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Empowering Non-Terrestrial Networks with Artificial Intelligence: A Survey

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ABSTRACT 6G networks can support global, ubiquitous and seamless connectivity through the convergence of terrestrial and non-terrestrial networks (NTNs). Unlike terrestrial scenarios, NTNs pose unique challenges including propagation characteristics, latency and mobility, owing to the operations in spaceborne and airborne platforms. To overcome all these technical hurdles, this survey paper presents the use of artificial intelligence (AI) techniques in learning and adapting to the complex NTN environments. We begin by providing an overview of NTNs in the context of 6G, highlighting the potential security and privacy issues. Next, we review the existing AI methods adopted for 6G NTN optimization, starting from machine learning (ML), through deep learning (DL) to deep reinforcement learning (DRL). All these AI techniques have paved the way towards more intelligent network planning, resource allocation (RA), and interference management. Furthermore, we discuss the challenges and opportunities in AI-powered NTN for 6G networks. Finally, we conclude by providing insights and recommendations on the key enabling technologies for future AI-powered 6G NTNs.

INDEX TERMS Non-Terrestrial Networks (NTNs), Artificial Intelligence (AI), 5G/6G, Unmanned Aircraft System (UAS), Resource Allocation (RA), Reinforcement Learning (RL), Deep Learning (DL)

I. INTRODUCTION

The evolution of wireless communication technology has been rapid in recent years, with mobile network operators deploying the fifth-generation (5G) technology worldwide. The Third Generation Partnership Project (3GPP) has begun the standardization of 5G-Advanced, which is expected to offer higher data rates, lower latency, increased capacity, and more efficient spectrum utilization than any of its predecessors [1]-[2]. However, due to limited coverage areas and geographic constraints, it is challenging to guarantee ubiquitous coverage everywhere with existing network infrastructures. In times of natural disasters, connectivity outages are widespread, which can be detrimental to critical actions necessary for saving lives and properties. To address these challenges, research on 5G-Advanced and sixth-generation (6G) communication networks are shifting towards non-terrestrial networks (NTNs), which include Low/Medium/Geostationary (LEO, MEO, GEO) satellites, high altitude platform stations (HAPS), unmanned aircraft systems (UASs), or a combination of these technologies [3]. NTNs can provide uninterrupted communication and high data transfer rates in remote, disaster-stricken, and rural areas where terrestrial networks are not available. Recent studies have shown that NTNs can offer high availability and low latency, making them an ideal candidate for 6G communication systems [4]-[5].

Despite these advantages, NTNs present significant challenges related to their deployment and management. One of the primary challenges is how to deploy and manage efficiently, including the physical and ground-based infrastructure, such as antennas, base stations (BSs), and backhaul networks. Furthermore, the dynamic nature of NTNs, with platforms moving at high speeds and in different directions, introduces additional challenges related to signal propagation, interference, and handover management [6]-[7].

Researchers are turning to artificial intelligence (AI) as a promising solution to address these challenges. AI can help to optimize the performance of NTNs by analyzing data from various sources, predicting network behavior, and adapting to changing conditions [8]. For example, AI can enable intelligent power management and beamforming to maximize resource utilization while minimizing interference and maintaining the quality of service (QoS) [9]. Also, AI can provide advanced analytics and automated decision-making to enhance the efficiency and reliability of NTNs.

The integration of AI in cellular networks is still in its early stages compared to other fields, primarily due to wireless networks' complexity and time-varying nature [10]. The multi-dimensional topology of the next-generation wireless networks adds an additional layer of complexity to the existing communication networks, making it challenging to solve problems that arise in real networks. Nevertheless, AI techniques can be exploited to overcome these challenges and provide efficient solutions. NTNs, being an integral part of next-generation wireless networks, holds great potential for the application of AI. However, implementing these algorithms in real-world environments while ensuring reliable vertical connectivity between ground and space networks can present practical challenges. Proper AI solutions must complement theoretical advancements in communication systems design to achieve optimal performance in future networks.

A. RELATED WORKS AND PAPER CONTRIBUTION

Several studies and surveys have been conducted to explore the possibility of NTNs for 6G wireless communications. However, it is very rare to explore the concept of AI for NTNs. Instead, numerous research has focused on network architectures, standards, regulations, and use cases. For instance, [11] and [12] give an overview of different NTN use, including satellite communication, aerial drones, and terrestrial devices. In [13], challenges associated with satellite communication in 6G are examined, including power constraints, latency issues, and frequency allocation. The works in [14] and [15] explore the potential impact of 6G networks on various industries, including agriculture, transportation, and healthcare. Unlike [14] and [15], the works in [16] and [17] focus on the potential security threats of NTNs by discussing the technical aspects of NTNs, such as the different radio access technologies available and the requirements and challenges of integrating 6G with existing technologies. Overall, these works provide valuable insights into the potential of NTNs for 6G and the various challenges to consider for their successful implementation. The overview of the vision, requirements, and challenges of 6G wireless networks are explained in [18] and [19]. The current status and future directions of 6G wireless networks are reviewed in [20] and [21]. Furthermore, [22] and [23] discuss the key enabling technologies for 6G networks, such as terahertz (THz) communication, visible light communication (VLC), and wireless power transfer. The applications, technologies, and challenges of 6G wireless networks are explored in [24] and [25]. The challenges and opportunities in 6G networks, including ultra-reliable, low-latency, and massive machine-type communication, are discussed in [26], [27], and [28]. A comprehensive 6G wireless communication survey is presented in [29] and [30]. The concept and standardization of 6G networks, including new spectrum bands and wireless technologies, are explained in [31] and [32]. In [33] and [34], the authors explore the opportunities and challenges of 6G networks, including the use of satellite communication and energy-efficient design. A comprehensive survey of 6G networks, including new radio access technologies and security challenges, is presented in [35] and [36]. In [37], the authors present a comprehensive survey of 6G wireless networks, including new antenna technologies and network slicing. Similarly, [38] explains the five facets of the new wireless generation, along with its research challenges and different opportunities for the new wireless generation.

The aforementioned studies do not incorporate the use of AI in their analysis. In contrast, this survey paper analyzes AI's utilization in NTNs to enhance 6G wireless communications networks, as summarized in Table 1. Firstly, we discuss the potential benefits and challenges of integrating AI in NTNs, including its impact on network performance, reliability, and security. Secondly, we show different AI techniques that can be applied to NTNs, such as machine learning (ML), deep learning (DL), and deep reinforcement learning (DRL). Finally, this survey paper discusses the potential applications of AI-powered NTNs in various industries, including healthcare, transportation, and smart cities. We analyze the use cases for AI-powered NTNs in these industries, including how they can improve efficiency and reduce costs.

The main contributions of this survey paper can be summarized as follows:

1) We provide an overview of NTNs, including their introduction in the context of 6G networks, their role in enhancing network performance, and their key features and requirements. Additionally, we analyze the unique security and privacy concerns associated with NTNs, providing valuable insights into their intrinsic nature.
2) We discuss the AI approaches by explaining the fundamental aspects of AI techniques used in the NTNs. As a result, we can select appropriate AI approaches for dealing with various NTN issues.

Table 1. Summary of Related Works on 6G

Ref	Year	Contribution and Main Focus
[22]	2019	A vision for 6G networks in 2030 for superior performance and enabling emerging services and applications is discussed. The focus is to propose a large-dimensional, autonomous network architecture integrating various networks and advanced technologies.
[17]	2020	The security and privacy issues associated with 6G networks are being explored as next-generation solutions due to the limitations of 5G networks. The main focus is to discuss four key aspects of 6G networks and their associated security and privacy issues.
[19]	2020	Vision, technology trends, and challenges for 6G are discussed. The main focus is providing the key enabler of a ubiquitous intelligent mobile society and suggesting a roadmap for the 6G standards.
[21]	2020	Recent advances in 6G wireless systems are discussed. The main focus is to present a taxonomy of key technologies and open research challenges and propose practical guidelines such as neural networks and blockchain-based secure business models.
[31]	2020	A discussion of 6G wireless communication technologies is provided, emphasizing fundamental breakthroughs at the physical layer. The main focus is to provide an overview of these technologies, including holographic radio, terahertz communication, large, intelligent surface, and orbital angular momentum.
[32]	2020	The limitations of 5G and the need to develop the 6G wireless system are discussed. The main focus is to provide the vision for 6G and outline a research agenda for enabling the new services and technologies required.
[13]	2021	The potential of UAVs in beyond 5G and 6G wireless networks are discussed. The main focus is to highlight the use of cellular networks, advanced technologies, machine learning, and non-terrestrial networks to support UAVs in 6G.
[23]	2021	A fiber-wireless network architecture is presented based on full spectrum, fully adaptive, and coordinated radio access networks (RANs). The main focus is to offer promising scenarios such as NR-free space optical backhauling and indoor systems via visible light communication for high-speed data link and VLC-aided positioning systems.
[24]	2021	The need for 6G to overcome the limitations of current cellular networks and support high-bandwidth applications are discussed. The main focus is to provide an overview of system requirements, potential technologies, and recent research progress.
[25]	2021	The overviews of reconfigurable intelligent surfaces (RISs) for 6G wireless networks are explained. The main focus is to provide the use case of RISs to create a favorable propagation channel and improve performance gains.
[26]	2021	A comparison of 5G and 6G technologies, including terahertz communication, RIS, and blockchain, are presented. The main focus is to illustrate how IRS can enhance signal quality by controlling passive reflecting elements and how blockchain can enhance system security.
[16]	2022	The possibility of integrating terrestrial and NTNs is discussed as a means of improving user experience and connecting unconnected devices. The main focus is identifying the opportunities and challenges for defining and orchestrating a new 3D wireless network architecture.
[28]	2022	The challenges of 5G technology and the potential benefits of 6G technology for edge networks in processing real-time applications are examined. The focus is on integrating ultra-reliable 6G technology into edge computing networks.
[33]	2022	The potential of IoT devices and energy-efficient 6G wireless communication in transforming smart cities into super-smart cities is conferred. The main focus is to review key technologies and applications, including quantum communication, blockchain, and VLC and identifies promising trends for using 6G through IoT devices in smart cities.
[39]	2022	An overview of 6G mobile networks, including motivations, use cases, requirements, and research projects, are reviewed. The main focus is on the transition from 5G to B5G and on the advanced features that will be required for 6G.
[40]	2022	The role of wireless backhauls in 5G networks and its integration with new technologies like UAV, HAPS, mmWave, mMIMO, and beamforming are presented. This article focuses mainly on rural connectivity, mobile edge computing, and security issues related to wireless backhaul in 5G and B5G.
[34]	2023	The design of an energy-efficient resource allocation system for NTNs is explained. The main focus is to maximize system energy efficiency by collaboratively optimizing user equipment association, power control, and UAV deployment.
[38]	2023	Researchers are exploring five Facets of 6G to develop next-generation solutions, i.e., next-generation architectures, networking, IoT, wireless positioning and sensing, and deep learning applications. The main focus is to review promising techniques and architectures, address vulnerabilities, and advocate for multi-component Pareto optimization for optimal solutions.
[41]	2023	Distributed edge learning (EL) techniques and their integration with advanced communication optimization designs for B5G wireless networks are explored. The main focus is to present the open problems and emerging application opportunities for the B5G network.
This work		We discuss the use of AI in NTNs for 6G communication networks. The main focus of the survey is: 1. NTNs role in 6G networks and unique security/privacy concerns. 2. Applicable AI approaches for NTN problems and proper technique selection. 3. AI-enabled NTN research avenues and superiority over traditional methods. 4. AI-based NTN resource allocation case studies and research. 5. Future open issues in AI for NTNs, considering constraints for its maximum potential.

3) We provide a holistic overview of AI-enabled NTN research and a motivating argument for their implementation. We explore the challenges of NTNs, outline the issue associated with traditional methods, and provide ideas for the superiority of AI techniques.
4) We summarize relevant case studies and existing research used to solve the resource allocation problem associated with AI in NTNs.
5) We summarize the main challenges and opportunities of using AI for NTNs. In addition, we provide a set of recommendations for future research directions in this area. We also identify potential AI applications in areas such as network optimization and resource allocation.

B. PAPER ORGANIZATION

This paper is organized as follows. Section II provides an overview of NTN and its potential role in 6G networks. Different security and privacy concerns of NTNs are discussed in Section III. In Section IV, we introduce an overview of AI techniques that can be used to optimize the performance of NTNs. Section V discusses the recent research in AI-powered NTN for 6G networks. Section VI identifies the key research directions and challenges in this field, and Section VII concludes the paper. The structure of the paper is shown in Fig. 1.

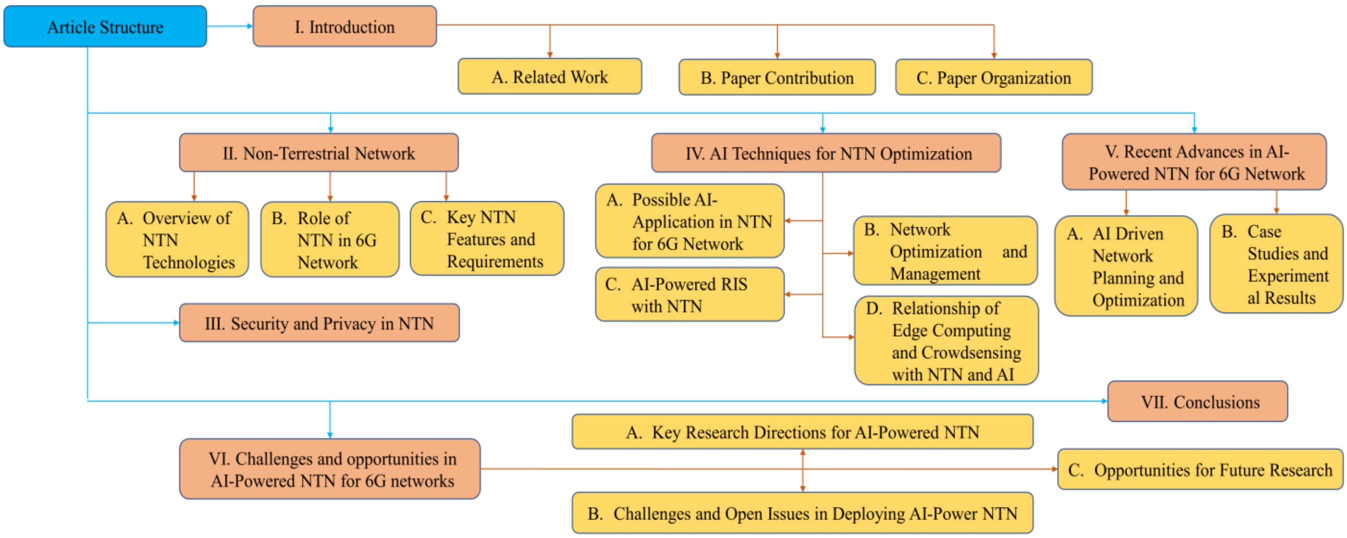

Figure 1. Article Structure

To facilitate the readability of this paper, Table 2 provides the list of abbreviations with the terms associated.

II. NON-TERRESTRIAL NETWORKS

NTNs have emerged as a promising solution for extending coverage and improving connectivity in 6G networks. NTNs are a class of wireless networks that operate using non-earth-based platforms to provide connectivity [3],[10],[11]. Unlike terrestrial networks, NTNs can cover large areas, operate independently of terrestrial infrastructure, and be quickly deployed in areas without adequate terrestrial infrastructure [8].

A. OVERVIEW OF NTNs TECHNOLOGIES

I. Low Earth Orbit (LEO) Satellites: LEO satellites are satellites that orbit the Earth at altitudes between 200 and 2000 kilometers. They have emerged as a promising platform for providing connectivity to remote and rural areas. Recent developments in satellite technology have reduced the cost of launching and operating LEO satellites, making it a viable option for commercial use. Some specific technologies for LEO include the International Space Station (ISS), the Hubble Space Telescope, and the Global Positioning System (GPS) [42]-[43].

II. Medium Earth Orbit (MEO) Satellites: MEO satellites are positioned in orbits between approximately 2,000 and 35,786 kilometers above the Earth's surface. They offer a compromise between the coverage area and the signal delay. MEO satellites are commonly used for navigation and communication purposes. MEO allows longer communication windows than LEO satellites, resulting in reduced handovers and a more stable connection for users. MEO is often used for global navigation satellite systems (GNSS) like GPS, GLONASS, and Galileo, as well as for remote sensing and communication purposes.

III. Geostationary Orbit (GEO) Satellites: GEO satellites are positioned at approximately 35,786 kilometers above the equator. These satellites have an orbital period that matches the Earth's rotation, allowing them to remain fixed relative to a specific point on the Earth's surface. This characteristic makes them ideal for applications that require continuous coverage of a specific geographic area, such as television broadcasting and weather monitoring.

IV. High Altitude Platform Stations (HAPS): HAPS are unmanned platforms that operate in the stratosphere at altitudes between 17 to 22 kilometers. They have the potential to provide connectivity to areas that are difficult to access or where terrestrial infrastructure is not feasible. HAPS can be used for a range of applications, including communication, surveillance, and environmental monitoring. HAPS includes balloons and airships. Some specific examples might include Google's Project Loon, Facebook's Aquila, and the Stratobus airship [44]-[45].

V. Unmanned Aircraft Systems (UASs): UASs operate without a pilot. UASs can be quickly deployed to provide connectivity in areas affected by natural disasters or emergencies. They can be used for a variety of applications, including communication, surveillance, and delivery. Some specific examples that use the UASs are DJI Mavic, the Parrot Bebop 2, and Lockheed Martin Indago3 [46],[47],[48],[49].

B. ROLE OF NTNs IN 6G NETWORKS

6G wireless communications networks will require a variety of new technologies to meet the high data rate, low latency, and mobility requirements of the future network. One possible solution is using NTNs that offer a viable option to provide these services cost-effectively and efficiently. They

Table 2. List of Abbreviations

Abbreviation	Definition
3GPP	3rd generation partnership project
5G	Fifth generation
6G	Sixth generation
AI	Artificial intelligence
AP	Access point
B5G	Beyond fifth generation
BSs	Base stations
CNN	Convolutional neural networks
DBN	Deep belief network
DL	Deep learning
DRL	Deep *reinforcement learning*
EL	Edge learning
FL	Federated learning
GA	Genetic algorithms
GPS	Global positioning system
HAPs	High-altitude platforms
IDS	Intrusion detection systems
IoT	Internet of things
IPS	Intrusion prevention system
ISS	International space station
LEO	Low earth orbit
MARL	Multi-agent reinforcement learning
MIMO	Multiple input multiple output
mMIMO	Massive multiple input multiple output
ML	Machine learning
NFV	Network function virtualization
NTNs	Non-terrestrial networks
ORAN	Open radio access network
PCA	Principal component analysis
QoS	Quality of service
RA	Resource allocation
RAN	Radio access network
RIS	Reconfigurable intelligent surfaces
RL	Reinforcement learning
SDN	Software-defined networks
SL	Supervised learning
SVMs	Support vector machines
UASs	Unmanned aircraft systems
UAV	Unmanned aerial vehicle
UL	Unsupervised learning
VLC	Visible light communication
VNFs	Virtual network functions

are expected to play a vital role in enabling the full potential of 6G networks.

The terrestrial network infrastructure, including 5G networks, has limitations in terms of coverage (e.g., remote/rural areas, sea/air, etc.). One of the key roles of NTNs in 6G networks is to complement the terrestrial network infrastructure and overcome its limitations. NTNs can provide broader coverage, higher capacity, and mobility support in areas where terrestrial networks are unavailable or impractical. Moreover, NTNs can also serve as a backup or redundant network in case of network failures or disasters, ensuring high reliability and availability of communication services.

To date, several research efforts have been undertaken to explore the potential of NTNs for 6G networks. For instance, the integration of LEO satellites into 6G communications networks has been studied extensively, with a focus on optimizing the satellite constellation design, routing algorithms, and interference management techniques [50].

Similarly, the use of HAPs in 6G networks has been investigated, focusing on developing efficient communication protocols, beamforming techniques, and energy-efficient power management schemes [51]. The use of UASs in 6G networks has also been explored, with a focus on developing aerial base stations and efficient trajectory planning algorithms [52].

Overall, the role of NTNs in 6G networks is crucial for providing ubiquitous, reliable, and high-capacity wireless communication services. The unique characteristics of NTNs, such as high altitude, 3D mobility support, and broad coverage, make them a promising solution for meeting the requirements of future wireless networks. Ongoing research efforts are expected to further improve the performance and efficiency of NTNs in 6G networks and pave the way for the realization of the full potential of these networks.

C. KEY NTNs FEATURES AND REQUIREMENTS

NTNs are critical for ensuring their success in 6G communication systems. NTNs architecture must be designed to address key challenges such as 3D mobility link reliability, latency, energy efficiency, and capacity. The NTNs system must be able to support a large number of devices with high data rates and low latency while also being scalable, flexible, and cost-effective.

One key feature of NTNs is the use of advanced antenna technologies, such as beamforming, which can enhance signal strength and reduce interference. Other key features include the use of multi-frequency bands, efficient power management techniques, and advanced modulation schemes. NTNs must have strong authentication, encryption, and access control mechanisms to ensure security and privacy.

NTN requirements for 6G communication systems include their ability to provide ubiquitous connectivity, reliability, and high data rates with low latency. The system must support seamless integration with terrestrial networks and enable global coverage with minimal delay. Additionally, NTNs must be designed to meet the specific needs of various applications, such as the Internet of Things (IoT), smart cities, and connected vehicles. It must be able to support high-altitude platforms, LEO satellites, and geostationary orbit satellites. The system should also be resilient to natural disasters and cyber-attacks.

Fig. 2 summarizes the key features and requirements of NTNs for 6G communication systems.

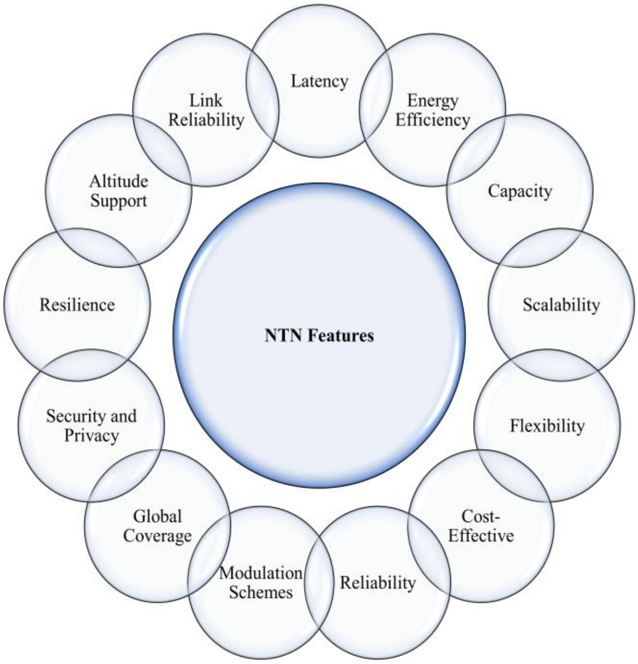

Figure 2. Basic Features of NTN

III. SECURITY AND PRIVACY IN NTN

Security and privacy are critical considerations in designing and implementing NTNs for 6G. The increasing reliance on advanced technologies in the telecommunications industry means that network security threats are becoming more sophisticated and complex. As the next generation of wireless networks, 6G networks are expected to bring a revolutionary transformation to the world of communication. In the context of 6G, security and privacy concerns are magnified due to the large-scale deployment of networked devices and the increasing complexity of network architectures. These concerns include data leakage, identity theft, and unauthorized access to sensitive information. Developing secure and privacy-preserving technologies is essential to ensure the secure operation of 6G networks. The following is a list of security and privacy concerns for the NTNs in 6G networks.

Authentication and Authorization: Authentication and authorization refer to verifying the identity of devices or users and determining their level of access privileges within the network. These mechanisms are crucial for ensuring the security and privacy of the network, as they prevent unauthorized devices or malicious actors from gaining access and potentially causing harm.

Advanced technologies and protocols will be required to achieve strong authentication in 6G networks. One potential approach is biometric authentication, which relies on individuals' unique physical or behavioral traits, such as fingerprints or facial recognition. These biometric characteristics can serve as strong authentication factors, making it difficult for unauthorized entities to impersonate legitimate users [53].

Another important aspect of authentication and authorization in 6G networks is the regular updating of policies. As security threats evolve over time, it is crucial to keep authentication and authorization policies up to date to address new vulnerabilities and prevent potential security breaches. Regular updates help ensure that the network remains secure against emerging threats and that any new authentication methods or standards are implemented effectively [54].

Privacy and Confidentiality: Privacy and confidentiality are crucial considerations for the 6G network due to the vast amount of data generated and the increased use of AI-powered devices. With the proliferation of IoT devices and the integration of AI technologies, 6G networks are expected to handle a massive volume of data, including personal, sensitive, and confidential information.

One of the main challenges for privacy and confidentiality in 6G networks is ensuring that this data is protected from unauthorized access as it traverses across various network segments. Data transmitted over the network may pass through multiple nodes, edge computing systems, and cloud infrastructures, increasing the risk of interception or unauthorized access at any point in the network. Therefore, robust security measures must be implemented to safeguard data privacy and maintain confidentiality [55].

Network Congestion: The 6G network’s high-speed capabilities can cause network congestion, leading to a higher risk of network attacks. With more devices connected to the network, the chances of network congestion increase, creating a larger attack surface [56].

Malware and Hacking: As 6G networks become more complex, the risk of malware and hacking increases, putting the security and privacy of the network at risk. It is essential to have robust, secure technologies in place, such as encryption, authentication, and firewalls, to protect the network. Additionally, users should follow best practices for online security, such as using strong passwords and being aware of potential phishing scams [36].

Resource Allocation: 6G technology is expected to have enhanced security features to ensure data is protected from unauthorized access. Additionally, the network must be able to allocate resources to meet users' demands efficiently. Finally, the network must be able to adapt to changing user needs and respond quickly to changing conditions [57].

Fault Tolerance: Identifying and mitigating faults in the network is essential for maintaining the network’s security and privacy. This is done by detecting errors, isolating them, and recovering from them without impacting the system. Fault tolerance is a key element in network security and helps prevent unauthorized access or misuse of the network. It also helps to protect against data loss [58].

Trust Management: Trust management is vital to the 6G network security, enabling secure interactions and collaborations between different devices, services, and users.

As 6G networks become more complex, with a diverse range of devices, services, and stakeholders, managing trust becomes increasingly challenging. Trust-related attacks, such as malicious entities masquerading as trusted devices or services, pose a significant risk. These attacks can lead to unauthorized access, data breaches, or disruptions in network operations.

To address the trust management challenges in 6G networks, several approaches can be considered. One such approach is the use of trust models and frameworks that assess and quantify the trustworthiness of devices, services, or entities based on their behavior, reputation, or credentials. These models can help establish a trust hierarchy and determine the level of trustworthiness associated with different entities within the network.

Additionally, secure authentication protocols, such as public key infrastructure or certificate-based authentication, can be employed to verify the identities of devices or entities and ensure that only trusted entities are granted access to the network [59].

AI can play a crucial role in mitigating these security and privacy concerns. AI can be leveraged to provide enhanced security and privacy features that go beyond traditional security measures. The following are some of the ways AI can help resolve these concerns.

Threat Detection and Prevention: Threat detection and prevention play a crucial role in ensuring network security. As the complexity of the 6G network increases; therefore, advanced mechanisms are required to detect and mitigate potential threats in real-time.

AI can be a powerful threat detection and prevention tool in 6G networks. AI algorithms can analyze large volumes of network data and identify patterns or anomalies that indicate potential security threats. By leveraging machine learning techniques, AI systems can continuously learn and adapt to new attack vectors and evolving threats, effectively detecting known and unknown threats.

Anomaly Detection: AI can be used to identify and flag unusual behavior on the network, which may be an indicator of a potential security breach.

Predictive Analysis: Predictive analysis uses AI techniques to forecast potential security threats and take proactive measures to prevent them before they materialize. AI-powered predictive analysis can identify indicators that may lead to future security incidents or attacks by analyzing historical data, network patterns, and security trends.

Using ML algorithms, predictive analysis models can learn from historical data to recognize patterns and correlations associated with security threats. These models can then analyze real-time data and identify early warning signs or anomalies that could indicate an imminent security breach.

The proactive measures taken based on predictive analysis can include strengthening network defenses, implementing additional security controls, or raising alerts to security teams to investigate potential vulnerabilities or suspicious activities. Organizations can significantly reduce the risk of successful attacks and mitigate potential damage by acting preemptively.

Identity Management: AI can manage identities and access control more effectively, ensuring that only authorized devices and users can access the network resources. AI can facilitate advanced authentication mechanisms such as biometric recognition, behavior analysis, and contextual information to verify the identity of users and devices accurately. By leveraging AI-driven identity management solutions, 6G networks can enhance security, prevent unauthorized access, and mitigate privacy risks.

Encryption: AI can contribute to enhancing encryption techniques by improving encryption algorithms, key management, and overall cryptographic processes. Leveraging AI algorithms can strengthen encryption mechanisms to withstand increasingly sophisticated attacks and cryptographic vulnerabilities. AI can assist in developing more robust encryption algorithms, optimizing key generation and distribution, and detecting potential weaknesses or patterns that attackers may exploit. This helps create a more secure data transmission and storage environment in 6G networks [60].

Behavioral Analysis: AI algorithms can analyze user and device behavior patterns, allowing the network to detect and prevent abnormal activities that could signify a potential security threat. By continuously monitoring behavior in real-time, AI-based systems can identify suspicious actions, such as unauthorized access attempts, unusual data transfers, or anomalous user behaviors. This proactive approach enables the network to respond swiftly and mitigate potential threats before they can cause harm [17].

In summary, the 6G network's security and privacy concerns are significant and must be adequately addressed to ensure the network's safety and secure operation. AI can provide enhanced security and privacy features, enabling the network to mitigate these concerns.

IV. AI TECHNIQUES FOR NTNs OPTIMIZATION

The optimization process plays an important role in improving the performance and efficiency of wireless networks deployed in non-terrestrial environments such as satellites, drones, and balloons. Optimization can be used to identify the best settings for the network, such as the power level, frequency, and type of antenna, as well as the optimal placement of devices. This can lead to improved coverage, increased bandwidth, and reduced latency. Additionally, optimization can save energy by reducing the amount of power required to operate the network.

Numerous approaches were defined for NTN optimization. These traditional methods are based on mathematical models and simulations that use prior knowledge of the network parameters and environment to make predictions and decisions. For example, network planning involves designing the network architecture, coverage area, and capacity based on the expected traffic and user requirements [61]. Link budget analysis involves calculating the power budget and signal-to-noise ratio for each link in the network to ensure reliable and high-quality communication [62]. Antenna design involves selecting the antenna's type, size, and orientation based on the frequency, gain, and radiation pattern [63]-[64]. Signal processing involves filtering, equalizing, and modulating the signal to optimize transmission and reception [65].

These traditional approaches have been used for a long time, but they have some limitations when it comes to NTN optimization. First, they require prior knowledge of the network parameters and environment, which may not be accurate or up-to-date, especially in dynamic and uncertain environments. Second, they are not adaptive enough to handle the changing conditions and demands of the network, as they rely on fixed and predefined models and rules. Third, they may not be able to handle the heterogeneity and complexity of the network, as they assume a uniform and idealized network topology and behavior. Therefore, exploring new approaches based on AI techniques can overcome these limitations and provide more accurate and adaptive solutions for NTN optimization [66]. These AI techniques can learn from the data and adapt to changing environments. The AI techniques can be broadly classified into three categories: supervised learning (SL) [67], unsupervised learning (UL) [68], and RL [69]. The basic architecture of AI can be shown in Fig. 3.

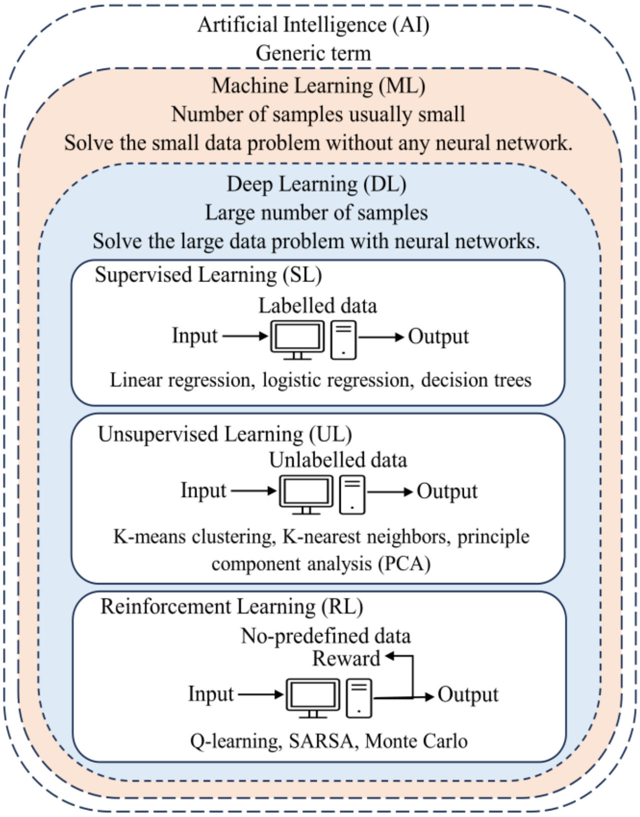

Figure 3. Artificial Intelligence Architecture

SL involves training a model using labelled data, where the input-output pairs are known in advance. The model can then be used to make predictions on new inputs. In NTN optimization, SL can be used for various tasks, such as channel estimation [70], interference mitigation [71], and resource allocation [72]. For example, a deep neural network (DNN) can be trained to predict the best channel and power allocation for a given set of users and resources. The advantage of supervised learning is that it can produce accurate results with high precision. SL requires labelled data, where the input-output pairs are known in advance. However, in NTN optimization, it may be difficult to obtain labelled data, as the network operates in dynamic and uncertain conditions, and the ground truth may not be available. In addition, the labelled data may not be representative of the entire network, leading to biased or inaccurate models. SL is shown in Fig. 4.

UL involves training a model using unlabeled data, where the input-output pairs are not known in advance. The model can then discover patterns and structures in the data and group them into clusters or categories. In NTN optimization, unsupervised learning can be used for various tasks, such as anomaly detection [73], network clustering [74], and traffic analysis [75]. For example, a self-organizing map can be used to cluster the satellites or drones based on their location and connectivity [76]. The advantage of unsupervised learning is that it can find hidden patterns in data that may not be easily visible. Unsupervised learning does not require labelled data, but it relies on the assumption that the data has some inherent structure or pattern that can be discovered. However, in NTN optimization, the network may be too complex or heterogeneous, and the data may not have clear patterns or clusters that can be easily identified. In addition, unsupervised learning may suffer from the problem of overfitting, where the model memorizes the data instead of learning the underlying structure. The basic structure of UL is seen in Fig. 5.

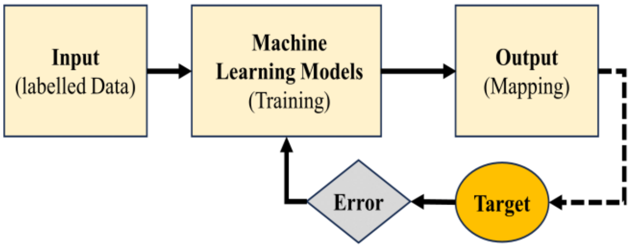

Figure 4. Supervised Learning

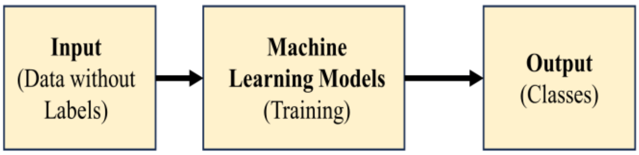

Figure 5. Unsupervised Learning

RL involves training an agent to interact with an environment and learn an optimal policy to maximize a cumulative reward [77]. In NTN optimization, RL can be used for various tasks, such as beamforming, routing, and scheduling. For example, a Q-learning algorithm can be used to find the optimal beamforming angles and power levels for a given set of antennas and users [78].

One of the advantages of RL is that it can handle dynamic environments with large state and action spaces. However, it is important to note that RL is typically used for discrete state and action spaces and is not well-suited for problems with continuous state and action spaces. Additionally, while

RL can handle dynamic environments but may struggle with large and complex ones. Overall, while RL has shown promising results in a range of domains, it is crucial to consider its applicability to the specific problem. In the context of NTN optimization, RL can be a powerful tool, but it may not always be the best choice depending on the complexity and nature of the problem. A basic representation of RL is shown in Fig. 6.

DRL is an extension of RL that has been shown to be more effective in handling complex and high-dimensional problems. In RL, the policy and value functions are represented using simple linear or nonlinear models, whereas, in DRL, deep neural networks are used to represent these functions. This allows the DRL models to learn more complex and abstract representations of the state and action spaces, which can result in better performance and more efficient exploration of the environment.

DRL has been able to achieve state-of-the-art performance in various domains, such as robotics, games, wireless communication, and natural language processing. These successes have motivated researchers to explore the use of DRL for NTN optimization, where the state and action spaces are often high-dimensional and continuous. By using DRL, it is possible to learn an optimal policy for resource allocation [79], [80], [81],[82], routing [83], and scheduling [84] that operate in dynamic and uncertain conditions in NTN.

Another advantage of DRL is that it can handle the heterogeneity and complexity of the network, which is difficult to model using traditional approaches. For example, in a satellite network, the number and position of the satellites may change over time, the users may move in different directions, and the signal quality may vary depending on the atmospheric conditions. DRL can adapt to these changes by continuously updating the policy and value functions based on the new observations, which can result in more robust and efficient operations.

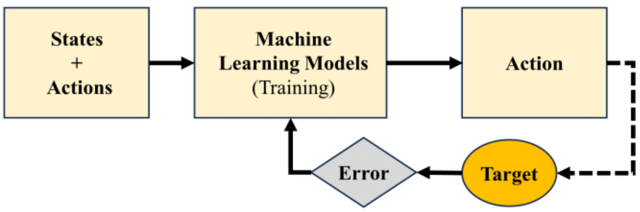

Figure 6. Reinforcement Learning

As summarized in Table 3. SL can address some issues of NTN optimization, such as anomaly detection, channel estimation, interference mitigation, and resource allocation. UL can address issues like network clustering and traffic analysis. However, neither of them can address the dynamic and uncertain environment of NTN optimization, which is a critical factor for NTNs.

DRL, on the other hand, can address all of the above issues, as it can learn the optimal policy for complex and dynamic environments where the state and action spaces are high-dimensional and continuous. DRL can be used for beamforming, routing, and scheduling tasks requiring real-time decision-making and optimization. Therefore, RL, especially DRL, is preferred for NTN optimization in 6G networks, where the goal is to provide reliable and high-speed connectivity to remote and underserved areas.

A. POSSIBLE APPLICATIONS OF AI IN NTNs

AI has the potential to revolutionize NTN optimization in 6G networks by enabling faster and more efficient communication. There are several possible applications of AI in NTNs for 6G adoption, including Terahertz Communications, Optical Wireless Communication, Remote Sensing, and Industrial Internet of Things (IIoT).

One possible application is satellite communication. AI can be used to optimize communication between satellites, ground stations, and users. It can also help reduce latency and interference, thereby improving the system's overall performance. For instance, AI can be used to optimize the scheduling and routing of satellite links and predict and mitigate the effects of atmospheric attenuation and weather conditions.

Another application is drone-based connectivity. AI can be used to optimize the coverage and capacity of drone-based networks, which can be used for various applications, such as search and rescue, environmental monitoring, and precision agriculture. For example, AI can be used to

Table 3. Dynamics of SL, UL and RL

Issues	SL	UL	RL
Dynamic and uncertain environment	x	x	✓
Heterogeneity and complexity of the network	x	✓	✓
High-dimensional and continuous state and action spaces	x	x	✓
Anomaly detection	✓	✓	x
Channel estimation	✓	x	x
Interference mitigation	✓	x	x
Resource allocation	✓	x	x
Network clustering	x	✓	x
Traffic analysis	x	✓	x
Beamforming	x	x	✓
Routing	x	x	✓
Scheduling	x	x	✓

optimize the trajectory and positioning of drones and manage the handover between drones and ground stations.

AI can also be used to optimize the altitude, trajectory, and communication of balloon-based networks. AI can help optimize the positioning and deployment of balloons and predict and mitigate the effects of atmospheric conditions and other environmental factors.

Finally, AI can be used to optimize energy consumption, data processing, and transmission of IoT and remote sensing devices. This can be particularly important in limited energy applications, such as remote and off-grid locations. AI can be used to optimize the routing and processing of data and predict and mitigate the effects of interference and other environmental factors.

Table 4 summarizes the possible applications of AI in NTNs for 6G networks.

B. AI-POWERED NETWORK OPTIMIZATION AND MANAGEMENT

AI-powered network optimization and management involves the application of AI techniques to improve the performance, efficiency, and reliability of 6G communication networks. These techniques include ML, DL, and RL, which can be used to learn from network data, predict network behavior, and make automated decisions.

One of the key benefits of AI-powered network optimization is its ability to handle the complexity and heterogeneity of modern communication networks. With the rise of 5G and the advent of 6G, networks are becoming more diverse and dynamic, with a wide range of devices, protocols, and services. AI can help manage this complexity by providing automated monitoring, analysis, and optimization tools.

There are several areas in which AI-powered network optimization can be applied. One of these is network planning and design, where AI can be used to optimize the placement and configuration of network elements such as antennas, base stations, and routers. This can help to improve coverage, capacity, and QoS while minimizing costs and energy consumption.

Table 4. AI Possible NTN Applications

Application	Description
Satellite communication	Optimize communication between satellites, ground stations, and users; reduce latency and interference; optimize scheduling and routing of satellite links.
Drone-based connectivity	Optimize coverage and capacity of drone-based networks; manage handover between drones and ground stations; enable search and rescue, environmental monitoring, and precision agriculture.
Balloon-based networks	Optimize altitude, trajectory, and communication of balloon-based networks; provide connectivity to remote and underserved areas; predict and mitigate effects of atmospheric conditions and environmental factors.
IoT and remote sensing	Optimize energy consumption, data processing, and transmission of IoT and remote sensing devices; optimize data routing and processing; predict and mitigate effects of interference and environmental factors.

Another area is resource allocation, where AI can optimize network resource allocation, such as bandwidth, power, and spectrum. This can help to improve network efficiency and capacity while minimizing interference and congestion.

AI can also be used for fault detection and diagnosis, automatically identifying and diagnosing network faults and anomalies and providing recommendations for remedial action. This can help to reduce downtime and improve network availability and reliability.

Finally, AI can be used for network security, automatically detecting and preventing security threats such as intrusion, malware, and denial-of-service attacks. This can help to protect network assets and data and maintain user privacy and trust.

In summary, AI-powered network optimization and management have the potential to transform the way we design, operate, and maintain communication networks. By providing automated monitoring, analysis, and decision-making tools, AI can help improve network performance, efficiency, and reliability and enable new applications and services.

C. AI-POWERED RECONFIGURABLE INTELLIGENT SURFACE WITH NTNs

Reconfigurable intelligent surface (RIS) is a new technology that can manipulate electromagnetic waves by dynamically changing their surface properties [85]. They consist of a planar array of small, passive, and tunable elements that can manipulate electromagnetic waves to improve the performance of wireless networks. RIS technology can enhance wireless networks' coverage, capacity, and QoS by adjusting the phase, amplitude, and direction of electromagnetic waves.

RIS can be used to optimize the signal strength and quality of NTN, improving its coverage and capacity. When RIS technology is combined with NTNs, the resulting system can improve wireless communication performance even more. This performance improvement is especially beneficial in areas with poor network coverage. RIS is also more cost-effective than other methods of improving NTN signal strength, making it a great solution for both small and large networks [86]. Recent research has shown that integrating AI with RIS technology can improve the performance and reliability of NTNs, such as those used for satellite communications, deep-space exploration, and interplanetary networks. These networks face unique challenges, such as limited bandwidth, high latency, and harsh environmental conditions that can impede data transmission and connectivity [87]-[88].

AI-powered RIS can help to overcome some of these challenges by optimizing the wireless channel in real-time. By leveraging AI algorithms, RIS can adapt to changing network conditions and dynamically adjust its configuration to improve signal quality, increase network capacity, and reduce interference [89]-[90]. For example, AI-powered RIS can intelligently direct signals to avoid obstacles and optimize coverage, which can be especially useful in deep-space communications where distance can severely attenuate signal strength [91]. Moreover, AI-powered RIS can enable more efficient use of the available spectrum, which is an important resource in NTNs [92]. By intelligently managing signal strength and direction, RIS can increase the capacity of the existing spectrum, reduce the risk of interference, and enable more reliable data transmission.

One of the key benefits of AI-powered RIS is its ability to create a more dynamic and adaptive wireless environment. By constantly analyzing and adjusting the wireless channel, RIS can ensure that the network remains resilient and reliable, even in the face of equipment failure or environmental disturbances. Additionally, RIS can be used to create more secure and resilient NTNs by controlling and manipulating the propagation of radio waves to prevent unauthorized access and mitigate the risk of cyber-attacks [93]. AI-powered RIS also has the potential to revolutionize the field of space exploration. By enabling more advanced and sophisticated communications systems, RIS can improve the accuracy and reliability of spacecraft navigation systems, enabling more precise targeting and maneuvering. Furthermore, RIS can create more efficient and robust data transmission systems for deep-space exploration, enabling more rapid and reliable transmission of scientific data and images [94].

Although the integration of AI and RIS technology has great promise for enhancing the performance and reliability of NTNs for future advancements in space exploration, satellite communications, and interplanetary networks, however, the technical challenges still need to be addressed; ongoing research and development in this field suggests that AI-powered RIS will play an increasingly important role in shaping the future of wireless technology in non-terrestrial environments.

D. RELATIONSHIP OF EDGE COMPUTING AND CROWDSENSING WITH NTN AND AI

With its decentralized approach, edge computing revolutionizes data processing and analysis by bringing computational power closer to the edge of the network. This proximity to data sources enables real-time insights and analysis, minimizing latency and bandwidth usage and making it ideal for time-sensitive applications. By leveraging a network of devices such as edge servers, gateways, and edge sensors, edge computing infrastructure collaboratively processes and filters data at the edge, enhancing efficiency and scalability [95].

Crowdsensing, a collective sensing paradigm, taps into the power of connected individuals and their mobile devices to gather data about the environment [96]. Through mobile apps or wearable devices, individuals contribute data on various aspects like traffic conditions, air quality, noise levels, and social behaviors. This distributed data collection approach provides extensive coverage and delivers real-time insights into the physical world, empowering communities with a deeper understanding of their surroundings. The relationship between edge computing, crowdsensing, NTN, and AI is pivotal in advancing the capabilities of modern systems. In [97], a Stackelberg game-based computation offloading method can be integrated into edge computing and crowdsensing systems to optimize data processing at the network edge. Building upon this, the [98] proposes a Stackelberg game approach with the assistance of UAVs, enhancing the offloading process in mobile edge computing networks. The proposed approaches optimize RA and enhance system performance by leveraging the insights gained from crowdsensing data and utilizing AI techniques, such as ML. Furthermore, [99] focuses on cost-minimization-oriented computation offloading and service caching, employing an advanced ML-based approach. Integrating such methodology with edge computing, crowdsensing, and NTN enables efficient resource management, reduced operational costs, and intelligent decision-making based on data collected from NTN-enabled devices and sensors. Collectively, [97]-[99] contribute to integrating edge computing, crowdsensing, NTN, and AI, fostering advancements in various domains, including smart cities, industrial IoT, and remote sensing applications.

When edge computing, crowdsensing, NTNs, and AI come together, the possibilities for transformative applications across domains become endless. In the realm of smart cities, this integration enables edge devices connected through NTNs to monitor traffic flow, analyze real-time air quality data, and optimize energy consumption based on demand and availability. Advanced AI algorithms identify congestion hotspots, predict air pollution levels, and recommend efficient routes or dynamically adjust energy usage, fostering sustainable urban environments.

Furthermore, this integration profoundly impacts public safety and emergency response. In the event of natural disasters or emergencies, the combination of edge computing and crowdsensing allows for rapid data collection and analysis. By harnessing data from mobile devices, sensors, and surveillance systems, AI algorithms can detect critical situations in real-time, such as identifying earthquake-prone areas or predicting the spread of wildfires. This timely information enables emergency responders to allocate resources effectively, coordinate evacuation plans, and save lives. The healthcare sector benefits tremendously from this synergy. Crowdsensing facilitates remote patient monitoring, collecting vital signs, medication adherence, and activity levels through wearable devices. Edge computing and AI process this data in real-time, enabling healthcare providers to monitor patients' health conditions, detect anomalies, and intervene promptly. Moreover, AI-powered algorithms analyze population-level health data to identify patterns, predict disease outbreaks, and allocate resources efficiently during public health emergencies, ultimately saving lives.

The symbiotic relationship between edge computing, crowdsensing, NTNs, and AI also extends to agriculture, where edge devices combined with NTNs monitor soil moisture levels, temperature, and crop health. AI algorithms analyze this data to optimize irrigation, predict crop yields, and identify disease or pest outbreaks, empowering farmers to make informed decisions, increase productivity, and reduce resource waste.

Edge computing enables real-time equipment performance and predictive maintenance monitoring in industrial settings, ensuring optimal productivity and minimizing downtime. Coupled with crowdsensing and AI, this convergence enhances worker safety by detecting hazards in real-time and providing immediate alerts, mitigating accidents, and improving overall workplace security.

However, as these technologies advance, addressing important considerations such as data privacy and security is crucial. Robust security measures must be implemented to protect sensitive information as data is collected and processed at the edge. Additionally, establishing data governance frameworks and ethical guidelines is imperative to ensure the responsible and transparent use of data, building trust, and fostering the long-term sustainability of these technologies.

In summary, the relationship between edge computing, crowdsensing, NTNs, and AI represents a powerful force that has the potential to revolutionize various industries and significantly improve the quality of life. By bringing computational power closer to the source of data generation, leveraging the crowd's collective intelligence, extending connectivity beyond traditional networks, and harnessing the analytical capabilities of AI, this integration unlocks unprecedented opportunities for real-time insights, intelligent decision-making, and enhanced efficiency. As these technologies continue to advance and intertwine, their intricate synergy will shape the future of connectivity, data analytics and redefine the way we interact with the digital world, paving the way for a smarter, more sustainable future. This transformative potential is not only limited to large-scale industries but also has the ability to empower individuals and local communities, democratizing access to information and fostering innovation at every level.

V. RECENT ADVANCES IN AI-POWER NTN FOR 6G NETWORK

In recent years, significant progress has been made in developing AI-powered NTNs. The use of AI in NTNs provides numerous benefits, such as intelligent network management, automatic network optimization, and predictive maintenance. In the past few years, researchers have explored various AI-based approaches, such as DL, RL, and DRL to improve network performance [66],[100]. These approaches have been used for various applications such as intelligent network slicing, load balancing, and resource allocation, enabling the network to operate optimally in dynamic and unpredictable environments.

The integration of AI into NTNs has also led to the development of new and innovative network architectures that can efficiently handle the vast amounts of data generated by 6G networks. One such architecture is the AI-powered Open Radio Access Network (ORAN) [101], which utilizes AI to optimize network coverage and capacity and minimize interference and latency. The AI-powered ORAN also allows for dynamic network configuration, enabling the network to adapt to changing network conditions in real-time. Furthermore, researchers have also explored the use of AI for network security and privacy in 6G networks. AI-based security solutions such as Intrusion Detection Systems (IDS) and Intrusion Prevention Systems (IPS) can identify and prevent security threats in real-time, improving the network's overall security [102]. AI-powered privacy solutions such as differential privacy can also protect user data while enabling network operators to collect valuable data for network optimization and management. In addition, AI is being used to address energy efficiency challenges in 6G networks [66]. With the increasing demand for high-speed connectivity, the energy consumption of 6G networks is expected to increase significantly. However, AI-based approaches such as energy-efficient resource allocation, dynamic sleep mode management, and intelligent power control can help to reduce energy consumption and improve the overall energy efficiency of the network.

A. NETWORK PLANNING AND OPTIMIZATION

The use of AI algorithms in network planning and optimization offers numerous benefits, including efficient network management, automatic optimization, and intelligent decision-making. AI-driven network planning can help ensure optimal resource allocation, reduce the cost of network deployment, and enhance network performance. With the ability to analyze vast amounts of data from multiple sources, such as user behavior, network traffic, and resource utilization, AI can enable efficient network management and improve users' QoS.

ML algorithms, such as Support Vector Machines (SVMs) and Random forests, have been utilized to predict network traffic, optimize routing, and allocate resources effectively. SVMs can be used to classify network traffic based on various criteria, such as the source of the traffic, the type of data being transmitted, and the destination of the traffic. This enables service providers to allocate network resources more efficiently and reduce congestion. On the other hand, Random Forests can be used to predict network traffic based on historical data and network behavior, enabling service providers to allocate network resources more effectively.

DRL and Genetic Algorithm (GA) have also been applied to improve the network architecture and adapt to changing environmental conditions, enhancing the network's overall performance. DRL is an AI technique that involves training an agent to act in an environment to maximize a cumulative reward. This approach has been used to optimize network routing, enabling the network to adapt to changing traffic patterns and reduce latency. Conversely, GA has been used to optimize network parameters such as the number of BSs and the frequency allocation, enabling the network to operate optimally in dynamic and unpredictable environments.

AI can analyze data from multiple sources, such as user behavior, network traffic, and resource utilization to identify areas where network resources are being underutilized or overutilized. This can help service providers optimize their network architecture and allocate resources more efficiently, reducing the overall cost of network deployment. Furthermore, AI-driven network planning can ensure efficient resource allocation and reduce the cost of network deployment, thereby enabling service providers to deliver high-quality services while reducing operational costs.

The application of AI in network planning and optimization is expected to become more widespread with the advancement of technology and the increasing demand for high-speed and reliable connectivity in 6G networks. However, there are several challenges that must be addressed to ensure the effective implementation of AI in network planning and optimization. These challenges include the need for standardized data formats, the integration of AI algorithms with existing network infrastructure, and the development of ethical guidelines for the use of AI in network management.

In summary, AI-driven network planning and optimization have emerged as critical research areas in developing AI-powered NTNs for 6G networks. AI algorithms offer numerous benefits, such as efficient network management, automatic optimization, and intelligent decision-making. ML algorithms such as SVMs and Random Forests have been utilized to predict network traffic and allocate resources effectively, while DRL and GA have been applied to improve the network architecture and adapt to changing environmental conditions. AI-driven network planning can ensure efficient resource allocation and reduce the cost of network deployment, thereby enabling service providers to deliver high-quality services while reducing operational costs. However, there are several challenges that must be addressed to ensure the effective implementation of AI in network planning and optimization.

B. CASE STUDIES AND EXPERIMENTAL RESULTS

With the rapid development of 6G networks, AI-powered NTNs have emerged as a critical area of research to improve network management, optimization, and performance. Several recent case studies have been conducted to evaluate the effectiveness of AI-based approaches in 6G networks. One such study focused on using AI in network slicing, which allows network operators to partition the network into virtual slices with customized functionalities and resources. The study demonstrated that the use of AI-based approaches such as DL and CNNs could significantly improve network slicing performance, enabling better resource utilization and enhancing the QoS for end-users [103].

The authors in [110] propose a cooperative transmission scheme between a satellite and an aerial BS based on two unsupervised ML algorithms, namely K-means and K-medoids. The simulation results show that the proposed approach demonstrates promising gains in terms of spectral efficiency and system sum rate. In [111], the authors consider the issue of mobility management due to the movements of LEO satellites. They group user equipment in different clusters based on K-means clustering algorithm and decide handover process based on the distance from its cell center.

In [104], the authors focused on using RL to optimize network resource allocation in dynamic and unpredictable environments. The study proposed a new approach to resource allocation, which combined RL with the GA to enable the network to adapt to changing environmental conditions. The experimental results demonstrated that the proposed approach can significantly improve network performance by optimizing the allocation of resources to different network functions.

The work in [105] adopted similar MARL strategy for dynamic network slicing. However, the proposed approach accelerated the policy deployment by integrating a transfer learning method. The results showed that the proposed approach can achieve 27% better network performance and utilization compared to traditional approaches.

In [106], an AI-based approach for energy-efficient resource allocation in 6G networks is proposed. The proposed approach utilized a GA to optimize the allocation of network resources, considering each network function's energy consumption. The results demonstrated that the proposed approach can significantly reduce the network's energy consumption while maintaining the desired level of network performance.

Another study by [107] focused on using AI in network function virtualization (NFV) to improve network efficiency and resource utilization. The study proposed an AI-based approach for the placement of virtual network functions (VNFs) in the network, which utilized a DRL algorithm. The results showed that the proposed approach can significantly improve network performance and reduce the resource utilization of the network.

In a different study [108], the authors proposed an AI-based approach for network traffic prediction in 6G networks. The proposed approach utilized a two-dimensional CNN-based long short-term memory (LSTM) to predict network traffic, which can enable better resource allocation and network management. The experimental results showed that the proposed approach can achieve higher prediction accuracy compared to traditional approaches.

In [109], the authors focused on the use of AI in network function placement for edge computing in 6G networks. The study proposed an AI-based approach for the placement of network functions in the network, which utilized a Q-learning algorithm. The results showed that the proposed approach could significantly improve network performance. The above-explained case studies are summarized in Table 5.

VI. CHALLENGES AND OPPORTUNITIES IN AI-POWERED NTNs FOR 6G NETWORKS

The development of the 6G networks is rapidly advancing, and AI has emerged as a key technology in realizing the vision of intelligent and efficient 6G networks. AI-powered network management is expected to provide numerous benefits, including improved network performance, enhanced user experience, and reduced operational costs. However, achieving these benefits comes with significant challenges and requires overcoming various technical and practical obstacles. Therefore, this survey paper discusses the challenges and opportunities in AI-powered network management for 6G networks.

A. KEY RESEARCH DIRECTIONS FOR AI-POWERED NTNs

As AI technologies continue to evolve, they offer tremendous potential to revolutionize the way future 6G networks are designed, deployed, and managed. AI-powered NTNs is an emerging research area that aims to leverage AI techniques to enhance the performance and efficiency of 6G networks. However, realizing the full potential of AI-powered NTNs requires identifying key research directions that can overcome the challenges posed by the highly dynamic and complex nature of 6G networks. This section discusses some of the most promising research directions for AI-powered NTNs in 6G networks.

Table 5. Summary of AI Use Cases

AI	Related Work(s)	Relevance to NTNs
SL	[103] - LSTM [106] - CNN [108] - CNN-LSTM	Smart network slicing, node clustering or traffic prediction for increasing energy efficiency.
UL	[110] – K-means	Cooperative transmission between terrestrial networks and NTNs.
UL	[111] – K-means	Handover of user equipment between satellites and ground stations.
RL	[104] - DQN [105] - MADRL	Smart resource management for reducing multi-cell interference.
RL	[107] - DQN [109] - Soft Actor Critic	Computation offloading via coverage deployment or multi-access edge computing (MEC).

Multi-objective optimization for AI-powered NTNs: 6G networks are expected to support diverse applications with different quality-of-service requirements. Multi-objective optimization can help balance conflicting objectives, such as energy efficiency, spectral efficiency, and reliability, in AI-powered NTNs.

Intelligent network planning and deployment: AI-powered NTNs can leverage intelligent algorithms to automate the network planning and deployment process. This includes using ML to identify the optimal network topology, antenna placement, and resource allocation to minimize interference and maximize coverage.

AI-driven resource allocation and management: The use of AI can help to efficiently allocate and manage network resources, including frequency bands, power levels, and computing resources. This can improve network performance and reduce energy consumption.

Federated learning for distributed NTNs: Federated learning is an ML technique allowing devices to collaboratively learn a shared model without sharing data. This can be used to train AI models for NTNs in a privacy-preserving and energy-efficient manner.

Network slicing for AI-powered NTNs: Network slicing allows multiple logical networks to be created on top of a shared physical infrastructure. This can help to meet the diverse requirements of different applications in AI-powered NTNs, such as low latency, high bandwidth, and high reliability.

Edge intelligence for AI-powered NTNs: Edge computing can perform AI computations at the network edge, reducing latency and improving energy efficiency. This includes using edge devices, such as BSs and user equipment, to perform AI computations and make real-time decisions.

Explainable AI for NTNs: The development of explainable AI can enhance the transparency and interpretability of NTNs powered by AI. This includes developing algorithms that can explain how AI models make decisions and identify potential biases in the data.

AI-driven security for NTNs: The use of AI can help to improve the security of NTNs, including detecting and mitigating attacks, identifying vulnerabilities, and enhancing privacy and data protection.

AI for network optimization and self-healing: AI can be used to continuously monitor and optimize network performance and detect and repair faults automatically. This includes using AI to predict and prevent network failures, optimize routing and traffic flow, and manage network congestion.

AI for user experience and behavior analysis: AI can be used to analyze user behavior and preferences and predict and personalize services and content. This includes using AI to optimize user engagement, enhance content delivery, and improve overall user experience. The key research directions for AI-Powered NTNs are summarized in Fig. 7.

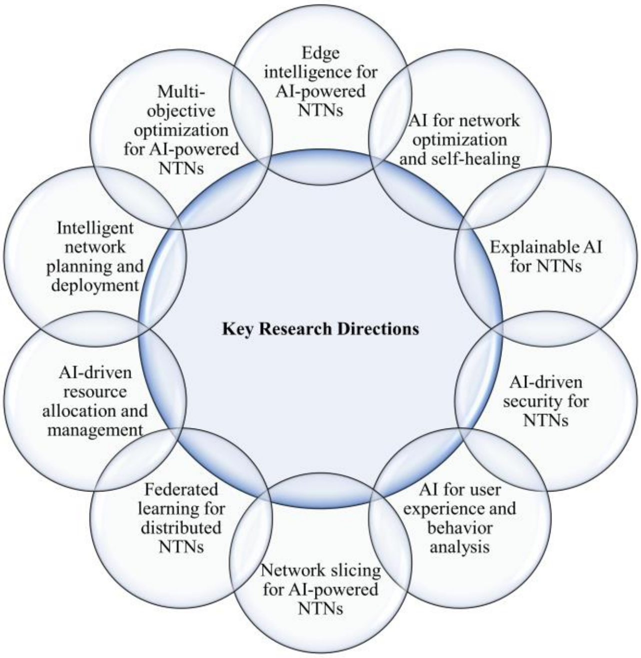

Figure 7. Key Research Directions

B. CHALLENGES AND OPEN ISSUES IN DEPLOYING AI-POWERED NTNs

While AI-powered NTNs have significant potential, there are also several challenges and open issues that must be addressed. These include but are not limited:

Data privacy and security: AI techniques require large amounts of data to train models, but ensuring data privacy and security is a significant concern. Organizations must ensure that sensitive data is protected and not accessible to unauthorized personnel. Additionally, organizations must be transparent about the data they are collecting, how it will be used, and who has access to it.

Trustworthiness: AI-powered networks must be trustworthy and reliable, with clear accountability mechanisms in place to ensure the network functions as intended. Organizations must ensure that AI-powered networks are transparent and explainable so that users can understand how the network is making decisions. Additionally, organizations must be transparent about the limitations of AI-powered networks so that users understand when the network may not be appropriate for specific use cases.

Integration and interoperability: AI-powered networks must be able to integrate and interoperate with existing networks and devices, including legacy systems. Organizations must ensure that AI-powered networks are designed to work with existing infrastructure and can operate within existing networks. Additionally, organizations must ensure that AI-powered networks can communicate with other devices and networks using standard protocols.

Human factors: AI-powered networks must consider the human factors involved in network management, including user behavior, network administrator skills, and organizational structures. Organizations must ensure that AI-powered networks are designed to meet the needs of the users and the organization. This requires understanding the skills and knowledge of the network administrators and users and the organizational structure and culture.

Resource limitations: AI-powered networks may require significant computational resources, which can be a challenge in resource-constrained environments. Organizations must ensure that AI-powered networks are designed to operate within the resource constraints of the environment. Additionally, organizations must consider AI-powered networks' power consumption and environmental impact.

Lack of standardization: There is a lack of standardization in AI-powered network technologies and protocols, which can hinder interoperability and scalability. Organizations must work together to develop standards for AI-powered networks that promote interoperability and scalability.

Bias and fairness: AI-powered networks must address bias and fairness issues in decision-making, particularly in areas such as resource allocation and network management. Organizations must ensure that AI-powered networks are designed to be fair and unbiased and that decisions made by the network are transparent and explainable.

Ethical concerns: AI-powered networks must consider ethical concerns related to the use of AI, including transparency, accountability, and potential unintended consequences. Organizations must ensure that AI-powered networks are designed to be transparent and accountable and that they do not have unintended negative consequences.

Regulatory and legal frameworks: AI-powered networks must comply with regulatory and legal frameworks related to privacy, security, and other issues. Organizations must ensure that AI-powered networks are designed to meet regulatory and legal requirements and that they are transparent and accountable to regulators and other stakeholders.

Lack of domain expertise: Developing AI-powered networks requires domain expertise in networking and AI, which can be challenging to find in a single individual or organization. Organizations must ensure that they have access to the necessary expertise to develop and deploy AI-powered networks and that they are able to collaborate with other organizations to share expertise and resources. We have summarized these challenges and open issues in Fig. 8 for better and easier understanding.

C. OPPORTUNITIES FOR FUTURE RESEARCH

Despite the challenges and open issues, AI-powered NTNs for 6G networks present numerous future research opportunities. In the following, we list such opportunities:

Development of new AI techniques: AI-powered NTNs for 6G networks require the development of new AI techniques

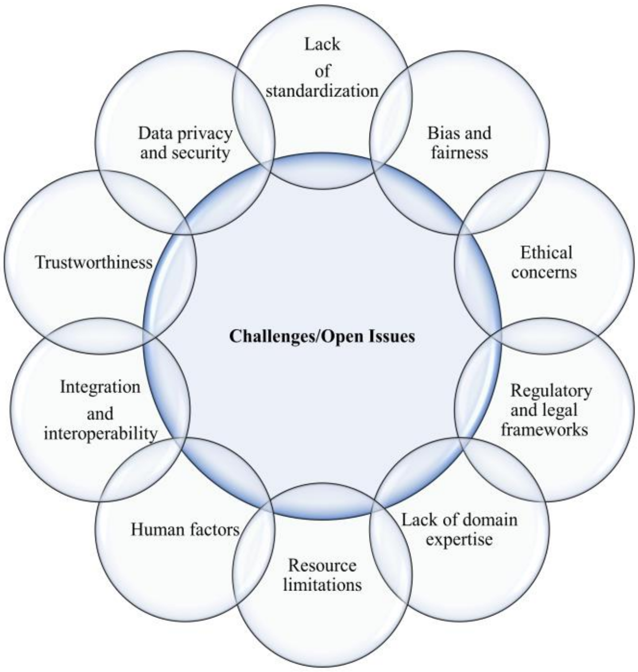

Figure 8. Summary of Challenges and Open Issues

that can address the unique challenges of 6G networks. These challenges include the need for real-time processing, large-scale data analysis, and dynamic network management. Research in this area can lead to the development of new algorithms and models that can provide better performance, accuracy, and efficiency in network management.

Integration with emerging technologies: The integration of AI-powered network management with emerging technologies such as edge computing, blockchain, and the IoT can create intelligent and efficient networks. Research in this area can lead to the development of new architectures and protocols that can leverage the benefits of these emerging technologies. For example, edge computing can reduce latency and improve network response time, while blockchain can provide a secure and decentralized network management.

Adoption of new network architecture: AI-powered NTNs for 6G networks requires adopting new network architectures optimized for AI-powered network management. Research in this area can lead to the development of new architectures and protocols that can provide better scalability, reliability, and performance in network management. For example, software-defined networks (SDNs) and NFV can provide greater flexibility and programmability in network management, which AI-powered techniques can leverage.

Exploration of new applications: AI-powered NTNs for 6G networks can enable a wide range of new applications, such as immersive virtual reality, connected vehicles, and smart cities. Research in this area can lead to the development of new use cases and applications that can leverage the benefits of AI-powered network management. For example, AI-powered network management can optimize network performance and resource allocation for virtual reality applications or enable intelligent traffic management for connected vehicles.

Standardization: This is an important area for future research in AI-powered NTNs for 6G networks. Standardization involves the development of consistent and uniform technology and protocols across the industry. This is important to ensure the interoperability and scalability of AI-powered network technologies. In other words, standardization ensures that different AI-powered network management systems can work together seamlessly and that they can be easily scaled up or down depending on the network size and complexity. To achieve standardization, researchers can work on developing new standards and protocols that can facilitate the adoption and deployment of AI-powered NTNs for 6G networks. This can involve creating standardized communication protocols, data formats, and interfaces that can be used across different network management systems. Researchers can also work with industry stakeholders and regulatory bodies to create industry-wide standards and guidelines that can promote the development and adoption of AI-powered NTNs for 6G networks. By achieving standardization, AI-powered NTNs for 6G networks can become more efficient, effective, and reliable, ultimately leading to a better user experience and improved network performance.

Sustainability: AI-powered NTNs for 6G networks must also consider the sustainability of network management, including the use of renewable energy sources, the reduction of energy consumption, and the optimization of network resources. Researchers can work on developing new techniques and protocols that can ensure the sustainability of AI-powered network management.

Explainability and transparency: AI-powered network management should be explainable and transparent to ensure trust and accountability. Researchers can work on developing new techniques and models that can provide insights into how AI-powered network management makes decisions and provide explanations for these decisions.

Resilience: AI-powered NTNs for 6G networks must be resilient to cyber-attacks and other security threats. Researchers can work on developing new techniques and protocols that can ensure the resilience of AI-powered network management and protect against these threats.

Collaboration and partnerships: AI-powered NTNs for 6G networks require collaboration and partnerships between academia, industry, and government to address the complex challenges involved in network management. Research in this area can lead to the development of new collaborative models and frameworks that can facilitate sharing of knowledge, resources, and expertise.

Sustainability: AI-powered NTNs for 6G networks must also consider the sustainability of network management, including the use of renewable energy sources, the reduction of energy consumption, and the optimization of network resources. Research in this area can lead to the development of new techniques and protocols that can ensure the sustainability of AI-powered network management.

In summary, AI-powered NTNs for 6G networks present significant challenges and opportunities. Addressing the challenges and leveraging the opportunities will require significant research and development efforts, but the potential benefits of intelligent and efficient networks are worthy of these efforts.

VII. CONCLUSIONS

In this paper, we comprehensively surveyed AI-powered NTNs for 6G wireless communication networks. We first discussed the background and motivation for using NTNs in 6G networks and their deployment and management challenges. We then highlighted the key features and requirements of NTNs, including the role of LEO/MEO/GEO satellites, HAPS, and UAVs in 6G networks. Then, we discussed various AI techniques for optimizing NTNs, including ML, DL, RL, and DRL, and explored the recent advances in AI-powered NTNs for 6G networks. We also identified key research directions, challenges, and opportunities in AI-powered NTNs for 6G networks.

Our survey sheds the light that AI-assisted techniques are the key ingredients for realizing 6G since AI facilitates NTNs to operate optimally in dynamic and unpredictable environments. However, the reliability of AI models depends on the quantity and quality of training dataset. How to create a synthetic training dataset which mimics real-world 6G observations will be crucial. In this context, utilizing digital twin to generate virtual replicas of real-world 6G communications data could be an interesting avenue for future research.

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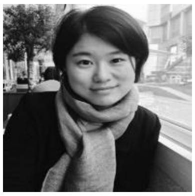

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