Digital Twin for Enhanced Resource Allocation in 6G Non-Terrestrial Networks

Hayder Al-Hraishawi, Madyan Alsenwi, Junaid ur Rehman, Eva Lagunas, and Symeon Chatzinotas

The authors explore the integration of digital twin technology with 6G NTNs to enhance resource allocation and network management.

Abstract

Non-terrestrial networks (NTNs) are poised to play an important role in the future communication landscape, particularly with the advent of 6G technology. This article explores the integration of digital twin (DT) technology with 6G NTNs to enhance resource allocation and network management. We outline the vision and architecture for developing DT-NTNs, discussing key integration challenges such as data freshness, computational power, reliable interconnections, interoperability, and data security procedures. Various enabling technologies are also presented to facilitate integration and overcome these challenges. Moreover, a case study demonstrates the practical application of artificial intelligence (AI) and learning algorithms within DT-NTNs for optimizing network resources. Through these efforts, this article aims to provide insights and guidelines for developing highly intelligent and dynamic non-terrestrial communication systems in the era of 6G technology, particularly by proposing a novel DT-NTN-based resource allocation approach, and demonstrating the effectiveness of AI-driven optimization.

Introduction

As the demand for data increases in the 6G era, traditional terrestrial networks are about to reach their capacity limits. In this ever-connected future, non-terrestrial networks (NTNs) are envisioned to augment existing infrastructure by providing seamless and ubiquitous connectivity, especially in remote or sparsely populated areas where terrestrial coverage is challenging. NTNs, with their constellations of satellites and aerial vehicles, offer a compelling solution to extend connectivity beyond the constraints of terrestrial infrastructure [1]. Thus, 6G NTNs have a crucial role in ensuring global coverage for applications requiring high availability and resilience, bridging the digital divide, fostering innovation, stimulating economic growth, and driving social progress. However, these benefits of NTNs come at the expense of higher complexity due to their vast scale and constantly changing environments. Hence, the design and resource management of NTNs become increasingly costly and difficult. Besides, *scalability* is another major concern in NTNs due to the exponential growth in users and network nodes, leading to daunting resource allocation challenges [2].

To face these challenges, digital twin (DT) technology emerges as a promising solution, offering virtual models that replicate real-world physical assets in real-time within a digital environment. In this context, a DT-NTN serves as a virtual representation of the physical NTN, continuously fed with real-time data. This enables advanced simulations to test network behavior, real-time monitoring to proactively identify and address technical issues, and data-driven decision-making to optimize network performance and resource allocation [3]. For instance, DT-NTNs can enhance network energy efficiency by leveraging historical traffic data to dynamically adjust the power levels of network elements during periods of low activity, thereby conserving energy resources.

Unlike traditional simulation tools, DT-NTNs maintain a real-time connection with the physical NTNs through sensors and devices attached to network entities. This continuous data feedback loop provides immediate insights into network performance, enabling high-fidelity design, dynamic control, and optimization based on actual network conditions [4]. Further, conventional resource allocation methods for NTNs often rely on pre-defined policies and static allocation strategies, adjusting based on periodic monitoring and historical data analysis. These approaches struggle with the dynamic nature of NTNs, where factors like signal strength and user mobility constantly change. In contrast, DT-based approaches integrate real-time data from various network entities, enabling dynamic and adaptive resource allocation, which ensures optimal resource distribution in rapidly changing environments. While conventional methods react to current states and past trends, DT-based strategies use predictive analytics and simulations to forecast conditions and demands, enabling proactive management and mitigating congestion issues [5].

DT-NTN models extend beyond mere network replicas. They leverage optimization theory, game theory, and artificial intelligence (AI) to enable online optimization and algorithmic decision-making for resource management. These capabilities empower the development of sophisticated models and simulations, crucial for training AI-based resource management methods. By incorporating these tools, DT-NTNs become more adept at optimizing network performance, managing

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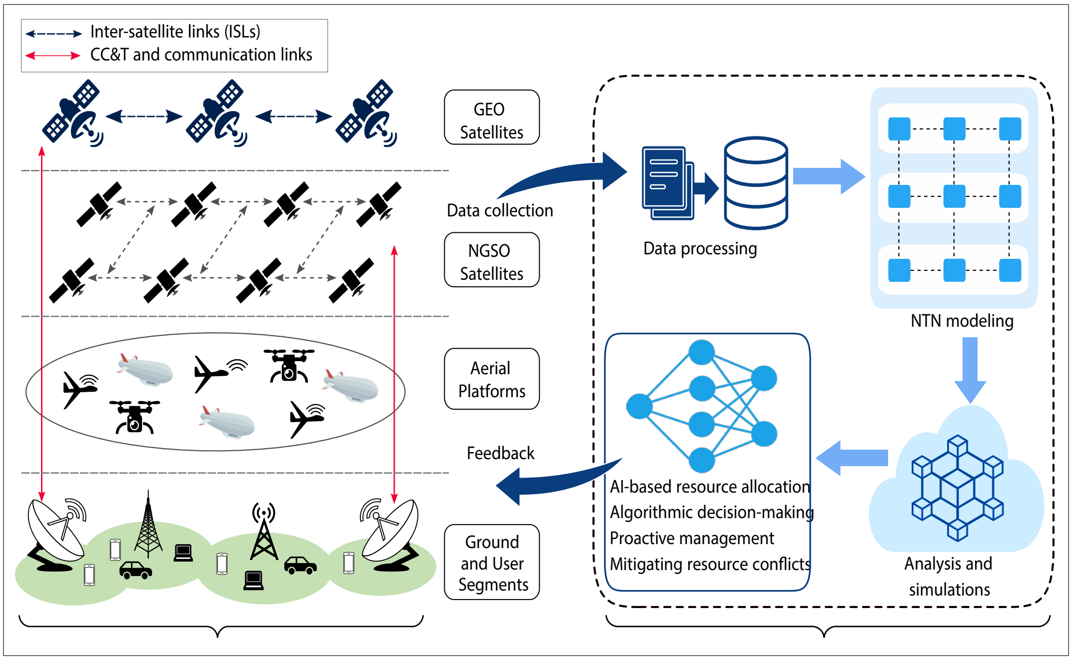

FIGURE 1. Reference architecture depicting a DT-NTN system model for resource management.

resources dynamically, and adapting efficiently to real-time changes. This multifaceted role of DTs underscores the significant value of DT-NTNs in enhancing resource allocation and management within NTNs. For example, to address the challenges of dynamic satellite topology and handover loops, a DT-assisted storage strategy for satellite-terrestrial networks was proposed in [6]. Further demonstrating the potential of DT-NTNs, the study in [7] developed an autonomous scheduling model aimed at mitigating the issue of inefficient task scheduling caused by dynamic changes in task priority and satellite position.

To harness these intriguing potentials, this article explores the essential aspects of constructing DT-NTNs for resource management. It begins by discussing the architecture of DT-NTNs, identifying deployment challenges, and examining key enabling technologies. Following this, we focus on using DT-NTNs for optimizing resources in quality of service (QoS)-aware scenarios. We present a case study on dynamic resource allocation in NTNs, with the goal of managing the coexistence of enhanced mobile broadband (eMBB) and ultra-reliable low-latency communications (URLLC) services.

System Model of DT-NTN

According to the 3rd Generation Partnership Project (3GPP) specifications, NTN is defined as an umbrella term for communication networks that involve non-terrestrial flying objects including space-borne vehicles such as geostationary earth orbit (GEO), medium earth orbit (MEO), and low earth orbit (LEO) satellites, as well as airborne vehicles, that is, high altitude platforms (HAPs), and unmanned aerial vehicles (UAVs) [2]. The communication architecture of an NTN is generally characterized by:

- A space-aerial segment including satellites, HAPs, and UAVs
- A ground segment involving a number of ground stations/gateways that relay data to and from the space-aerial segment; and finally
- A user segment, which includes the terminals, for example, ships, airplanes, and other various ground users.

The ground segment includes the network control center (NCC) for real-time management and control of NTN communications, and the network management center (NMC) responsible for monitoring and managing network element performance and health.

The proposed DT-NTN concept aims to establish a high-fidelity virtual replica, facilitating continuous monitoring, simulation, and optimization. Drawing inspiration from DT architectures in industrial domains and aligning with the International Telecommunication Union (ITU) recommendations for communication networks in [8], the proposed DT-NTN for resource allocation is depicted in Fig. 1. Specifically, building a DT-NTN involves several key steps, each crucial for creating an accurate and functional digital representation of the physical network and its operations. The process can be outlined as follows.

Data Collection: The first step involves continuous data collection from NTN assets, including satellites, HAPs, UAVs, ground stations, and user terminals. This data includes telemetry, tracking, and control (TT&C) data, communication network data, and IoT sensor data.

Modeling Physical Assets: The DT-NTN leverages collected data to continuously refine digital models of network assets. These high-fidelity replicas strive to accurately represent the real-world behavior, performance, and interactions of each entity within the NTN.

Processing and Simulation: Advanced simulation techniques replicate the behavior of the physical NTN in the DT environment. These simulations can predict network performance under various conditions, identify potential issues, and test different resource allocation strategies. Further, AI and learning algorithms are applied to the digital models and processed data to enable adap-

Enabling Technology	Potential	Targeted Challenge
Narrow-band Internet of things (NB-IoT)	Real-time data collection, asset tracking, condition monitoring, predictive maintenance, mission simulation	Data freshness
AI and learning techniques	Dynamic resource allocation and optimization, improved decision-making, anomaly detection, failure prediction	Computational complexity
Space-based cloud computing	NB-IoT data analysis, multi-user DT-NTNs, data archiving, AI model training, redundancy and backup in space, immunity to natural disasters occurring on Earth	Resource-limited devices, security and reliability
Neuromorphic computing	Energy-efficient computation, autonomous device learning, dynamic data analysis and decision-making, self-adaptive networks, AI model integration	Computational complexity, resource-limited devices
Quantum cryptography	Unconditionally secure communication, quantum-safe cryptography, quantum key distribution, post-quantum security, protection against eavesdropping	Security and reliability
Quantum computing	Solving complex optimization problems, parallel processing quantum machine learning, AI model acceleration complex simulation and modeling in DT-NTNs	Computational complexity
Quantum sensing	Highly accurate measurements, enhanced NB-IoT sensing, environmental monitoring, ultra-precise positioning, remote sensing, precision time synchronization	Data freshness and accuracy
Open radio access network (O-RAN)	Flexible deployment, multi-vendor interoperability, real-time configurations, service-specific network slices open interfaces, virtualized network function (VNF) integration	Interoperability and standardization

TABLE 1. Comparison of DT enabling technologies and targeted challenges.

tive and predictive capabilities. AI-driven models can optimize resource allocation by dynamically adjusting network parameters to maintain optimal performance. The ability to learn from data and improve over time is a key advantage of DT-NTNs.

Feedback Loop: A continuous feedback loop is established between the DT-NTN and the physical network. The DT-NTN provides actionable insights and recommendations to the network, ensuring synchronization with the actual NTN conditions. This feedback mechanism enables proactive management and rapid response to changes, facilitating efficient network operation and meeting the diverse requirements of various services.

In this setting, establishing standardized interfaces is essential for bridging the physical NTN with its virtual DT-NTN, as well as facilitating seamless information exchange between DT-NTNs and network applications. On one side, two primary interfaces enable real-time interactive mapping between the physical NTN and DT-NTN. The first interface collects TT&C data from flying assets, ensuring system health and control. The second interface gathers communication-related data, such as traffic demands, channel states, topological routes, and connection/failure incidents, supporting effective network management to meet user demands. On the other side, DT-NTN interfaces must align with the requirements of various network applications, including regular network management, protocol validation, and performance optimization.

Challenges and Enabling Technologies for DT-NTN

This section identifies the key challenges for the proposed DT-NTN and the enabling technologies that address them.

DT-NTN Challenges

While DT technology offers unequivocal benefits and enhancements, its deployment for resource allocation within NTNs faces several challenges.

Data Freshness: This is particularly challenging due to the heterogeneity and dynamicity of NTNs as they operate in remote and harsh environments, where data collection and real-time transmissions may experience delays. While it is feasible to collect and use data for offline operations, achieving online optimization through DTs needs further enhancing real-time data processing capabilities.

Ownership and Privacy Concerns: This challenge emerges from the diverse ownership structures within NTNs, compounded by regulatory frameworks such as the general data protection regulation (GDPR) in the European Union. Ensuring the protection of customers' private data is a paramount concern for DT-NTNs. Compliance with local laws based on the locations of the NTN infrastructure or its DT is critical to safeguarding user privacy and maintaining regulatory compliance.

Computational Complexity: The complex and ever-changing characteristics of NTNs require sophisticated modeling techniques. For instance, parameters like flight dynamics, autonomous navigation trajectories, constellation patterns, and communication link performance need to be modeled as accurately as possible. This requires substantial computational resources and access to high-performance computing infrastructure. Besides, many resource allocation problems in NTNs are inherently non-convex or involve challenging combinatorial optimization, demanding high computational power.

Resource-Limited Devices: NTN entities, including LEO small satellites, downstream nano-satellites (nanosats), and HAPs, face substantial challenges due to their constrained computational capacity, limited memory, and often restricted power supply. Processing and managing the extensive data required for effective digital twinning poses difficulties for these devices. Hence, it is crucial to alleviate their burden by offloading storage and computing capabilities. This measure is essential to maintain sustained functionality and extend their operational lifespan in challenging NTN environments.

Interoperability and Standardization: NTNs often incorporate equipment and systems from various vendors with incompatible configurations, which imposes a challenge for seamless integration and operational efficiency. The lack of interoperability and standardization among vendor equipment further complicates the modeling of NTN element interactions. Therefore, DT-NTNs must be able to collect and integrate data from diverse, autonomous, and heterogeneous sources.

Security and Reliability: For an accurate representation of the physical NTN in the virtual DT-NTN, secure and reliable communication channels are essential. Any interruption or tampering in these channels can result in inaccurate or incomplete data, compromising the quality of analysis and decision-making. Therefore, robust communication protocols and security measures are crucial to safeguard against such issues and to maintain the DT-NTN's fidelity to the physical NTN.

DT-NTN Enabling Technologies

This section explores enabling technologies and their key features aimed at tackling challenges within DT-NTNs. Table 1 outlines these technologies and their potential solutions for deployment issues. These technologies are critical enablers for constructing DT-NTNs designed for optimized resource allocation. By leveraging these advancements, DT-NTNs can dynamically adapt to changing conditions and demands, thereby significantly improving resource allocation efficiency compared to traditional methods. We specifically address challenges such as computing, sensing, and interoperability, offering a deeper understanding of their significance in the context of DT-NTNs.

Narrow-Band Internet of things (NB-IoT): The 3GPP organization in its Release-17 has outlined guidelines to incorporate narrow-band IoT (NB-IoT) over satellites [9]. Renowned for its low power consumption, NB-IoT is ideal for battery-operated devices, enabling data collection from remote and power-limited assets within NTNs. Its adoption is crucial for enabling DT-NTNs, allowing real-time data collection, remote monitoring, and predictive maintenance, thereby improving the precision of DT-NTN models. NB-IoT provides network operators with valuable insights, enhancing network management capabilities. Despite potentially exhibiting slightly higher latency than other IoT technologies, NB-IoT generally fulfills the requirements for many DT applications. Tolerating this marginal increase in latency in exchange for global coverage makes NB-IoT as a crucial enabler. By implementing techniques like prediction, data summarization, and prioritization, DT-NTNs can still offer significant benefits even with less-than-instantaneous data updates. For example, a few seconds of delay might be acceptable for most monitoring purposes, allowing the DT-NTN to identify trends and potential issues.

Moreover, NB-IoT devices can be used for security monitoring, ensuring the safety and integrity of the NTNs. Particularly, DT-NTNs can incorporate security measures based on NB-IoT data to respond to potential threats and vulnerabilities. More importantly, NB-IoT technology can act as a bridge between diverse communication standards within NTNs by leveraging specific communication protocols to create a unified platform capable of understanding and translating data from multiple sources. This synergy enhances the overall adaptability and performance of the NTN ecosystem.

AI and Learning Techniques: DT-NTN models rely on extensive data, which has to be thoroughly analyzed to extract insights about physical assets. In this regard, AI and learning algorithms are essential for analyzing data collected from NB-IoT and sensor devices. These advanced algorithms empower enhanced decision-making, predictive maintenance, and anomaly detection, thereby improving the DT-NTN role in network management and resource allocation. Moreover, AI can accelerate DT-NTN algorithms, potentially enabling real-time operations and large-scale technology testing. For instance, deep learning techniques have shown a remarkable ability in modeling complex satellite communication networks. Researchers have effectively employed diverse learning approaches to investigate and improve various aspects such as network modeling, resource optimization [10], and network slicing [11]. With these advancements, it is evident that AI and learning algorithms will play a significant role in shaping the DT-NTN paradigm. However, these tools may require higher computational power.

Furthermore, the *modular architecture* of DT technology allows for the creation of individual DT for each asset component. This modular approach involves breaking down the system into smaller, manageable modules or components, each representing a specific aspect or function of the asset. These components can then be seamlessly interconnected into a comprehensive integrated DT-NTN, providing a holistic view of the entire NTN. This modularity supports process replication, facilitates knowledge transfer, and empowers intelligence at the edge. It enables techniques like *federated learning* and *transfer learning*, which enhance system resilience by leveraging distributed intelligence and diverse data sources. This approach not only helps avoiding costly redundancies within NTNs but also enables the prediction of potential disruptions by identifying weak points.

Space-Based Cloud Computing: Cloud platforms are crucial for the creation and operation of DTs due to their ability to provide the necessary computational power and storage capacity for developing, maintaining, and running twin models effectively. Particularly, space-based cloud computing (SCC) has immense potential for the development of DT-NTNs, offering unique capabilities such as ultra-low latency and high bandwidth connectivity [12]. These features significantly enhance real-time data processing and model execution within the DT-NTN system, leading to faster and more accurate network behavior predictions. This enables more efficient resource allocation and service management across geographically dispersed NTN elements. By positioning cloud platforms closer to physical NTN entities, SCC can reduce latency and improve real-time performance. Additionally, these platforms offer resilience against Earth-based disruptions, ensuring continuous monitoring and management of physical NTNs. Moreover, SCC enables scalable and flexible resource management by dynamically allocating computational resources based on the network needs. This scalability is essential for handling the varying demands of different services, such as high-throughput applications or latency-sensitive communications.

Neuromorphic Computing: Unlike conventional computers that follow the von Neumann architecture, neuromorphic computers emulate the structure of biological brains with artificial

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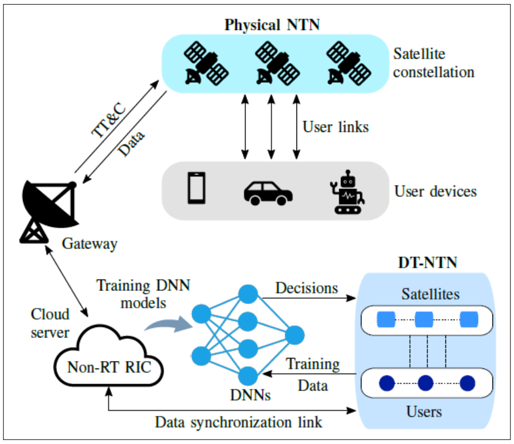

FIGURE 2. Twin AI-based model for resource allocation in NTNs.

neurons and synapses. This unique structure enables them to execute complex tasks such as pattern recognition and learning in ways similar to the human brain. Neuromorphic computing is particularly valuable in scenarios characterized by temporal signals and the necessity for continual learning from diverse data sources within complex environments such as NTNs. Furthermore, neuromorphic hardware and algorithms excel in handling complex, dynamic, and adaptive processes, making them ideal for real-time data analysis and decision-making, thus enhancing the capabilities of DT-NTNs to simulate and respond to changing network conditions. In the field of satellite communications, ongoing research is exploring the use of neuromorphic processors for AI-based applications. These processors offer significant advantages in tasks requiring extensive parallelism and matrix-based operations, thereby enhancing satellite payload performance, reliability, and power efficiency [13].

Neuromorphic technology presents a compelling advantage for DT-NTNs due to its exceptional energy efficiency. Unlike traditional architectures, neuromorphic computers can perform complex computations with significantly lower power consumption. This characteristic is crucial for resource-constrained environments often encountered in NTNs, where minimizing power demands translates to extended network operation and reduced reliance on external power sources. Beyond energy efficiency, neuromorphic computing offers additional advantages for DT-NTNs. Their ability to process information similar to the human brain enables real-time analysis of the vast amount of data generated by NTNs. This real-time processing capability is essential for timely decision-making and optimization within the dynamic environment of DT-NTNs. Furthermore, inspired by the brain's natural redundancy, neuromorphic computers exhibit inherent fault tolerance. This means they can continue functioning even if some components experience failures, a valuable feature for ensuring the reliability of DT-NTNs. In addition, neuromorphic systems can be scaled efficiently to accommodate varying workloads and network sizes, making them suitable for DT-NTNs of different scales and complexities.

Quantum Technologies: From an implementation perspective, NTN entities are mostly interconnected via free-space optical (FSO) links, which are favored in quantum communications protocols due to negligible background thermal radiation at optical frequencies [14]. In this context, the development of secure communication channels is paramount for DT-NTNs. However, the complex and distributed nature of these networks creates significant security challenges. *Quantum cryptography*, with protocols like quantum key distribution (QKD), offers a compelling solution. Unlike traditional encryption methods, QKD leverages the laws of quantum mechanics to establish keys with unconditional security, which effectively addresses the inherent vulnerabilities of DT-NTNs, ensuring robust protection across the entire system.

Beyond secure communications, quantum technologies offer further advantages for DT-NTNs. *Quantum sensing* provides precise measurements of crucial parameters for accurately representing a DT-NTN, such as position, velocity, and environmental conditions. These sensors, based on atomic and molecular systems, offer unparalleled precision in time and frequency. This enables detailed analysis of signal propagation, interference patterns, and noise within the physical NTN. Further, *quantum computing* represents a revolutionary leap in computing capabilities. Classical computers often struggle with large-scale optimization problems encountered in DT-NTNs. However, quantum computing algorithms can tackle them efficiently due to the exponential nature of the quantum computational space. This unprecedented scalability paves the way for optimized modeling and resource allocation within the dynamic and complex environments of DT-NTNs.

Open Radio Access Network (O-RAN): RAN is a transformative architecture aimed at fostering interoperability and innovation within the RAN domain. By decoupling hardware and software components, it enables flexible deployment of network infrastructure. This separation facilitates interoperability among hardware from different vendors and promotes openness in software and interfaces, encouraging collaboration and advancement within the RAN ecosystem. Moreover, the open interfaces within the O-RAN architecture facilitate multi-vendor interoperability and coexistence across functions, ensuring seamless integration of various components and efficient data exchange through standardized interfaces. Thus, data-driven network control and management solutions can be effectively incorporated into O-RAN architecture [15].

O-RAN architecture offers significant advantages for developing DT-NTNs. Its flexibility and programmability contribute to efficient resource management, reduced network latency, and ultimately, enhanced DT-NTN performance. Specifically, the openness of O-RAN software and interfaces simplifies data collection and management, which reduces the complexity of modeling interactions between diverse network elements within the DT-NTN. Furthermore, O-RAN functional partitioning allows for flexible representation of the physical NTN in its DT-NTN, leading to more accurate simulations and enhanced predictive and optimization capabilities. This synergy is further amplified by DT technology itself. DT-NTNs leverage virtual modeling capabilities for testing and optimizing scenarios before implementation in the physical NTN, minimizing risks and ensuring efficient network operation.

Case Study: DT-NTNs for Resource Optimization

In the context of the challenges and enabling technologies discussed earlier, the integration of DT and AI technologies emerges as a powerful paradigm for addressing the complexities of 6G NTNs. This section delves into a case study illustrating the practical application of DT-NTNs in optimizing resources within QoS-aware scenarios. Specifically, we explore the implementation of learning techniques for dynamic resource allocation within O-RAN-based NTNs. The primary objective is to enable the seamless coexistence of conflicting eMBB and URLLC services, accommodating their divergent requirements. While eMBB demands high data rates and URLLC necessitates ultra-low latency, optimizing these services simultaneously poses a significant challenge. Addressing these conflicting demands requires advanced resource management and network design strategies. Through this case study, we aim to demonstrate how DT-NTNs can effectively manage these challenges and optimize resource allocation to meet diverse service requirements within 6G NTNs.

Network Scenario

We consider a network of LEO satellites at a 550 km altitude, operating in the Ku band (12-18 GHz) with a 12.5 GHz carrier frequency. Each satellite node transmits at 40 dBm with a 10 dBi antenna gain. Noise power is set at –174 dBm/Hz. eMBB traffic follows full-buffer traffic, while URLLC traffic follows a Poisson process with rate λ. This constellation of multiple LEO satellites serving multiple distributed users with distinct requirements, as shown in Fig. 2. Specifically, LEO satellites collect network information, including channel states, network traffic, and QoS requirements, and then send the collected data to the non-real time RAN intelligent controller (non-RT RIC) located at a cloud server through a gateway. The DT-NTN process the collected network information, which will be updated over time to keep synchronizing with the physical network. We developed a Python-based simulator for modeling the LEO network, utilizing its libraries for wireless environment simulations and machine learning. TensorFlow is used for implementing deep learning models. A learning model based on deep neural networks (DNNs) is installed at the non-RT RIC and trained by interacting with the DT-NTN to improve the spectral efficiency while satisfying the QoS requirements of each service. Specifically, the QoS for eMBB services is characterized by a defined minimum data rate threshold, whereas the QoS for URLLC is determined based on the outage probability.

The resource allocation decisions are then performed based on the trained models within the DT-NTN and sent to the physical network. In the DNN architecture, we use a model consisting of three hidden layers: the first hidden layer is configured with 600 neurons, the second with 300 neurons, and the third contains 250 neurons. The number of neurons in the input layer is aligned with the considered network information, including channel states, network traffic, and QoS requirements. Furthermore, the number of neurons in the output layer corresponds to the size of the resource allocation matrix. We utilize the rectified linear unit (ReLU) activation function for the hidden layers, while the output layer employs the Softmax function.

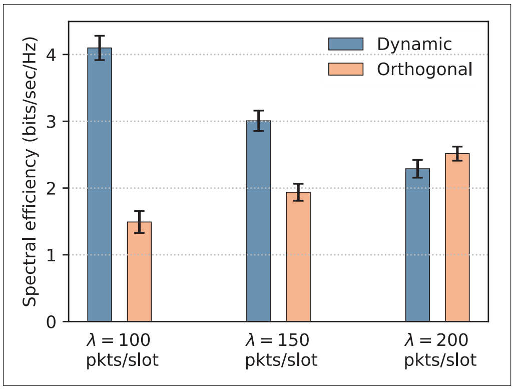

FIGURE 3. Downlink spectral efficiency.

Results Discussion

Figure 3 shows the downlink spectral efficiency for different settings of URLLC traffic rate (λ). Here, spectral efficiency is obtained as the sum data rate of eMBB and URLLC users divided by the system bandwidth. A fully buffered traffic model is considered for eMBB users. We compare the dynamic resource allocation-based approach to the static orthogonal method, where pre-determined fixed resources are assigned to each service. The findings reveal that the AI-based dynamic resource allocation approach within the DT-NTN provides better resource utilization compared to the orthogonal technique. Nevertheless, in case of heavy URLLC traffic, the orthogonal method may perform slightly better than the dynamic approach, as most resources allocated to URLLC users are utilized effectively. As illustrated in Fig. 3, the dynamic approach achieves approximately 60 percent higher spectral efficiency than the orthogonal method when λ = 100 packets/time slot. However, this efficiency gap narrows with increasing URLLC traffic, as more eMBB resources are diverted to serve the high-priority URLLC traffic, thereby affecting the overall eMBB data rate. When the URLLC traffic rate reaches λ = 200 packets/time slot, the spectral efficiency of the orthogonal method rises to about 2.2 b/s/Hz, while the dynamic approach drops to roughly 2.1 b/second/Hz. This is because the static approach can fully utilize its pre-allocated resources for URLLC traffic, whereas the dynamic method requires ongoing monitoring and adjustment, introducing additional signaling overhead. The dynamic allocation also attempts to meet stringent URLLC reliability by reallocating more resources, which impacts eMBB data rates and results in decreased spectrum utilization due to the reduction in eMBB performance.

Figure 4 depicts the cumulative distribution function (CDF) of URLLC reliability defined in terms of the outage probability $\Pr[R_u(t) \leq \zeta\lambda(t)] \leq \varepsilon_{\max}$, where $R_u(t)$ is the obtained sum data rate of URLLC users at time slot t, ζ represents the URLLC packet size and $\varepsilon_{\max}$ denotes the maximum threshold of the outage probability. The results obtained at $\varepsilon_{\max} = 0.07$ and $\zeta = 32$ bytes, while the value of λ varies over time slots. Specifically, the cumulative probability that the outage

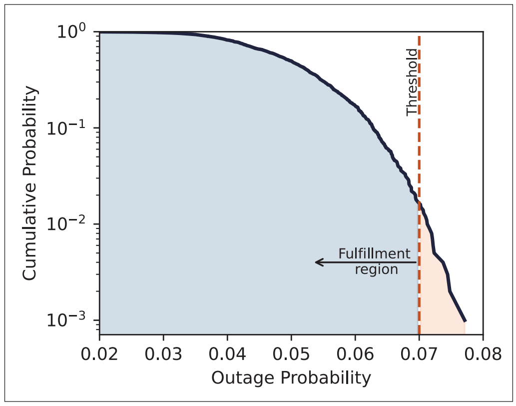

FIGURE 4. URLLC outage probability.

probability exceeds the threshold ε_{max} is around 0.02. This outcome is due to the fact that the dynamic scheduling algorithm prioritizes critical URLLC traffic by allocating resources from eMBB users over time slots, considering the stochastic network dynamics. In short, these findings highlight the potential advantages of incorporating AI models within DT-NTNs for enhancing the performance of 6G NTNs, ensuring the required reliability, and meeting the diverse QoS requirements.

Conclusions

This article has introduced and explored the integration of DT technology into 6G NTNs, presenting a novel approach for enhancing resource allocation and network management. We outlined the vision and architecture for developing DT-NTNs, and discussed the key deployment challenges such as data freshness and accuracy, computational power, reliable interconnections, interoperability, and data security procedures. Various enabling technologies were explored to facilitate the integration and address these challenges. Furthermore, a case study was presented to illustrate the practical application of AI and learning algorithms within DT-NTNs for optimizing NTN resources. In essence, this article introduced practical aspects of DT-NTN development that can potentially trigger more in-depth research into creating highly intelligent and dynamic non-terrestrial communication systems.

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