accommodate sudden communication demands. While this approach enhances flexibility and reduces error accumulation during transmission, it also imposes stringent requirements on frame detection technology, which must be capable of rapidly adapting to changing conditions in a dynamic communication environment.

- Shared Media: Current wireless systems are not optimally designed to handle massive connectivity with numerous devices, particularly in satellite communications. The traditional random access method involves multiple steps, including preamble transmission, response phases, and contention resolution, which can be inefficient in high-demand scenarios. The necessity of close-loop signaling and extensive message exchanges can lead to congestion, further complicating the management of resources in these environment. As such, there is a pressing need to adopt more efficient access schemes that can streamline resource allocation and enhance spectrum efficiency.

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- Synchronization: The complex operational environment of NTNs necessitates advancements in frame detection technology. Traditional methods must evolve to meet the challenges posed by high-speed motion, varying signal conditions, and the need for rapid adaptation to dynamic communication scenarios. This evolution includes employing distributed synchronization headers to enhance frequency offset estimation and developing innovative access methods, such as Non-Orthogonal Multiple Access (NOMA) schemes, to efficiently manage simultaneous transmissions from multiple users.

Because of orbital dynamics, a LEO satellite passes over a ground station receiver in a few minutes. As a result, it is common in satellite networks to transmit data as quickly as possible during this brief window, utilizing the full available bandwidth. Consequently, much of the previous research has focused on enhancing the radio technology in both satellites and ground stations to maximize data transfer within these short contact periods. Significant advancements have been made in this area, and now even small CubeSats in Low Earth Orbit can achieve Gbps data links to the ground [1].

This approach of "fast" data transmission from satellites to ground stations can produce long queues at some ground stations, while other stations experience shorter queues and are underutilized. This imbalance occurs for two main reasons. First, ground stations are unevenly distributed geographically due to factors like spectrum licensing, country-specific regulations, and proximity to the poles. As a result, the amount of new data a satellite accumulates between its contacts with ground stations can vary significantly, leading to unbalanced queue lengths. The second reason is that different ground stations have varying backhaul bandwidths to the cloud, ranging from hundreds of Mbps to several Gbps. This causes significant fluctuations in queue lengths across different locations and times. As a result, images at stations with large queues and low bandwidth experience considerable delays. The issue is becoming more pronounced as additional compute resources are integrated into ground stations for edge-style processing, which exacerbates load imbalances due to both network and computational delays [2].

As LEO constellations and systems become more complex, there is a need to address these issues and provide solutions that provide predictable performance across the entire network [3]. In the following we describe different approaches and solutions for efficient frame transmission.

2.2 Efficient frame transmission

The main factors to take into account to schedule frame transmission to optimize overall network performance are:

- Position of the satellites: this determines the feasibility, quality, and duration of contacts with ground stations. A key factor is the predictable orbital movement of each satellite, meaning the sequence and timing of ground station connections are known in advance. However, link quality can fluctuate, for example due to atmospheric conditions and may conditions scheduling [4]. For example, if link quality is expected to be poor, it may not be ideal to hold back large amounts of data for transmission.
- Ground station contention: ground stations are relatively few compared to the large number of satellites. As a result, multiple satellites may compete for access to the same ground station. While ground stations may have several antennas, each antenna can only communicate with one satellite at a time, creating a one-to-one relationship. Additionally, receiving data from several satellites at the same time puts pressure on the outgoing link of the ground station and may lead to long queues.
- Traffic Pattern: queue sizes at ground stations change over time. For example, if several satellites decide to delay transmitting data to a particular ground station, that station may become idle, while later ground stations face long queues.

The problem can be formulated in terms of a Time Expanded Network (TEN) [5], i.e. a network whose topologies and node change over time, in our case due to the movement of satellites [6]. Once formally

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defined, different optimization functions can be used to achieve the desired performance objectives which can include:

- Maximize the end-to-end throughput for the data transfer process from the satellites to the cloud.
- Ensure a given latency for data transfers.
- Provide trade-offs between throughput and latency for all satellites or for a subset of them.

Simulation results show that the traditional scheme of transmitting greedily to the ground station as much data as possible does not lead to the best performance in many scenarios. Instead other strategies in which satellites defer the transmission of some data to another ground station at a later time result in better performance. This type of strategy is denoted as withhold scheduling in [2] and shown to balance queue sizes across ground stations, resulting in higher throughput and lower latency for satellite data transfers to the cloud. The deferral of transmissions can be triggered by a number of factors:

- Better link quality with another ground station.
- Faster backhaul link with another ground station.
- Less loaded ground station.

The simulation studies show the potential of this transmission withholding strategies and the next challenge is to implement the optimization in real-time and run it on a satellite constellation. This requires not only real-time implementations of the TEN optimizers but also the collection of the network data in real-time which is challenging, for example in Internet of Things applications [7].

3. Reinforcement Learning for optimal routing

3.1. Overview of reinforcement learning

Reinforcement Learning (RL) is a subset of machine learning where an agent learns to make sequential decisions by interacting with an environment to maximize a cumulative reward. Unlike supervised learning, which uses labeled data, RL relies on feedback in the form of rewards or penalties to optimize its behavior. This interaction is modeled as a Markov Decision Process (MDP), defined by states, actions, transition probabilities, and rewards [8][9].

3.1.1. Core Components of RL:

1. **Agent**: The learner or decision-maker.
2. **Environment**: The system with which the agent interacts.
3. **Policy (π)**: A strategy mapping states to actions.
4. **Value Function**: Measures the expected cumulative reward from a given state or state-action pair.
5. **Reward Signal**: Feedback indicating the immediate gain of an action.

RL has evolved from classical algorithms like Q-Learning and SARSA to more advanced techniques, including Deep Reinforcement Learning (DRL). DRL leverages neural networks to handle high-dimensional state spaces, enabling its application in complex domains like autonomous systems and games (e.g., AlphaGo) [8][9][11].

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3.1.2. Categories of RL:

- **Model-Free RL**: Learns directly from experience without modeling the environment (e.g., Q-Learning, Policy Gradient methods) [8][10].
- **Model-Based RL**: Constructs a model of the environment for planning and decision-making [11].
- **On-Policy vs. Off-Policy**:
    - On-Policy algorithms improve policies based on the actions taken by the current policy.
    - Off-Policy algorithms evaluate or improve a policy different from the one used to generate data.

3.1.3. Challenges and Mechanisms:

Reinforcement Learning (RL) has achieved remarkable success in diverse applications; however, several significant challenges remain. These challenges stem from the inherent complexity of dynamic environments, the high computational demands of RL algorithms, and limitations in scalability and generalization. Below, we explore these challenges in detail along with the techniques employed to address them.

3.1.4. Exploration-Exploitation Trade-off

One of the fundamental challenges in RL is balancing exploration (trying new actions to discover better rewards) and exploitation (leveraging known actions to maximize immediate rewards). This trade-off is particularly difficult in large or continuous action spaces where exhaustive exploration is impractical. The main techniques employ to deal with this trade-off are:

- **Epsilon-Greedy Strategies**: A simple heuristic where actions are mostly chosen based on current knowledge, but random actions are periodically taken to explore alternatives.
- **Upper Confidence Bound (UCB)**: A method that balances exploration and exploitation by assigning higher priority to actions with uncertain rewards.
- **Entropy-Based Regularization**: Often used in Policy Gradient methods, this approach ensures the agent maintains diverse action distributions during learning [8][9].

3.1.5. Sparse and Delayed Rewards

In many environments, rewards are either infrequent or significantly delayed, making it hard for an agent to associate specific actions with outcomes. This is a critical issue in long-horizon problems like robotic manipulation or routing optimization in networks. The main techniques to deal with this issue are:

- **Reward Shaping**: Augmenting the reward signal with intermediate incentives to guide learning. For example, using distance to a goal as a proxy reward.
- **Hindsight Experience Replay (HER)**: Reframes failures as successes by rewriting the reward for achieved goals post hoc, often used in goal-directed tasks.

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- **Temporal Abstraction via Hierarchical RL**: Breaks tasks into smaller sub-goals, enabling rewards at intermediate stages [9][10].

3.1.6. Scalability to High-Dimensional State and Action Spaces

The curse of dimensionality affects RL when the state or action space grows exponentially, as in non-terrestrial networks with dynamic topologies. Classical tabular methods fail in such cases. Thus, several ways of dealing with this problem have been proposed:

- **Function Approximation**: Using deep neural networks (as in Deep Q-Networks, DQN) to approximate value functions or policies.
- **Actor-Critic Frameworks**: These combine policy-based and value-based methods to scale effectively in continuous action spaces.
- **Policy Optimization Algorithms**: Techniques like Trust Region Policy Optimization (TRPO) and Proximal Policy Optimization (PPO) maintain stability and scalability [9][11].

3.1.7. Non-Stationarity in Environments

In dynamic systems like NTNs, the environment is constantly changing due to factors like satellite movement or varying user demands, leading to non-stationary reward dynamics. There exist different ways to tackle this issue:

- **Adaptive Learning Rates**: Adjust the learning process to rapidly adapt to environmental changes.
- **Meta-RL (Learning to Learn)**: Trains agents to quickly adapt to new environments by leveraging prior knowledge.
- **Ensemble Methods**: Combine multiple policies or models to provide robust performance under uncertainty [9][11].

3.1.8. Multi-Agent Coordination

In many applications, including NTNs, multiple agents must work collaboratively, which introduces challenges in credit assignment, competition, and communication. The way in which this is handled, is usually by employing one the following approaches:

- **Centralized Training with Decentralized Execution (CTDE)**: Agents are trained with shared information but operate independently during deployment.
- **Multi-Agent Reinforcement Learning (MARL)**: Incorporates mechanisms for cooperation and competition, such as sharing global rewards or using game-theoretic approaches.
- **Graph Neural Networks (GNNs)**: Model interactions between agents in structured environments like networks or graphs [9][10].

3.1.9. Sample Inefficiency

RL algorithms often require millions of interactions with the environment to converge to optimal policies, which is computationally prohibitive in complex systems like NTNs. The following techniques are typically used to address this:

- **Experience Replay**: Stores and reuses past experiences to improve sample efficiency, as in DQN.
- **Simulation-Based Training**: Pre-trains agents in simulated environments before deploying them in real systems.
- **Transfer Learning**: Uses knowledge from related tasks or domains to speed up learning in the target environment [10][11].

3.1.10. Ethical and Safety Concerns

In real-world applications, poorly designed reward functions can lead to unintended and harmful behaviors. For instance, optimizing routing in NTNs might prioritize throughput over fairness. Or might cause agents to congest low-priority nodes to optimize latency for specific users. Also, some agents can find “loopholes” in the reward function and cause undesirable behavior, such as causing artificial bottlenecks at some network points to maximize its reward. The main ways this is controlled is by:

- **Reward Engineering**: Carefully designing reward structures to reflect ethical and practical considerations.
- **Safe Exploration Algorithms**: Constrain agents to avoid unsafe actions during exploration.
- **Explainability in RL**: Developing interpretable policies to ensure human oversight [11].

3.2. Optimal Routing in Non-Terrestrial Networks (NTNs)

Optimal routing refers to the process of determining the most efficient paths for data packets to travel across a network to minimize delays, maximize throughput, and optimize resource utilization. In the context of Non-Terrestrial Networks (NTNs), which include satellites, high-altitude platforms (HAPs), and unmanned aerial vehicles (UAVs), routing becomes significantly more complex due to unique characteristics such as mobility, dynamic topology, latency, and limited bandwidth.

This section explores the concept of optimal routing in NTNs, emphasizing the challenges, performance metrics, and existing frameworks to address these challenges.

3.2.1. Characteristics of NTNs

NTNs differ from terrestrial networks due to their dynamic and heterogeneous nature. These differences profoundly affect routing strategies. The mobility of satellites and UAVs leads to rapidly changing network structures, necessitating routing protocols that can adapt in real time. For example, Low Earth Orbit (LEO) satellite constellations require frequent handovers as satellites

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move in and out of view of ground stations and other satellites [12]. Beyond the dynamic topology, there is the problem of latency. Signals in NTNs travel over long distances, introducing significant propagation delays. This is especially pronounced in Geostationary Earth Orbit (GEO) systems where the one-way delay can exceed 250 milliseconds [13]. Another specific characteristic of NTNs is the limited bandwidth and the need for sharing the radio spectrum. NTNs often operate in constrained frequency bands and must share resources among users, making efficient routing critical to avoid congestion and ensure fairness [14].

3.2.2. Objectives of Optimal Routing in NTNs

The objectives of optimal routing in Non-Terrestrial Networks (NTNs) are focused on addressing the unique challenges posed by satellite constellations and aerial systems, particularly in relation to efficiency, latency, and scalability. The goal is to ensure reliable communication while minimizing delay and optimizing resource usage. In the context of NTNs, routing protocols must dynamically adjust to the changing topology and mobility of satellites and UAVs, ensuring continuous service even as nodes constantly move or go out of range. For instance, LEO constellations require frequent updates to routing paths as satellites pass over ground stations or switch from one satellite to another, which requires protocols that minimize disruption and avoid packet loss during handovers [11].

Moreover, reducing latency is a critical objective in NTN routing. The propagation delay between ground stations and orbiting satellites can significantly affect real-time communication services, especially for high-demand applications such as video streaming or IoT systems. In GEO systems, this latency can exceed 250 milliseconds, which can be unacceptable for certain applications. Therefore, optimizing routing to minimize this delay while ensuring robustness against interference from other satellites or atmospheric conditions is vital [12]. Another important aspect is maximizing the utilization of the available bandwidth. Given the limited frequency spectrum in NTNs, efficient routing must prioritize data flows to avoid congestion, manage network resources effectively, and guarantee fairness among users. This is especially challenging as these networks often rely on shared frequency bands and must accommodate varying levels of demand across multiple users and applications [17].

Thus, optimal routing in NTNs aims to achieve not only low latency and efficient resource allocation but also a scalable and adaptable system that can handle the dynamic nature of space-terrestrial networks.

3.2.3. Challenges in Achieving Optimal Routing in NTNs

Achieving optimal routing in Non-Terrestrial Networks (NTNs) is fraught with several unique challenges due to the dynamic and heterogeneous nature of these networks. One of the primary challenges is the dynamic topology caused by the mobility of satellites, UAVs, and other aerial platforms. As satellites orbit in Low Earth Orbit (LEO) or other altitudes, the network topology changes constantly, requiring frequent updates to routing tables. This dynamic nature complicates the design of routing protocols, which must be able to handle such frequent topology changes without incurring significant delays or packet loss. Moreover, these networks often need to handle frequent handovers between satellites, ground stations, and aerial systems as they pass out of range or transition between coverage areas. These handovers are crucial in maintaining seamless

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communication but are resource-intensive and can lead to disruptions in connectivity if not managed properly [15].

Another challenge in NTN routing is the high latency inherent in space communications. For example, communication with satellites in Geostationary Earth Orbit (GEO) introduces significant one-way delays of over 250 milliseconds due to the vast distance between the satellite and ground stations. While Low Earth Orbit (LEO) constellations help reduce latency by positioning satellites closer to Earth, they require complex routing strategies to manage the continuous movement of the satellites and handovers that occur frequently. The propagation delay and the time it takes for signals to travel from satellites to ground stations or between satellites in the constellation create additional complexity in designing protocols that maintain low delay and high throughput [15].

Bandwidth limitations are another critical concern. Unlike terrestrial networks, NTNs must operate in constrained frequency bands, which are shared among various users and services. Efficient management of this bandwidth is essential to avoid congestion and ensure fairness in resource distribution. In many cases, the spectrum availability is limited, especially for high-data-rate applications like video streaming or large-scale data transfer, making the need for efficient routing protocols even more pressing. These protocols must not only find the most optimal paths but also manage resources in a way that prevents congestion and interference between satellite links.

Finally, there is the need for scalability in NTN routing solutions. With the rapid growth of satellite constellations, there is a constant increase in the number of nodes in these networks. Scalability becomes a challenge as routing protocols must handle large networks while ensuring that updates and path calculations remain efficient and manageable. The combination of these challenges necessitates the development of advanced routing algorithms that can dynamically adjust to real-time conditions, minimize delays, and optimize the use of network resources to achieve optimal performance across the entire NTN.

3.2.4. Traditional Approaches to Routing in NTNs

Traditional routing approaches in Non-Terrestrial Networks (NTNs) are primarily based on established techniques that have been adapted from terrestrial network routing algorithms, but these methods often require significant modifications to cope with the unique characteristics of NTN architectures. One of the foundational approaches is distance-vector routing, where each node in the network exchanges information with its neighbors to determine the best path to a destination. In satellite networks, this approach faces challenges due to the dynamic topology and the frequent handovers between satellites and ground stations [15]. While effective for more stable networks, this technique requires frequent updates, which can lead to inefficiencies in NTNs, particularly in Low Earth Orbit (LEO) constellations where satellites move quickly across the sky.

Another widely used traditional routing technique is link-state routing, where each node maintains a map of the entire network and uses this information to determine the shortest path to each destination. While this method can provide more accurate and efficient routing compared to distance-vector approaches, it also faces challenges in NTNs due to the high mobility of nodes. For example, in a satellite constellation, frequent changes in the connectivity between satellites and ground stations require constant recalculation of routing paths, which can lead to higher computational overhead and delays [14]. Moreover, this method requires each node to have knowledge of the entire

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network's topology, which becomes more complex and difficult to maintain as the number of satellites or nodes in the network increases.

Path-vector routing is another traditional approach that is commonly used in hybrid networks, such as those that combine space-based and terrestrial communication systems. This approach, while effective in reducing overhead compared to link-state routing, still faces similar challenges in NTNs, especially when dealing with inter-satellite communication. The complexity of inter-satellite links and the continuous reconfiguration of routes due to satellite movement can create situations where routing decisions are outdated by the time they are made [16].

Lastly, hybrid routing protocols have been proposed for NTNs, combining elements of both proactive and reactive routing. Proactive protocols maintain up-to-date routing tables, ensuring that nodes can communicate instantly when needed, while reactive protocols only compute routes when necessary. These hybrid protocols attempt to balance the need for fast communication with the efficiency of reduced updates, but their effectiveness in NTNs can be hindered by the limited bandwidth and high latency associated with satellite communication [17].

While traditional approaches have provided useful starting points, they often require further refinement to meet the specific challenges of NTN environments, such as dynamic topology, mobility, latency, and bandwidth constraints. As such, more advanced and specialized routing algorithms are increasingly being explored for optimal performance in NTN contexts. In this regard, Deep Reinforcement Learning is gaining traction as a useful alternative to allow the different nodes to optimize different aspects of the communication.

3.2.5. Emerging Trends in Optimal Routing for NTNs

Emerging trends in optimal routing for Non-Terrestrial Networks (NTNs) reflect the growing role of advanced technologies like deep reinforcement learning (DRL) and multi-agent systems. Traditional satellite routing methods, which rely on static or pre-defined paths, are being supplemented or replaced by more dynamic and adaptive strategies. The unique characteristics of NTNs, such as their time-varying topologies, the dynamic nature of Low Earth Orbit (LEO) constellations, and satellite mobility, make conventional approaches increasingly ineffective. In response, researchers are focusing on algorithms that can adjust in real-time to these changing conditions.

One significant development is the use of Deep Reinforcement Learning (DRL) for routing optimization in LEO satellite networks. DRL-based routing systems can learn from past experiences and adjust their decisions based on real-time network states, including congestion and satellite positioning. This approach significantly outperforms traditional methods like Dijkstra’s algorithm, which does not consider the dynamic nature of satellite movements or the impact of congestion [18][19]

A particular area of interest is multi-agent reinforcement learning (MARL), where each satellite in a network is treated as an independent agent making decisions based on its local observations. These agents can coordinate to optimize the routing process in a decentralized manner, reducing the need for centralized control, which can be costly in terms of bandwidth and processing power [21]. This has led to improved routing efficiency in satellite constellations, especially when compared to traditional routing protocols that cannot adapt quickly to changing network topologies [19].

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Furthermore, research has increasingly focused on hybrid models that combine DRL with other AI techniques, such as graph-based algorithms or metaheuristics, to improve the routing process. These methods aim to provide a more holistic solution by addressing not just connectivity and latency but also factors such as energy consumption, fairness, and load balancing [20]. As the deployment of 6G networks draws closer, the integration of such emerging technologies will likely play a pivotal role in addressing the complex challenges of NTN routing.

The continued exploration of these innovative routing strategies underscores the shift toward more intelligent, adaptable systems capable of meeting the demands of modern satellite communication networks. As NTNs expand, especially with the rise of mega-constellations, the use of AI-driven approaches will be essential in ensuring efficient and scalable communication.

3.3. Deep Reinforcement Learning for Optimal Routing in Non-Terrestrial Networks (NTNs)

Reinforcement Learning (RL) has emerged as a transformative tool for optimal routing in Non-Terrestrial Networks (NTNs), particularly due to its ability to adapt to dynamic environments and optimize complex decision-making processes in real time. NTNs, which include satellite networks, unmanned aerial vehicle (UAV) systems, and other space-based communication platforms, are characterized by rapidly changing topologies, long propagation delays, and limited resources. These challenges make traditional routing protocols inadequate, paving the way for RL-based methods to ensure efficient data flow and connectivity.

3.3.1. DRL for NTNs: Key Ideas

The application of DRL to NTNs requires the definition of specific components: state, action, observation, and reward, all of which are tailored to the characteristics of the network. Below, we break down these components and provide examples of reward signals to illustrate how they are designed:

- **State**: The state represents the current configuration of the NTN as perceived by the DRL agent. In NTNs, the state can include the network topology, link capacities, traffic demands, satellite positions, and available bandwidth. For example, in LEO satellite networks, the state may track the relative positions of satellites, the number of active inter-satellite links (ISLs), and congestion levels at each node. A more comprehensive state representation might also include predictions of future network conditions derived from historical data [18][20].
- **Action**: The action is the decision made by the DRL agent to change the network's behavior. In NTN routing, this involves selecting paths for data packets, allocating bandwidth, or modifying transmit power. For instance, an action might be to route a packet through a specific sequence of LEO satellites or adjust the number of active ISLs to balance load across the network [19].
- **Observation**: Observation is the partial or full view of the state that the agent perceives. In distributed NTN systems, observations may be localized, meaning each node (e.g., a satellite) has access only to its own state and immediate neighbors' states. This constraint highlights the importance of designing algorithms that can operate under incomplete information, often addressed using partially observable DRL (POMDP frameworks) [18].
- **Reward**: The reward is the feedback signal that guides the agent towards optimal policies. In NTN routing, rewards are designed to align with network objectives, such as minimizing

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end-to-end latency, maximizing throughput, or balancing energy consumption. Rewards can be instantaneous (reflecting performance for a single step) or cumulative (evaluating long-term benefits). The reward design directly influences the agent's learning behavior and outcomes [21].

3.3.2. DRL for NTNs: Popular Methods

Q-Learning and Deep Q-Learning

Q-learning, a model-free RL algorithm, has been widely adopted for NTNs due to its simplicity and adaptability to discrete action spaces. Deep Q-Networks (DQNs), an extension of Q-learning, integrate deep learning to approximate Q-values for large state spaces, making them suitable for complex NTN topologies. For example, DQN has been applied to optimize routing by dynamically selecting links to minimize latency and improve throughput in Low Earth Orbit (LEO) satellite constellations [23][24].

Extensions of DQN, such as Double DQN and Dueling DQN, further address issues like overestimation and reward instability. Double DQN uses separate networks for action selection and evaluation, which reduces bias in Q-value estimation. Similarly, Dueling DQN splits the Q-function into value and advantage streams, enabling better policy evaluation [23][24].

Actor-Critic Approaches

Actor-critic methods combine policy-based and value-based learning. These approaches are particularly effective in NTNs, where continuous decision-making is needed. The actor learns the policy (mapping states to actions), while the critic evaluates the policy's performance using value functions. Policy Gradient methods, such as Proximal Policy Optimization (PPO) and Advantage Actor-Critic (A2C), have demonstrated potential for NTN routing by enabling stable convergence and efficient use of limited network resources [23][24].

Graph-Based DRL

With NTNs characterized by graph-like topologies (e.g., satellite and UAV networks), GNN-based DRL algorithms are gaining traction. These models encode spatial and topological information directly into the learning process. Graph Convolutional Networks (GCNs), when combined with DRL frameworks, help agents identify optimal routing paths by learning dependencies across nodes in NTN networks, making them particularly effective for dynamic scenarios [23].

Hybrid Techniques

Hybrid methods combine supervised learning with DRL to initialize models with domain-specific knowledge, speeding up convergence. For instance, some studies integrate heuristic algorithms like shortest-path routing with DRL to provide a baseline for exploration, thereby reducing computational complexity while maintaining flexibility in dynamic conditions [24].

These methods represent a diverse toolkit for addressing NTN routing challenges, ensuring robust and scalable solutions under dynamic and constrained conditions.

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3.4. Real World vs Simulation: an important trade-off

The development of reinforcement learning (RL) algorithms for routing in Non-Terrestrial Networks (NTNs) heavily relies on simulations during initial stages. Simulations provide a controlled environment to test algorithms under various scenarios, including dynamic topologies, latency variations, and bandwidth constraints. They allow researchers to quickly iterate, debug, and refine models without the significant costs or risks associated with testing on physical hardware. However, despite their advantages, simulations often fall short in accurately replicating the complexities of real-world NTN deployments. This discrepancy necessitates the eventual testing and fine-tuning of RL algorithms on real hardware to achieve practical success.

3.4.1. Why Simulations Are Critical for Initial Development

Simulations play a crucial role in providing a virtual testing ground for RL-based routing algorithms. They allow researchers to:

1. **Model Dynamic Conditions**: Simulators can replicate rapidly changing NTN topologies, such as satellite or UAV movement, which would be challenging to reproduce consistently on physical testbeds.
2. **Experiment with Hypothetical Scenarios**: By manipulating variables like link failures or extreme weather conditions, researchers can evaluate algorithm robustness without physical risks.
3. **Cost and Time Efficiency**: Setting up a real NTN testbed is expensive and time-consuming. Simulators, in contrast, provide a scalable and low-cost alternative.
4. **Hyperparameter Tuning**: RL algorithms involve tuning numerous hyperparameters (e.g., learning rate, discount factor). Simulations accelerate this process by offering fast feedback loops.

Examples of widely used simulators include STK (Systems Tool Kit) [25] for satellite network dynamics and ns-3 [26] for general-purpose networking simulations.

3.4.2. The Simulation-to-Reality Gap

Despite their utility, simulations cannot perfectly replicate the real-world conditions that NTN routing algorithms must handle. The simulation-to-reality gap arises due to the following factors:

1. **Simplified Models**: Simulators often use simplified propagation models, ignoring factors like atmospheric effects, hardware imperfections, or interference from other networks.
2. **Hardware Constraints**: Simulators fail to account for the processing delays, energy constraints, and communication inefficiencies of actual NTN hardware, such as satellite transponders or UAV payloads.
3. **Unpredictable Environments**: Real-world environments introduce uncertainties, such as weather variations or unexpected interference, that are hard to model in simulations.
4. **Policy Generalization Issues**: RL algorithms trained in idealized simulation environments often overfit to simulated conditions, leading to suboptimal performance in real-world deployments.

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For instance, an RL-based routing algorithm might achieve low latency and high throughput in a simulator by exploiting assumptions (e.g., perfect synchronization or uniform link quality) that do not hold in practice.

3.4.3. Bridging the Gap: Combining Simulations with Real Hardware

To overcome these challenges, a hybrid approach combining simulation and real hardware is essential:

1. **Simulations for Pre-Training**: RL models can be pre-trained in simulations to acquire baseline policies. This approach reduces the time and cost of training directly on hardware.
2. **Transfer Learning**: Knowledge gained from simulations can be adapted to real-world conditions using transfer learning techniques, enabling algorithms to fine-tune their policies based on hardware-specific data.
3. **Hardware-in-the-Loop Testing**: Integrating hardware components into simulations provides a more realistic testing environment. For instance, a satellite communication module can be tested in a simulated LEO constellation.
4. **Iterative Refinement**: Alternating between simulation and real-world testing allows researchers to iteratively improve algorithm performance while minimizing risks.

3.4.4. The Necessity of Real Hardware for Success

Real hardware testing is mandatory to ensure RL algorithms meet performance expectations in live NTN deployments. It validates the algorithm's ability to:

1. **Handle Hardware Limitations**: Real hardware tests expose computational, energy, and storage constraints that simulators overlook.
2. **Operate Under Realistic Conditions**: Testing on physical platforms reveals unforeseen environmental effects and interactions with other systems.
3. **Achieve Regulatory Compliance**: Simulated results cannot guarantee adherence to regulatory requirements, such as spectrum usage or power limits, which must be verified on actual hardware.

For example, companies like SpaceX and OneWeb have emphasized real-world testing to validate routing algorithms in their LEO satellite constellations, ensuring robust performance under practical operating conditions.

3.4.5. A Unified Reward Function for Realistic Applications

A promising approach is the use of composite reward functions that combine simulation-derived metrics with hardware-specific constraints. For instance, an RL algorithm could optimize a reward function that is a weighted sum of:

- Latency minimization (simulation-driven),
- Power efficiency (hardware-driven),
- Throughput maximization (hybrid),
- Packet delivery ratio (real-world testing).

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This hybrid reward structure ensures the algorithm's objectives align with both theoretical and practical requirements.

3.5. ML implementation code for privacy firewalling and telemetry applications

3.5.1. Introduction

Path optimization for traffic flows is a method available to enhance the Quality of Experience (QoE) perceived by users. Network automation facilitates this goal by monitoring and collecting telemetry information and network states for both optical and packet-based data. Advanced artificial intelligence, machine learning, or other intelligent algorithms are then applied to evaluate network performance. Additionally, privacy and firewalling mechanisms are crucial for safeguarding sensitive data as it traverses the network. Implementing robust firewall rules and encryption standards ensures data privacy, while intelligent filtering can adapt to evolving threats. Telemetry applications play a key role in this process by continuously gathering real-time data from network devices, enabling rapid identification of potential security breaches or performance issues.

Subsequently, decisions are made, and actions are taken over the network to prevent or correct possible performance issues that affect perceived QoE. This process is commonly referred to as closed-loop automation. Network automation is supported by various processes, including the implementation of Software Defined Networking (SDN), aimed at moving towards a zero-touch network and service management (ZSM) approach [45]. While having valid and up-to-date information is important, choosing the appropriate intelligent model to detect and correct performance problems allows for making the best decisions to optimize network operation.

In this section of the document, we focus on the second stage of zero-touch networking: optimal path decision for privacy firewalling based on both optical and packet-based telemetry information, using the well-known Reinforcement Learning (RL) methodology, which enables optimal network configurations by allowing the control plane to learn from its interactions with the network and make decisions without human intervention. In the past, RL has been proposed to enable ZTN by providing the network with the ability to learn from its own experience and make decisions without human input [46].

We provide a methodology for generating rewards in an RL environment, where such rewards are based on both optical telemetry information (i.e., pre-FEC BER) and packet routing measurements (i.e., latency and queue occupation). Open-source code is also provided for the interested reader willing to replicate the experiments and incorporate new features into the algorithm [47].

3.5.2. Background and Methodology

In general, Reinforcement Learning (RL) is a type of AI/ML strategy in which an agent learns to behave in an environment by trial and error, that is, by making decisions and receiving positive rewards (or penalties as negative rewards). The agent is rewarded for taking actions that lead to desired outcomes and penalized when undesired outcomes occur. Over time, the agent learns to take the best actions in each situation that maximize its rewards (or minimize penalties) [7]. RL is effective for a variety of tasks in optical networks, including resource allocation (wavelengths and bandwidth), traffic engineering of flows to minimize congestion, and resiliency against fault management [48][50].

The formulation of RL problems requires defining:

- A set of states ***S***, which are representations of the environment at a given point in time.
- A set of Actions ***A*** that can be taken by the agent at a given state.

- Rewards, which are feedback signals that the agent receives from the environment after taking an action in a given state. Rewards can be positive or negative.
- The policy π, which maps states to actions.

The goal of reinforcement learning is to find a policy that maximizes the agent's expected discounted return in the long term. The agent can do this by trial and error. It tries different actions at different states and observes the received rewards. Over time, the agent learns to take those actions that lead to higher expected discounted returns. There are many libraries with functions for different RL algorithms already coded, both in R and Python frameworks [50]. Examples, for the open-source programming language R, include *contextual*, *ReinforcementLearning*, and *MDPtoolbox*.

In this proposal, we used the *igraph* library for building network topologies and an implementation of the Q-learning algorithm for finding the optimal routing policy in a packet-optical network where a Path Computation Element (PCE) decides the best route selection for every source-destination pair, using both optical metrics (pre-FEC bit error rate) and packet latency measurements (including propagation delay and link load). The code is publicly available on GitHub for further developments by the research community [46].

The Q-learning algorithm, a form of model-free reinforcement learning, updates its value function based on an equation that considers the immediate reward received for an action, plus the maximum future rewards. The Q-value of a state-action pair ***(s, a)*** is updated as follows:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[R(s,a) + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \quad (1)$$

Where:

- **Q(s, a)** denotes the current estimate of the value of action **a** in state **s**.
- **α** is the learning rate, determining the impact of new information on the existing Q-value.
- **R(s, a)** is the immediate reward received after taking action **a** in state **s**.
- **γ** is the discount factor, which balances the importance of immediate and future rewards.
- **max Q(s′, a′)** represents the maximum predicted reward achievable in the next state **s′**, considering all possible actions **a′**.

The next section shows the applicability of code [47] in a few network scenarios.

3.5.3. Simulation scenario and RL-Based Solution

Example on a small network topology

Let us consider the network topology of Figure 1. 8-node topology exampleFigure 1, which comprises 8 nodes and 9 links. We assume that all nodes report telemetry measurements regularly to the control plane, in which our Reinforcement Learning algorithm is running to decide the best routing strategies between nodes. In particular, each node reports: measured pre-FEC bit error rate (BER) and link load, denoted as $\mathbf{BER_i}$ and $\boldsymbol{\rho_i}$ for the i-th link. This information, together with the link distance $\mathbf{d_i}$ in kilometers will be used by the RL algorithm to create negative rewards (penalties), as it follows:

- **Propagation delay** adds a penalty of $\mathbf{d_i \times 5}$ **μs/km**, that is, the classical 5 μs signal propagation latency per kilometer of silica fiber.
- **Traversing a given link** also adds a latency penalty of **μs · 1 / (1 − $\boldsymbol{\rho_i}$)**, which is the average transmission and queuing delay of a 1250-byte packet transmitted over a 10 Gb/s link with load $\boldsymbol{\rho_i}$ (for a classical M/M/1 queue).

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- **Monitored Pre-FEC BER** adds a penalty of **1000 μs** if the BER value of that link is **10^{-4}** or above; **50 μs** if the link's BER is in the range between **$10^{-5} < BER_i < 10^{-4}$; 0 μs** penalty otherwise.

As shown, traversing each link adds both packet-based penalty, propagation-delay penalty, and optical pre-FEC BER-related penalty to either encourage or discourage links in a path. This set of rules is crafted as Reward matrices for taking action **a** in state **s** (i.e., **R(s, a)** state-action pair), and inputs the Q-learning algorithm. Finally, node connectivity is also included as a bi-dimensional Matrix **P(s, s′)**, which contains the probability of jumping from state (or node) **s** to **s′**.

Table 1 shows the optimal routing policy decided by our RL algorithm for the 8-node topology of Figure 1. The policy finds the best next hop and primary path from source to destination, taking into account the rewards for a given pre-FEC BER, propagation delay, and link load. In the example of Figure 1, all links operate with good quality optical links, i.e., pre-FER under 10^{-5}, hence only propagation delay and link load contribute to finding the best primary end-to-end path. However, if the optical quality of a link degrades, then the RL algorithm finds an alternative or secondary route. This is the situation observed in Table 1 ("secondary" rows) when links 3-4 and 7-8 experience degraded pre-FEC BER. As shown, the RL algorithm finds new routes that avoid the use of such low-quality links (marked in bold font).

Extended example on a large topology: Tokyo MAN

Figure 2. tokyo topology exampleFigure 2 shows the 23-node MAN topology for Tokyo 53 for testing our algorithm. In this detailed examination, given the extensive scale and intricate nature of the network topology, our analysis will be concentrated on a select number of routing paths rather than the entire network. Key routes, including but not limited to the journey from Router 1 to Router 22, will be scrutinized. The optimal paths for these specific routes under normal conditions (primary) are depicted in Table 2, which also includes secondary routes after degradation of links 1-6, 1-4, and 10-11.

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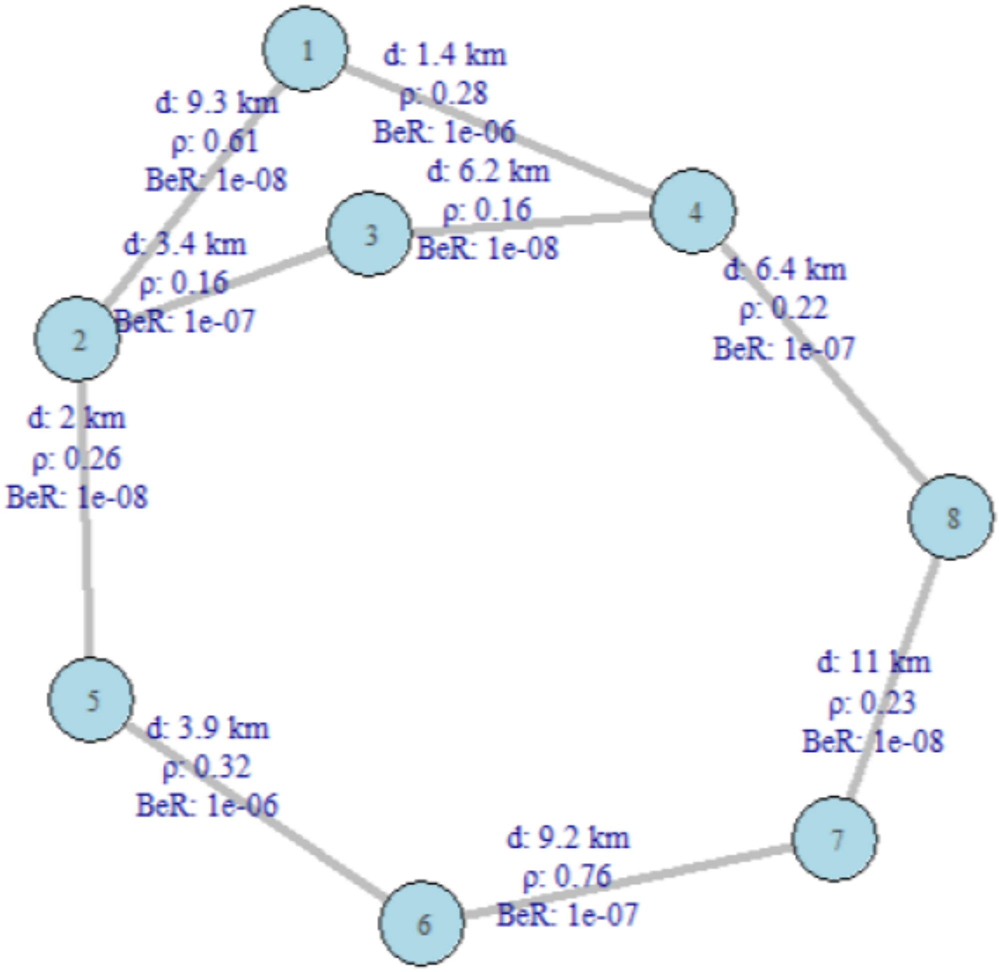

FIGURE 1. 8-NODE TOPOLOGY EXAMPLE

TABLE 1. OPTIMAL PATH (POLICY) SELECTION UNDER NORMAL CONDITIONS (LOW PRE-FEC BER VALUES) ALONG WITH SECONDARY ROUTES AFTER DEGRADATION OF LINKS 3-4 AND 7-8

		Dest							
Source	Path	1	2	3	4	5	6	7	8
1	primary	-	1-2	1-4-3	1-4	1-2-5	1-2-5-6	1-4-8-7	1-4-8
	secondary	-	1-2	1-4-3	1-4	1-2-5	1-2-5-6	1-4-8-7	1-4-8
2	primary	2-1	-	2-3	2-1-4	2-5	2-5-6	2-5-6-7	2-1-4-8
	secondary	2-1	-	2-3	2-1-4	2-5	2-5-6	2-5-6-7	2-1-4-8
3	primary	3-4-1	3-2	-	3-4	3-2-5	3-2-5-6	3-4-8-7	3-4-8
	secondary	3-2-1	3-2	-	**3-2-1-4**	3-2-5	3-2-5-6	**3-2-5-6-7**	**3-2-1-4-8**
4	primary	4-1	4-1-2	4-3	-	4-1-2-5	4-1-2-5-6	4-8-7	4-8
	secondary	4-1	4-1-2	**4-1-2-3**	-	4-1-2-5	4-1-2-5-6	**4-1-2-5-6-7**	4-8
5	primary	5-2-1	5-2	5-2-3	5-2-1-4	-	5-6	5-6-7	5-2-1-4-8
	secondary	5-2-1	5-2	5-2-3	5-2-1-4	-	5-6	5-6-7	5-2-1-4-8
6	primary	6-5-2-1	6-5-2	6-5-2-3	6-5-2-1-4	6-5	-	6-7	6-7-8
	secondary	6-5-2-1	6-5-2	6-5-2-3	6-5-2-1-4	6-5	-	6-7	**6-5-2-1-4-8**
7	primary	7-8-4-1	7-6-5-2	7-8-4-3	7-8-4	7-6-5	7-6	-	7-8
	secondary	**7-6-5-2-1**	7-6-5-2	**7-6-5-2-3**	**7-6-5-2-1-4**	7-6-5	7-6	-	**7-6-5-2-1-4-8**
8	primary	8-4-1	8-4-1-2	8-4-3	8-4	8-4-1-2-5	8-7-6	8-7	-
	secondary	8-4-1	8-4-1-2	**8-4-1-2-3**	8-4	8-4-1-2-5	**8-4-1-2-5-6**	**8-4-1-2-5-6-7**	-

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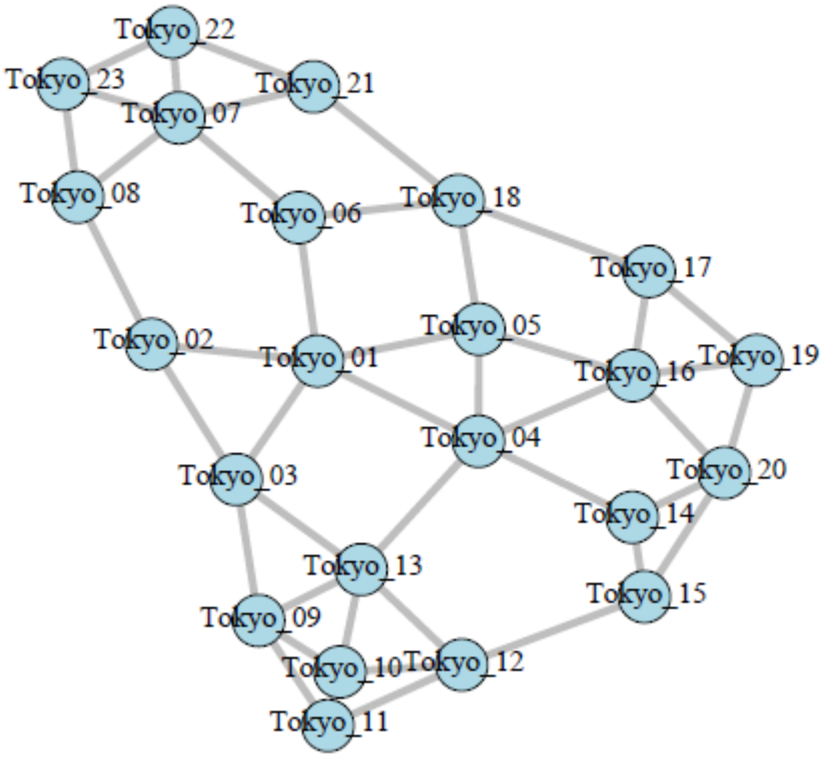

FIGURE 2. TOKYO TOPOLOGY EXAMPLE

TABLE 2. OPTIMAL POLICY: PRIMARY (IN NORMAL OPERATION) AND SECONDARY (AFTER DEGRADATION OF LINKS 1-6, 1-4, AND 10-11 FOR THE TOKYO TOPOLOGY

From	To	Primary	Reward	Secondary	Reward
1	22	1-6-7-22	-123.55	1-5-18-21-22	-151.00
4	7	4-1-6-7	-121.88	4-5-18-21-7	-157.61
4	11	4-13-10-11	-121.01	4-13-12-11	-122.83
1	19	1-4-16-19	-101.81	1-5-16-19	-108.21

4. Deployment of a Drone for NTNs Experimentation

4.1. Introduction

The Development of new communication systems for Non-Terrestrial Networks (NTNs) require a great deal of experimentation. Par of these experiments run over simulation software. But there is a need to test in the real world those algorithms to check whether the simulation results also apply when dealing with the full complexity of the final real-world scenario. For this reason, in this section of the document, we provide a comprehensive guide for building a small drone for testing and evaluating connectivity in the context of NTNs. There are other works in the literature aimed at a similar objective [27][28][29][30][31].

NTNs have various applications such as providing broadband Internet in underserved areas, enabling maritime and aviation communications, supporting emergency response and disaster relief efforts, facilitating Internet of Things (IoT) connectivity, and serving as backhaul for terrestrial networks [28][32][33].

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For example, about 20% of US population lives in rural areas, which account for about 97% of the total land [34]. This number grows to 28% in Europe, and about 40% worldwide. In many cases, fiber deployment does not reach rural areas (at least the last mile), since this results very expensive for network operators, hard to justify in terms of Average Revenue per User (ARPU). Indeed, it is estimated that every single meter of fiber connectivity costs approximately $100 USD. The largest share of this cost includes digging, trenching and the civil works in general [37]. NTNs can help provide broadband connectivity to such isolated areas where fiber deployment is not feasible [35][33][36].

Concerning satellites, another important piece of the NTN ecosystem, the research community has witnessed a race toward deploying different satellite constellations to provide connectivity globally, with more than 50,000 satellites estimated to be launched within 10 years [38]. Thanks to the cost reduction in launching Low-Earth Orbit (LEO) satellites [39], four major companies are already deploying LEO satellite mega-constellations, namely Telesat, Tesla's Starlink, OneWeb and Amazon Kuiper [34]. However, there are a number of challenges related with the integration of satellites into the 5G ecosystem, mainly due to latency and doppler effects, as analyzed in [40][41][42]. A detailed survey on this matter is exhaustively studied in [43]. Hence, satellites are expected to be also complemented with LAPS and UAVs like drones, which are inexpensive, easy to deploy and operate, and can be landed for operations maintenance and take off as quickly as needed and as many times as necessary.

In the upcoming sections, we provide a short guide for building a medium-sized drone for 5G connectivity experiments and use cases. This includes the component selection and assembly procedures for building a drone, along with open-source software libraries needed to have it up and running.

This drone is designed to weigh 6.5 Kg and cost less than 4,000 USD (at the time of writing, sept 2024), having an autonomy of 40 minutes. Such features open up a wide array of applications across various fields:

- Advanced Surveillance and Reconnaissance: The combination of 5G connectivity, 360-degree camera, and GPS allows for real-time, high-resolution surveillance with a panoramic view. This makes it ideal for law enforcement, search and rescue operations, or monitoring large-scale events.
- AI-Powered Environmental Monitoring: Utilizing the Jetson Orin's processing power and onboard AI models, the drone can perform real-time analysis of environmental data. It could be used to monitor wildlife populations, track deforestation, or assess the impact of natural disasters.
- Smart Agriculture: The drone's capabilities make it an excellent tool for precision agriculture and Internet of Things (IoT) applications. It can analyze crop health, detect pests or diseases, and even assist in targeted application of fertilizers or pesticides.
- Autonomous Inspection of Infrastructure: Thanks to computer vision and image processing state-of-the-art software, drones can now perform detailed inspections of bridges, power lines, wind turbines, or other large structures, identifying potential issues without human intervention.
- Enhanced Film making and Photography: The 360-degree camera and stable flight characteristics make this drone an exceptional tool for cinematographers and photographers, offering unique perspectives and immersive footage.
- Edge Computing for Scientific Research: The onboard GPU and ability to run deep learning models allow for complex data processing in the field, providing valuable data for scientific expeditions in remote areas, enabling real-time decision making and analysis of collected data.
- Emergency Response and Disaster Management: The drone's 5G connectivity and advanced imaging can provide critical real-time information to first responders and disaster management teams, helping to coordinate relief efforts more effectively.

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- Interactive Art Installations: The drone's combination of visual capabilities and processing power opens up possibilities for creating dynamic, AI-driven art installations or performances.

These applications demonstrate how the integration of advanced hardware and AI capabilities can transform a drone from a simple flying camera into a versatile, intelligent platform capable of tackling complex tasks across numerous industries.

4.2. Hardware Design

4.2.1. Initial Design and requirements

This guide begins by emphasizing the importance of clarifying the primary objective of the drone. Whether intended for filming purposes or prioritizing endurance, this initial consideration serves as the cornerstone for developing a professional-grade UAV. The following list outlines the functional requirements the drone should fulfill, such as emergency fire detection, Large-Language Model support, or video recording. Other special technical specifications and requirements before starting the design process are:

- Aerodynamics and propulsion efficiency
- Weight distribution and balance
- Flight stability and control
- Power management and battery life
- Payload capacity
- Environmental durability

Our drone is designed to have about 45 minutes of autonomy, weigh 6.5 kilograms, and require 600 Watts of power. Figure 3 shows the final assembled drone along with the individual components on top and bottom. Also, Table 3 provides a summary list of individual components, and the next section briefly overviews each hardware component in detail.

Before starting, it is important to have:

- Welding equipment
- A 3D printer

Next, we outline the basic building components used in the drone of Figure 3, namely frame and body, motors and propellers, flight controller, battery, sensors (e.g., GPS, accelerometers), and camera/payload systems, among others.

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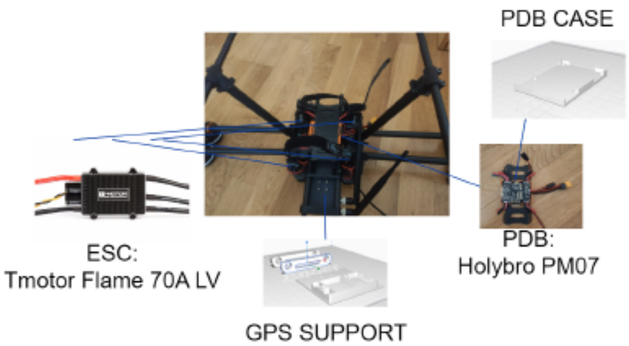

FIGURE 3. DRONE FINALLY ASSEMBLED (TOP); COMPONENTS AND TOP VIEW (BOTTOM LEFT), AND COMPONENTS AND BOTTOM VIEW (BOTTOM RIGHT)

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TABLE 3. INDIVIDUAL COMPONENTS AND APPROXIMATE COST (DECEMBER 2024)

Component	Description	Specifications	Approximate cost
Quadcopter Platform	Tarot XS690	17inch propeller	200$
Motors	T-motor U7 V2 490KV		150$x4
ESC	T-motor Flame 70A LV ESC	4-6S voltage, 70A continuous	70$
FC, GPS and PDB combo	Pixhawk 6C with PDB and GPS	GPS Precision 1.5m CEP	500$
Propellers	Tmotor 17x5.8 V2	17 Inch carbon propellers	72$x2
Telemetry and RC Control	RFD868 TXMOD V2 868Mhz	1W 40km of range	412$
BEC	HobbyWing Ubec 25A HV	25A 5V, 6V, 7.4V or 8.4V	57$
Charger	ISDT DUAL K4	400W	230$
Battery	TATTU 22000mAh 14.8V 30C	Li-po,EC5, 1677g	300$
Radiomaster	TX16S MAX ELRS	ELRS, EdgeTX	220$
Radiomaster battery	Radiomaster 2s 5000mah	Li-Ion, Xt30, 7.4V	30$
Lidar proximity sensor (optional)	MakerFocus Lidar Range Finder	0,2 to 8M, unidirectional	25$

Platform

Selecting the appropriate platform is a pivotal decision in the drone-building process, with the frame being the initial consideration. Given the goal of constructing a long-endurance drone capable of carrying substantial weight, we decided to opt for a quadcopter configuration. This choice is driven by the fact that quadcopters can accommodate larger propellers compared to hexacopters, thereby enhancing overall efficiency. While hexacopters excel in speed and stability, quadcopters offer superior endurance and efficiency, aligning more closely with the desired characteristics for this particular project's functional requirements.

For this, we have chosen the 17-inch propeller Tarot XS690.

Motors

Selecting the right motors is crucial for our quadcopter’s performance and is nearly as important as selecting the frame. After extensive research and evaluation, we have chosen to implement motors from T-motor, an industry leader renowned for its high-quality multirotor propulsion systems. From T-motor’s lineup, the T-motor U7 V2 490KV has emerged as our optimal choice, since it offers an exceptional balance of power, efficiency, and versatility. Key features include:

1. **Versatile power handling**: Capable of efficiently driving 17-inch propellers using either 4S (14.8V) or 6S (22.2V) LiPo batteries.
2. **Adaptive performance**: The 490KV rating allows for a wide operational range, balancing thrust output with power consumption.
3. **Robust construction**: Featuring high-quality materials and precise manufacturing for durability and reliability.
4. **Thermal efficiency**: Advanced design for optimal heat dissipation, ensuring consistent performance during extended flight times.

The U7 V2 490KV’s adaptability is particularly advantageous for our project, as it allows us to fine-tune our power system based on specific mission requirements. We can optimize for either extended flight time using 4S batteries or maximize thrust with 6S configurations, without needing to change motors.

Electronic Speed Controller

Now that we have selected our motors, the next critical component is choosing a suitable Electronic Speed Controller (ESC). The ESC is vital as it regulates power delivery from the battery to the motors, ensuring smooth and precise control. Continuing with our T-motor ecosystem, we have selected the T-motor Flame 70A LV ESC. Key features of the T-motor Flame 70A LV ESC include:

- **Current Rating**: 70A continuous current, allowing for high-power handling capability.

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- **Low Voltage (LV) Compatibility**: Specifically designed for use with lower voltage setups, including 4S LiPo batteries (14.8V nominal).
- **Voltage Range**: Supports 3S to 6S LiPo batteries (11.1V to 25.2V), providing flexibility in power system design.
- **Heat dissipation**: Optimized for heat dissipation and durability.

It is worth noting that we have selected the LV (Low Voltage) variant of the Flame ESC series. This choice is deliberate and essential for our build, as we intend to use 4S (14.8V) LiPo batteries. The LV models are optimized for these lower voltage ranges, ensuring efficient operation and proper motor control.

In contrast, the HV (High Voltage) models in the Flame series are designed for higher voltage systems, typically supporting 6S (22.2V) batteries and above. Using an HV ESC with our 4S setup would not work as there is not enough voltage supplied to power the components. By pairing the T-motor U7 V2 490KV motors with the Flame 70A LV ESCs, we create a well-matched and efficient power system. This ESC selection complements our motor choice, resulting in a reliable and versatile power system for our quadcopter drone.

Battery

We intend to incorporate a Jetson Orin as the primary processing unit, weighing 750 g, alongside a router weighing 600 g, resulting in a combined weight of 1,350 g. Due to the high energy consumption of these components, it is crucial to include a substantial battery to offset power demands and sustain flight duration.

Considering the motors, ESC, frame, and other components, the total weight of the drone is 6.4 kg. Ideally, the drone should hover at half its maximum power. Motors operating on a 4S configuration generate 1.1 kg of thrust at 50% throttle, necessitating a 900 g battery for the entire system.

A 900 g battery is insufficient for this UAV application. Therefore, adjustments must be made to accommodate a larger battery. Options include reducing the drone’s weight or enhancing its power output (utilizing a 6S configuration). However, to maintain build simplicity, we opt to operate at 60% throttle with a larger battery, albeit sacrificing some flight performance. Given the intended use of the drone for slow movements and hover predominantly, this compromise is deemed acceptable.

To address this, we will utilize a 4S 22Ah battery, weighing 2.5 kg, resulting in a total weight of 6.5 kg. Consequently, each motor will be required to pull 1.5 kg during hover.

Power Distribution Board

For our high-performance drone, we have chosen the Holybro PM07 Power Distribution Board (PDB). This PDB is ideal for our current 4S setup and is future proofed for potential 6S upgrades. Notable features are:

1. **Voltage support** up to 14S LiPo
2. **High current handling**: 90A continuous, 140A peak
3. **Integrated voltage and current sensing** (up to 140A)
4. **Built-in LC filter** for clean power output
5. **Multiple output options**:
    - 8 pairs of ESC solder pads
    - 5V 3A FC output
6. **Compact design**: 68 × 50 × 10 mm

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The PM07 meets our requirements for battery sensing without a separate sensor. This PDB ensures our drone's power system is robust, flexible, and capable of handling both current needs and future upgrades, making it an excellent fit for our build.

Power for Additional Electronics

Powering the electronic components of our drone, particularly the Jetson Orin and router, requires careful consideration to ensure stable and clean power delivery.

For the Jetson Orin, our most valuable and power-hungry component, we have selected the Hobbywing UBEC 25A. This choice may seem excessive, as the Jetson Orin typically requires around 10V and 3A. However, our decision is rooted in future-proofing and expandability. The Hobbywing UBEC 25A offers:

1. **High current capacity**: 25A continuous output
2. **Adjustable voltage**: 5V/6V/7.4V/8.4V/9V/10V
3. **Wide input voltage range**: 7V to 26V
4. **Built-in safety features**: Over-current, over-temperature, and short-circuit protection

This robust UBEC ensures clean, stable power to the Jetson Orin, crucial for its optimal performance and longevity. It also provides headroom for potential future upgrades or additional components.

For the router, which has different voltage requirements, we have opted for a standard BEC (Battery Elimination Circuit). This more modest BEC is sufficient for the router's power needs, balancing cost-effectiveness with reliable performance.

By using separate power regulation systems for these key components, we ensure each receives the appropriate, clean power supply, enhancing the overall reliability and performance of our drone's electronic systems.

Flight Controller

The flight controller is the central nervous system of our drone, responsible for processing sensor data, executing flight algorithms, and managing overall drone behavior. After careful consideration of several options including the Cube Orange, CUAV V5, and others, we have selected the Pixhawk 6C for our build.

Key features of the Pixhawk 6C include:

1. **Powerful STM32H7 processor** (480 MHz, 2 MB Flash, 1 MB RAM)
2. **Integrated vibration isolation**
3. **Multiple connectivity options**: USB-C, CAN, UART, I2C, SPI
4. **Dedicated safety switch and buzzer ports**
5. **Analog battery sensing input** compatible with our PM07 PDB

The Pixhawk 6C offers an excellent balance of performance and cost-effectiveness. Its analog battery sensing input is particularly valuable, allowing seamless integration with our chosen PM07 Power Distribution Board.

For the flight control firmware, we have chosen ArduPilot. This open-source platform supports various drone configurations, multiple sensors, and peripherals and is fully compatible with the most popular ground control stations. ArduPilot's ongoing development and broad capabilities make it an ideal choice for our project, providing a robust and flexible foundation for our drone's flight control system. Its open-source nature also allows for customization if needed in future iterations of our build.

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Transmitter and Receiver

For our drone's remote control system, we have selected the Radiomaster TX16S Max, widely recognized as the industry standard in RC controllers. This choice ensures we have a reliable, feature-rich interface for piloting our drone. The TX16S Max boasts a high-resolution color display for clear telemetry data and precise hall effect gimbals for accurate control inputs. Its customizable switches and buttons allow for versatile flight mode selection, while the EdgeTX firmware offers extensive customization options. The controller's multi-protocol support enables compatibility with various receivers, and an SD card slot facilitates easy firmware updates and model storage.

To enhance the capabilities of our control system, we have paired the TX16S Max with the TXMOD V2 module, incorporating the RFD868X system. This combination significantly extends our control range by operating on the 868MHz band, offering superior long-range performance compared to traditional 2.4GHz systems. The integrated telemetry feature provides real-time flight data transmission back to the controller, including crucial information like battery voltage, GPS coordinates, and altitude.

The RFD868X system employs frequency-hopping spread spectrum (FHSS) technology, ensuring a stable connection even in noisy RF environments. This robust link is crucial for maintaining control and data integrity during flight. Furthermore, the bidirectional communication capability allows for in-flight parameter adjustments and mission planning updates, adding a layer of flexibility to our drone operations.

By combining the Radiomaster TX16S Max with the TXMOD V2 and RFD868X, we have created a comprehensive control and telemetry solution in a single package. This setup offers the reliability, range, and flexibility required for our advanced drone application, ensuring we can maintain precise control and receive crucial flight data even in challenging conditions or at extended distances.

Final Additional Components

Lastly, before starting the assembly, a few additional parts are needed:

- 3.5mm bullet connector
- 4mm heatshrink
- 20 AWG wire
- 14 AWG wire
- JR style connectors
- JST GH 6 pin and 5 pin connectors
- 10 AWG wire (optional)

4.2.2. A Guide for Assembling the Drone

Step 1: The PDB

The first step to start with is the PDB: PM07 Power module (see Figure 4, top). Our drone's power distribution system is designed with both current needs and future expandability in mind. The heart of this system is the Power Distribution Board (PDB), which will manage seven distinct battery outputs. Four of these outputs are dedicated to the Electronic Speed Controllers (ESCs), which regulate power to our drone's motors. These connections are critical for flight performance and require robust wiring. We are using 14 AWG (American Wire Gauge) wire for these connections, which offers low resistance and can handle the high current draw of our motors. Each wire will be terminated with a 3.5mm female bullet connector, allowing for secure yet easily detachable connections to the ESCs.

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Another 14 AWG wire will power the Hobbywing BEC (Battery Elimination Circuit), which provides regulated power to our Jetson Orin. This thick gauge ensures minimal voltage drop, which is crucial for the stable operation of our main computing unit.

For our retractable landing gear and an additional expandability port, we are using 20 AWG wire. This gauge is sufficient for these lower-current applications. These wires will be fitted with JR-style connectors, standard in RC applications, ensuring compatibility with a wide range of components.

The physical layout of these connections on the PDB is crucial for weight distribution and ease of maintenance. The four ESC wires will be soldered to the B+ (positive) and GND (ground) pads at each corner of the PDB. The placement of the BEC wire should be chosen based on the physical layout of components in the drone, minimizing wire length where possible.

Lastly, we're addressing a potential frame clearance issue by relocating the PDB's capacitor. We will carefully remove it and extend its leads, allowing us to reposition it without compromising its crucial function of smoothing voltage fluctuations.

This comprehensive power distribution setup provides a solid foundation for our drone, ensuring reliable power delivery to all components while maintaining flexibility for future modifications or additions. By the end of this process, the PDB setup should resemble Figure 4 (bottom).

It is important to note that you might consider replacing these bullet connectors with XT60s if you are concerned about plugging peripherals in with the wrong polarity. However, since we don't have a lot of space, we have opted for this option, being very careful about the polarity of the components.

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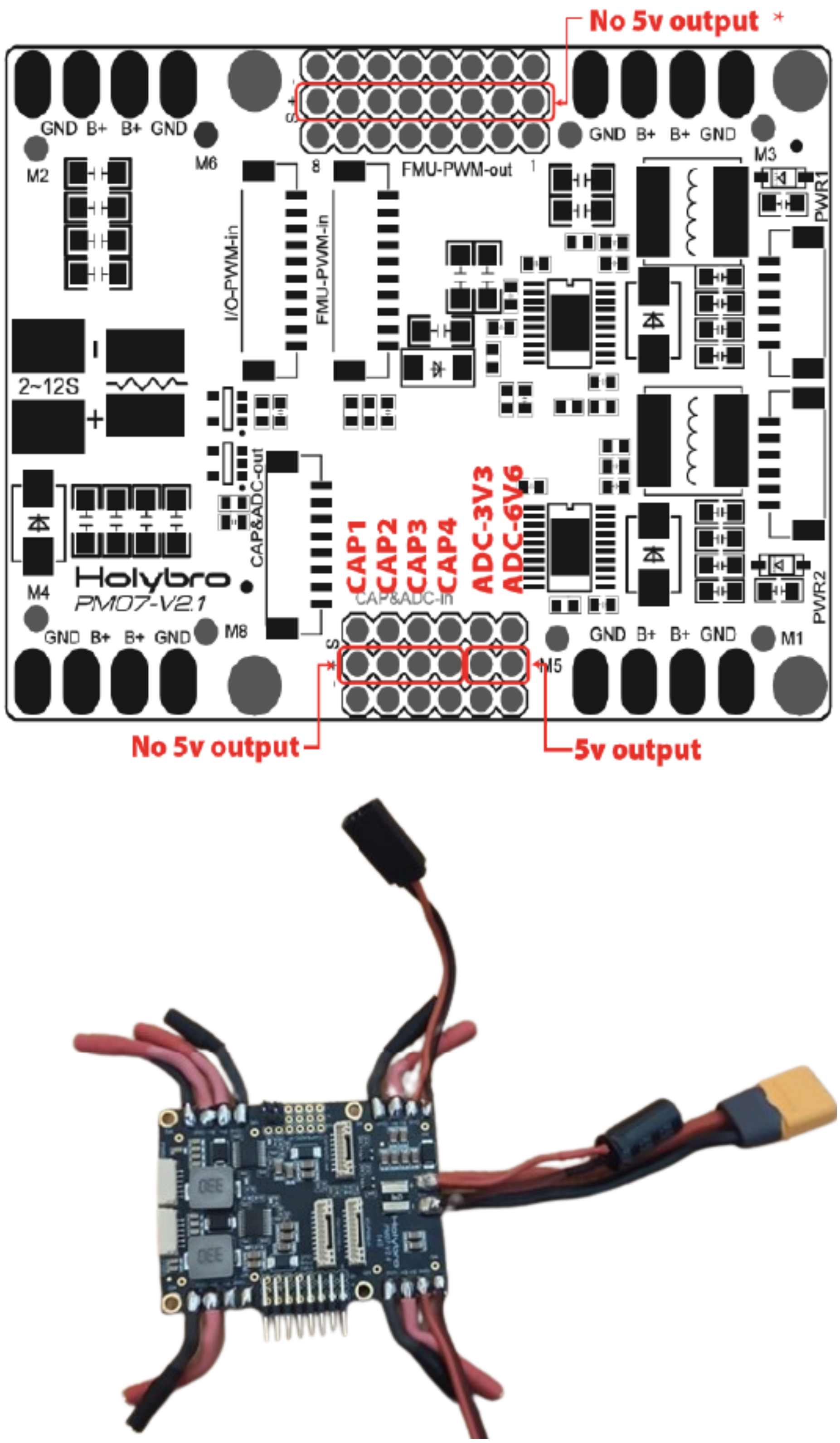

FIGURE 4. STEP 1 PDB DIAGRAM (TOP); PDB WITH SOLDERED CONNECTORS (BOTTOM)

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Step 2: The Frame

Transitioning to the frame and motors, our initial task is to assemble the frame (Figure 5, left) according to the provided image, omitting the assembly of the arms or the top plate. Although no specific instructions are provided, the assembly process is straightforward.

Before assembling the frame, we need a 3D printer for certain parts. Specifically, the landing gear T-junction on this frame is notably flimsy, prompting the creation of a more durable and reliable replacement requiring 4 M3 bolts and nuts for assembly (see Figure 5, middle and right).

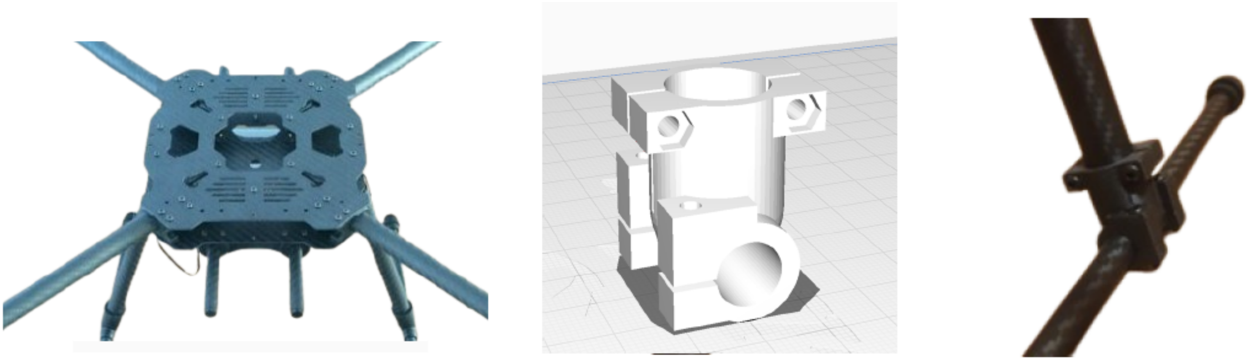

FIGURE 5. STEP 2. TAROT FRAME (LEFT); PRINTED PART LANDING GEAR (MIDDLE); LANDING GEAR (RIGHT)

Step 3: Motors

Moving forward to the motors, we need to affix each motor onto its motor mount and subsequently onto the arms. Given the size of these motors and the motor mounts, we must incorporate four washers with each screw to ensure clearance of the motor mount bolts, as depicted in Figure 6 (left).

Next, we weld 3.5mm male bullet connectors to the ends of the cables, as demonstrated in Figure 6 (right). These cables are then folded inside the arms and drawn out from the other end.

With these preparations completed, we can now proceed to mount the arms onto the frame using the bottom screws. Special care needs to be taken as the frame is now very fragile, since it does not have the strength of the top plate.

FIGURE 6. STEP 3. DETAIL OF THE MOTOR MOUNTING SOLUTION (LEFT); MOTOR CONNECTORS (RIGHT)

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Step 4: Preparation of the ESC

Next, we need to prepare the ESCs to be mounted onto the frame. Since these ESCs already come with female bullet connectors welded to the outputs, we only need to weld bullet connectors to the + and – cables of the ESCs and the Hobbywing BEC (or XT60s for added safety) as illustrated in Figure 7.

FIGURE 7. STEP 4. ESC CONNECTORS

Step 5: Other Cables

Now we need to make a cable that can connect to the power port of the PDB that we previously created (see Figure 8, left). We also need a servo cable to connect the signal of the FC to the box, as shown on the left. Additionally, we need to make a cable to establish the connection between the Pixhawk 6C and the RFD receiver, such as the one in Figure 8, right.

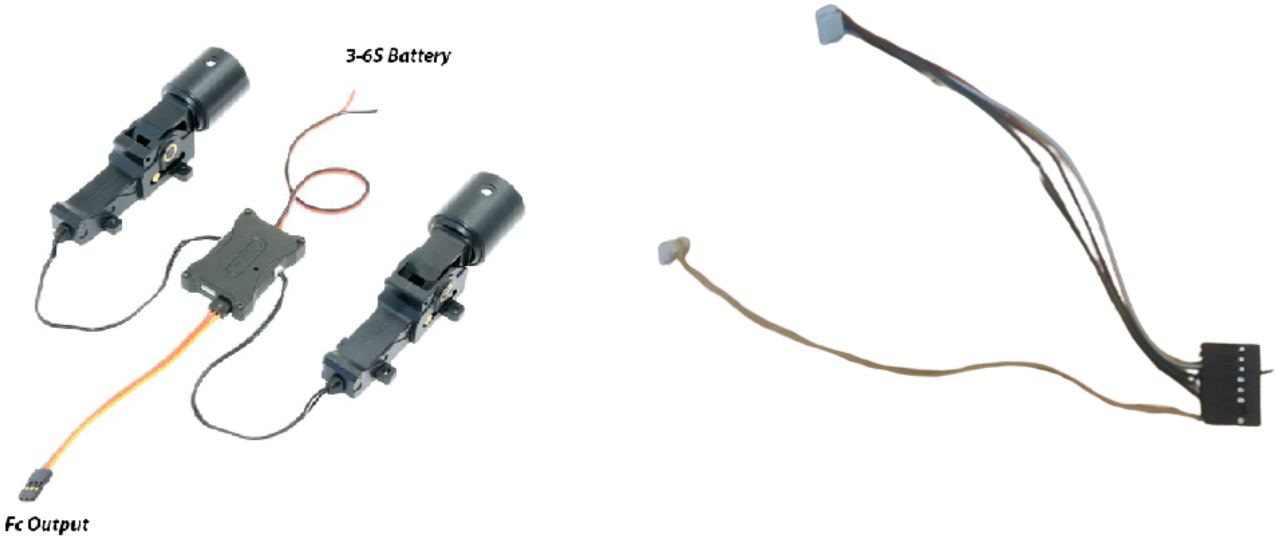

FIGURE 8. STEP 5. LANDING GEAR ELECTRONICS (LEFT); RFD CABLE (RIGHT)

Step 6: Step-by-step Component Placement

The selected approach optimizes frame utilization through strategic component placement. The flight controller (FC) is centrally mounted, as illustrated in Figure 9 (perspective 1), with full component integration pending. FC attachment utilizes four Velcro squares, providing vibration dampening and positional stability. Precise central positioning is critical, avoiding any contact with the arms.

Careful cable management is implemented for the FMU port, I/O PWM out, and power cables, routing them neatly beneath the FC.

For the next step, the drone is inverted to facilitate the installation of the Electronic Speed Controllers (ESCs) on the underside of the bottom plate, along with the mounting of the landing gear electronic box. The ESCs are secured using a combination of zip ties and double-sided adhesive. The diameter of the zip ties is chosen carefully to ensure that the arms retain full rotational freedom. The resultant configuration, illustrating this arrangement, is depicted in Figure 9 (perspective 2).

PDB installation follows, positioned between the bottom and battery plates. A custom 3D-printed mount, as shown in Figure 10 (left), provides electrical isolation. High-strength double-sided adhesive secures the case to the battery plate (Figure 10, right).

ESC power cables (black and yellow) are connected to the PDB's FMU/OUT port and the landing gear power cable. ESC placement is finalized, ensuring power cable accessibility. The configuration should mirror Figure 11 (left).

The plate is affixed to the frame's provided plastic components, with the PDB-containing section oriented inward. Post plate securement (via four M3 bolts), the ESC and Hobbywing BEC are connected with strict polarity observation. Meticulous cable management is crucial to prevent pinching or damage.

ESC outputs are connected to motors, with careful wire routing to avoid arm interference during frame folding. The final configuration is illustrated in Figure 11 (right). Wire positioning is confined between the metal standoffs limiting arm movement.

RFD868X and GPS integration follows, utilizing a custom 3D-printed mount (Figure 12, left) for optimal spacing. The pre-fabricated cable is connected to the module prior to case installation, as shown in Figure 12 (right).

Module power is sourced from the FC, with reduced power settings to mitigate potential FC damage. While a separate 5V BEC would be optimal for full-power operation, the current configuration suffices at 20 dBm for the intended application. Final module placement and connection is executed (Figure 13, left).

Top plate installation follows, with consideration for BEC placement and cable routing for PDB Bat+ and Bat- connections (Figure 13, right). Securement of top screws completes the assembly process, ensuring component stability and overall structural integrity.

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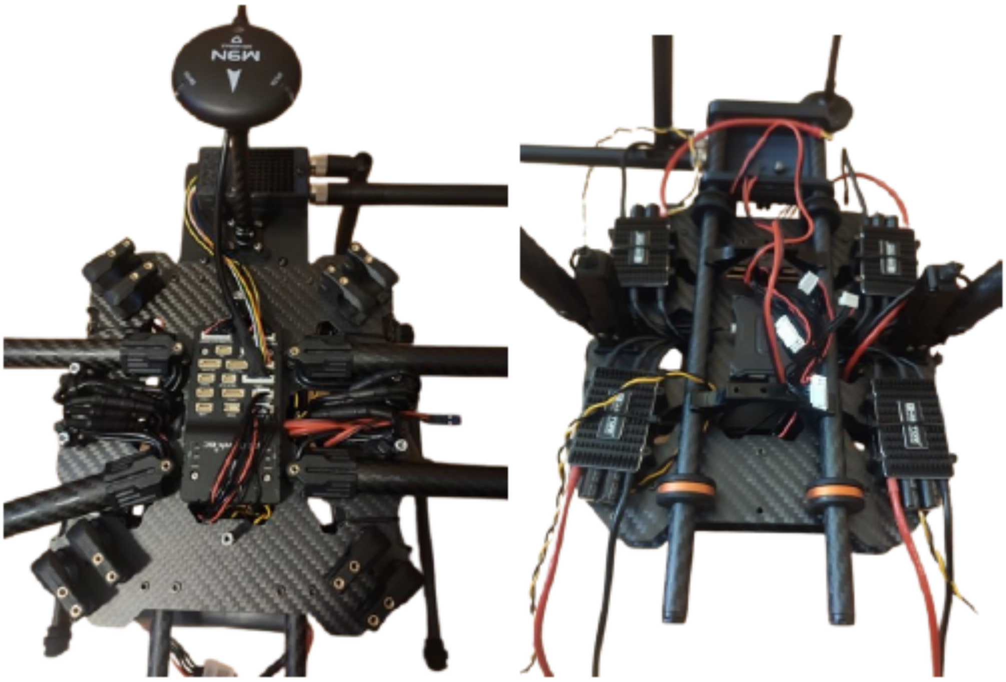

FIGURE 9. FLIGHT CONTROLLER CENTERED ON THE FRAME (PERSEPECTIVE 1); FLIGHT CONTROLLER CENTERED ON THE FRAME (PERSPECTIVE 2)

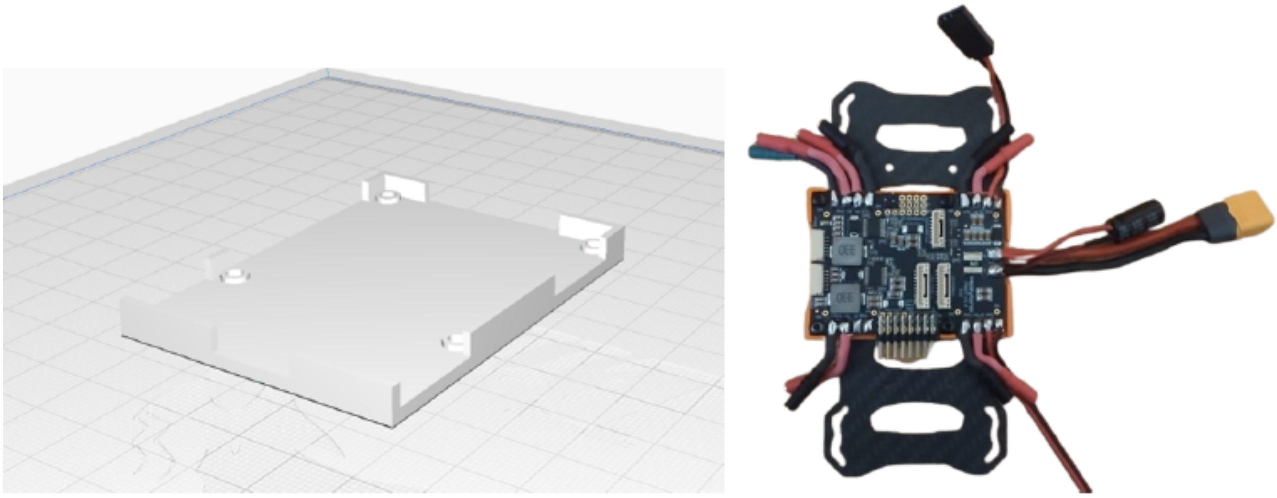

FIGURE 10. THE PDB CASE (LEFT); PDF MOUNTED IN THE CASE (RIGHT)

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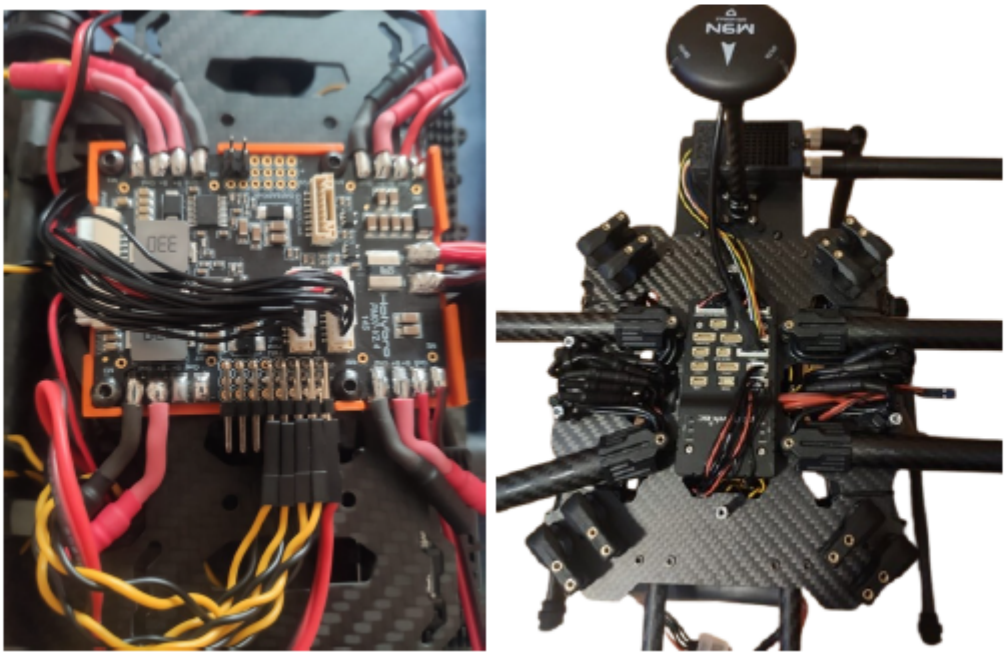

FIGURE 11. PDB WITH ALL THE CONNECTIONS (LEFT); FLIGHT CONTROLLER CENTERED ON THE FRAME (RIGHT)

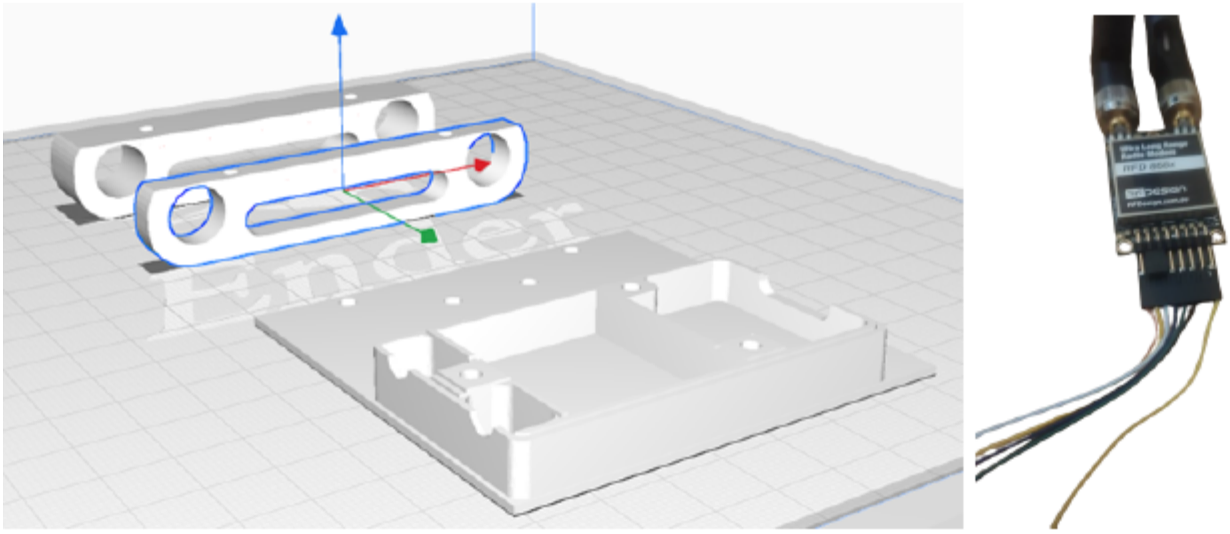

FIGURE 12. STL FILES FOR THE GPS AND TELEMETRY MODULE MOUNT(LEFT); RFD MODULE CONNECTED (RIGH)

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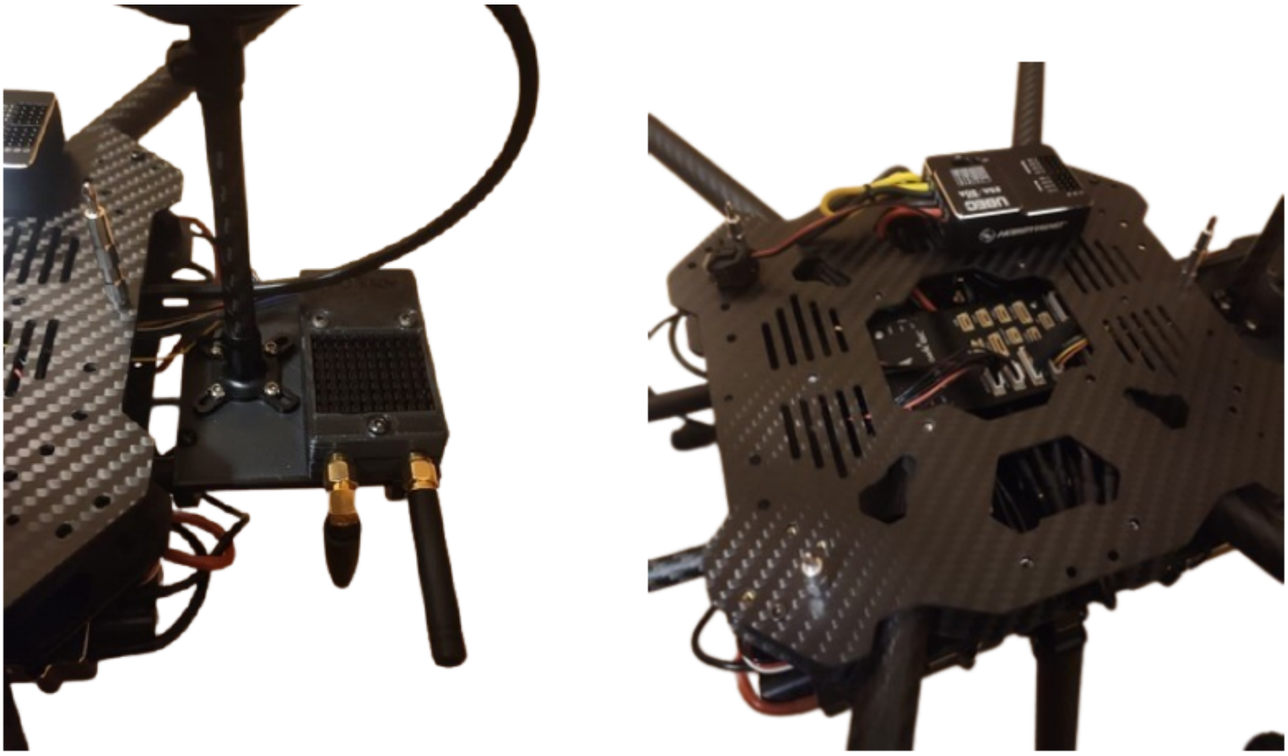

FIGURE 13. GPS AND RFD MODULE CONNECTED (LEFT); UBEC PLACEMENT AND TOP PLATE (RIGHT)

4.3. Extensions for 5G NTN Research and Experiments

Component integration necessitated modifications to several 3D-printed parts to accommodate the electronic modules. The 360-degree camera is secured via a standardized 1/4”-20 UNC tripod mount. The Jetson compute module is affixed using a custom-designed base, adhered to the carbon fiber frame with high-strength double-sided adhesive tape due to the absence of compatible mounting points. The router is secured using a tension-adjustable battery strap, with its position strategically placed between the antennas to prevent lateral displacement, as illustrated in Figure 14.

To facilitate high-bandwidth communication between the UAV and ground control station (GCS), a 5G router has been integrated into the system. This solution provides the requisite data throughput for real-time telemetry and payload data transmission. While latency is a consideration, it is not critical for this application, and we anticipate slightly elevated latency values during operation.

A key objective of this project is to establish a low-latency, high-fidelity video link between an onboard 360-degree camera and the pilot. The Ricoh Theta X was selected for its ability to output full-resolution imagery via USB interface. The video pipeline involves streaming the camera feed to the onboard NVIDIA Jetson Orin compute module, where an RTSP (Real-Time Streaming Protocol) server is configured to facilitate connection between the drone and pilot.

The Jetson Orin, running a customized Linux distribution, leverages its GPU capabilities for edge computing and computer vision tasks. This setup enables on-board processing of visual data, potentially including real-time fire detection algorithms implemented using Python libraries optimized for NVIDIA CUDA cores.

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FIGURE 14. FRONT AND REAR VIEWS OF 5G COMPONENT INTEGRATION

5. Evaluation of VR Applications: bandwidth and Latency

5.1. Introduction

In its latest report [52], the IEEE Standards Association has uncovered four key future-focused trends expected to shape the foundational technology landscape for 2024 and beyond: Evolution of the Metaverse, Building Trust with Data Governance, Child Safety Online, and Advances in Quantum Computing and New Applications. Indeed, the global AR/VR and VR headset market size reached US$ 16.6 Billion in 2023 and is expected to grow at a compound annual growth rate (CAGR) of 12.44% during the period 2024-2032. Concerning market share, the number of AR/VR headsets is rapidly growing at an exponential pace with Meta Quest 3 and Playstation VR Headset being the sales leaders. Recently, Apple Vision Pro has appeared in the market, selling all their stock. Other brands like Pico and HTC have a reasonable market share, while other consumer brands like Xiaomi and Samsung have recently announced plans for dealing AR/VR products sometime in 2024. These devices have penetrated 1-2% of households in North America, the EU, and China.

The Metaverse opens new possibilities with a wide range of applications and use cases: (1) 360 gaming (either online or local), (2) entertainment (concerts, sports events), (3) training and education, (4) remote healthcare, (5) immersive tourism, etc. Some of these use cases and related network-based experiments can be found in [53][54]. At a high level, the metaverse can be categorized into these three business sectors: Industrial, Enterprise, and Consumer.

A good example of Industrial Metaverse, as noted in [55], can be Tactile Internet for Remote Surgery: This use case delves into the challenges and requirements for remote telesurgery, including ultra-low latency (below 1 ms), high reliability (up to 99.9999999%) for UHD medical video over non-public networks (NPNs) [56], and massive data rates (up to 1 Tbit/s) to support applications like AR and Holographic Type Communication (HTC) [57]. Regarding Enterprise Metaverse, Academic/Professional e-Learning explores the potential of immersive technologies VR/AR in enhancing educational experiences, both in academic and professional settings. It discusses the requirements for high-quality video streaming (up to 2.35 Gbps for eXtended Reality XR), ultra-low

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network latency (haptic response time to 5.5 ms), and scalability to support a large number of students simultaneously [58].

Finally, as an example of use cases with high development potential within the Consumer Metaverse, Virtual Tourism in Smart City (Consumer Metaverse) focuses on the integration of virtual and augmented reality experiences in the context of smart cities, enabling immersive tourism experiences and metaverse-driven services for citizens and visitors. These services require efficient mobility and security solutions, with strict requirements for low latency (20 ms for Ultra-Reliable Low Latency Communications (URLLC)), high data mobility (10 km/h for AR/VR, 0.5 km/h for Telepresence), data rate (from 40 to 600 Mbit/s), and reliability (up to 99.9999%) to support these applications [59].

While new market opportunities appear with AR/VR products, integrating these technologies necessitates significant network upgrades to handle the increased bandwidth and latency demands they impose. AR/VR applications heavily rely on streaming high-resolution visuals and spatial data, requiring significantly more bandwidth than traditional voice or video calls. 5G networks with near-Gbps speeds are crucial for seamless AR/VR experiences. Regarding latency, high delay and delay variation (aka jitter) in data transmission can cause nausea and disorientation in VR environments. Real-time interaction requires ultra-low latency networks, pushing the boundaries of current telecommunication infrastructure. Thus, the proliferation of AR/VR devices will significantly increase overall network traffic, demanding higher capacity to avoid congestion and maintain consistent performance. Hence, telecom operators need to prepare for a possible exponential growth in the traffic injected by these applications into their networks and the related network requirements demanded by them. Among other aspects, telcos will be required to update their infrastructure, investing heavily in fiber optic rollouts, edge computing infrastructure, and 5G-A/6G deployments.

5.2. State of the art

Recent studies have focused on various aspects of AR/VR applications, highlighting critical factors such as network performance, privacy concerns, interaction with sensor networks, security vulnerabilities, and cloud-rendering architectures. In [60], the authors explore the relationship between Wi-Fi performance and the quality of VR streaming experiences. The study investigates the characteristics of VR traffic over Wi-Fi networks, particularly focusing on sustained network performance and the impact of frame rate on Wi-Fi efficiency. Notably, it identifies a segmentation mechanism in WebRTC-based services that affects Wi-Fi airtime consumption.

The study carried out in [61] addresses privacy risks associated with VR platforms, emphasizing the collection of sensitive data by VR sensors and the potential for user identification. The study introduces BEHAVR, a framework for analyzing sensor data across VR applications, demonstrating high accuracy in user identification. This highlights the importance of considering privacy implications in AR/VR research.

In [62], Makolkina et al. explore the interaction between augmented reality and flying ubiquitous sensor networks (FUSN), emphasizing the need for new traffic patterns to ensure the quality of experience. The study proposes a novel traffic pattern capturing service space, environment, and user behavior models, suggesting advancements in AR technologies.

The authors of [63] focus on security and privacy issues in mobile AR applications, specifically regarding the inference of user location based on network traffic patterns. The study demonstrates a side-channel attack against a popular AR application, highlighting vulnerabilities in location-based AR services and advocating for mitigation strategies.

In [64], the authors investigate cloud-rendering architectures for AR on lightweight glasses, emphasizing the challenges of low latency and high data rates in wireless networks. The study proposes a realistic traffic model based on video data analysis, aiming to assess network performance in cloud-rendered AR scenarios.

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In contrast to the aforementioned studies, in this work we provide a comprehensive overview of traffic patterns observed in various AR/VR applications, including onsite video gaming, external rendering video gaming, and virtual reality video streaming. While [60] and [64] address network performance in VR streaming and cloud-rendering architectures respectively, our study extends this by examining traffic profiles across different AR/VR scenarios. Furthermore, we complement [61] by focusing on traffic characteristics rather than privacy concerns, thereby contributing to a holistic understanding of AR/VR application dynamics. Moreover, while [62] explores new traffic patterns for augmented reality, our study extends this by examining traffic profiles in diverse AR/VR contexts.

In the next sections, we present multiple setups for studying the impact of different AR/VR applications on the network. In particular, we have collected packet traces in several application scenarios and measured latency and bandwidth requirements as they traverse the access networks. We observe that different applications and setups show various traffic profiles, in most cases similar to high-resolution video-streaming (like 4K or 8K resolution video).

5.3. AR/VR Setups

Gaming on the headset (Hyper Dash Game)

This scenario represents the use case where a consumer plays a low-resolution game that runs directly on the MetaQuest3 hardware (See Figure 15); the computational power required for rendering this game is affordable, and the headset itself can run the game without external support. Captured traces reveal that Kbps traffic (about 50 packet/s with periodic spikes) goes from the headset to the Internet, mainly the movements of the controllers and the keystrokes and commands (shoots, position, etc.), that is, important information for online gaming with other players around the world. This behaviour has been previously observed in previous online gaming studies (without AR/VR headset), see [65].

Gaming supported by external computer

Figure 15 shows a second gaming scenario where the game does not run on the headset but on a physically closed desktop computer. Here, the game demands high computational power (GPUs for graphics rendering), thus an external computer is needed to properly operate. The traces reveal a continuous flow of around 157 Mb/s from the local PC station towards the AR/VR headset, and again a few Kb/s towards the Internet.

Streaming 360 videos (YoutubeVR)

In this case, the user is watching a 360-video (Youtube VR application) streamed over the Internet. Figure 15 details the scenario and bitrate arrival from the streaming server (Youtube VR), showing an average bitrate of 60 Mb/s downstream; this is approximately the typical bitrate of 3x a classical 2K (i.e., 2048 × 1080) video stream.

Collaborative business meeting (with Meta Workrooms)

In the fourth scenario, two users from different cities in the Madrid region (Spain) are having a teleconference using Meta Workrooms, an application for teleconferencing (see Figure 15). The two users see each other's avatar and exchange some files while talking and drawing diagrams with their fingers. In this case, the traffic exchanged between them is approximately 15 Mb/s.

5.4. AR/VR Experiments

Figure 16 shows the bitrate (in bits/s) observed in the four scenarios. Table 4 presents a summary of the relevant bitrates, latency, and packet characteristics observed in each scenario.

In the "gaming on headset" scenario, games are processed directly on the headset's hardware, resulting in lower game resolution and visual quality. This setup transmits only keystrokes and essential online gaming information to the Metro network. We noted that the game performs smoothly. The Internet traffic in this scenario closely mirrors that of the "gaming on headset" scenario.

Regarding the 360-video streaming scenario to Youtube VR, the bitrates vary based on the Internet connection and the original video resolution, aligning with typical video streaming values.

Lastly, in the Meta Workrooms case, the bitrate and latency metrics are in line with those expected for FullHD resolution video streaming to a server in the Metro segment.

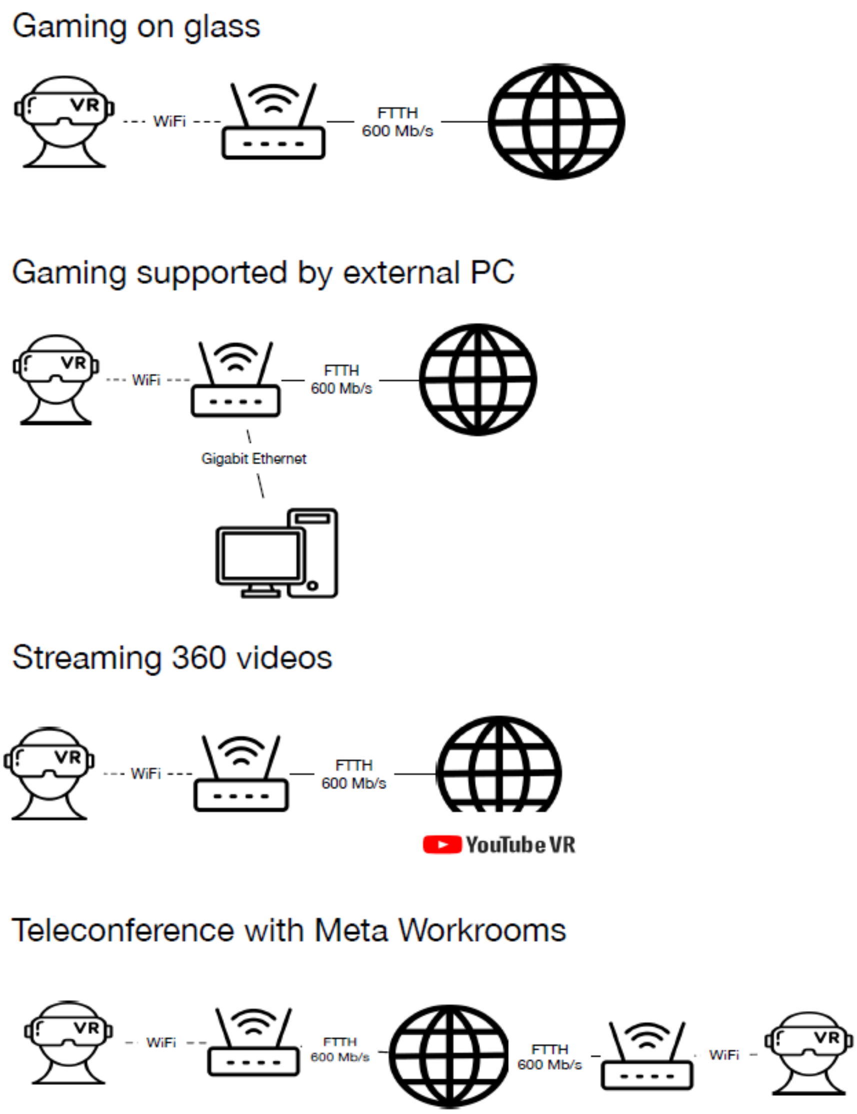

FIGURE 15. OVERVIEW OF THE DEPLOYED SCENARIOS

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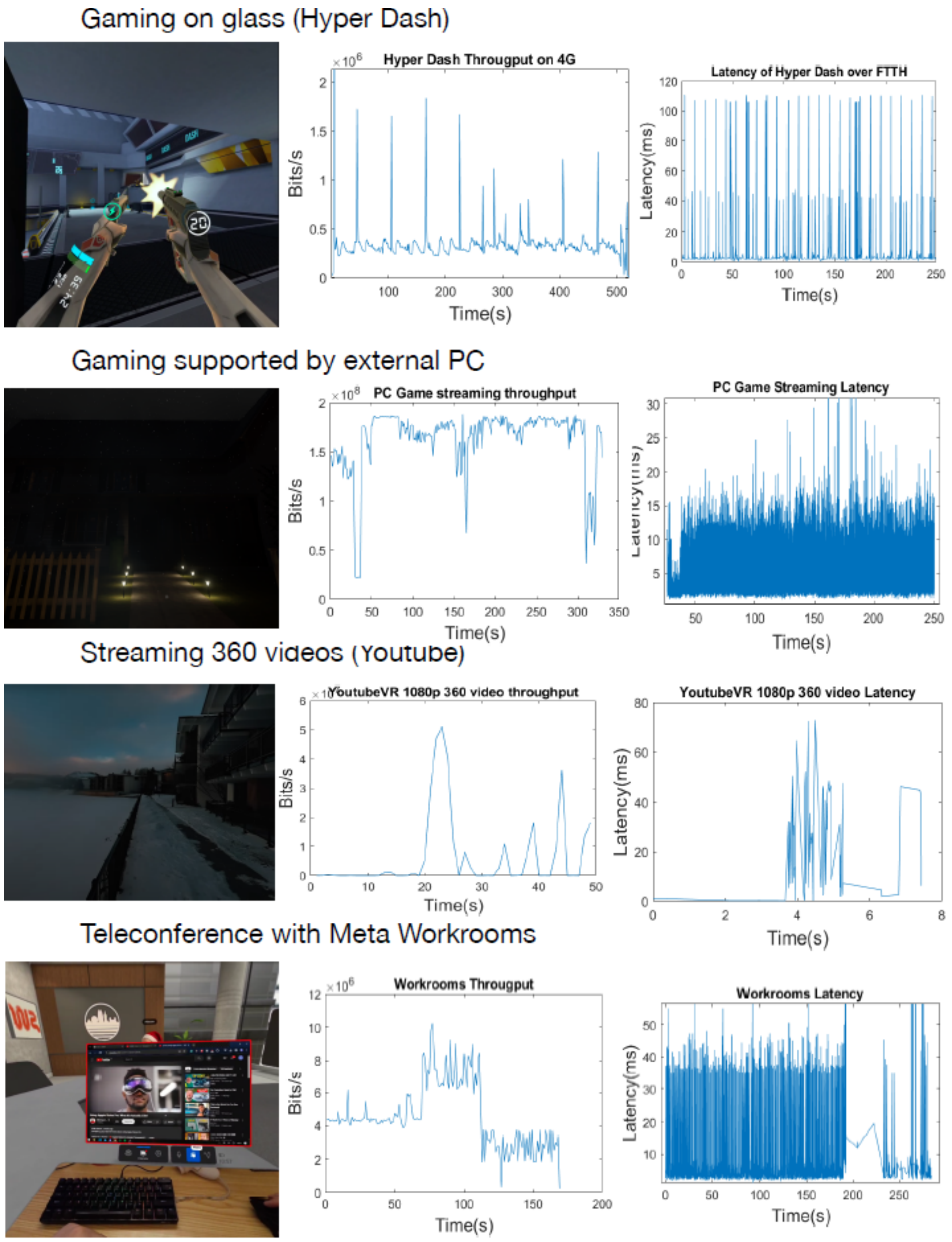

FIGURE 16. SCREENSHOT, BITRATE AND LATENCY MEASURED IN ALL SCENARIOS

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TABLE 4. SUMMARY OF TRAFFIC PROFILES OBSERVED IN ALL SCENARIOS (AVG: AVERAGE VALUE, SD: STANDARD DEVIATION)

Scenario	Avg Bitrate (Mb/s)	Sd Bitrate (Mb/s)	Avg Latency (ms)	Sd Latency (ms)	Avg Packet (bit)	Peak Packet (bit)
Gaming on headset (4G)	0.38	0.95	19.6	0.43	409	4200
Gaming on headset (FTTH)	0.38	0.20	12.1	0.32	450	18000
Gaming on external PC	157	32	6.2	0.01	4,556	64,054
360-video streaming	60	12.8	23.6	1.7	1,147	2,800
Meta Workrooms	15	1.95	12.5	0.14	700	18,000

5.5. Impact on telecommunication infrastructure

The rise of metaverse applications presents significant challenges and opportunities for Telecom Operators, necessitating substantial investments to enhance network capabilities. These enhancements include increased bandwidth, reduced latency, and improved reliability, along with advanced Edge Cloud infrastructure to support these bandwidth-intensive applications.

Operators are currently focusing on several key AR/VR use cases, such as industrial remote operations, tele-education in remote or global settings with satellite network assistance, and entertainment applications like gaming and virtual tourism. These applications demand stringent network requirements to ensure a seamless and immersive user experience. Some of these requirements include [66]:

- **Extreme Low Latency**: Essential for real-time social interactions and precise remote control in industrial settings, demanding network latencies ranging from 1 ms to less than 0.1 ms for the Radio Access Network (RAN). Specific latency needs vary by application, such as 0.5–2 ms for dynamic haptic feedback and up to 20 ms for Ultra-High Definition (UHD) video over significant distances.
- **High Symmetrical Transmission Bandwidth**: To support the complex data needs of AR/VR and HTC experiences, both downstream and upstream data rates will need to increase significantly. These rates range from tens or hundreds of Mbit/s for 4K video to 1 Tbit/s for holographic communications, ensuring a high-quality multisensory experience (QoE) for users.
- **Service Availability**: The reliability of these services is critical, with targets ranging from 99.999% (five nines) to 99.9999999% (nine nines) availability, indicating the network's expected operational excellence.

To meet the capacity requirements of these emerging use cases, more bandwidth needs to be made available in the RAN and other network segments, potentially through the exploitation of new frequency bands, massive MIMO processing, and innovative fiber technologies such as multi-core fibers or hollow-core fibers.

As AR/VR services and applications continue to gain traction, telecom operators must anticipate and address the associated challenges, including the need for higher bandwidth, lower latency, and improved reliability. This work aims to shed light on the bandwidth capacity requirements and latency

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of popular AR/VR applications through four different real experimental settings on the MetaQuest3 headsets and their potential impact on the network.

Conclusions

The integration of High Altitude Platform Systems (HAPS) into non-terrestrial networks (NTN) for 6G is a transformative step for global connectivity, as detailed in this document. One of the most significant contributions is the demonstration of how advanced AI and machine learning algorithms, especially reinforcement learning (RL), can be leveraged to optimize critical aspects of NTNs. These include resource allocation, optimal routing, network slicing, and mobility management, all of which are essential for the dynamic and heterogeneous environments characteristic of NTNs.

A key innovation is the development and evaluation of efficient frame transmission strategies tailored for LEO satellites and HAPS. The document highlights the limitations of traditional greedy transmission approaches and introduces “withhold scheduling” strategies, which balance data queues across ground stations and improve both throughput and latency. This approach demonstrates that deferring transmissions to more optimal ground stations can significantly enhance overall network performance.

Another important contribution is the application of deep reinforcement learning (DRL) for optimal routing in NTNs. The document details how DRL agents, designed with network-specific state, action, and reward structures, can dynamically adapt to changing topologies, congestion, and link quality. These agents outperform traditional routing algorithms by learning to make real-time decisions that minimize latency and maximize throughput, even under the constraints of limited bandwidth and high mobility.

The work also bridges the gap between simulation and real-world deployment. It presents a comprehensive methodology that combines simulation-based pre-training with real hardware validation. This hybrid approach ensures that algorithms not only perform well in idealized environments but also meet the practical requirements and constraints of actual NTN deployments, including hardware limitations and unpredictable environmental factors.

On the experimental side, the document describes the design and assembly of a modular drone platform equipped with edge computing (NVIDIA Jetson Orin), 5G connectivity, and advanced sensors. This drone serves as a testbed for validating NTN algorithms and architectures in real-world scenarios, enabling rapid iteration and practical assessment of new networking solutions.

The document also provides a detailed analysis of the requirements imposed by emerging applications, particularly augmented and virtual reality (AR/VR). Through real-world experiments with MetaQuest3 headsets, it quantifies the extreme demands these applications place on network bandwidth, latency, and reliability, with some use cases requiring up to 1 Tbps and latencies below 2 ms. These findings inform the design of MEC-enabled HAPS nodes capable of distributed caching and local processing to meet the stringent requirements of next-generation applications.

From an architectural perspective, the proposal of a convergent NTN-6G framework is a major innovation. By integrating multi-access edge computing (MEC) at HAPS nodes, the architecture supports distributed content caching, intelligent handover management, and real-time processing, which are critical for ensuring seamless service continuity and ultra-low latency across satellite, HAPS, and terrestrial segments.

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In terms of conclusions, the document emphasizes that the successful integration of NTNs into 6G requires a holistic approach, combining algorithmic advances, robust hardware design, and rigorous experimental validation. It also underscores the necessity of close collaboration between terrestrial and non-terrestrial sectors, particularly in spectrum allocation and regulatory frameworks, to realize the full potential of HAPS-based NTNs.

Looking ahead, the document identifies several promising areas for future work. These include scaling RL algorithms for mega-constellations with thousands of nodes, developing federated learning paradigms suitable for energy-constrained space environments, and standardizing open interfaces for unified NTN-TN integration with post-quantum security. Additionally, it calls for research into new lightweight materials for HAPS platforms and the continued evolution of hardware and software co-design to support the unique demands of 6G NTNs.

In summary, this document delivers a comprehensive roadmap for the integration of HAPS into NTNs for 6G, presenting validated innovations in AI-driven optimization, efficient transmission, hardware experimentation, and architectural convergence. These contributions lay the groundwork for the deployment of scalable, reliable, and high-performance non-terrestrial networks capable of supporting the most demanding applications of the future.

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