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Article

Roles of Artificial Intelligence in Non-Terrestrial Network Communication Management

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Abstract: This paper examines the roles of Artificial Intelligence (AI) in managing communication operations within Non-Terrestrial Networks (NTNs). A review research method was adopted to examine recent studies on AI applications in satellite and integrated NTN communication systems. The review focused on eight major roles: satellite handover optimisation, beam steering management, traffic routing, link quality adaptation, predictive maintenance, spectrum management, energy optimisation, and security monitoring. The reviewed studies indicate that AI can improve network adaptability by enabling predictive decision-making, intelligent resource allocation, dynamic routing, and automated network optimisation. AI also contributes to improved communication reliability, energy efficiency, interference management, satellite health monitoring, and protection against communication threats. Furthermore, AI enables NTN systems to respond intelligently to changing user demands, satellite mobility, traffic conditions, and communication link variations. The integration of machine learning and deep learning can reduce dependence on fixed network configurations and support more autonomous communication management. These capabilities are particularly important for future 5G and 6G NTN systems that require scalable, reliable, and efficient network operations across heterogeneous environments. The study concludes that AI provides an important foundation for developing more autonomous, efficient, reliable, secure, and adaptive NTN communication management systems.

Keywords: Artificial Intelligence, Non-Terrestrial Networks, Satellite Communication, Network Management, Machine Learning.



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1. Introduction

Non-Terrestrial Networks (NTNs) have emerged as an important component of next-generation communication systems because they can extend connectivity to remote, underserved, and geographically challenging areas beyond the reach of conventional terrestrial infrastructure. This integration of satellite and terrestrial communication technologies provides opportunities for ubiquitous coverage, improved connectivity, and enhanced support for emerging 5G and 6G applications across diverse geographical environments[1].However, the effectiveness of NTN communication is affected by several technical challenges, including satellite mobility, propagation delay, Doppler effects, large path losses, and rapidly changing channel conditions. These dynamic characteristics make conventional network management approaches increasingly difficult to apply because communication resources, user locations, traffic conditions, and link quality can change continuously during network operation[2]. As a result, there is a growing need for intelligent technologies capable of analysing changing network conditions and making timely decisions to maintain efficient communication services[3]. Artificial Intelligence (AI) provides such capabilities through machine learning and intelligent optimisation techniques that can support autonomous decision-making, resource allocation, network adaptation, and service management in NTN environments. The ability of AI to learn from network data and respond to changing conditions makes it particularly suitable for addressing the complex and dynamic requirements of satellite-terrestrial communication systems. Consequently, the application of AI can improve the efficiency, reliability, adaptability, and security of NTN communication while reducing the limitations associated with conventional management techniques. Therefore, this paper examines the roles of AI in NTN communication management, with emphasis on satellite handover optimisation, beam steering management, traffic routing, link quality adaptation, predictive maintenance, spectrum management, energy optimisation, and security monitoring.

What is Non-Terrestrial Network (NTN)?

Non-Terrestrial Network (NTN) refers to a communication network that uses platforms located above the Earth's surface, including satellites, high-altitude platforms, and unmanned aerial vehicles, to provide connectivity to users. Unlike conventional terrestrial networks that mainly depend on cellular towers and fixed infrastructure, NTN can extend communication coverage to remote, rural, maritime, and geographically difficult areas. The increasing deployment of satellite-based communication has therefore positioned NTN as an important component of future 5G and 6G communication systems. However, the effectiveness of these networks is influenced by several technical and environmental factors, including latency, atmospheric effects, satellite mobility, and communication coverage limitations. Satellite communication systems are affected by atmospheric conditions at one point or another, and this can cause degradation or attenuation of quality[4] identified these challenges as important factors affecting the effective deployment and utilisation of NTN communication. These challenges become more significant as NTN systems are expected to provide seamless connectivity across satellite, aerial, and terrestrial platforms. Consequently, effective management of NTN requires intelligent approaches capable of responding to changing network and communication conditions. This creates an important role for Artificial Intelligence (AI), which can support intelligent handover, beam steering, traffic routing, link adaptation, spectrum management, energy optimisation, predictive maintenance, and security monitoring.

2. Methodology

This study adopted a review research method to examine the roles of Artificial Intelligence in Non-Terrestrial Network (NTN) communication management. The method was selected because the study focuses on synthesising and explaining findings from existing research rather than collecting primary data from respondents or conducting physical experiments. Relevant academic publications were identified from scholarly databases and publisher platforms, with emphasis placed on studies published between 2020 and 2025. The selection focused on recent and verifiable studies addressing AI, machine learning, deep learning, reinforcement learning, satellite communication, LEO networks, and integrated satellite-terrestrial NTN systems. The reviewed literature was organised into eight thematic areas: satellite handover optimisation, beam steering management, traffic routing, link quality adaptation, predictive maintenance, spectrum management, energy optimisation, and security monitoring. For each theme, three relevant studies were examined based on their research objectives, AI techniques, application areas, and reported outcomes. The findings were then analysed comparatively and explained to establish how AI contributes to communication management within NTN environments. Particular attention was given to the ability of AI to support prediction, automation, optimisation, resource allocation, network adaptation, and security. The reviewed evidence was subsequently synthesised to identify the major contributions of AI to NTN communication and to explain its potential for improving network reliability, efficiency, scalability, and service continuity.

3. Results and Discussion

This section presents the reviewed findings on the application of Artificial Intelligence (AI) in improving the performance and efficiency of Non-Terrestrial Network (NTN) communication. The discussion focuses on key areas where AI supports reliable connectivity, efficient resource management, and improved network performance.

3.1. Satellite Handover Optimization

Satellite handover optimization is an important role of AI in NTN communication because LEO satellites continuously move relative to users and ground stations. AI can analyse satellite positions, user locations, traffic conditions, and signal quality to predict when a handover will be required. Explanatory studies indicate that predictive AI models can select the most suitable neighbouring satellite before the existing connection becomes weak. This reduces unnecessary handover failures, service interruptions, and communication delays. AI can also learn from previous mobility and network conditions to improve future handover decisions. Therefore, AI supports seamless and more reliable connectivity in highly dynamic NTN environments.

Wang[5] examined seamless handover in LEO-based NTN and proposed a conditional handover mechanism to improve service continuity. The study showed that satellite mobility makes frequent handovers a major challenge for maintaining stable connections. Their results showed that intelligent handover decisions can reduce service interruption and improve network continuity. In the same way, Jiang[6] investigated LEO satellite handover using graph modelling and multi-objective multi-agent path finding. The study simultaneously considered handover frequency, received power, and conflicts among users to determine better handover paths.

3.2. Beam Steering Management

AI contributes to beam steering management by enabling NTN systems to dynamically adjust satellite beams according to changing communication demand. AI models can analyse user distribution, traffic intensity, geographical coverage, and network conditions to determine where stronger or wider beams are required. Instead of maintaining fixed beam patterns, intelligent systems can redirect available resources toward areas experiencing high demand. This improves spectrum utilisation and reduces the waste of transmission resources in areas with few users. AI-based beam management can also respond rapidly to changes in population movement and traffic patterns. Consequently, AI improves coverage efficiency, capacity, and quality of service in NTN

communication networks.

According to Jamshed[7] AI and advanced beamforming can support NTN systems by adapting beams according to user location, traffic demand, and changing satellite conditions. Their review highlights intelligent beamforming as an important technology for achieving efficient integration between terrestrial and non-terrestrial networks.

Dakkak[8] investigated federated beamforming for B5G/6G LEO NTN and showed that distributed beamforming can improve spectral efficiency and interference management. Their findings demonstrate that intelligent coordination of antenna arrays can provide more effective and flexible beam coverage for users.

In the view of Jamshed[9] user-centric beamforming allows LEO satellites to direct communication resources toward users according to their location and service requirements. The authors demonstrate that combining AI with beamforming can improve system capacity and support dynamic resource allocation in NTN environments.

3.3. Traffic Routing

AI plays a significant role in traffic routing by determining efficient paths for data transmission across interconnected satellites, gateways, and terrestrial networks. In NTN environments, network conditions can change rapidly because of satellite movement, varying traffic loads, link availability, and congestion. AI can analyse these conditions in real time and select routes that provide lower delay, higher reliability, and better network performance. Predictive algorithms can also anticipate congestion and redirect traffic before network performance deteriorates. This reduces packet loss, transmission delays, and unnecessary congestion across satellite and ground segments. Therefore, AI-based traffic routing enables NTN networks to provide more efficient, adaptive, and reliable communication services.

According to work by Ding[10] reinforcement learning can improve traffic routing in LEO satellite networks by allowing satellite nodes to adapt forwarding decisions to changing link conditions. Their proposed approach improved average delay, packet arrival ratio, and network load balancing compared with the Dijkstra algorithm. As reported by Xu[11] combining Graph Neural Networks (GNN) with Deep Reinforcement Learning (DRL) enables intelligent routing decisions in rapidly changing LEO satellite topologies. Their approach considered both end-to-end delay and link-load distribution when selecting communication paths. In the view of Chen[12] GNN and DRL can jointly optimise routing in LEO mega-constellations by considering network topology, node load, transmission delay, and service-function constraints. Their simulations showed reduced transmission delay and network load, while improving traffic access success and network capacity.

3.4. Link Quality Adaptation

AI supports link quality adaptation by continuously monitoring communication conditions across NTN links. It can analyse signal strength, atmospheric conditions, interference, and weather-related effects that may degrade communication quality. Based on these conditions, AI can automatically adjust modulation schemes, coding rates, transmission power, and other link parameters. This allows the network to respond quickly when signal quality changes rather than relying only on fixed configurations. AI can also predict possible link degradation and initiate corrective actions before serious service disruption occurs. Therefore, AI improves the stability, reliability, and overall quality of NTN communication links.

According to Li[13] adaptive coding and modulation can improve LEO satellite link performance by responding to changing atmospheric attenuation and channel conditions. Their study found that adaptive techniques increased transmission efficiency and reduced communication outage periods. As reported by Shen[14] rainfall, terminal conditions, and satellite mobility can significantly affect Ka-band LEO communication links. The authors proposed an adaptive coding and modulation scheme that responds to these changing conditions and reduces signal fading while maintaining communication efficiency. In the view of Zhang[15] deep learning and deep

reinforcement learning can make link adaptation more intelligent by using real-time weather and location information to select suitable encoding schemes. Their results showed that the proposed AI-based approach increased correctly transmitted bits and improved satellite-to-ground communication throughput.

3.5. Predictive Maintenance

AI enables predictive maintenance by analysing satellite telemetry, sensor measurements, and historical operational data to identify abnormal equipment behaviour. Machine-learning models can detect patterns associated with component degradation before an actual hardware failure occurs. This allows satellite operators to identify potential problems early and schedule maintenance or corrective actions before communication services are affected. AI can also prioritise equipment requiring attention based on the severity and likelihood of failure. Such predictive analysis can reduce unexpected outages, maintenance costs, and operational risks. Consequently, AI contributes to improved satellite reliability and longer operational availability in NTN systems.

According to Zhang[16] machine-learning-based anomaly detection of satellite telemetry can identify abnormal operational patterns before they develop into serious failures. The authors proposed a hybrid data-driven framework using real satellite telemetry data to improve anomaly detection. Their findings demonstrate that intelligent telemetry analysis can strengthen satellite health monitoring and operational reliability.

As reported by De Canio[17] AI can support short-term satellite health forecasting by continuously analysing large volumes of telemetry parameters. The authors noted that manual monitoring of thousands of telemetry variables is difficult and time-consuming for flight-control teams. Their work therefore demonstrates the value of AI for identifying deviations and supporting earlier intervention in satellite operations.

In the view of Li an attention-BiLSTM model can improve satellite operational prediction by learning relationships among large and complex telemetry datasets. Using telemetry from the FY-3E meteorological satellite, the study achieved better prediction accuracy than the compared methods. The findings show that AI-based prediction can contribute to intelligent satellite health management and help prevent operational faults.

3.6. Spectrum Management

AI plays an important role in spectrum management by intelligently coordinating frequency resources between NTN systems and terrestrial 5G or emerging 6G networks. NTN communication can operate in frequency bands that may also be used by terrestrial systems, creating potential interference problems. AI can continuously analyse spectrum occupancy, signal characteristics, network demand, and interference levels to identify suitable frequency resources. It can then support dynamic frequency allocation and transmission adjustments to minimise harmful interference. Predictive models can also anticipate periods of high spectrum demand and recommend appropriate allocation strategies. Therefore, AI improves spectrum efficiency while supporting reliable coexistence between terrestrial and non-terrestrial communication networks.

As observed by Mahboob and Liu[18] spectrum sharing is one of the major challenges in satellite-based NTN because increasing satellite deployments create greater possibilities for interference. The authors reviewed AI-enabled approaches for managing spectrum and network resources in 6G NTN environments. Their work shows that intelligent techniques can support dynamic resource allocation and interference management. This makes AI useful for coordinating spectrum between NTN and terrestrial networks.

As reported by Saifaldawla[19] AI can improve interference detection in increasingly congested satellite frequency environments. The authors developed generative-AI models, including a variational autoencoder and transformer-based interference detector, for identifying NGSO-to-GSO interference. Their results showed that the transformer-based detector improved interference-detection accuracy by up to 31.23% compared with the traditional energy detector.

In the view of Shang[20] spectrum sharing between satellite and terrestrial networks can improve spectrum efficiency by allowing NTN systems to access underutilised terrestrial spectrum in remote areas. However, the authors identified mutual interference between NTN and terrestrial networks as a major challenge requiring effective management. Their study reviewed spectrum-sharing frameworks and interference-management approaches for satellite-terrestrial integrated networks.

3.7. Energy Optimisation

AI contributes to energy optimisation by intelligently managing the limited power resources available to satellites and UAV-based NTN platforms. AI algorithms can analyse traffic demand, battery levels, solar energy availability, and communication requirements to determine when network components should transmit, reduce activity, or enter sleep modes. During periods of low demand, unnecessary energy consumption can be reduced without significantly affecting service availability. AI can also predict future energy requirements and schedule communication activities according to expected power availability. This is particularly important for satellites that depend on solar panels and have limited onboard energy storage. Consequently, AI helps extend operational endurance while improving the energy efficiency of NTN communication systems.

According to Liang[21] AI can improve energy efficiency in satellite-UAV NTN by jointly optimising UAV trajectory, transmission power, and sensing strategies. The authors applied a Deep Q-Network to determine efficient UAV trajectories while maintaining communication reliability. Their results showed that intelligent resource management can reduce unnecessary energy consumption in integrated satellite-UAV networks.

As reported by Xie[22] deep reinforcement learning can support energy-efficient computation offloading in LEO satellite-terrestrial integrated networks. The authors developed a delay-based DRL framework for making offloading decisions while also improving task scheduling efficiency. Their findings demonstrate that AI can reduce energy consumption while maintaining effective computing and communication performance.

In the view of Zhang[23] AI-based power control can improve the energy efficiency of machine-learning operations over LEO satellite communication systems. Their study developed an adaptive power-control algorithm that determines suitable satellite transmission power according to communication requirements. The results showed higher energy efficiency than benchmark approaches, demonstrating the importance of intelligent power management in resource-constrained satellite networks.

3.8. Security Monitoring

AI strengthens NTN security by continuously analysing network traffic, communication behaviour, and system activity to identify potential threats. AI-based detection models can recognise unusual patterns associated with jamming, spoofing, unauthorised access, and other cyberattacks affecting satellite communication links. Unlike conventional security approaches that may depend mainly on predefined rules, AI can identify emerging threats from deviations in normal network behaviour. When suspicious activity is detected, AI can support rapid responses such as changing communication parameters, isolating affected links, or redirecting traffic. Continuous learning can further improve the ability of the system to recognise new and evolving attack patterns. Therefore, AI provides an adaptive security mechanism for protecting NTN infrastructure and maintaining reliable communication services.

According to Saifaldawla generative AI can improve interference detection in satellite communication systems where NGSO satellites share frequency bands with GSO systems. Their study developed AI-based models for detecting interference from received signal data. The proposed transformer-based detector achieved up to 31.23% higher detection accuracy than the conventional energy detector. These findings demonstrate the potential of AI for continuously monitoring NTN links and identifying harmful interference.

As reported by Nabi[24] machine-learning techniques can effectively identify structured interference and spoofing signals affecting satellite-based navigation systems. The authors evaluated logistic regression, support vector machines, K-nearest neighbours, and decision-tree models using spoofing data. Logistic regression and SVM achieved a mean F1-score of about 94%, showing strong detection capability. The study demonstrates how AI can support automated identification of abnormal signals and improve satellite communication security.

In the view of Han[25] deep learning can be applied to develop anti-jamming mechanisms for satellite communication systems. Their study proposed a deep-learning-based satellite communication anti-jamming system and investigated its ability to deal with malicious interference. The work demonstrates that AI can analyse interference conditions and support appropriate countermeasures. This makes deep learning a useful approach for improving the resilience of NTN communication links against jamming attacks.

4. Conclusion

This study examined the roles of Artificial Intelligence (AI) in Non-Terrestrial Network (NTN) communication management through a review of recent research. The findings show that AI can significantly support satellite handover optimisation, beam steering, and traffic routing by enabling intelligent and adaptive network decisions. AI also improves link quality adaptation by responding to changing channel, weather, interference, and communication conditions.
The review further established that AI-based predictive maintenance can support early identification of satellite faults and improve operational reliability.
In addition, intelligent spectrum management can reduce interference and improve the efficient sharing of communication resources between NTN and terrestrial networks.
AI can also optimise energy consumption and strengthen security monitoring through intelligent power management, anomaly detection, anti-jamming, and spoofing detection.
Overall, the reviewed studies demonstrate that AI can make NTN communication systems more efficient, reliable, adaptive, secure, and capable of supporting future 5G and 6G connectivity requirements. Therefore, continued development and integration of AI techniques into NTN management is recommended to achieve more autonomous, scalable, and resilient non-terrestrial communication networks.

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