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An In-Depth Survey on Virtualization Technologies in 6G Integrated Terrestrial and Non-Terrestrial Networks

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ABSTRACT 6G networks are envisioned to deliver a large diversity of applications and meet stringent Quality of Service (QoS) requirements. Hence, integrated Terrestrial and Non-Terrestrial Networks (TN-NTNs) are anticipated to be key enabling technologies. However, the integration of TN-NTNs faces a number of challenges that could be addressed through network virtualization technologies, such as Software-Defined Networking (SDN), Network Function Virtualization (NFV), and Network Slicing (NS). In this survey, we provide a comprehensive review of the adaptation of these networking paradigms in 6G networks. We begin with a brief overview of Non-Terrestrial Networks (NTNs) and virtualization techniques. Then, we highlight the integral role of Artificial Intelligence (AI) in improving network virtualization by summarizing major research areas where AI models are applied. Building on this foundation, we identify the main issues arising from the adaptation of SDN, NFV, and NS in integrated TN-NTNs, and propose a taxonomy of integrated TN-NTNs virtualization offering a thorough review of relevant contributions. The taxonomy is built on a four-level classification that indicates — for each study — the level of TN-NTNs integration, the virtualization technology used, the problem addressed, the type of the study, and the proposed solution, which can be based on conventional or AI-enabled methods. Finally, we discuss open issues and give insights on future research directions for the advancement of integrated TN-NTNs virtualization in the 6G era.

INDEX TERMS 6G, AI, Integrated Terrestrial and Non-Terrestrial Networks, NFV, Network Slicing, Network Virtualization, SDN.

I. INTRODUCTION

Since the introduction of first generation (1G) in the 1980s, cellular networks have been evolving rapidly with the development of a new generation roughly every ten years. First, analog mobile networks provided voice communications in the 1G era. Then, digitization was introduced in second generation (2G), allowing not only voice calls but also data services. At the beginning of the second millennium, the third generation (3G) emerged to offer new data services such as video calling and internet access. Around ten years later, the fourth generation (4G) revolutionized the daily lives of people around the world with the proliferation of smart devices and the development of mobile-oriented applications and social media. To achieve high data transmission rates, multiple technologies were employed in 4G Long-Term Evolution (LTE) networks, including Multiple-Input and Multiple-Output (MIMO) antennas and Orthogonal Frequency-Division Multiplexing (ODFM) [1]. Subsequently, fifth generation (5G) networks enabled a variety of applications such as high-definition video streaming, Virtual Reality (VR) applications, Internet of Things (IoTs), remote healthcare, and industrial automation. These applications can be classified into the three categories of 5G use cases identified by the ITU-R; namely enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and massive

Machine-Type Communications (mMTC) [2]. Technologies including network densification, massive MIMO, and NS were employed in 5G to cope with the increasing number of connected devices and support new services.

While 5G networks are still being deployed and commercialized, researchers are already shifting their focus to the next generation of communication networks. 6G networks are envisioned to have enhanced capabilities compared to 5G, particularly in terms of Key Performance Indicators (KPIs). Higher data rates, lower latency, increased reliability and security, as well as massive connectivity are expected. For example, peak data rates of 100-200 Gb/s are anticipated in 6G, compared to a few tens of Gb/s for 5G [3]. A reduced latency is also envisaged going from one ms in 5G to 0.1 ms in 6G. Additionally, reliability is estimated to reach seven nines (99.99999 $\%$) in 6G compared to five nines (99.999 $\%$) for 5G, while security is expected to attain very high levels in next-generation networks. Furthermore, other key capabilities of 6G are envisioned by Huawei's researchers in their book "6G: The Next Horizon" [4], including better spectral, energy, and cost efficiency, very high localization and sensing accuracy, and higher intelligence. Regarding application scenarios, 6G networks are envisaged to support six categories, according to the ITU-R IMT 2030 vision [3]. On the one hand, the three categories of 5G use cases are extended; (i) *Immersive Communication* is an extended version of eMBB in 5G, providing rich and interactive immersive video experience to end-users. (ii) *Hyper Reliable and Low-Latency Communication* is an enhanced version of URLLC from 5G, supporting applications with stricter reliability and latency requirements, such as remote surgery. (iii) *Massive Communication* extends the mMTC of 5G to offer connectivity to a massive number of devices with reduced energy consumption. On the other hand, three new usage scenarios are defined; (i) *Ubiquitous Connectivity* improves the connectivity with NTNs for remote areas, bridging the digital divide. (ii) *AI and Communication* enables AI applications and distributed computing such as autonomous driving and collaboration between devices. (iii) *Integrated Sensing and Communication* provides wide area multi-dimensional sensing for use cases, including navigation, detection, and tracking.

In order to support the large variety of applications and satisfy the target KPIs of 6G networks, six categories of key enabling technologies are discussed in [4]. (i) *New Spectrum*, including the millimetre Wave (mmWave), Terahertz (THz), and optical bands, is necessary to serve applications requiring ultra-high data rates, such as VR and holographic applications. (ii) *Joint Sensing and Communication (JSAC)* enables higher accuracy and resolution by incorporating sensing features into communication systems. (iii) *AI technologies* play an integral role in 6G networks [5]. This can be examined from two perspectives: networking for AI, where 6G networks will be designed and optimized to natively accommodate AI applications, and AI for networking where AI techniques are employed to optimize the network's operation and management including intelligent Radio Access Network (RAN) slicing [6]. (iv) *Native Trustworthiness* is another significant aspect, as 6G is expected to be human-centric, where network security and data privacy are critical features. (v) *Green Communications and Sustainable Networking* are essential in 6G as energy efficiency becomes critical with the expanding networks. (vi) *Integrated TN-NTNs* are key 6G enablers advocating for cost-effective, seamless global connectivity and bridging the digital divide. In addition to the aforementioned technologies, the ITU-R IMT 2030 vision also considers RAN slicing and digital twins as technology enablers to improve the radio network [3].

In this work, we focus on the integration of TN-NTNs in the 6G era, specifically with respect to the aspects of network virtualization. In fact, the integration of non-terrestrial platforms in 6G networks introduces multiple challenges, particularly in terms of network management, network interoperability, and QoS requirements assurance. This is mainly due to the large-scale and heterogeneous network topology, the dynamic environment, and the limited onboard resources of network nodes, such as satellites, High-altitude Platform Stations (HAPSs), and Unmanned Aerial Vehicles (UAVs). In this context, network virtualization technologies, including SDN, NFV, and NS, can be adopted to tackle these issues. On the one hand, SDN promotes network programmability and reconfigurability, by decoupling the data/control planes, and logically centralizing the network control logic using SDN controllers [7]. This simplifies the network management and orchestration in heterogeneous TN-NTNs. Particularly, it facilitates resource allocation and service provisioning across multiple administrative domains in integrated networks. On the other hand, NFV improves network flexibility and reduces deployment costs through the separation of Network Functions (NFs) from the underlying hardware, and the creation of Virtual Network Functions (VNFs) [8]. These VNFs are software-based instances of NFs, capable of running on commodity hardware. This enables the deployment of NFs on different terrestrial and non-terrestrial platforms, without the need for dedicated hardware equipment. Additionally, updating and introducing new services is simplified in NFV-enabled networks. This is particularly important for NTN nodes. Moreover, NS provides multi-tenant software-oriented networks and offers optimized solutions for various market scenarios with different performance requirements. NS enables multiple virtual customized networks to operate on shared physical infrastructure [9]. Therefore, employing these networking paradigms in next-generation networks will enable seamless TN-NTN integration, efficient network management, and enhanced network performance.

This survey offers a comprehensive review on the application of network virtualization approaches in 6G integrated TN-NTNs. We consider three NTN segments; specifically, Satellite-Terrestrial (S-T), Aerial-Terrestrial (A-T), and Satellite-Aerial-Terrestrial (S-A-T). In addition, this survey covers the three main virtualization technologies; namely, SDN, NFV, and NS. In Table 1, we provide a summary of the main related surveys and a comparison in terms of the covered topics. Firstly, surveys in [10]–[13] provide a global overview of NTNs, taking into account the unique characteristics of three segments. They present the NTNs integration with terrestrial networks from different aspects, including architectures, use cases, network management, performance analysis, and network optimization. Secondly, references [9], [14]–[16] present comprehensive reviews on network virtualization and softwarization, particularly concepts of SDN, NFV, and NS, detailing their architectures, key principles, enabling technologies, and use cases. Hence, these works focus on either integrated TN-NTNs or on virtualization technologies independently. Thirdly, studies presented in [17]–[19] review research efforts combining network virtualization technologies with NTNs. Researchers in [17] and [19] focus on SDN/NFV and NS in 5G, respectively, in the context of UAV networks. In contrast, the authors of [18] discuss the SDN paradigm in satellite networks (S-T segment). Therefore, although the aforementioned surveys [17]–[19] combine NTNs with virtualization techniques, they either consider only one NTN segment, or cover a specific virtualization technology. The main contributions of this work can be summarized as follows:

- We give an overview on NTNs and the challenges of their integration in 6G, as well as a background on network virtualization and its enablers, i.e., SDN, NFV, and NS.
- We highlight the role of AI models in network virtualization and summarize the major research areas where AI algorithms are usually used in SDN, NFV, and NS.
- We outline the main challenges associated with the adaptation of SDN, NFV, and NS technologies in integrated TN-NTNs.
- We propose a taxonomy of integrated TN-NTNs virtualization, in which we comprehensively review and categorize the relevant contributions based on a four-level classification.
- We identify several open issues and give insights on future research directions.

The remainder of this paper is organized as follows. Section II gives an overview on NTNs, indicating their unique characteristics, the key drivers, the application scenarios, and the challenges of their integration in 6G. In section III, we explain the fundamentals of network virtualization and its leading enabling technologies, i.e., SDN, NFV, and NS. Section IV highlights the role of AI models in network virtualization, discussing the motivation and the primary research areas where AI algorithms are often used in SDN, NFV, and NS. Section V describes the proposed taxonomy based on a four-level classification and gives a brief overview of the most prevalent challenges facing the implementation of virtualization technologies in integrated TN-NTNs. Sections VI, VII, and VIII are dedicated to reviewing the relevant contributions on the application of virtualization technologies in integrated networks. Subsequently, Section IX provides a summary and insights gained from the surveyed works. In section X, we identify several open issues and discuss potential research directions for advancing the adaptation of virtualization technologies in next-generation networks. Finally, section XI concludes the paper.

II. OVERVIEW ON NON-TERRESTRIAL NETWORKS

In this section, we provide an overview on NTNs, highlighting the unique characteristics of NTN platforms, including satellites, HAPS and UAVs. We also present the key drivers, application scenarios, and challenges of NTNs integration in 6G.

A. CHARACTERISTICS OF NON-TERRESTRIAL NETWORKS

NTNs are composed of two types of platforms; namely, aerial platforms including UAVs and HAPS, and spaceborne platforms including Non-Geostationary Earth Orbit (NGEO) (Low Earth Orbit (LEO), Medium Earth Orbit (MEO)) and Geostationary Earth Orbit (GEO) satellites. Table 2 provides a comparison between different Non-Terrestrial (NT) platforms in terms of altitude, mobility, propagation delay, coverage, and energy supply. NTs nodes are accessed through earth gateway stations, that connect them to end-users and the core network. The end-users are Very Small Aperture Terminals (VSATs), which can be specific satellite terminals or 3rd Generation Partnership Project (3GPP) User Equipment (UE). In TN-NTN architectures, two types of links can be identified: service links and feeder links. The service link is established when terrestrial or non-terrestrial platforms provide services to NT nodes or end-users. In contrast, the feeder link connects NT nodes to terrestrial gateways [10], [20].

NT nodes can play a variety of roles when integrated into the functioning of terrestrial networks to serve a particular application, as illustrated in Fig.1. In general, the NT node can be a user, a relay, or a Base Station (BS) [10], [12]. First, in the case where it acts as a user, the NT platform is served through Terrestrial BSs (TBSs). For example, a UAV can be served directly by a TBS or by a satellite relaying data from a terrestrial gateway as shown in Fig.1 (a). Second, the NT platform, with a transparent payload, can act as a relay for two goals. On the one hand, the NT node can enable connectivity by relaying data from TBSs to end-users, as illustrated in Fig.1 (b). On the other hand, it can offer backhaul services by connecting a TBS to the core network

TABLE 1. Summary and comparison of related surveys ("✓": topic covered, "∂": topic partially covered, "×": topic not covered).

Ref.	Summary	Covered Topics					
		NTNs Segment			Virtualization Technologies		
		S-T	A-T	S-A-T	SDN	NFV	NS
[10]	Review on the characteristics and architectures of non-terrestrial networks and their role in 3G, 4G, and 5G ecosystems, highlighting the main contributions on NTNs and the research efforts conducted by the 3GPP.	✓	✓	✓	@	@	
[11]	Survey on SAGIN focusing on related works in system integration design, resource allocation, mobility management, and routing, as well as optimization and performance analysis.	✓	✓	✓	@	@	
[12]	Survey on the evolution of integrated terrestrial and non-terrestrial networks from 5G to 6G, from the perspective of IoT and MEC networks, mmWave and THz spectrum bands, as well as ML applications.	✓	✓	✓	@	@	
[13]	Survey on NTNs in 6G networks focusing on the role of AI approaches in tackling NTNs challenges.	✓	✓	✓			@
[14]	Survey on SDN paradigm presenting its key principles and detailing building blocks of an SDN architecture.				✓	@	
[9]	Review on NS in the 5G era, explaining its main concepts, use cases, and enablers and describing RAN and core NS.				@	@	✓
[15]	Review on NFV architecture, design considerations and implementations, and standardization efforts while discussing related notions, including cloud computing and SDN.				@	✓	
[16]	Survey on works in 5G NS using SDN and NFV, emphasizing NS architectures, management and orchestration, and practical implementations developed in industry and academia.				✓	✓	✓
[17]	Review on efforts in SDN-based and NFV-based UAV networks, providing taxonomies of the works based on application scenarios enabled by SDN/NFV in UAV networks.		✓		✓	✓	
[18]	Survey on studies in software-defined satellite networks, highlighting three satellite network architectures (single, two, and three-layer architecture) based on the integration of LEO, MEO, and GEO satellites.	✓			✓		
[19]	Survey on works in NS with UAVs focusing on the roles of UAVs in different categories of 5G use cases (eMBB, mMTC, URLLC).		✓				✓
This work	Survey on network virtualization technologies in 6G integrated TN-NTNs considering the three NTN segments and the three main virtualization technologies, namely SDN, NFV, and NS, while highlighting the role of AI algorithms.	✓	✓	✓	✓	✓	✓

through feeder links as depicted in Fig.1 (c). Third, the NT node can play the role of a BS serving terrestrial UEs or NT platforms as indicated in Fig.1 (d). Hence, the NT should support regenerative payload with sufficient computing and processing capabilities.

As a result of the high altitude and mobility of NT nodes, NTNs are distinct from conventional terrestrial networks by a number of key features. They differ mainly in terms of signal propagation, coverage and handovers, Doppler effect, and platform deployment [10], [12], [22], [23]. NT nodes, especially GEO and MEO satellites, are located at large distances from terrestrial end-users. Thus, NTN communications suffer from longer propagation delays and higher path loss compared to their terrestrial counterparts. Such features of NTNs present a bottleneck for applications where low or even ultra-low latency is a critical requirement. Moreover, as shown in Table 2, NT nodes have different coverage areas leading to different frequencies of handovers [24]. For instance, NGEO satellites have variable coverage, resulting in periodic and frequent handovers, while GEO satellites have large and stable coverage. Specifically, because of their mobility, NGEO satellites are characterized by their visibility window, defined as the time period during which a specific ground area is covered by the satellite. Meanwhile, handovers occur in Terrestrial Networks (TNs) during the movement of users between cells, due to the small and fixed coverage of TBSs. Furthermore, although Doppler effects exist in both types of networks (TN and NTN), the Doppler shifts induced by the high mobility of NT platforms in NTNs, primarily LEO satellites, are greater than those caused by user mobility in TNs. Finally, deploying TNs is an expensive and long-term investment. This makes it an unfavourable option in certain cases, including remote areas connectivity. In such scenarios, using

TABLE 2. Comparison of the characteristics of NTN platforms [10], [11], [21]–[23].

	GEO Satellite	MEO Satellite	LEO Satellite	HAPS	UAV
Altitude Range	35786 km	7000 25000 km	300 1500 km	around 20 km	10 km
Mobility	stationary	medium fast	fast	quasi-stationary	very fast
Propagation delay (one way)	about 270 ms	about 100 ms	<40 ms	about few ms	about few µs
Coverage	up to 3500 km	up to 1000 km	up to 1000 km	around 60 km	small
Energy supply	Solar panel and battery	Solar panel and battery	Solar panel and battery	Solar panel and battery	Lithium battery

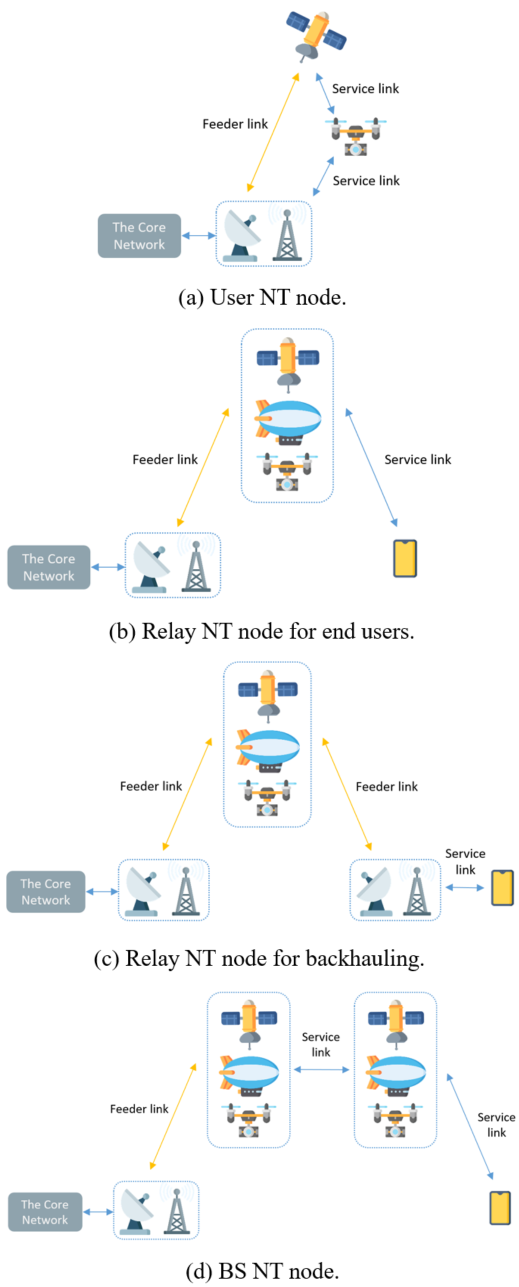

FIGURE 1. Different roles of NTN platforms in integrated TN-NTN.

NTNs can be an appealing alternative where aerial platforms can be deployed quickly and temporarily at economical rates. Additionally, although satellites have costly and long-term deployment, they offer vast coverage areas compared to aerial and terrestrial nodes.

B. INTEGRATION OF NON-TERRESTRIAL NETWORKS IN 6G

The integration of TN and NTN gave birth to a new paradigm of networks characterized by a three-layered architecture composed of ground, air, and space segments. Such networks are referred to as integrated TN-NTN, Space-Air-Ground Integrated Networks (SAGINs), or Ground-Air-Space (GAS) integrated networks. Each SAGIN segment has its own benefits and limitations, which are summarized in Table 3. Numerous applications with different QoS requirements will be supported by 6G networks. Because of their distinct characteristics from TNs, NTNs can complement 6G terrestrial networks to meet the needs of various use cases. In essence, *service ubiquity*, *continuity*, and *scalability* are the main key drivers for TN-NTN integration [4], [10], [12], [23]:

- *Service ubiquity*: airborne and space platforms can cost-efficiently deliver ubiquitous services, by covering remote and rural locations. This expands the coverage of 6G networks.
- *Service continuity*: NTN nodes offer continuous services for IoT devices or onboard mobile vehicles to enhance 6G service reliability.
- *Service scalability*: NTNs facilitate 6G service scalability with broadcast and multicast capabilities. This ensures streaming content delivery to wide regions and data offloading to network edges.

The efficient integration of the three segments is expected to enable a wide range of use cases, particularly in the 6G era. In [12], six categories of 6G integrated TN-NTN use cases are envisioned:

- *Ubiquitous Internet* can be achieved by integrating NTN access points, such as satellites and airborne platforms, into the terrestrial Internet. This promotes Internet services availability everywhere on the planet.
- *Pervasive intelligence* is enabled by AI for networking and networking for AI. In fact, space/air nodes can

TABLE 3. Benefits and limitations of SAGIN segments [11], [22], [25]

Segment	Benefits	Limitations
Space	- Large coverage - Broadcast/multicast capabilities	- High mobility - Long propagation delay - Limited capacity
Air	- Large coverage - Flexible deployment - Low cost	- High mobility - Low reliability - Limited capacity
Ground	- High data rates - Abundant resources	- Limited coverage - Vulnerability to natrual disasters

provide a global dataset to improve the performance of AI-based solutions. They also can serve as computing and storage units, facilitating AI-based network management through edge AI.

JSAC services are key enabling technologies of 6G networks. The NTN platforms can offer reliable Line-of-Sight (LoS) links and information on the device's location and orientation in 3D fashion. This improve the accuracy of sensing and localization measurements and allow context-aware communications.

Beyond Visual LoS (BVLOS) connected UAVs can be supported by integrated terrestrial and satellite networks to expand the control and reachability of UAVs beyond a visual LoS. This would result into improvements in the reliability, throughput, and coverage of aerial networks.

Aerial Interactive telepresence allows virtual human presence via UAVs in scenarios, where physical human presence can be dangerous or costly. This can be improved via Augmented Reality (AR) technology to offer haptic interactions in a 3D environment and through TN-NTN integration for seamless connectivity.

Convergence of networking and computing can be attained through NT nodes which can provide computing services and perform coordination between network edge units in order to achieve computing-aware networking.

Nonetheless, the integration of NTNs into 6G networks faces several challenges. On the one hand, network management is highly complex, and flexible network reconfiguration is difficult [11], [25]. This is due to the large number of diverse devices present in integrated TN-NTNs. These equipment differ in terms of configuration and control interfaces, as well as hardware and software specifications. On the other hand, network interoperability is limited, especially in the context of integrated TN-NTNs. This limitation arises from the vertically integrated stacks, provided by the operators in current communication systems [26]. QoS requirements assurance is another issue in the 6G era, where integrated TN-NTNs are expected to provide a wide variety of services. These applications have different requirements in terms of latency, reliability, and throughput. Hence, efficient and dynamic resource allocation should be carried out to ensure QoS provisioning for each service [25]. Besides, the mobility of NTN platforms results in variation of resource availability and a high frequency of handovers. This requires 3D mobility management strategies and dynamic resource allocation [25], [26]. Additionally, as integrated networks feature dynamic topologies, open links, and mobile nodes, enabling high levels of security is a challenging task [11]. Aside from conventional security techniques, secure communications based on quantum technologies can improve network security and data privacy [27]. Moreover, multiple business actors can be included in integrated TN-NTNs service delivery. Thus, new business models should be developed to identify the roles of each party and the relationships between different entities [28].

III. BACKGROUND ON NETWORK VIRTUALIZATION

The 3GPP have included the definition of standardized open network interfaces in the Next Generation Radio Access Network (NG-RAN) architecture, since Release-15 [29]. This promotes Open-RAN deployment and enables interoperability and flexibility for future mobile networks. Additionally, the Service-based Architecture (SBA) was defined for 5G networks where a functionality is realized by a set of network functions providing different services. This type of architecture is also expected in 6G networks which provides a modular framework that is future-proofed and service-oriented. The SBA allows services from separate vendors to be combined into one product, enabling network slicing. The architecture is supported by network virtualization techniques and AI models. This section covers the fundamentals of network virtualization, where we present its basic concepts and its main enabling technologies, including SDN, NFV, and NS.

A. NETWORK VIRTUALIZATION AND SOFTWARIZATION

Network virtualization and softwarization are two innovative paradigms introduced in 5G networks to enable network reconfigurability, programmability, and flexibility by separating the network functionalities and the underlying hardware.

Network softwarization: Softwarization defines the concept where network functionalities run on software rather than hardware, severing the software-hardware coupling. As a result, updating existing functions or adding new functionalities is realized by updating the software, which increases the network flexibility and reduces the capital expenditures (CAPEX) and operating expenses (OPEX) [16], [30].

Network virtualization: Virtualization in networking is the concept of creating virtual instances, defined by abstracted software-based representations, of the network entities and network hardware and software resources. This allows the software to run on commodity hardware rather than specific equipment [9], [16], [30]. Network virtualization is based on three main principles; namely abstraction, co-existence, and isolation [6]. The abstraction creates virtual instances of network components, including nodes and links and network resources masking the physical infrastructure's specifics. The co-existence allows multiple virtual networks to share the same physical infrastructure. The isolation ensures the independent functioning of the various virtual networks that share the same physical infrastructure [6], [31]. Network virtualization offers simplified network management and scalability, flexible service provisioning, and efficient resource utilization. It also provides service-centric networking and guarantees QoS requirements. Virtualization can be realized on different levels, including node, link, resource levels, and the network level.

B. ENABLING TECHNOLOGIES

Implementing network softwarization and virtualization in next-generation networks requires multiple enabling technologies, including SDN, NFV, and NS, as well as cloud and edge computing [6], [9], [16], [30], [31]. In this survey, we focus on the use of the first three main technologies i.e. SDN, NFV, and NS in integrated TN-NTNs. We refer the reader to references [12], [32]–[34] for details on the adaptation of cloud/edge computing in integrated networks.

1) Software-Defined Networking (SDN)

Conventional networks have inflexible decentralized architecture due to the coupling of the data and control planes. In contrast, SDN is a networking paradigm that separates the two planes and implements the network control logic in a logically centralized fashion. To promote network flexibility, programmability, and reconfigurability, SDN is based on four key concepts [7], [14]:

- Separation of the control and data planes.
- Logical centralization of the control logic in external SDN controller.
- Flow-based packet forwarding decisions.
- Network programmability through software applications that run on top of the controller.

We note that logically centralized network control does not imply its physical centralization. Additionally, SDN can be identified as a network architecture with three planes, as illustrated in Fig.2. (i) The *data plane* includes the network infrastructure and southbound interfaces [14]. With the aforementioned SDN principles, networking devices in the physical infrastructure become simple packet-forwarding devices without any intelligence. In order to control and communicate with these data plane elements, the SDN controller uses southbound interfaces defined as standard and open Application Programming Interfaces (APIs). This highlights the data/control planes decoupling. Multiple southbound APIs can be found in the literature, notably OpenFlow [35], which is the most used protocol in SDN architectures. (ii) The *control plane* is composed of network hypervisors, the SDN controller, and northbound interfaces [7], [14]. Network hypervisors enable the virtualization of the SDN architecture, allowing multi-tenancy and slicing of the OpenFlow-based infrastructure. The SDN controller, also known as the Network Operating System (NOS), is the key component in the SDN paradigm. It is a software platform running on commodity hardware offering abstractions and THE necessary resources for developers to simplify the programming of data plane devices. By logically centralizing the network intelligence, the NOS offers a global view of the network and solves issues of traditional networks in terms of flexibility, reconfiguration, and programmability. Northbound interfaces are APIs that enable the abstraction of the instructions employed by southbound APIs for programming of forwarding elements. They are provided by the SDN controller for application developers in the management plane. (iii) The *management plane* contains network applications that define the control logic, which will be enforced by the control plane and executed by the data plane [14]. Network applications in the SDN architecture can be divided into five categories; namely traffic engineering, applications related to mobile and wireless networks, network monitoring and measurement applications, security-oriented applications, and data centers networking.

Therefore, in SDN architecture, a network policy is defined by the management plane, enforced by the control plane, and executed by the data plane. For example, in order to send packets from source S to destination D, the network application in the management plane should select the routing path and command the NOS in the control plane to set corresponding forwarding rules that will be used by data plane devices to route packets from S to D [14].

2) Network Function Virtualization (NFV)

For deployment of NFs such as firewalls, Intrusion Detection Systems (IDSs), and Network Address Translators (NATs), conventional networks utilize middleboxes — which are hardware equipment designed for specific purposes. This results in inflexible networks in which the implementation of a new network function is expensive and time-consuming. NFV is based on the idea of separating the NFs from the underlying hardware on which they are running [8], [15]. Various virtualization approaches can be used to create and implement the VNFs. This includes not only Virtual Machines (VMs) but also other technologies such as containers and unikernels. As a result, the CAPEX and OPEX are significantly reduced, and new services can be deployed with higher flexibility and shorter time to market [9]. In [36], the European Telecommunications Standards Institute (ETSI) describes the NFV architecture containing

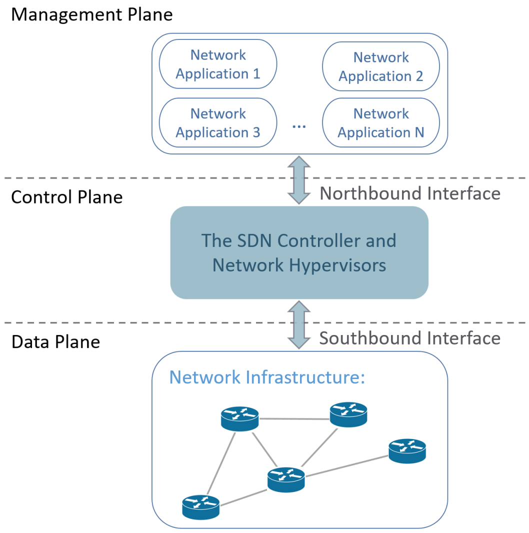

FIGURE 2. Illustration of SDN architecture.

four main blocks as shown in Fig.3: (i) the Network Function Virtualization Infrastructure (NFVI) composed of the physical and virtual resources needed for the NFV implementation, (ii) the VNFs which are the software-based implementation of the NFs and the Element Management (EM) responsible for the fault, accounting, configuration, performance, and security management functionalities for the VNFs, (iii) the Operations Support Systems (OSS) and Business Support Systems (BSS) that offer management and orchestration for the operator's legacy systems, (iv) the which ensures the VNFs provision and manages the life cycle of the resources and the VNFs [9], [15]. In particular, the block includes the NFV Orchestrator (NFVO), VNF Managers (VNFMs), and Virtualised Infrastructure Managers (VIMs). The NFVO manages the lifecycle of network services and orchestrates the NFVI resources across the VIMs. Meanwhile, the VNFMs and VIMs manage the VNF instances lifecycles and the NFVI resources, respectively.

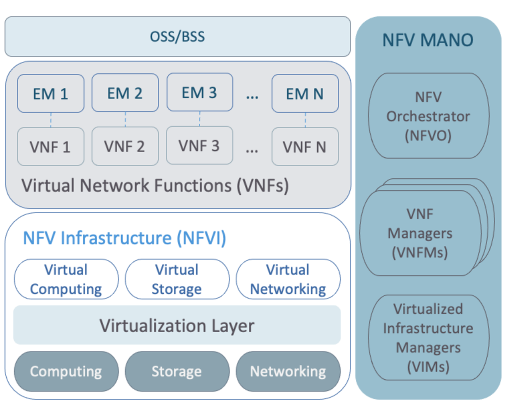

FIGURE 3. Illustration of NFV architecture [36].

3) Network Slicing (NS)

In 2015, The Next Generation Mobile Networks (NGMN) Alliance introduced network slicing in 5G networks as part of their 5G white paper [37]. NS enables multiple virtual networks to operate on shared physical infrastructure, providing multi-tenant software-oriented networks [9]. It is defined by the 3GPP as a technology that allows operators to build customized networks to offer optimized solutions for various market scenarios with different performance requirements [9], [38]. NS is based on several key principles, including automation, isolation, customization, elasticity, programmability, end-to-end (E2E) property, and hierarchical abstraction, defined as follows [9], [16], [39]:

Automation permits third parties to request the creation of a slice with the needed Service Level Agreements (SLAs) defining the desired requirements without manual intervention or fixed contractual agreements, offering on-demand NS configuration.

Isolation guarantees that each tenant obtains the desired performance and security requirements by properly specifying the level of resource separation.

Customization ensures efficient utilization of the resources allocated for each tenant, in order to satisfy their service requirements.

Elasticity assures that, with varying network parameters, the resource allocation of each network slice can meet the specified service requirements under varying network conditions.

Programmability permits third parties to manage the resources allocated to their slice using open APIs, which enables the automation, customization, and elasticity properties of the NS.

E2E is a NS property that facilitates service delivery from service providers to end-users by unifying different network layers and heterogeneous technologies.

Hierarchical abstraction offers different levels of abstraction by repeating the resource abstraction in a hierarchical manner, allowing multiple network slice services to be built on top of each other.

The principles of NS are implemented through its three-layered architecture, which is described by the NGMN alliance in [40]. The three layers are the service instance layer, the network slice instance layer, and the resource layer, as illustrated in Fig.4. The service instance layer comprises services offered by either the network operator or by third parties, such as application providers and verticals, where each service is defined by a service instance. The network slice instance layer includes network slice instances. Each instance refers to a set of network functions and resources that form a complete logical network customized to satisfy specific performance requirements demanded by service instances. A network slice instance is created by the network operator using the network slice blueprint and it can be shared by several service instances. Additionally, it can include a number greater or equal to zero of sub-network instances, which can be shared by other network slices. A sub-network instance is a collection of network functions and resources that do not necessarily constitute a complete logical network. Finally, the resource layer contains network functions and physical/logical resources offered by the network infrastructure.

The 5G/6G NS can be based on different architecture configurations. While some advocate for a two-domain structure including the Core Network (CN) and the RAN, others adopt a three-domain architecture where the transport network is linking the RAN to the CN. In this work, we consider the second network architecture where the NS can be carried out in three domains [16], [41], [42]. *CN Slicing* involves virtualization, isolation, and customization of main core network functions such as the User Plane Function (UPF), the Session Management Function (SMF), the Policy Control Function (PCF) and the Access and Mobility Management Function (AMF) [9], [43], [44]. These functions can be either shared among multiple network slices to reduce management complexity, or they can be dedicated to particular slices based on specific requirements. Using the NFV technology, these functions can be implemented as VNFs. Hence, the main objectives in CN slicing include the optimization of VNF embedding, Service Function Chaining (SFC) provisioning, and virtual resource allocation to deliver different services for multiple slices. *Transport Network Slicing* revolves around virtualization, isolation, and customization of transport domain resources, which is composed of the physical infrastructure (routers, switches, gateways, links, etc) responsible for data transmission [19], [41]. The SDN paradigm can be employed to facilitate transport network slicing, performing resource allocation and path splitting and reconfiguration to satisfy QoS requirements of various slices. *RAN Slicing* refers to virtualization, isolation, and customization of radio access components such as base stations, antennas, and other radio equipment that provide wireless connectivity to end-users [19], [41]. Since computation and storage are moving towards the edge network in 5G/6G, the RAN not only includes communication (networking) resources but also computing and caching resources. Thus, RAN slicing involves management and orchestration of different resources, as well as device/user association meeting QoS requirements and adapting to network changes.

Although certain use cases may not require NS, implementing E2E NS is essential to deliver a variety of 6G applications. It involves the creation and management of complete slices dedicated to a specific service from the core network passing by the transport network to the radio access network [42], [45]. E2E slice admission control, E2E slice resource management and orchestration, and E2E slice lifecycle management are the main building blocks of E2E NS. Moreover, to achieve the co-existence of various network slices providing multiple services with different performance requirements, network management, and orchestration is another major component in NS [9], [39], [46]. It can be divided into two layers: the service management layer and the network slice control layer [9]. While the latter deals with resource management and network slice management and orchestration, the former handles service operations, including abstraction, admission control, and creation. Additionally, the key enabling technologies of NS include hypervisors, virtual machines, containers, SDN and NFV, as well as cloud and edge computing [9], [46].

IV. AI IN NETWORK VIRTUALIZATION

As a key enabler of 6G, AI is expected to play a major role in the advancement of next-generation networks. In this section, we present an introduction to the applications of AI in the realm of network virtualization. In particular, we discuss the rationale behind the use of AI models in 6G networks where conventional approaches are not able to offer the required levels of efficiency and optimality. We also give an overview of AI techniques, including supervised, unsupervised, and reinforcement learning. Additionally, we briefly highlight the primary research areas where AI algorithms are often used in the context of virtualization technologies, namely SDN, NFV, and NS.

A. MOTIVATION

With large numbers of users, diversified applications, and integrated topologies, 6G networks become substantially larger, more dynamic, and heterogeneous. This increases the complexity of realizing efficient network virtualization, network management, resource allocation, and traffic prediction. Consequently, conventional methods can no longer provide the necessary efficiency and optimality required for proper network operation [42], [47]. In fact, traditional approaches are typically model-based, which imposes several limitations. First, they require a priori knowledge of the network traffic, which is not suitable for highly dynamic networks [47], [48]. Second, they are intractable and computationally demanding for large-scale networks. Third, they may provide sub-optimal solutions depending on the statistical models' accuracy [42]. Meanwhile, AI-based methods present improved solutions that are more suitable for future 6G networks compared to traditional techniques [47]–[52]. They can provide model-free algorithms with low computational complexity after offline training. This not only solves the issues of conventional approaches but also introduces network management automation and improves network performance.

B. OVERVIEW ON AI

AI is a discipline of computer science that seeks to develop intelligent machines and systems capable of thinking and acting like humans. These smart machines would have the ability to carry out tasks such as learning, decision-making,

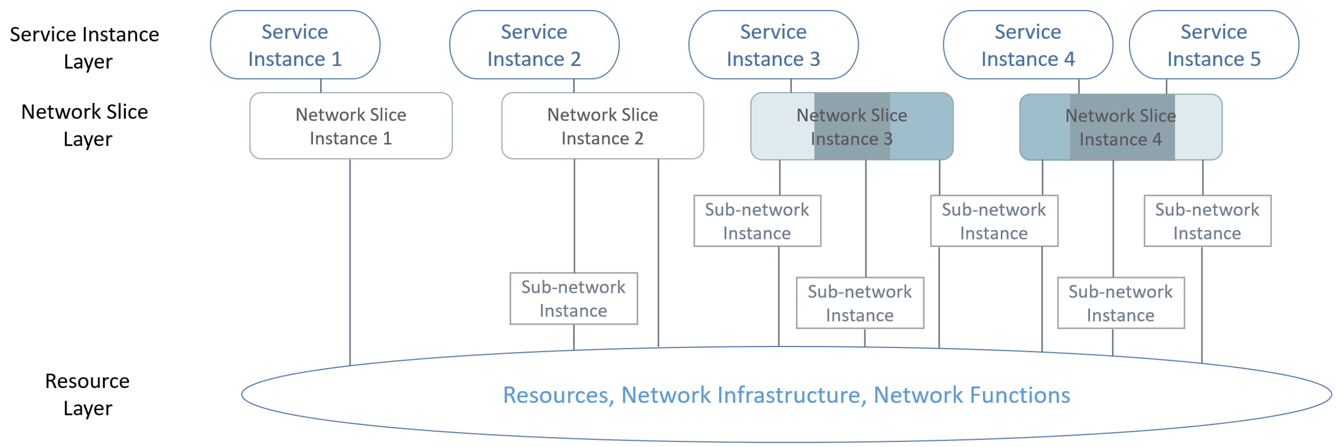

FIGURE 4. Network slicing architecture by NGMN [40].

and perception, which usually involve human intellect. AI is a broad field that includes both learning-based and non-learning-based approaches [53], [54]. On the one hand, non-learning methods, such as rule-based systems, solve problems using well-defined rules provided by the programmers. This allows them to excel at solving explicit problems without relying on a data-based learning process. However, they perform poorly when dealing with sophisticated, less-structured tasks like speech and image recognition. On the other hand, learning-based AI techniques rely on algorithms that learn patterns from data and improve over time without explicit programming. Consequently, they can learn how to accomplish a certain task autonomously, allowing them to thrive in the face of complex problems. Learning-based methods involve Machine Learning (ML) algorithms, which have recently drawn the attention of researchers from numerous domains, including finance, biology, and robotics.

In the field of wireless communications, ML algorithms have been adopted to solve a variety of problems such as resource management, network optimization, channel prediction, traffic forecasting, and network security [55], [56]. In particular, supervised and unsupervised learning algorithms have shown supremacy in terms of prediction and classification problems, which promotes proactive decision-making and resource allocation [41], [57]. Additionally, Reinforcement Learning (RL) techniques are efficient for decision-making tasks in dynamic environments, which facilitate network and resource management and orchestration [58]. Moreover, Federated Learning (FL) solves the issues of data privacy and reduces communication costs by promoting distributed learning [41], [58].

ML is a sub-field of AI where the machine is trained to learn patterns in provided data without explicit programming in order to solve a specific problem [53], [59]. ML algorithms can be classified based on different factors, as illustrated in Fig. 5. Considering the model's architecture and complexity, ML approaches are typically categorized as shallow and Deep Learning (DL) models. On the one hand, shallow ML techniques rely on simple architectures and require manual feature engineering to facilitate their learning. While they can be advantageous in specific situations with limited complexity and scarce data, they exhibit poor performance when faced with complex problems. Examples of shallow models include linear regression, shallow neural networks, and decision trees. On the other hand, DL is a subfield of ML that involves training artificial neural networks to solve sophisticated problems. These Deep Neural Networks (DNNs) are composed of multiple layers of interconnected neurons. These neurons process data hierarchically by extracting higher-level features in each layer to generate the final output. DL models have demonstrated outstanding performance in complicated tasks such as image and speech recognition, natural language processing, and gameplay. However, they usually require large training datasets and high computational resources. Commonly used DNNs architectures include Convolutional Neural Networks (CNNs) for computer vision, Recurrent Neural Networks (RNNs) for sequential data processing tasks, and Generative Adversarial Networks (GANs) for new data generation [60].

Another classification of ML algorithms involves the learning approach which the model adopts to learn from the data. Four main categories can be distinguished:

Supervised learning: The algorithm is trained on a labeled dataset, known as the training set, where data points are annotated with the target values. The supervised ML algorithm learns a mapping function between the input data points and their target outputs. The function then can predict the output labels for previously unseen inputs. Supervised learning algorithms are typically used for classification and regression problems. Examples of such models include linear regression, logistic regression, Support Vector Machine (SVM), decision trees, and neural networks [59], [61].

Unsupervised learning: The algorithm is trained on an unlabeled dataset, where inputs are provided without target

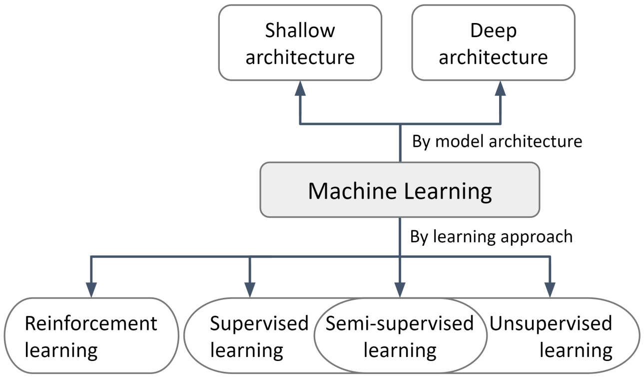

FIGURE 5. **Classification of ML algorithms.**

outputs. The unsupervised ML algorithm learns to identify the hidden patterns and structures in the data. Unsupervised approaches are employed for different purposes, such as clustering, dimensionality reduction, and data visualization. Such methods comprise K-means, hierarchical clustering, Principal Component Analysis (PCA), and Locally Linear Embedding (LLE) [59], [61].

Semi-supervised learning: This method combines both supervised and unsupervised learning by training the model on a dataset that contains both labeled and unlabeled data. Semi-supervised techniques are beneficial when labeled data is limited or costly to collect [61].

Reinforcement learning: RL algorithms learn through the interaction with the environment. Based on the knowledge it gathers from observing its environment, an agent learns to select the actions that will maximize a certain reward. The objective is to learn a policy maximizing long-term rewards. Q-learning, State–Action–Reward–State–Action (SARSA), and Actor-Critic are examples of RL algorithms that are commonly utilized for decision-making in dynamic environments [62].

In the aforementioned ML techniques, data is collected in a single location, and centralized learning is conducted to train the model. FL presents a paradigm shift in ML that promotes distributed learning [63]. It enables the distributed devices to train local models using their own data, and only the learned features are sent to a central entity for aggregation. This solves privacy preservation issues and reduces data transfer expenses.

C. AI APPLICATIONS IN NETWORK VIRTUALIZATION

AI is expected to become an intrinsic and embedded feature in future networks. It is envisioned to deeply integrate into every aspect of 6G networks, including network virtualization [4], [6]. In particular, ML algorithms show great potential in solving SDN, NFV, and NS issues, where traditional methods are no longer efficient in dynamic, heterogeneous, and large-scale networks. Several surveys are reported in the literature reviewing the applications of AI techniques in virtualization [42], [47], [51], [57], [64]–[68]. Here, we briefly highlight the main research directions where ML algorithms are commonly used in the context of SDN, NFV, and NS, as summarized in Table 4.

1) AI Applications in SDN

In the context of SDN-based networks, unsupervised and supervised learning techniques can be used to solve the Controller Placement Problem (CPP). Methods such as K-means, neural networks, and decision trees can predict the optimal locations of the SDN controller using traffic distribution [65], [69]. Moreover, RL algorithms can be employed in routing optimization, where the controller, which is responsible for traffic flow control and routing, can be considered as an agent in a decision-making RL algorithm. It interacts with the environment described by the network status and learns to select the routing paths that optimize specified metrics; namely packet loss rate, and energy efficiency [57], [70]. Additionally, supervised learning models, including LSTM, linear regression, and Naive Bayes, among others, are combined with heuristic algorithms to offer dynamic routing. Consequently, network performance metrics such as delay and Quality of Experience (QoE) are optimized. Traffic prediction and classification, resource management, and network security issues can be addressed and optimized by applying ML algorithms [57], [65], [66].

2) AI Applications in NFV

In NFV-enabled networks, AI models are utilized for NFV management and orchestration [58], [98]–[100], VNF and SFC deployment [72], [79]–[81], as well as network security [106]. In particular, the SFC and VNF embedding problem involves the mapping, configuration and placement of VNFs at suitable hosting locations for service provision. These problems can be formulated as a decision-making task where RL and DRL agents can be used to obtain optimal VNF placement and configuration strategies [74]. This enables automated and dynamic SFC and VNF deployment, which improves resource utilization efficiency and service delivery.

3) AI Applications in NS

The applications of AI in NS include slice admission control [67], [83], slice traffic prediction [47], [89], slice resource management and orchestration [68], [82], [101], E2E NS [84], [85], and network security [41], [104]. Slice admission control is a decision-making task, where the algorithm decides whether to accept or deny a new slice request in multi-tenancy networks, taking into account resource availability and QoS requirements [42], [68]. To improve network efficiency and provide slice admission automation, RL and DRL approaches are used. They learn optimal admission strategies to optimize a specified

TABLE 4. AI Applications in Network Virtualization.

	Applications	AI approaches	References
SDN	Controller Placement	Unsupervised and supervised learning techniques (K-means, neural networks, decision trees...)	[65], [66], [69]
	Routing Optimization	RL algorithms, Supervised learning (LSTM, linear regression, Naive Bayes...)	[64]–[66], [70], [71]
NFV	VNF and SFC Deployment	RL and DRL approaches	[50], [72]–[81]
NS	Slice Admission Control	RL and DRL approaches	[42], [47], [67], [68], [82], [83]
	E2E NS	RL algorithms, DNNs, FL approaches	[42], [45], [84]–[86]
Common Applications	Traffic Prediction and Classification	Classification methods (decision tree, random forest, SVM...), Regression methods (linear regression and LSTM...), DNNs (RNNs and CNNs), RL algorithms	[6], [42], [47], [65], [66], [87]–[89]
	Resource Management and Orchestration	Prediction techniques (graph neural networks, LSTM, k-nearest neighbors...), RL and DRL approaches	[6], [41], [50], [57], [58], [67], [68], [82], [90]–[101]
	Network Security	Classification algorithms (SVM, DNNs, random forests..), RL algorithms, Hidden Markov Models	[41], [50], [65]–[67], [84], [102]–[106]

objective, such as profit maximization, resource utilization enhancement, and utility maximization. Meanwhile, ML algorithms can enable automatic, intelligent, and proactive E2E NS. Specifically, reinforcement, deep, and federated learning can be adopted for E2E slice admission control, E2E slice resource management and orchestration, and E2E slice lifecycle management.

4) Common AI Applications

Applying AI approaches in traffic prediction and classification, resource management and orchestration, and network security is common to the three virtualization technologies. On the one hand, traffic prediction and classification is mainly considered in SDN for proactive and efficient resource management and optimized routing. It is used in NS to enhance slice resource utilization and lifecycle management, minimize SLA violations and ensure fairness in terms of resource allocation to each slice. Classification methods, including decision tree, random forest, and SVM, as well as DNNs — particularly RNNs and CNNs — are employed to identify and classify different types of network traffic flows. Meanwhile, regression ML algorithms such as linear regression and Long Short-Term Memory (LSTM) are adopted to predict future network traffic [6], [42], [47], [65], [66]. On the other hand, AI-based resource management and orchestration is adopted in SDN, NFV, and NS, offering efficient resource utilization, dynamic resource allocation, and optimized network performance. Various ML algorithms can be utilized in this context. For instance, graph neural networks, LSTM, and k-nearest neighbors are used for NFV resource prediction, whereas model-free RL and DRL approaches are adopted to dynamically optimize VNF resource allocation and automate VNF management functionalities [58]. Also, since the SDN and slice resource allocation problems can be considered as optimization problems, they can be solved by model-free RL or DRL algorithms, offering efficient, adaptive, and intelligent resource management [42], [47]. Moreover, the utilization of AI models such as DNNs and RL agents can improve network security by autonomously and proactively detecting and mitigating cyber-attacks and malicious activities in based-virtualization networks [41], [50], [67]. ML-based classification algorithms, including SVMs and random forests, can identify and detect malicious activities such as Distributed Denial of Service (DDoS) attacks by analyzing the network traffic. In SDN-enabled networks, the controller can automatically identify the appropriate strategies for network protection in real-time, using RL [65], [66]. In addition, IDS can employ ML algorithms such as Hidden Markov Models for attack prediction to proactively protect the network.

V. TAXONOMY OF VIRTUALIZATION IN INTEGRATED TERRESTRIAL AND NON-TERRESTRIAL NETWORKS

In this section, we provide a comprehensive taxonomy of virtualization in integrated TN-NTNs. In addition, we present a brief summary of the main challenges associated with the adaptation of SDN, NFV, and NS technologies in these networks.

As shown in Fig.6, the taxonomy offers a structured framework to categorize and organize the works reported in the literature. Using a four-level classification, this taxonomy serves as a guide for comprehending the scope of documented research on the subject matter. The first categorization is based on the level of TN-NTNs integration, resulting in three categories: the Satellite-Terrestrial, Aerial-Terrestrial, and Satellite-Aerial-Terrestrial segments. Then, we concentrate on the primary virtualization technology on which the reported work focuses, yielding three types of networks: SDN-, NFV-, and NS-based networks. The next classification level focuses on the type of studies conducted by the authors. They either examine architectural considerations and experimental implementations or tackle the virtualization issues employing conventional or AI-enabled methods. As a result, the contributions are divided into three classes: architectural and experimental implementations, traditional approaches, and AI-based approaches. Lastly, the reported works are further classified according to the category of the addressed problem, associated with the adaptation of virtualization technologies in integrated networks.

The development of virtualization technologies in integrated TN-NTNs is confronted with multiple difficulties. In Table 5, we outline the most prevalent challenges and their respective categories, as well as the most common optimization objectives and evaluation metrics. For SDN-enabled networks, CPP, routing optimization, satellite handover management, and resource allocation are the primary concerns. The main focus in NFV-enabled networks is on VNF Placement (VNF-P) and SFC embedding. In NS-based networks, the issues pertain to user association and RAN resource management. Although the obstacles mentioned are specific to each virtualization technology, the implementation of SDN, NFV, and NS approaches in integrated networks presents common challenges. This includes traffic scheduling and offloading, as well as network security and resilience. These problems are typically formulated as graph-based optimization problems since the integrated TN-NTNs are generally modeled as a graph describing their topology. The graph nodes represent the network components such as end-users, controllers, switches, satellite gateways, etc. The graph edges are the communications links connecting these components. Compared to terrestrial networks, these problems become more complex because of the dynamic environment, the large-scale topology, and the limited on-board resources of NTN platforms. Additionally, these challenges can be jointly considered with the satellite gateway placement and the UAV positioning problems. While this enhances the network's performance, it further increases the complexity of the problems. Consequently, these issues are often classified as NP-hard with multiple constraints. Researchers attempted to solve them by employing both conventional optimization techniques and AI algorithms to cope with the characteristics of these networks.

VI. VIRTUALIZATION IN THE SATELLITE-TERRESTRIAL SEGMENT

The integration of GEO and NGEO satellites with terrestrial networks offers global connectivity and bridges the digital divide. To enable seamless S-T integration, virtualization technologies are employed while considering the unique characteristics of these spaceborne platforms. In this section, we review the numerous efforts that have been conducted to tackle the challenges arising from the application of SDN, NFV, and NS technologies in S-T networks.

A. SDN-ENABLED NETWORKS

Researchers have recently been dedicating their efforts to developing SDN-enabled integrated S-T networks. They explored key architectural considerations and experimental implementations. In addition, they tackled obstacles associated with the implementation of SDN concepts using conventional or AI-enabled methodologies.

1) Architectures and Experimental Implementations

The SDN paradigm was first introduced into satellite networks in [111] to improve efficiency and flexibility. Several works have focused on the characterization of SDN-based S-T networks for specific use-case scenarios. For example, the authors of [107] propose an SDN-enabled architecture for post-disaster communication. They model the network as a graph-based meta-model to solve networking problems. In [108], an architecture that combines SDN with Information-Centric Networking (ICN) is proposed for multimedia broadcast communications. Heuristic caching schemes are designed for efficient content retrieval based on a multi-controller structure. Another application-oriented SDN-based architecture is developed in [114] and [121] for broadband communications. The authors of [114] present a flexible and reconfigurable broadband satellite network architecture. They also propose an optimized resource management strategy using a time-evolving resource graph. In [121], a cloud-based architecture for SDN/NFV-enabled integrated S-T networks is introduced, with a detailed analysis of its functionalities. Additionally, the researchers in [113] introduce the Software-Defined Space and Terrestrial Integrated Network (SD-STIN) to promote ubiquitous global connectivity by combining SDN and Mobile Edge Computing (MEC) technologies. They discuss the issues of the proposed architecture, involving mobility management, resource allocation, and security.

Meanwhile, other efforts were concentrated on the implementation aspects of SDN-based integrated S-T networks, utilizing simulation tools. For instance, the OpenFlow protocol was used in [112] to implement and validate a prototype of the proposed SD framework. The authors also provide two QoS-based heuristic algorithms for routing and bandwidth allocation in delay-tolerant networks. Moreover, to study the feasibility of the Heterogeneous Network (HetNet) architecture in [109], the EmuStack emulation platform was utilized to assess the proof-of-concept prototype. Enabled by SDN and NFV, HetNet is a flexible network architecture based on ICN and locator/ID split concepts. It offers routing scalability, heterogeneous network convergence, mobility support, and efficient content delivery. The network simulator NS3 and the OpenFlow protocol are extended in [110] to implement the proposed SDN-based network and evaluate the designed routing algorithm. This integrated

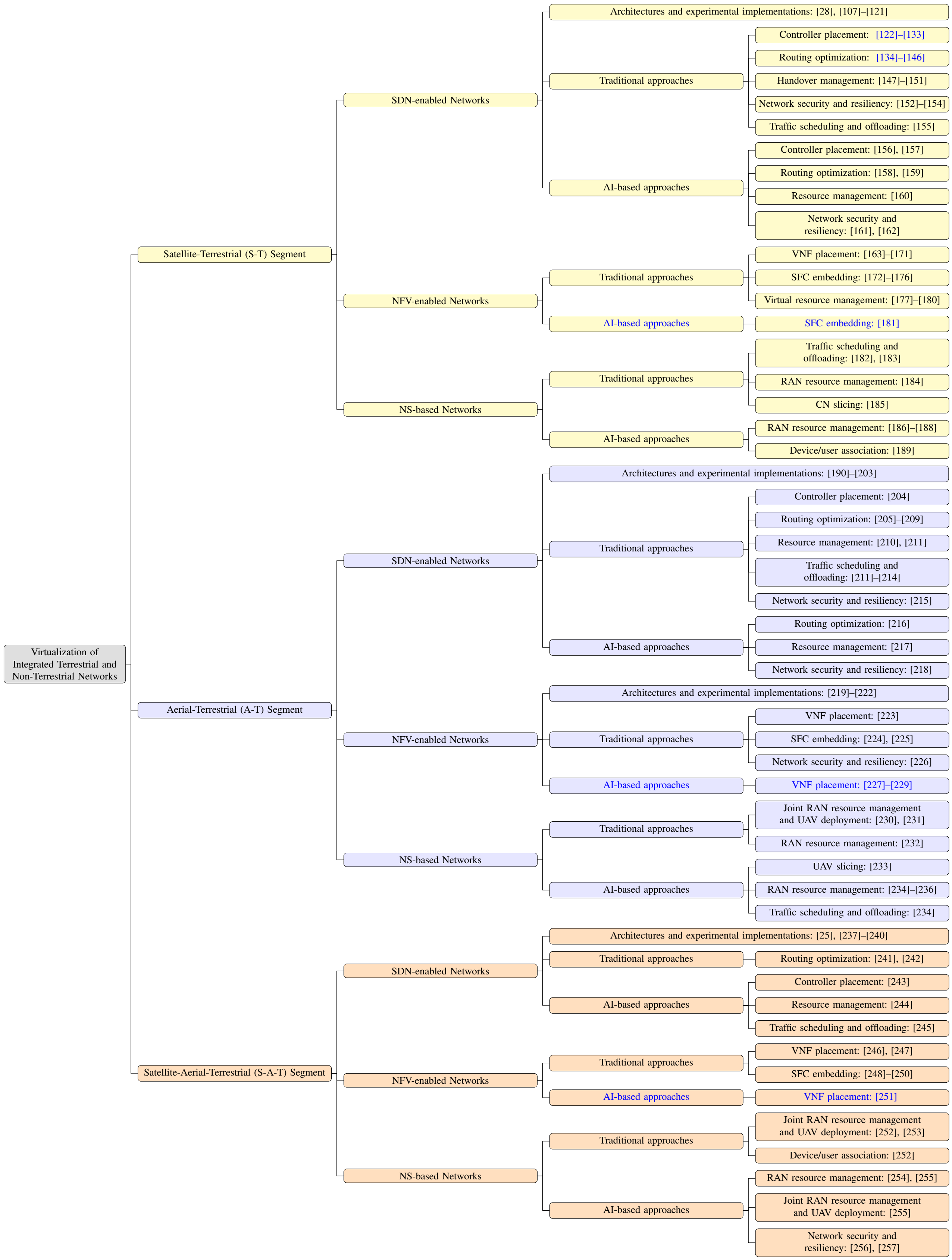

FIGURE 6. Taxonomy of Virtualization in Integrated Terrestrial and Non-Terrestrial Networks.

TABLE 5. Summary of main virtualization challenges in integrated TN-NTNs

Challenge	Definition	Categories	Optimization objectives	Evaluation metrics
		SDN-based Networks		
Controller placement problem	Determining the optimal locations to deploy the SDN controllers within the network infrastructure	i. SDN controller structure: single controller, multi-controllers, and hierarchical multi-controllers ii. Type of problem: static and dynamic CPP	Latency minimization, network reliability maximization, and deployment cost minimization	Network latency, network reliability, load balancing, average flow setup time, computational complexity, and running time
Routing optimization	Selecting the optimal paths to transfer data packets from a source to a destination	i. Type of problem: single- and multi-path routing ii. SDN controller structure	Congestion and cost minimization, link utilization maximization, and load balancing	Latency, packet drop rate, throughput, bandwidth utilization, and load balancing
Satellite Handover management	Determining the optimal strategy to follow when a handover occurs	i. Type of handover link: satellite, spotbeam, and ISL handover	Handover frequency and drop-flow minimization, RSSI and UE utility maximization	Average number and latency of handovers, transmission quality, throughput, and user QoE
Resource management	Obtaining the optimal allocation of network resources	Type of problem: control and data plane resource management	Network utility and revenue maximization, latency and energy consumption minimization	Throughput, latency, energy consumption, and network utility
		NFV-based Networks		
VNF placement	Determining the optimal positioning of VNFs in the network's physical and/or virtual infrastructure	N/A	Network cost and E2E delay minimization, and resource utilization optimization	Network cost, service deployment delay, and energy consumption
SFC embedding	Finding the optimal resource allocation and forwarding paths to execute the desired SFCs	N/A	Service delivery latency and resource consumption minimization, load balancing, and number of completed tasks maximization	Cost and revenue average ratio, service acceptance rate, reliability, and resource utilization efficiency
		NS-based Networks		
RAN resource management	Obtaining optimal strategies to reserve the RAN resource to each network slice and to allocate them to end-users in each slice.	Type of problem: RAN resource reservation (inter-slice) and orchestration (intra-slice)	Slice cost minimization, network utility maximization, and energy and resource consumption minimization	Slice request acceptance and recovery ratios, user service completion time, energy consumption, slice and overall cost, and QoS level of satisfaction
Device/user association	Finding optimal policies to assign end-users to a specific network slice	N/A	Overall cost and resource consumption minimization	User acceptance ratio, slice costs, and resource utilization efficiency

S-T architecture comprises hierarchical controllers for heterogeneous resource management. Additionally, the feasibility of the OpenFlow protocol in S-T networks was studied in [119] using a terrestrial SDN controller. The authors employ the Linktropy mini2 emulator to emulate the S-T channel and the Trema framework to design the OpenFlow controller. The Mininet environment is a widely used simulation tool to develop SDN-enabled networks. The researchers in [120] combine the Mininet environment, the POX SDN controller, and the OpenFlow protocol. They study the network performance of the proposed S-T network in massive multimedia content delivery applications. For S-T mobile backhaul networks, the authors of [118] implement an SDN-based laboratory testbed. To enable SDN-based traffic engineering applications, they use a Ryu SDN controller, OpenSAND, and OpenFlow. In [28], an SDN-based S-T network architecture is proposed with an implementation roadmap using extended OpenFlow. Furthermore, the Virtual Network Embedding (VNE) problem is taken into account when designing SDN-based S-T networks in [115]–[117]. In [115], Ryu controller and Mininet are employed for VNE algorithm evaluation in highly dynamic LEO S-T backhaul networks. Also, a dynamic VNE algorithm is validated in [116] through laboratory testbed implementation using the STK toolkit, Ryu controller, and OpenFlow.

2) Traditional Approaches

Controller placement problem: Acting as the brain of SDN-based networks, the controller provides logically centralized intelligence, enabling network flexibility and facilitating its management. Hence, the CPP emerges as a key issue requiring the strategic positioning of the SDN controllers [258]. The CPP can be categorized based on the SDN controller structure, which involves three configurations:

- Single controller configuration: the entire network relies on a single centralized SDN controller, enabling simplified implementation and reduced complexity. However, it is not suitable for large-scale networks because of single-point failure and scalability limitations.
- Distributed multi-controller configuration: alleviates the limitations of a single controller by deploying multiple SDN controllers within the network. The distributed controllers work cooperatively to manage their respective sub-networks. This enhances fault tolerance and adaptability at the cost of increased complexity and coordination overhead.
- Hierarchical multi-controller configuration: extends the previous approach by organizing the distributed controllers into a hierarchical structure. Higher-level controllers oversee the network by coordinating between lower-level controllers, improving scalability and flexibility.

Moreover, the CPP can be addressed in a static or dynamic manner [123]. In static CPP, controller locations are optimized once during the initial network design and are not altered throughout its lifetime. This assumes time-invariant network conditions leading to adaptability and scalability issues, especially in highly dynamic NTNs. Meanwhile, the dynamic CPP continuously adjusts the Controller Placement (CP) based on the changing network topology, traffic patterns, and service requirements. This results in adaptive, scalable, and optimized CP. Due to the incompatibility of terrestrial CPP solutions, efforts have been dedicated to resolving this problem in S-T networks using multi-controller and hierarchical multi-controller configurations.

On the one hand, the works in [127]–[132] focus on designing CP techniques in networks with multi-controller structure while considering different types of CPP. In [127], the static CPP is formulated as a joint optimization of the average control path reliability and the controller to gateway latency. It is solved using a heuristic greedy algorithm, producing near-optimal solutions. In addition, the dynamic CPP is studied in [129] and [132] with the objectives of average flow setup time minimization and traffic load minimization, respectively. The authors of [129] solve the CPP using the Python Gurobi framework and show that their solution outperforms the static technique in LEO constellation-based networks. Meanwhile, in [132], two online algorithms are designed to solve the dynamic CPP using a regularization framework. The approximate algorithm offers global optimal solutions, whereas the heuristic approach is proposed for large-scale networks.

On the other hand, the efforts reported in [122]–[126] address the CPP using hierarchical multi-controller configuration. The static CPP is studied in [122] with the objective of joint cost minimization and stability enhancement. A slave controller selection strategy is proposed and validated in terms of switch-to-controller and controller-to-controller delays. Besides, the dynamic CPP with hierarchical control is examined in [124]–[126], [133]. The authors of [124] propose the dynamic controller placement and adjustment algorithm, minimizing the cost of controller deployment and management. The NS3 simulation results show that their algorithm presents improved load balancing compared to the solutions in [123], [130]. In addition, an adaptive controller placement and assignment algorithm minimizing the management cost is designed in [125]. The algorithm is built on the control relation graph technique, and it outperforms existing works [129], [130]. With the goal of networking response latency minimization, the CPP is modeled as a capacitated facility location problem in [126]. The on-demand dynamic approximation algorithm is proposed to obtain an approximate solution satisfying the dynamic demands. Moreover, the authors of [123] investigate both the static and dynamic CPPs to minimize the cost of controller deployment and assignment. They design a heuristic algorithm based on the Particle Swarm Optimization (PSO) method. Meanwhile, a Simulated Annealing (SA)-based dynamic CP scheme is proposed in [133]. The algorithm aims to minimize both delay and controller load for SDN-enabled S-T networks.

In integrated S-T networks, the CPP can be jointly considered with the satellite gateway placement problem. This results in a multi-objective optimization problem. The Joint Controller and Gateway Placement problem (JCGPP) is considered in [130] and [131], with the objective of network reliability maximization. The problem in [130] is solved using the proposed simulated annealing and clustering hybrid algorithm. This solution provides approximate optimal results with lower computational complexity compared to the enumeration algorithms. Meanwhile, the JCGPP in [131] is solved using two meta-heuristic algorithms, namely a double SA algorithm, and a genetic algorithm-based approach. The results show that they outperform the solution in [130] in accuracy and computational complexity.

Routing algorithms: Due to the large-scale and dynamic topology, routing algorithms designed for terrestrial networks are inefficient in the S-T segment. Thus, developing routing

TABLE 6. **SDN-enabled integrated Satellite-Terrestrial networks: Architectures and experimental implementations.**

Ref.	Controller placement	Use case scenario	Implementation Tools	Comments
[107]	Ground station	Post-disaster communication	N/A	Describe the satellite network as a graph-based meta-model to solve networking problems
[108]	GEO/MEO satellites	Multimedia broadcast communication	N/A	Propose an ICN/SDN-based architecture with caching schemes for efficient content retrieval
[109]	Ground station	N/A	EmuStack emulation platform	Propose a flexible network architecture based on ICN and Locator/ID split concepts
[110]	GEO/MEO satellites and ground station	N/A	Extended NS3 simulator, OpenFlow protocol	Propose an architecture based on hierarchical controllers for heterogeneous resource management
[111]	GEO satellites	N/A	N/A	Describe the first SDN-based satellite network architecture
[112]	GEO satellites and ground station	Delay Tolerant Networks	OpenFlow protocol	Provide two QoS-based algorithms for routing and bandwidth allocation
[113]	Ground station	Global connectivity	N/A	Discuss the issues of the proposed integrated S-T architecture
[114]	Ground station	Broadband communications	N/A	Propose a flexible and reconfigurable satellite network architecture with optimized resource management
[115]	Non-GEO satellites or ground stations	S-T backhaul networks	Mininet environment, Ryu controller	Implement SDN-based laboratory testbed to evaluate VNE algorithms' performance
[118]	GEO/MEO satellites	S-T mobile backhaul networks	OpenSAND emulator, Ryu controller, OpenFlow protocol	Implement SDN-based laboratory testbed to enable SDN-based traffic engineering applications
[119]	Ground station	N/A	OpenFlow, Linktropy mini2 emulator, Trema framework	Study the feasibility of OpenFlow protocol in Satellite-Terrestrial networks
[120]	GEO satellite	Massive multimedia content delivery	Mininet environment, POX controller, OpenFlow protocol	Study the network performance in massive multimedia content delivery applications
[116]	Ground station	N/A	STK toolkit, Ryu controller, OpenFlow protocol	Implement SDN-based laboratory testbed to validate the feasibility of VNE algorithms
[28]	Ground station, GEO/LEO satellites	N/A	Extended OpenFlow protocol	Propose an SDN-based S-T network architecture with management strategies and implementation roadmap
[121]	Ground station	Broadband communications	OpenSAND emulator, OpenFlow protocol	Introduce a cloud-based architecture for SDN/NFV-enabled integrated satellite-terrestrial networks

mechanisms that adapt to these characteristics is crucial in S-T integration. In SDN-based routing, the controller plays an integral role as the central entity responsible for controlling and selecting paths to route traffic flows. Hence, routing schemes can be classified according to the control structure.

Routing algorithms in SDN-enabled S-T networks with single control structures are reported in [134]–[140]. A congestion-aware load balancing routing algorithm is proposed in [134] to optimally distribute traffic load and minimize link congestion. The proposed scheme outperforms Dijkstra's and Explicit Load Balancing techniques in terms of latency, packet drop rate, and throughput. Another work that focuses on load balancing optimization is reported in [135]. It mitigates the problems of load imbalance and congestion through a Multi-Path TCP (MPTCP)-based load balancing-aware routing method. The MPTCP routing technique is also used in [136], [139] while satisfying different optimization objectives. Moreover, in [139], the network utility is maximized, and two algorithms are developed based on SDN cooperated MPTCP. These methods select and adjust sub-flow routes while avoiding other sub-flow bottlenecks and adapting to the load dynamics. The joint cost minimization and traffic flow maximization are considered in [136]. The proposed segment control-based MPTCP path selection algorithm combines segment control technology with the SDN paradigm. This reduces the network delay and enhances the transmission reliability and efficiency, as shown by the experimental results. The authors of [137] employ segment routing in SDN-enabled CubeSat networks while minimizing the link cost. They propose an online segment routing-based algorithm to compute routes in a near-optimal manner. In addition, link cost minimization is also considered in [138] for large-scale LEO S-T networks. The Depth First Search (DFS) technique and Dijkstra's algorithm are combined to design a dynamic routing algorithm that outperforms the DFS in delay and packet drop rate. The software-defined multicast routing is studied in [140] for large-scale multimedia LEO satellite networks. With the goal of bandwidth-saving maximization, the authors build a multicast routing algorithm based on a Multi-Layer Rectilinear Steiner Tree (ML-RST).

Furthermore, the works in [141]–[145] study routing optimization in networks with multi-controller structures. A dynamic routing algorithm is introduced in [141] for LEO satellite networks. The authors maximize the path utility to obtain optimal routes, considering the effect of the ISL attributes on link quality. The focus of [142] is to optimize the QoS requirements in the design of a routing algorithm based on Bresenham's and Dijkstra's techniques. Also, in [143], researchers propose an E2E service-oriented fragment-aware routing algorithm for LEO S-T networks. They optimize the load balancing, latency, and wavelength fragments and employ a heuristic approach based on an ant colony. In [145], the joint network overhead minimization and transmission reliability maximization are considered. The proposed multi-path selection algorithm relies on a PSO based heuristic approach. Moreover, the authors of [146] design a load-balanced routing scheme in S-T networks with hierarchical multi-controller structure. They employ a distributed heuristics-based approach to minimize the signaling overhead. Latency and packet drop rate are the metrics they use to assess their solution.

Satellite handover management: In integrated S-T networks, satellite handover management is a key issue because of the dynamic topology. The strategies can be categorized based on the handover link [147]:

- Satellite handover refers to the transfer of the connection from one satellite to another.
- Spotbeam handover takes place between the multiple beams of the same satellite.
- ISL handover occurs when links between satellites in neighboring orbits are temporarily lost, resulting in the handover of the current connections relying on these ISLs.

Most research on handover management in SDN-based S-T networks focuses on satellite handover [147], [149]–[151]. In [147], a potential game-based handover strategy is proposed to maximize the utility of mobile terminals in LEO S-T networks. The authors of [149] develop a seamless handover algorithm with the goal of selecting the UE-satellite link with the highest RSSI. Compared to the hard and hybrid handover schemes in [259] and [260], the seamless handover demonstrates increased throughput, reduced handover latency, and a higher level of user QoE. Meanwhile, researchers in [150] and [151] concentrate on the problem of flow table management during handovers in SDN-based S-T networks. They designed a heuristic timeout strategy-based mobility management algorithm aiming to minimize the handover drop-flow. Besides, the traffic gateway handover is considered in [148], where the traffic is reallocated between the satellite gateways. A handover control strategy is developed based on the Smart Gateway Diversity (SGD) management logic. The scheme minimizes the number of reallocated groups of user beams and demonstrates improved throughput and Signal-to-Noise Ratio (SNR) quality.

Other research directions: Another area of research in integrated TN-NTNs virtualization is traffic scheduling and offloading. While scheduling involves orchestrating data transmissions, offloading refers to the redirection of tasks and traffic between network nodes. Computation offloading and data traffic offloading are two categories of the offloading problem. Researchers in [155] tackle the issue of data traffic offloading and spectrum management in SDN-enabled S-T networks. They propose a scheme based on auction theory that maximizes the utility of the satellite and the Mobile Network Operator (MNO) for multicast multimedia communications. In addition, network security is examined in [152], where the authors propose a two-step secure dynamic access method in a hierarchical multi-controller architecture. Network resilience is improved through traffic engineering for S-T backhaul networks in [154] and [153]. The available terrestrial and satellite capacity allocation is optimized to maximize network utility.

3) AI-based Approaches

The combination of AI techniques and SDN in the S-T segment is aimed at solving networking issues, including CPP, resource management, routing, and security. In [156], the JCGPP is solved using an AI-based approach in a multi-controller S-T network architecture. A SA partition-based K-means algorithm is designed to maximize network reliability. Compared to enumeration algorithms and existing work in [130], the AI-based method shows better performance in terms of latency and network reliability. Also, a multi-agent deep Q-learning technique is employed to design a dynamic CP scheme in [157]. The joint optimization of flow setup delay, load balance, and switching cost yields the optimal controller locations and controller-switch assignments. The results demonstrate the superiority of the DRL-based approach over K-means in delay, load balance, and switch number. Moreover, AI-based routing algorithms for SDN-enabled S-T networks are examined in [158] and [159]. A dynamic congestion control mechanism based on Multi-Agent Deep Deterministic Policy Gradient (MADDPG) is proposed in [158] to improve adaptability for massive data delivery applications. It achieves reduced delay and enhanced content delivery rate and throughput compared to the delay-based path-specified congestion control protocol. Additionally, the authors of [159] propose an ensemble Support Vector Regression (SVR)-based QoS-aware dynamic routing strategy. Compared to the algorithms in [112], this solution shows improvements in delay, packet loss rate, and throughput while ensuring better QoS.

TABLE 7. SDN-enabled integrated Satellite-Terrestrial networks: Traditional and AI-based approaches.

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
		Traditional approaches		
Controller placement	[127]	Path reliability and controller to gateway latency optimization	Heuristic greedy CP algorithm	Average control path reliability
	[122]	Joint cost minimization and stability enhancement	Slave controller selection strategy	Switch/controller to controller delays
	[123]	Cost minimization	Accelerate Particle Swarm based Dynamic and static CP schemes	Delay, jitter, controller load, reliability, and cost
	[129]	Average flow setup time minimization	Dynamic CP algorithm based on Python Gurobi framework	Average flow setup time, number of controllers
	[124]	Controller deployment cost minimization	Heuristic-based dynamic CP algorithm	Average response time, load balancing
	[130]	Network reliability maximization	Simulated annealing and clustering hybrid JCGP algorithm	Average latency, reliability
	[131]	Network reliability maximization	Double SA and Genetic algorithms based JCGP technique	Average reliability, running time
	[125]	Management cost minimization	Control relation graph based dynamic CP algorithm	Response time, load balancing
	[126]	Networking response latency minimization	On-demand dynamic CP approximation algorithm	Average flow setup time, response latency
	[132]	Traffic load minimization	Regularization-based online dynamic CP algorithms	Control overhead, scalability, latency
	[133]	Delay and controller load minimization	SA-based dynamic CP algorithm	Delay, controller load
Routing optimization	[134]	Congestion minimization and load balancing	Congestion-aware load balancing routing algorithm	Latency, packet drop rate, throughput
	[141]	Path utility maximization	ISL attributes-based dynamic routing algorithm	Delay, packet drop rate, throughput
	[142]	QoS requirements optimization	QoS-aware routing algorithm	Latency, packet loss rate, average route finding time, load balancing
	[135]	Load balancing	MPTCP based load balancing algorithm	Delay, throughput
	[136]	Cost minimization and traffic flow maximization	Segment control-based MPTCP path selection algorithm	Delay, packet drop rate, bandwidth utilization
	[137]	Link cost minimization	Online segment routing-based algorithm	Demand satisfaction, average link utilization, control traffic volume
	[138]	Link cost minimization	DFS and Dijkstra-based dynamic routing algorithm	Delay, packet drop rate
	[139]	Network utility maximization	Load and bottleneck aware sub-flow route selection algorithm	Aggregated throughput
	[143]	Optimization of load balancing, latency, and wavelength fragment	E2E service-oriented ant colony-based heuristic routing algorithm	Latency, bandwidth utilization, load balancing
	[145]	Joint network overhead and transmission reliability optimization	PSO based multi-path selection algorithm	Resource utilization, retransmission probability, throughput
	[140]	Bandwidth saving maximization	ML-RST-based multicast routing algorithm	Average delay, bandwidth consumption
	[146]	Signaling overhead minimization	Heuristics-based distributed load-balanced routing scheme	Packet drop rate, latency
Traffic offloading	[155]	Utility maximization	Auction theory-based data offloading and spectrum sharing scheme	Maximum expected utility

TABLE 8. SDN-enabled integrated Satellite-Terrestrial networks: Traditional and AI-based approaches (Cont.).

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
		Traditional approaches		
Handover management	[147]	Mobile terminal utility maximization	Potential game-based satellite handover strategy	Average handover number, SNR quality
	[149]	RSSI maximization	Maximum RSSI link selection based satellite handover strategy	Handover latency, user QoE, throughput
	[150] [151]	Handover drop-flow minimization	Heuristic timeout strategy-based mobility management algorithm	Drop-flow rate, flow table size, transmission quality
	[148]	Number of reallocated groups of user beams minimization	SGD network configuration-based handover control strategy	Aggregated throughput, SNR quality
		AI-based approaches		
Controller placement	[156]	Network reliability maximization	SA partition-based K-Means JCGP algorithm	Latency, network reliability, complexity
	[157]	Joint optimization of flow setup delay, load balancing, and switching cost	Multi-agents deep Q-learning based dynamic CP algorithm	Delay, load balance, switch number
Routing optimization	[158]	Congestion minimization	Dynamic MADDPG-based congestion control mechanism	Content delivery rate, throughput, delay
	[159]	QoS optimization	Ensemble SVR-based QoS-aware dynamic routing strategy	Delay, packet loss rate, throughput
Resource management	[160]	Network utility maximization	Deep Q-learning resource allocation algorithm	Network utility per resource
Network security	[161]	DDoS attack detection	SVM-based attack detection algorithm	Accuracy, false alarm rate, F1 score
	[162]	Data privacy improvement and attack detection	Attack detection technique based on FL and ML models	Accuracy, F1-score, precision and recall

Because of their high performance in classification tasks, AI models are used for attack detection to enhance network security in SDN-based S-T networks. In [161], SVM is adopted to detect DDoS attacks considering the time-variance of satellite networks. Based on Mininet simulations, the proposed technique outperforms traditional approaches in terms of detection accuracy, false alarm rate, and F1 score. Meanwhile, ML classifiers are combined with a FL framework in [162] to classify the traffic and detect attacks while improving data privacy. The OpenMined-based FL security solution is implemented, and experimental trials show improved accuracy, F1-score, precision, and recall.

Resource management is another challenge in SDN-enabled S-T networks. We can distinguish between two types of resource management. The first category pertains to the control plane, which mainly focuses on the allocation of network hypervisor computing resources [57]. The second category deals with the independent or joint management of data plane resources, including networking, computing, and caching (storage). The literature particularly covers data plane resource management in SDN-enabled integrated TN-NTNs. In this regard, AI-based approaches are showing promising results because of their efficient decision-making, especially in dynamic environments. For instance, a deep Q-learning resource allocation algorithm is proposed in [160] to maximize network utility. The proposed scheme jointly and dynamically allocates the three types of resources, showing increased network utility per resource.

B. NFV-ENABLED NETWORKS

Combining NFV with integrated S-T networks offers efficient resource utilization, flexible NF deployment, and improved service provisioning. NFV-enabled integrated S-T networks are based on different network architectures. This includes SDN/NFV-enabled S-T networks that adopt both SDN and NFV paradigms [163], [168], [261]. S-T edge/cloud computing networks are also used where NFV is combined with mobile edge and cloud computing [169], [170]. Considering such architectures, researchers focus on tackling the issues of VNF placement, SFC deployment, and virtual resource management.

1) Traditional Approaches

VNF placement problem: The virtualization of NFs significantly impacts the scalability, reliability, and deployment costs of network services. Hence, the VNF-P is pivotal to ensuring efficient resource utilization, optimized traffic routing, and diversified service provisioning. The problem is typically formulated as a Linear Programming (LP), Integer Linear Programming (ILP), and Mixed Integer Linear Programming (MILP) problem. The VNF-P problem becomes more complex in integrated S-T networks due to their dynamic, time-variant, and large-scale topology. As a result, terrestrial VNF-P solutions are inapplicable in the S-T segment. This has prompted efforts to find optimal solutions in these highly mobile networks [168], [169]. A dynamic heuristic-based VNF-P strategy is proposed in [165] for E2E delay minimization in terrestrial and LEO CubeSats networks. Formulated as an ILP, the problem is solved using three heuristic-based algorithms, including SA, Tabu Search, and genetic local search algorithms. The service provisioning delay minimization is also considered in [168]. The authors propose a dynamic security VNFs deployment strategy, using Tabu Search, in SDN/NFV-enabled S-T networks. Further, a dynamic distributed VNF-P algorithm is developed in [169] for satellite edge cloud networks serving IoT users. The scheme jointly minimizes the bandwidth cost and the service E2E delay and combines the Viterbi algorithm with a path selection scheme. The two techniques are used to search for VNF-P strategies for user requests on satellite edge servers and on cloud data center servers. Adopting similar edge/cloud computing architecture, the authors in [170] aim to dynamically allocate network resources for VNF-P. Using potential game theory, they propose a VNF-P strategy based on a decentralized technique to maximize the overall network payoff. The scheme demonstrates minimized service delay, bandwidth cost, and energy consumption compared to the Viterbi and greedy algorithms.

While these studies focus only on solving the VNF-P problem, others advocate the joint optimization of VNF-P and Flow Routing (VNF-PR). In [163], a time-evolving graph is used to describe the network topology, capturing its time-variance. The VNF-PR is considered as a multi-slot ILP problem minimizing the network cost. The time-slot decoupled algorithm is proposed as a heuristic-based solution. In addition, the authors of [166] propose a VNF-PR algorithm for resource utilization minimization, leveraging user service information. Considering different architectures, they implement two location-aware resource allocation-based VNF-PR algorithms. Moreover, researchers examine the VNF-PR for NFV-based space information networks in [164] and [167], with two optimization objectives. The authors of [164] formulate a convex optimization problem to maximize the network flow while satisfying the SFC constraints. They propose a group sparse-based algorithm that can obtain optimal solutions with lower complexity compared to conventional convex optimization techniques. The researchers in [167] develop a QoS-aware VNF-PR strategy that maximizes the number of completed missions under SFC constraints. Furthermore, the VNF-P problem is jointly considered with the virtual link mapping problem in [171]. A dynamic heuristic-based VNE algorithm is designed, jointly maximizing service revenue and minimizing the costs of power consumption and VNF deployment. Compared with existing works, the method shows improved average service revenue, reduced power consumption, and deployment costs.

SFC embedding: Network service providers and infrastructure providers utilize the concept of SFC to deliver customized services satisfying specific QoS requirements [262]. To do so, multiple VNFs, also known as Service Functions (SFs), are invoked following a predefined order imposed by the SFC. Thereby directing the network traffic through the ordered SFs to deliver a specific service. The objective of SFC embedding is to determine the optimal SF placement and establish the appropriate connections to build the chain while meeting the SFC constraints and ensuring optimized network performance.

Recently, researchers have been dedicating their efforts to designing SFC embedding schemes that are suitable for the S-T segment. For instance, the authors of [174] design a multiple SFC embedding scheme for ultra-dense LEO S-T networks. The goal is to minimize the service delivery latency while considering the SFCs competition and resource sharing. They formulate the problem as a non-cooperative game and propose three algorithms based on potential games. The E2E delay minimization is also studied in [173] in the context of multi-domain SFC. The authors consider that the required SFs are distributed across multiple administrative domains. They propose a multi-domain SFC mapping algorithm based on a heuristic approach and combined with a cooperative inter-domain path calculation technique. Additionally, an SFC mapping approach based on the concepts of SF multiplexing and SFC merging is introduced for S-T hybrid cloud networks in [175] and [176]. With the goal of resource consumption minimization, the proposed SFC mapping scheme is implemented as a proof-of-concept in the HetNet architecture [109]. Lastly, a load balancing-aware SFC deployment strategy is proposed in [172]. The objective is to minimize the VNF migration cost while balancing the load of service chains. The optimization problem is modeled as a hidden Markov model and solved using the MLB-Viterbi algorithm. The proposed solution outperforms existing work in terms of satellite node load rate and migration cost.

Virtual resource management: Optimizing virtual resource allocation in NFV-based networks is crucial in guaranteeing optimal network performance and efficient resource utilization while satisfying QoS requirements [179]. In integrated S-T networks, the task becomes more challenging because of the dynamic and heterogeneous environment [177]. A joint MEC caching placement and power allocation scheme is proposed in [179] for MEC-enabled S-T networks. The designed technique is based on the Mayfly algorithm and jointly maximizes revenue and minimizes power consumption. The results show that it outperforms the greedy and the PSO methods. The authors of [177] develop a resource management strategy based on the idea of user intent while optimizing the resource distribution in SDN/NFV-enabled satellite networks. The intent-driven resource management mechanism follows a decomposition process to obtain optimal resource allocation policies. Moreover, the researchers in [178] and [180] incorporate VNF orchestration in the design of resource management algorithms. In [180], they tackle the communication resource consumption minimization problem using the Dantzig-Wolfe decomposition, branch-and-bound algorithm, and column generation method. Then, in [178], they address the satellite-to-satellite resource consumption minimization problem by adopting the same approach.

2) AI-based Approaches

Adopting AI techniques in NFV-enabled integrated S-T networks is still in its infancy. The authors of [181] propose two SFC orchestration schemes aimed at maximizing service acceptance and satellite load fairness. A load-aware heuristic algorithm and a Graph Attention Network (GAT)-based hierarchical RL approach are proposed. They evaluate their solutions in terms of service acceptance, satellite load fairness, and robustness of dynamic LEO satellite networks.

C. NS-ENABLED NETWORKS

Incorporating NS in integrated S-T networks allows operators to ensure efficient resource utilization and enhanced network performance [263], [264]. Nonetheless, adopting NS in the S-T segment is still in its infancy, as research efforts in this area are limited and mainly investigate the issues of traffic scheduling and resource management, employing traditional or AI-enabled methodologies.

1) Traditional Approaches

In [182] and [183], traffic scheduling and offloading are simultaneously studied for NS-based integrated S-T networks. The authors of [182] design a hybrid satellite-LTE downlink data scheduler. The algorithm derives the service priorities in the same URLLC slice while optimizing network reliability and latency. Additionally, computation offloading and scheduling are examined for edge computing-based satellite networks in [183]. A multi-objective optimization of latency, E2E transmission power attenuation, and computational power is formulated. The problem is solved using two heuristic algorithms, namely the Multi-objective Tabu Search (MOTS) and the golden-section technique. While the former determines the offloading scheme for different slices, the latter computes the sliced edge computing-based satellite network scheduling technique for different users. Simulations validate the strategy in terms of latency, transmission power, and computational power. Moreover, core NS is considered in [185], where the authors propose an on-demand resource allocation method for VNF and SFC provisioning. They formulate the slicing problem as a MILP problem for resource consumption minimization and solve it using the AIMMS optimization framework.

RAN resource management is another major challenge in NS-based networks, and it involves two categories [82]:

- RAN resource reservation (inter-slice resource management), where network resources are allocated to each network slice based on their specific service demands and requirements.
- RAN resource orchestration (intra-slice resource management), where the reserved resources are managed and allocated to end-users in each slice.

The inter-slice RAN resource reservation is examined in [184] for S-T network slice planning. Compared to terrestrial networks, network planning is more complex in the S-T segment due to the frequent handovers caused by satellite mobility. The slice planning problem is modeled as VNE and satellite handover management problems. Considering the optimization of latency, transmission, and computational power, four handover-based VNE schemes are designed. The proposed mechanisms are implemented using shortest-path algorithms in an SDN-enabled network. They are also evaluated in terms of the number of handovers, cost, latency, and throughput.

2) AI-based Approaches

In NS-based networks, AI models are mainly employed to solve issues related to resource management. For instance, intra-slice RAN resource management is considered as a case study in [186]. The efficiency of AI models, including CNN and DRL, in addressing NS issues for highly dynamic S-T networks is demonstrated. With the goal of slice cost minimization, the available radio resources are optimally allocated to the end-users while meeting the QoS and slice isolation constraints. Additionally, the RAN resource orchestration of the 5G eMBB slice is studied in [188] with the objective of providing eMBB services to train passengers via an S-T network. Considering the different QoS levels required to satisfy the users' demands, the packet delivery latency is minimized to obtain the optimal strategy for each slice. Two algorithms are designed based on queuing theory and neural networks to solve the optimization problem. Moreover, the authors of [187] formulate the problem of joint RAN resource reservation and orchestration as Joint Slicing and Scheduling of spectrum Resources (JRSS) in S-T vehicular networks. They use stochastic optimization to model the problem, minimizing the long-term system cost. They also develop a two-layered RL-based JRSS technique by decomposing the problem into two sub-problems: resource slicing and resource scheduling. Compared to existing algorithms, the proposed solution shows reduced system cost and bandwidth consumption while meeting QoS constraints.

Meanwhile, a NS framework with a dynamic ML-based user association strategy is introduced in [189]. The proposed scheme utilizes an ML-based ant colony optimization

TABLE 9. NFV-enabled integrated Satellite-Terrestrial networks: Traditional and AI-based approaches.

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
		Traditional approaches		
VNF placement	[163]	Network cost minimization	Time-slot decoupled algorithm-based VNF-PR strategy	Total network cost, computational complexity
	[164]	Network flow maximization	Group sparse VNF-PR strategy	Network maximum flow, averaged number of active nodes
	[165]	E2E delay minimization	Dynamic heuristic-based VNF-P strategy	Service deployment delay, computing resources consumption
	[166]	Network resource utilization minimization	Location-aware resource allocation-based VNF-PR algorithm	Average resource utilization
	[167]	Number of completed missions maximization	QoS-aware VNF-PR strategy	Mission complete ratio, number of function nodes
	[168]	Sum of service provisioning delays minimization	Dynamic security VNF-P strategy	Service provisioning delay, running time
	[171]	Revenue and cost optimization	Dynamic heuristic joint VNF-P and VNE algorithm	VNF deployment cost, service revenue, power consumption
	[169]	Joint bandwidth cost and service E2E delay minimization	Dynamic distributed VNF-P algorithm	Average network bandwidth cost, service E2E delay
	[170]	Overall network payoff maximization	Dynamic potential game-based VNF-P algorithm	Service delay, bandwidth cost, energy consumption
SFC embedding	[174]	Service delivery latency minimization	Potential game-based multiple SFC embedding scheme	Overall service delivery latency, convergence performance
	[173]	E2E delay minimization	Multi-domain heuristic SFC mapping algorithm	Bandwidth utilization, delay
	[175] [176]	Resource consumption minimization	SFC mapping approach based on SF multiplexing and SFC merging	Cost and revenue average ratio
	[172]	VNF migration cost and load balance optimization	Load balancing-aware SFC deployment strategy	Satellite node load rate, migration cost
Virtual resource management	[179]	Joint power consumption and revenue optimization	Joint caching placement and power allocation scheme	Power consumption, total system utility function
	[177]	Resource distribution optimization	Intent-driven resource management mechanism	Delay, resource costs
	[178]	Resource consumption minimization	VNF orchestration-based resource management algorithm	Resource consumption, execution time, task completion ratio
	[180]	Resource consumption minimization	VNF orchestration-based service provision scheme	Task completion ratio, resource, and energy consumption
		AI-based approaches		
SFC embedding	[181]	Service acceptance and satellites load fairness maximization	GAT-based hierarchical RL SFC orchestration scheme	Service acceptance, satellites load fairness, robustness

algorithm, minimizing the delay and link cost. The scheme classifies user requests and assigns the appropriate slice to each user. Compared to the shortest delay and best-fit slicing schemes, the ML-based method offers efficient resource management with an increased user acceptance ratio.

Tables 6, 7, 8, 9, and 10 give a summary of research efforts on the adaptation of SDN, NFV and NS technologies in integrated S-T networks.

VII. VIRTUALIZATION IN THE AERIAL-TERRESTRIAL SEGMENT

Aerial platforms, including UAVs and HAPS are integrated with terrestrial networks to meet the constantly changing user demands in a flexible and cost-efficient manner. Virtualization technologies are used to enhance the agility of A-T networks and support diverse application scenarios. This section presents the literature on the implementation of SDN, NFV, and NS in the A-T segment. In particular, it discusses the associated challenges stemming from the distinct features of these airborne nodes.

A. SDN-ENABLED NETWORKS

The network programmability offered by the SDN paradigm prompted researchers to investigate the introduction of the SDN paradigm in integrated A-T networks, with

TABLE 10. NS-based integrated Satellite-Terrestrial networks: Traditional and AI-based approaches.

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
Traditional approaches				
Traffic scheduling and offloading	[182]	Network reliability and latency optimization	Hybrid satellite-LTE downlink scheduler	Delay
	[183]	Optimization of latency, transmission, and computational power	MOTS-based offloading and sliced network scheduling strategies	Latency, transmission, computational power
CN Slicing	[185]	Resource consumption minimization	On-demand resource allocation method for VNF and SFC provisioning	Delay, average number of QoS violations, accepted slice requests
RAN resource management	[184]	Optimization of latency, transmission, and computational power	Handover management and VNE schemes for RAN resource reservation	Number of handovers, cost, latency, throughput
AI-based approaches				
RAN resource management	[186]	Slice cost minimization	Various AI-based RAN slicing algorithms	Loss and cost values
	[187]	Long-term system cost minimization	Two-layered RL-based JRSS technique	System cost, bandwidth consumption
	[188]	Packet delivery latency minimization	QoS-aware neural networks-based resource allocation technique	Latency, QoS satisfaction
Device/user association	[189]	Delay and cost minimization	Dynamic ML-based user association strategy	User acceptance ratio

an emphasis on UAV-assisted networks [265]. While a number of studies examined the critical architectural considerations and experimental implementations, others tackled the arising issues, including routing optimization, resource management, traffic offloading, and network security, employing conventional or AI-enabled techniques.

1) Architectures and Experimental Implementations

Researchers proposed various SDN-enabled A-T network architectures for mobile and WiFi connectivity applications [190]–[192], [197], [198], [200]. The authors of [191] consider the scenario that UAVs could serve as access points or handover links for ground UEs moving between macro cells. They propose an SDN-UAV architecture to deploy shifting policies and network management, where the macro BS on the ground acts as a controller and UAVs operate as SDN switches. In [192], the proposed architecture SkyCore relocates the BS's Evolved Packet Core (EPC) entity to run on the UAVs. The EPC functionalities are defined as lightweight SDN applications to eliminate distributed interfaces and reduce function complexity. To further enhance the network performance, a software-defined hierarchical multi-controller UAV architecture is proposed in [197] for mobile connectivity, where the UAVs serve as backhaul BSs. Additionally, the authors of [200] design an SDN-based framework for UAV mesh networks taking into account the UAVs' location and energy constraints and propose a traffic load balancing path selection algorithm. Moreover, several architectures proposed mixed ground and UAVs controller structure [190], [198]. In [198], UAVs not only serve as data plane forwarding devices but also as SDN controllers which can be placed either on the ground or aerial platforms. In this architecture, the UAV controller is responsible for controlling the location and battery storage of UAVs, while the SDN controller is responsible for network management. Researchers in [190] propose a Temporospatial SDN (TS-SDN) architecture, by which the future network state could be predicted based on knowledge of the dynamic nature and physical relations between UAVs and ground stations.

Meanwhile, post-disaster applications are considered in [193], [194]. An SDN architecture is proposed to deliver a life video surveillance service for disaster recovery combining aerial and terrestrial networks, using UAV relays and a UAV global controller in [193]. Based on a ground controller, an SDN system is proposed in [194] to predict aerial gateway link outages by analyzing the aircraft' location and link performance. The UAVs serve as gateways for connecting disjointed networks in post-disaster and military scenarios. For the vehicular networks scenario, the authors of [196] propose an SDN-enabled three-tier architecture where the communication between ground vehicles, UAVs, and BSs enables a real-time road traffic navigation strategy. The ground vehicles and the UAVs, acting as SDN switches, provide instantaneous road traffic information to the SDN controllers to suggest the best shortest time path planning for the ground vehicles. Meanwhile, using hierarchical multi-controller, researchers in [199] design an SDN-based UAV-assisted infrastructure-less architecture for vehicular ad-hoc networks where the UAVs are used to assist emergency vehicles in road incidents. They introduce a monitoring platform to analyze the UAV information with a load-balancing algorithm. In addition, an agricultural application is targeted in the design of a cloud-based softwarization architecture for UAVs and Wireless Sensor Networks (WSNs) in [195]. The UAV controller, WSN controller, orchestration, and application layers, are implemented into the cloud.

Furthermore, architectures for UAV swarms have been proposed in [201]–[203]. An SDN architecture for battlefield UAV swarms is proposed in [201]. Each UAV in the swarm can act as a master or a slave in the swarm by switching on and off the onboard functions. The SDN controller estimates the topology and calculates a multi-path solution meeting QoS requirements. The architecture introduced in [202] is also designed for military UAV swarms. It includes one controller UAV node, a set of relay UAV nodes, and a set of independent nodes. The controller is responsible for setting up routing table rules for all nodes and managing the topology network. Another SDN-based swarm architecture is studied in [203] providing security features. Securing the Ad-hoc On-Demand Distance Vector (AODV) routing protocol is the primary action to prevent routing attacks. The SDN controller becomes a source of credentials and a building block for public critical infrastructure for protection.

2) Traditional Approaches

Routing optimization: In the context of SDN-based integrated A-T networks, routing algorithms are developed considering different controller configurations. Firstly, the single controller structure is adopted in [206]–[208] to achieve different objectives. Targeting the joint throughput, delay, and load balancing optimization, the authors of [206] design a priority-based ad-hoc routing scheme employing Dijkstra's and Ford-Fulkerson's algorithms. The results show that the proposed scheme outperforms other ad-hoc routing algorithms in throughput, delay, and packet delivery ratio. Meanwhile, the E2E delay is minimized in [207], [208]. A resilient multi-path routing algorithm is proposed, combining the Vertex Splitting method and Dijkstra's algorithm for vehicular applications. Secondly, the authors of [209] consider the multi-controller configuration in their airborne backbone network architecture. With the goal of reliability and bandwidth utilization maximization, they developed a reliable multi-path routing scheme based on segment routing. Thirdly, the hierarchical multi-controller structure is employed in [205] for SDN-based flying ad-hoc sensor networks. Targeting delay minimization and reliability maximization, an ant colony-based traffic-differentiated routing algorithm is designed and validated in terms of throughput, delay, and packet-dropping ratio.

Resource management: In integrated A-T networks, researchers focus on optimal data plane resource allocation in UAV-assisted networks where the UAVs act as forwarding devices managed by the SDN controller [210], [211]. For instance, a hybrid cloud/edge computing resource allocation algorithm based on a SA technique and a greedy algorithm is designed in [211]. The controller allocates the computing resources to the UAVs for the processing of its applications. The hybrid approach allows the controller to select the optimal server, which can be located on-board at the UAVs or at cloud/edge servers. The algorithm minimizes the average application latency and the UAV energy consumption while satisfying the QoS requirements. Moreover, the authors of [210] exploit the SDN controller's capabilities to jointly optimize the resource allocation, user association, and 3D UAV placement. They maximize the overall users data rate utility for UAV-assisted cellular networks. They propose a distributed alternating maximization iterative resource allocation scheme based on Successive Convex Optimization (SCO) and modified Alternating Direction Method of Multipliers (ADMM) techniques.

Traffic scheduling and offloading: SDN-enabled integrated UAV-terrestrial networks offers the opportunity to offload traffic and tasks from one network node to another in a flexible manner [212]–[214]. The authors of [213] propose a data traffic offloading scheme aiming to offload the data of cellular subscribers from the licensed UAV link to the unlicensed WiFi link in SDN-based UAV-WiFi networks. Based on heuristics and convex optimization techniques, they design a data offloading algorithm minimizing the queuing delay of cellular subscribers and meeting the delay requirements of WiFi subscribers. Additionally, the UAV charging is considered with data offloading in [214] with the goal of network utility maximization. An SDN–enabled location-aware opportunistic data offloading and UAV charging mechanism is developed aiming to avoid congested paths and extend the UAV flight time. Meanwhile, researchers in [212] examine the issue of computation offloading. They design a dynamic game theory-based computation offloading mechanism for SDN/MEC-enabled UAV-based vehicular networks. Targeting the minimization of energy consumption and execution time of computing tasks, vehicular users offload them to the flying UAVs, which can either execute the computation tasks or offload them to edge servers.

Other research directions: The CPP is studied in [204] for SDN-enabled aeronautical networks. Based on a hierarchical multi-controller structure, two dynamic placement schemes are proposed with the objective of maximum controller load ratio minimization. The first algorithm optimally places the controllers using an enumeration technique and assigns the switches based on the fastest shortest-path method. The second CPP scheme dynamically optimizes the controllers' placement and switches assignment using a genetic algorithm. Network security is another issue that has been examined in the literature where the authors of [215] develop an SDN-based topology deception scheme to mitigate the target selection attack and protect key UAVs in UAV-assisted WSNs. Thanks to centralized control, the mechanism deceives the attackers by creating a virtual topology using honeypot drones, impairing their judgment.

TABLE 11. SDN- and NFV-enabled integrated Aerial-Terrestrial networks: Architectures and experimental implementations.

Ref.	SDN Controller placement / NFV network architecture	Use case scenario	Implementation Tools	Comments
		SDN-enabled Networks		
[190]	Ground and aerial platforms	Backhaul mesh mobile networks	OpenFlow-inspired CDPI protocol	Design an SDN-enabled architecture using network state prediction based on UAVs physical position and trajectory
[191]	Ground station	Mobile networks	Mininet, OpenFlow	Employ SDN to solve the problem of UEs handover in UAV-assisted mobile network
[192]	UAVs	LTE mobile networks	P4 w/OpenFlow, Lagopus, Open vSwitch	Propose the SkyCore architecture where the EPC functionalities are lightweight SDN applications running on UAVs
[193]	UAVs	Post-disaster applications	OMNeT++	Design an SDN-based UAV network for disaster recovery applications using UAV relays and a UAV global controller
[194]	Ground station	Post-disaster and military applications	Mininet, OpenDayLight NS3, OpenFlow, Open vSwitch	Develop an SDN system predicting aerial gateway link outages by analyzing aircrafts' location and link performance
[195]	Cloud	Agricultural applications	NodeJS	Propose a Cloud-based softwarization architecture for UAV-based WSNs
[196]	Ground station	Vehicular applications	OMNeT++, SUMO, MobiSim	Design an SDN-enabled UAV-based architecture for vehicle path planning
[197]	Ground station	Mobile connectivity	OpenDaylight, MATLAB SimEvents	Propose a holistic UAV system with hybrid routing and adaptive load-balancing algorithms
[198]	Ground and aerial platforms	WiFi connectivity	Mininet-WiFi, POX controller	Design an SDN architecture for UAV backbone network with monitoring platform and load-balancing algorithm
[199]	Ground station and UAVs	Vehicular ad-hoc networks	MATLAB for numerical evaluation	Propose an SDN-based UAV-assisted architecture for emergency vehicle assistance in road incidents
[200]	Ground station	WiFi connectivity	OpenFlow	Design SDN-based framework for UAV networks with traffic load balancing path selection algorithm
[201]	UAVs	Military applications	N/A	Propose a UAV swarm SDN-based architecture with a QoS-based multi-path routing scheme
[202]	UAVs	Military applications	OMNet++, M3WSN	Propose a SDN-based centralized UAV topology management algorithms for ad-hoc networks
[203]	Ground stations and UAVs	UAV swarm security applications	OpenFlow, Ryu controller, OFSoftSwitch13, AODV	Proposed two SDN-based architectures to improve the security of UAV swarms with an ad-hoc routing
		NFV-enabled Networks		
[219]	NFV-based ad-hoc UAV networks	Multiple UAV applications	Open Source MANO, OpenStack Ocata	Study the feasibility of NFV-based ad-hoc UAV system through prototype tests
[220]	MEC/SDN-enabled FANETs	Massive users/device connectivity	N/A	Propose a MEC/SDN/NFV-enabled architecture with VNF migration-based relay selection algorithm
[221]	MEC/SDN-enabled IoT UAV networks	IoT emergency applications	OpenStack Stein, OpenFlow, Open vSwitch	Propose a MEC/SDN/NFV-enabled UAV architecture with security management and VNF placement schemes
[222]	NFV-based UAV FANETs	5G connectivity	Linux containers, NS3 simulator	Design a virtualized environment emulation framework to facilitate the development of multi-UAV networks

3) AI-based Approaches

Thanks to their ability to adapt to highly dynamic environments, RL models are employed to design dynamic resource management and routing mechanisms for SDN-based UAV-terrestrial networks. On the one hand, the authors of [217] propose a data plane resource allocation algorithm based on deep Q-learning in SDN-enabled ad-hoc UAV networks. They minimize the number of active UAVs to optimally allocate WiFi channels to end-users while maintaining desired QoS and optimizing UE coverage and energy efficiency. They also validate the proposed solution through testbed experiments taking into account the QoS satisfaction, UE coverage, and power consumption as performance metrics. On the other hand, a dynamic single-path routing strategy, named the Air-to-ground Intelligent Information Pushing Optimization (AIIPO) algorithm, is developed in [216]. The AIIPO is based on a deep Q-learning model that solves the optimization problem of throughput maximization, while adapting to network changes in IoT data collection UAV networks. The simulation results show that AIIPO outperforms benchmark methods with respect to throughput and computation complexity. Moreover, the K-means clustering model is combined with the Autoregressive Integrated Moving Average (ARIMA) algorithm in [218] to improve the security of data dissemination in SDN-enabled UAV-based IoT networks. K-means and ARIMA are employed with a blockchain technique to secure data transmission from IoT devices to UAVs to SDN controllers by detecting eavesdropping and malicious data and mitigating cyber-attacks on the controllers.

B. NFV-ENABLED NETWORKS

Adapting the NFV technology further enhances the flexibility and agility provided by the integrated A-T networks with reduced deployment costs [17]. Only a few works have been reported in the literature discussing the use of NFV in the A-T segment with a focus on UAV-based networks. They provide insights on architecture and implementation considerations and propose potential solutions to issues related to VNF placement and SFC deployment.

1) Architectures and Experimental Implementations

In [219], an NFV-enabled UAV-based system is proposed to deliver different services in an ad-hoc communication network. The feasibility of the system is tested using a prototype and the results show that using lightweight VNFs increases the flexibility and cost efficiency of network service deployment over resource-limited UAVs. Another architecture combining NFV, SDN, and MEC technologies is designed in [220] for FANETs to provide massive connectivity to devices and mobile users. With the objective of sum-rate maximization, the authors propose a NOMA-based multiple-access mechanism and a relay selection algorithm based on VNF migration. Moreover, the Virtualized Environment for Multi-UAV Network Emulation (VENUE) is designed in [222] to offer an ecosystem to implement, prototype, and validate the development of multi-UAV services. The framework is based on Linux containers and the NS3 simulator, taking into account the specific features of UAV-based networks. Furthermore, the authors introduce an NFV/MEC-based UAV architecture with a security management framework in [221] to investigate network security. They also develop a security VNF-P algorithm optimizing security orchestration and resource utilization.

2) Traditional Approaches

Challenges related to SFC deployment are addressed in [223]–[225]. On the one hand, the SFC migration problem, defined as the re-mapping of the ordered VNFs to the network resources under the SFC constraints, is studied in [224] for dynamic MEC-based networks. The authors formulate the problem as an integer programming problem with the objective of long-term cost and latency minimization. Using Lyapunov optimization, they propose a dynamic topology-aware min-latency SFC migration algorithm offering a balanced cost-latency trade-off. On the other hand, the SFC deployment is optimized in [225] for UAV edge computing networks. A heuristic two-stage SFC deployment strategy is designed to simultaneously maximize the revenue and minimize the task completion time. Additionally, the SFC planning problem is formulated as a joint VNF-P and traffic routing problem in [223]. The authors employ the Integer Non-linear Programming (INLP) formulation and propose a heuristic approach to solve the problem of maximizing revenue, while minimizing the costs for vehicular integrated networks. They also introduce a novel metric, aggregation ratio, to capture the trade-off between communication and computing resource costs. Besides, network resilience is examined in [226] in UAV-based NFV/MEC-enabled networks. The authors study the resilience of service chains, composed of multiple VNFs, by designing a quantitative modeling approach to observe the system's behavior and identify potential resilience bottlenecks.

3) AI-based Approaches

Only a handful of studies consider the use of AI-based approaches in NFV-enabled A-T networks. For example, the authors of [227] propose a hierarchical DRL-based scheme for the joint design of UAV trajectory and VNF-P. In their hybrid method, they employ DDPG and deep Q-network to account for both continuous and discrete actions. The algorithm jointly minimizes the average delay and maximizes the energy efficiency. Considering both single-

TABLE 12. SDN-enabled integrated Aerial-Terrestrial networks: Traditional and AI-based approaches.

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
		Traditional approaches		
Routing optimization	[205]	Delay minimization and reliability maximization	Ant-colony-based traffic-differentiated routing algorithm	Throughput, delay, and packet-dropping ratio
	[206]	Throughput, delay, and load balancing optimization	Priority-based ad-hoc routing scheme based on Dijkstra and Ford-Fulkerson	Throughput, delay, and packet delivery ratio
	[207] [208]	Delay minimization	Resilient multi-path routing algorithm based on Vertex Splitting and Dijkstra	E2E resiliency, delay, and outage probability
	[209]	Reliability and bandwidth utilization maximization	Segment routing-based reliable multi-path routing scheme	Reliability, delay, and bandwidth utilization
Resource management	[210]	Overall users' data rate utility maximization	SCO and ADMM-based Iterative resource allocation scheme	Throughput and network utility
	[211]	UAV energy consumption and average application latency minimization	Heuristics-based hybrid computing resource allocation algorithm	UAV energy consumption and application latency
Traffic scheduling and offloading	[212]	Execution time and energy consumption minimization	Dynamic game theory-based computation offloading scheme	Cost and number of completed tasks per minute
	[213]	Cellular subscribers' queuing delay minimization	Heuristic and convex optimization based cellular subscribers data offloading scheme	Cellular subscribers' average queuing delay
	[214]	Network utility maximization	Location-aware opportunistic data offloading and UAV charging mechanism	Throughput, E2E delay, and handover latency
Controller placement	[204]	Maximum controller load ratio minimization	Dynamic CP with fastest and dynamic assignment strategies	Load balancing and controller load ratio
Network security	[215]	Target selection attack mitigation	Topology deception-based attack mitigation scheme	Connectivity loss
		AI-based approaches		
Resource management	[217]	Active UAV number minimization	Deep Q-learning-based resource allocation algorithm	QoS satisfaction, UE coverage, and power consumption
Routing optimization	[216]	Throughput maximization	Deep Q-learning-based dynamic routing strategy	Throughput and computation complexity
Network security	[218]	Eavesdropping and malicious data detection	Blockchain-enabled IoT data dissemination scheme based on K-means	Accuracy, precision, recall, and f1 score

and multi-agent scenarios, they evaluate their solutions in terms of service latency and energy efficiency. In addition, the joint VNF-P and UAV deployment is considered in [229]. An online DRL-based algorithm is designed for MEC-enabled UAV networks. It optimizes the cost, energy consumption and the number of accepted requests under latency and resource constraints. The authors of [228] also consider MEC in UAV-terrestrial networks. They propose an asynchronous federated Deep Q-Network VNF-P algorithm. The scheme aims to minimize the energy consumption and the average Age of Information (AoI).

C. NS-ENABLED NETWORKS

NS in the A-T segment is still in its infancy, with most research focusing on networks employing UAVs or drones as aerial platforms for the terrestrial network extension to provide 5G slices (eMBB, URLLC, mMTC) to end-users [234], [266]. Integrated UAV-Terrestrial networks can benefit from NS technologies to increase reliability, enhance security, and improve energy efficiency [267]. A NS framework named AirSlice is proposed in [268] for 5G UAV communications. Following the 3GPP standardization, AirSlice is designed to support traffic differentiation based on QoS requirements, and a proof of concept implementation is validated, offering URLLC services in a realistic setup. The major issues of NS in UAV-based networks include mainly RAN resource management and UAV slicing. To enhance network performance and efficiency, UAV deployment is typically optimized in conjunction with these problems. Such challenges can be addressed through conventional or AI-based approaches.

1) Traditional Approaches

To optimally customize network slices sharing the same infrastructure, the resource management problem is usually considered jointly with UAV deployment and slicing in integrated UAV-Terrestrial networks. For example, the authors of [232] propose a RAN resource orchestration algorithm, the repeatedly energy-efficient and fair service coverage (RE^2FS) scheme. RE^2FS jointly optimizes the UAV trajectory, its transmission power, and the slice

TABLE 13. NFV-enabled integrated Aerial-Terrestrial networks: Traditional and AI-based approaches.

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
Traditional approaches				
SFC embedding	[224]	Long-term cost and latency minimization	Dynamic topology-aware min-latency SFC migration algorithm	Latency and migration cost
SFC embedding	[225]	Task completion time and revenue optimization	Heuristic two-stage SFC deployment strategy	Overall revenue, task execution time, and success ratio
VNF placement	[223]	Revenue and cost optimization	Heuristic VNF-PR algorithm	Aggregation ratio and resource consumption
Network resiliency	[226]	Potential resilience bottlenecks identification	Quantitative modeling-based service chains analysis	Network resilience
AI-based approaches				
VNF placement	[227]	Energy efficiency and average delay optimization	Hierarchical hybrid DRL-based joint trajectory design and VNF-P scheme	Service latency, energy efficiency
VNF placement	[228]	Energy consumption and average AoI minimization	Asynchronous FL Deep Q-Network VNF-P algorithm	Energy consumption, AoI violation percentage
VNF placement	[229]	Number of accepted requests, energy consumption and cost optimization	Joint online DRL-based VNF-P and UAV deployment algorithm	Number of accepted requests, sum of energy consumption and cost

access requests acceptance, to physically configure the UAV eMBB slices. Based on the successive convex approximation (SCA) method, the RE^{2}FS aims to minimize the UAVs transmit power and maximize the data rates of the payload eMBB slice ground users. Moreover, the joint RAN resource reservation and UAV deployment are considered in [231], where the UAV is optimally deployed to serve eMBB slice users and mMTC slice devices. A binary-search-based RAN resource reservation and UAV deployment algorithm is proposed with the goal of BB users' average rate maximization. Using an SDN/NFV architecture, the authors of [230] study RAN slicing, including RAN inter-and intra-slice resource management, jointly with UAV placement and UAV-device association in multi-Drone Small Cells (DSCs) networks. The integrated DSC-terrestrial network provides connectivity to two types of devices. Mobile user and IoT machine-type devices have different QoS requirements. The authors design a clique-based joint UAV deployment and resource slicing algorithm that minimizes the radio resource consumption with two-level partitioning.

2) AI-based Approaches

In [235], [236], AI techniques are utilized for RAN inter-slice resource management in the A-T segment to achieve different objectives. On the one hand, the management and slicing of radio resources are examined in [236] for UAV-aided vehicular communications. To maximize bandwidth efficiency, the authors develop an LSTM-based resource allocation algorithm. The ML model is employed for the prediction of vehicles and UAVs mobility. Compared to other ML-based methods, the proposed solution shows improved average bandwidth efficiency. On the other hand, the researchers in [235] consider the slicing of three types of resources, i.e., computing, networking, and storage, in a multi-dimensional manner. They investigate the scenario of autonomous vehicles supported by SDN/MEC-enabled networks. The UAVs are required to meet the QoS of URLLC and eMBB slices for driving services and passengers eMBB services, respectively. Targeting slice embedding energy consumption minimization, the authors propose an LSTM-based survivable resource slice embedding algorithm. Simulation results demonstrate that this technique offers improved slice request acceptance, recovery ratios, and reduced energy consumption. Meanwhile, computation offloading in MEC-enabled UAV-terrestrial networks is examined in [234], to support 5G URLLC slices. A computing resource management scheme is designed to optimize power consumption, delay, and loss probability. The algorithm leverages the superiority of RL approaches in the decision-making process.

Furthermore, UAV slicing is another major challenge in NS-based integrated networks. In particular, UAV-assisted networks usually rely on remotely controlled UAVs to deliver connectivity services. Consequently, NS requires the creation of a minimum of two slices [269]:

- UAV control slice is used to control the movements of the UAVs. It usually has similar characteristics as the URLLC slice.
- UAV payload slice is utilized to provide diversified communication services, including mobile broadband connectivity and machine-type communications.

Using AI models, the authors of [233] address the problem of inter-slice RAN resource management in UAV slicing. They consider the URLLC and eMBB slices dedicated for UAV control and payload, respectively. With the objective of optimizing UAV energy consumption and service coverage fairness, they propose an updated version of the RE^2FS algorithm, which they introduced in [232]. Their method involves employing an Echo State Network (ESN) based approach and a DNN for user location prediction and channel estimation, respectively.

Tables 11, 12, 13, and 14 give a summary of relevant works reported in the literature investigating SDN-, NFV-, and NS-enabled integrated A-T networks.

VIII. VIRTUALIZATION IN THE SATELLITE-AERIAL-TERRESTRIAL SEGMENT

The integration of satellite, aerial, and terrestrial networks harnesses the capabilities of the different platforms to support a variety of 6G applications. SDN and NFV paradigms are adopted to improve network flexibility and efficiency. They are also combined with AI techniques to offer intelligent network management [270]. Although the virtualization of the S-A-T networks offers seamless and ubiquitous connectivity, it increases the complexity of the related problems. In this section, we review the existing research that has been dedicated to addressing the issues of SDN, NFV, and NS in the S-A-T segment.

A. SDN-ENABLED NETWORKS

The SDN paradigm facilitates the integration of the satellite, aerial, and terrestrial segments, producing a three-layered network architecture as introduced in [237]–[239]. Nonetheless, the large-scale, dynamic, and heterogeneous characteristics of these networks result in more complex SDN-related problems compared to terrestrial and other integrated networks. Few works have been reported in the literature addressing such issues, including CPP, routing optimization, and resource management in the S-A-T segment employing conventional methods and AI-based techniques.

1) Architectures and Experimental Implementations

The authors of [238] propose a hybrid SDN-based architecture for QoS and security-aware routing, where both SDN and traditional network protocols are adopted for Vehicle-to-Everything communication. Using a hierarchical controller configuration, they introduce the routing service composition layer. This layer composes E2E paths with the aim of route reliability maximization while satisfying QoS and security requirements. Vehicular communications are also considered in the design of an SDN-based SAGIN architecture in [25]. Using hierarchical multi-controller configuration, the proposed framework adopts SDN and NS technologies to support both vehicular and legacy services in isolated network slices. Another multi-layered architecture is presented in [237], where the main controller at the ground station performs cross-domain orchestration to improve network efficiency. Meanwhile, researchers in [239] adopt the SDN paradigm, MEC, and AI technologies to build an integrated aeronautical federation framework. Deploying the controller on HAPS, the proposed framework enables aeronautical applications such as aeronautical edge computing and aircraft in-cabin connectivity and sensing. In [240], the authors propose the Software-defined Space-Air-Ground Integrated Moving Cells (SAGECELL) framework for ultra-dense networks supporting multiple applications. The architecture is validated through a case study of eMBB services, and simulation results show improved throughput performance.

2) Traditional Approaches

The routing issue is studied in [242] and [241] using a single controller configuration. On the one hand, an intelligent flow forwarding scheme combining multi-path routing and multi-protocol mechanism is proposed in [242]. With the goal of path reliability maximization, the algorithm offers enhanced resilience and security, compared to conventional routing strategies. On the other hand, the authors of [241] design a dynamic transmission control technique for SDN-enabled S-A-T networks. The proposed method is based on queueing game theory with the objective of system social welfare maximization. It presents improved performance in terms of throughput and service value delay, as shown by the simulations.

3) AI-based Approaches

As SDN-related issues become more complicated in the S-A-T segment, solutions based on conventional techniques become inefficient. Hence, researchers turn to AI models. First, a controller deployment scheme with a hierarchical multi-controller structure is designed in [243]. Adopting K-means clustering, the authors divide the network into multiple sub-networks, each with a local secondary controller. They formulate the multi-objective optimization of delay and controller load balance, and solve it using the Genetic algorithm to determine the optimal controller deployment scheme. Next, resource management is investigated in [244], with the goal of the joint optimization of user request acceptance rate and long-term revenue rate. A distributed hierarchical hybrid DRL-based resource allocation scheme is designed, where the RL agents are deployed on the hierarchical controllers. It outperforms the conventional and centralized approaches in terms of average revenue and service success rate. Meanwhile, the problem of traffic scheduling in the S-A-T segment is examined in [245], with the objective of flow maximization. The authors develop an RL-based traffic scheduling algorithm for single controller SAGIN, where Q-learning is used to optimize the scheduling decision-making process. The results demonstrate its superiority over existing

TABLE 14. NS-based integrated Aerial-Terrestrial networks: Traditional and AI-based approaches.

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
		Traditional approaches		
Joint RAN resource management and UAV deployment	[230]	Resource consumption minimization	Clique-based joint UAV deployment and resource slicing algorithm	Cost and resource utilization
	[231]	Users average rate maximization	Binary-search-based RAN resource reservation and UAV deployment algorithm	Average rate increase
RAN resource management	[232]	Optimization of UAV transmit power and UE data rate	RE^2FS resource orchestration scheme based on SCA	Jain's fairness index and energy efficiency
		AI-based approaches		
Traffic scheduling and offloading	[234]	Optimization of power consumption, delay, and loss probability	RL-based computing resource management scheme	Delay, loss probability, and power consumption
RAN resource management	[235]	Slice embedding energy consumption minimization	LSTM-based survivable resource slice embedding algorithm	Slice request acceptance and recovery ratios, energy consumption
	[236]	Bandwidth efficiency maximization	LSTM-based resource allocation algorithm	Average bandwidth efficiency
UAV slicing	[233]	Optimization of energy consumption and service coverage fairness	RE^2FS resource reservation scheme based on ESN and DNN	Jain's fairness index and energy efficiency

TABLE 15. SDN-enabled integrated Satellite-Aerial-Terrestrial networks: Architectures and experimental implementations.

Ref.	Controller placement	Use case scenario	Implementation Tools	Comments
[238]	Satellite, aerial, and ground platforms	Vehicular communication	N/A	Propose a hybrid SDN-based architecture with hierarchical multi-controller for QoS and security-aware routing
[25]	Satellite, aerial, and ground platforms	Vehicular communications	N/A	Design a SAGIN architecture based on SDN and NS technologies for vehicular communications
[237]	Ground station, GEO satellite, and HAPS	N/A	OpenFlow protocol	Propose a cross-domain SDN-based architecture with hierarchical multi-controller to improve configuration updating
[239]	HAPS	Aeronautical applications	STK toolkit	Propose AI/SDN-based integrated aeronautical federation framework to enable aeronautical applications
[240]	Satellite, aerial, and ground platforms	Moving cells for ultra-dense networks	N/A	Propose a software-defined SAG integrated moving cells framework for ultra-dense networks supporting multiple applications

algorithms in terms of load balancing and network capacity utilization.

B. NFV-ENABLED NETWORKS

Because of the unique characteristics of these next-generation networks, the adoption of NFV technology in integrated S-A-T networks is still in its early stages, with only a handful of studies focusing on VNF placement and SFC deployment.

1) Traditional Approaches

The VNF-P problem is studied in [246] and [247] with different optimization objectives. The authors of [246] aim to maximize the total profit of the service provider. Considering the delay and cost of VNF migration, they jointly formulate the VNF-P and the VNF scheduling problems as a MILP problem. Then, they propose two dynamic Tabu search-based VNF mapping and scheduling schemes. In [247], the resource utilization is maximized while meeting the SFC requests delay constraint. A resource-efficient and delay-aware VNF-P scheme is designed based on graph matching theory. Furthermore, the SFC deployment issue is investigated in [248]–[250]. In [250], the deployment delay is minimized, and a delay-aware SFC mapping scheme is designed based on the k-shortest path algorithm for delay-sensitive applications. The authors of [249] maximize the number of completed tasks while satisfying the deployment, flow, and resource constraints. Employing the reconfigurable time expansion graph representation, they design an SFC deployment algorithm based on matching game theory. Moreover, the number of completed missions is jointly optimized with the cost of computing and bandwidth

TABLE 16. SDN-enabled integrated Satellite-Aerial-Terrestrial networks: Traditional and AI-based approaches.

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
Traditional approaches				
Routing optimization	[242]	Path reliability maximization	Intelligent multi-path multi-protocol hybrid flow forwarding scheme	Average path reliability, packet delay, throughput
	[241]	System social welfare maximization	Queueing game-based dynamic transmission control technique	Throughput and service value delay
AI-based approaches				
Controller placement	[243]	Optimization of delay and controller load	K-means-based dynamic controller deployment scheme	Latency and load balancing
Resource management	[244]	Joint optimization of user request acceptance rate and long-term revenue	Hierarchical hybrid DRL algorithm	Average revenue and service success rate
Traffic scheduling	[245]	Flow maximization	Q-learning based SAGIN traffic scheduling algorithm	Load balancing and network capacity utilization

resources in [248]. The authors propose an NFV-based bidirectional mission offloading framework to enhance network flexibility. They design an SFC embedding scheme to validate their framework for computation-intensive and delay-sensitive applications.

2) AI-based Approaches

The research efforts utilizing AI-based methods in NFV-enabled S-A-T networks are scarce. Researchers in [251] propose a hybrid DRL and greedy algorithm-based VNF-P scheme. They aim service energy consumption minimization in MEC-enabled SAGIN. They validate their approach using metrics such as energy consumption, average delay, request acceptance ratio.

C. NS-ENABLED NETWORKS

Due to the dynamic, large-scale, and heterogeneous nature of integrated S-A-T networks, employing NS paradigm to improve resource management efficiency and overall performance is a challenging task [256], [257], [271], [272]. The research works in this area are limited to a few studies on resource slicing and management adopting traditional and AI-based methods.

1) Traditional Approaches

Dynamic RAN resource management is examined in [252] and [253], considering different use case scenarios. On the one hand, the authors of [252] focus on user association jointly with intra-slice RAN resource allocation for edge computing and SDN-based networks. They aim to maximize the aggregate transport capacity capturing the overall network performance. They design a dynamic resource orchestration and user selection algorithm based on derived scaling laws describing the network behavior in function of its size. On the other hand, joint spectrum resource reservation and UAV deployment is examined for SAGIN vehicular communications in [253]. A service-aware dynamic resource slicing scheme based on Lyapunov optimization is proposed, with the objective of long-term revenue and system stability maximization. The algorithm carries out the service request admission and scheduling, the UAV deployment, as well as the resource slicing to serve the different network slices.

2) AI-based Approaches

The inter-slice RAN resource management problem is solved using AI techniques in [254] and [255] with the objective of the maximization of network utility, and the joint optimization of throughput, service delay, and coverage area, respectively. In [254], a distributed dynamic resource slicing scheme is proposed to reserve the processing and transmission resources to network slices. The algorithm combines a graph neural network-based DL model and an online ADMM decomposition technique to obtain optimal resource slicing in MEC-enabled SAGIN. Compared to existing algorithms, the proposed solution improves user service completion time, network utility, and reliability. Meanwhile, the authors of [255] develop a dynamic RAN slicing algorithm that can conduct not only dynamic inter- and intra-slice power resources allocation but also dynamic user association and optimal virtual UAV positioning. To achieve the Pareto optimality of the formulated multi-objective optimization problem, their proposed algorithm is based on a joint central and distributed MADDPG approach. Compared to benchmarks, the proposed solution shows increased throughput and reduced average delay. Furthermore, network security and resiliency are studied in [256], [257]. The authors of [256] review the role of DL in the privacy preservation of sliced integrated networks. Meanwhile, the researchers in [257] look into the resilience of NS in the S-A-T segment and propose a resilient multi-domain slicing framework for S-A-T edge computing IoT networks.

TABLE 17. NFV-enabled integrated Satellite-Aerial-Terrestrial networks: Traditional and AI-based approaches.

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
Traditional approaches				
VNF placement	[246]	Total profit maximization	Two dynamic Tabu search-based VNF mapping and scheduling algorithms	Service acceptance ratio, total profit, and QoS satisfaction
	[247]	Resource utilization maximization	Graph matching theory-based delay-aware VNF-P scheme	Resource utilization efficiency and running time
SFC embedding	[248]	Optimization of resources cost and number of completed missions	SFC embedding based on bidirectional mission offloading framework	Reliability and resource utilization efficiency
	[249]	Number of completed tasks maximization	Matching game-based SFC deployment algorithm	Completed tasks number and resource utilization efficiency
	[250]	Delay minimization	Delay-aware SFC mapping scheme	Delay, resource consumption, and service acceptance rate
AI-based approaches				
VNF placement	[251]	Service energy consumption minimization	Hybrid DRL and greedy algorithm-based VNF-P scheme	Energy consumption, average delay, request acceptance ratio

TABLE 18. NS-based integrated Satellite-Aerial-Terrestrial networks: Traditional and AI-based approaches.

Research focus	Ref.	Objective	Proposed solution	Evaluation metrics
Traditional approaches				
Device/user association	[252]	Aggregate transport capacity maximization	Dynamic resource orchestration and user selection algorithm based on scaling laws	Aggregate transport capacity
Joint RAN resource management and UAV deployment	[253]	Long-term revenue and system stability maximization	Service-aware dynamic resource slicing scheme	Time-averaged throughput and queue size
AI-based approaches				
RAN resource management	[254]	Network utility maximization	Distributed dynamic resource slicing scheme based on DL and online ADMM methods	User service completion time, network utility, and reliability
Joint RAN resource management and UAV deployment	[255]	Joint optimization of throughput, service delay, and coverage area	Dynamic RAN slicing and UAV deployment algorithm based on a joint central and distributed MADDPG approach	Throughput, average delay, and SINR
Network resiliency	[257]	Network failure mitigation	Resilient multi-domain NS framework	Network resilience

Tables 15, 16, 17, and 18 summarize the contributions examining the application of SDN, NFV, and NS in integrated S-A-T networks.

IX. SUMMARY & LESSONS LEARNED

In previous sections, we provided a taxonomy of integrated TN-NTNs virtualization, where we categorized the relevant contributions using a four-level classification. Specifically, we indicated for each study the level of TN-NTN integration, the used virtualization technology, the addressed problem, the type of the study, and the proposed solution, which can be based on conventional or AI-enabled methods. A number of insights could be acquired through the review and analysis of the documented research works.

From the perspective of the level of TN-NTN integration, varying degrees of research interest have been shown in the implementation of virtualization technologies in the three integrated segments. On the one hand, the S-T segment has received significant attention, compared to the other two segments. This is owing to the satellites' large coverage area, their broadcast/multicast capabilities, and the recent technological advancements in the satellite industry. On the other hand, documented studies have investigated virtualized integrated A-T networks are comparatively fewer. This is primarily due to the low reliability and limited capacity of the UAVs and the immaturity of HAPS technology. In particular, the virtualization of HAPS-based networks is still in its infancy due to the nascent state of the associated technologies. In contrast, there is an emphasis on the adaptation of virtualization techniques in UAV-assisted networks because of their flexible deployment and diverse application scenarios. Meanwhile, incorporating network virtualization enablers in the S-A-T segment is still in its early stages. This is because the related problems are significantly more complicated compared to terrestrial and other integrated networks, and their complexity increases as the networks become larger and more dynamic. In addition, the deployment of UAVs can be jointly studied with other issues in integrated A-T and S-A-T networks. This results in optimized resource utilization and improved network performance. Nonetheless, it further complicates the implementation of virtualization approaches in these segments.

In terms of the application of virtualization technologies, researchers have largely focused on SDN-enabled networks in the three segments. Studies typically investigate key architectural considerations by proposing multiple designs of integrated networks based on the concepts of SDN. Following the SDN data/control plane separation and centralization of the network logic; various use case scenarios have been explored, considering different controller structures, and several experimental implementations have been provided. Some researchers have also attempted to solve a number of issues that have emerged as a result of the introduction of SDN in next-generation networks. The CPP, the routing optimization, and the satellite handover management are the main problems that have been studied in SDN-enabled S-T networks. Conversely, in SDN-based A-T networks, resource management, traffic offloading, and routing optimization have primarily been researched, whereas the CPP is seldom examined. On the other hand, contributions employing SDN in the S-A-T segment are limited and mostly concentrate on architectural perspectives. Compared to SDN-enabled networks, the research on the adaptation of NFV is restricted in the three network segments. However, unlike the works on SDN-based networks, the studied NFV-enabled integrated networks can be based on architectures where both SDN and NFV paradigms are adopted. The core challenges that have been addressed include VNF placement, SFC embedding, and virtual resource management. Additionally, a few insights on architectures and experimental implementations have been provided in the A-T segment. As for the adaptation of NS, the contributions are considerably scarce compared to SDN and NFV. The primary issues that have been tackled are RAN resource management and device/user association, taking into account the three segments. UAV slicing has also been explored as a special case in NS-based integrated A-T networks. Moreover, although virtualization technologies can enhance network performance and efficiency, security and resiliency remain key challenges in the integration of TN-NTNs. Traffic scheduling and offloading present other common challenges that have been investigated in the virtualization of TN-NTNs.

Researchers tend to utilize traditional methods to solve the various problems associated with the introduction of SDN, NFV, and NS in integrated TN-NTNs. In particular, optimization techniques based on heuristic and meta-heuristic approaches have been widely used to deal with the majority of the aforementioned problems. This includes CPP, routing, handover management, VNF-P, and RAN resource allocation. Game theory is another approach that has been adopted to optimize handover and VNF-P mechanisms. In addition, routing and resource management issues have been addressed using shortest-path algorithms and approaches based on queuing theory, respectively. Nonetheless, a few efforts have been dedicated to the application of AI algorithms, especially in SDN and NS-based networks. In contrast, AI-powered solutions in NFV-enabled networks are scarce. The predominant techniques employed in TN-NTNs virtualization are RL approaches. In fact, RL agents have been used to solve CPP, resource allocation, and routing problems. Additionally, clustering algorithms and ML classifiers have been utilized in the design of CP and routing schemes in SDN-enabled networks. Besides, DRL approaches have been adopted to handle VNF and SFC deployment issues in NFV-based networks. Meanwhile, DNNs and LSTM models have been used to tackle resource allocation problems in NS-based integrated networks.

X. OPEN ISSUES AND RESEARCH DIRECTIONS

In this section, we highlight several open issues and discuss potential research directions for the advancement of integrated TN-NTNs virtualization. The primary challenges facing the adaptation of virtualization technologies in next-generation networks involve coping with non-terrestrial network characteristics, dealing with multi-domain network architecture, and ensuring network security and resiliency. Besides, because of the unique peculiarities of NTN platforms, the development of specialized simulation tools is necessary to design, optimize, and evaluate communication systems in integrated TN-NTNs. Moreover, since AI is expected to play a major role in the establishment of 6G networks, overcoming the obstacles arising from the introduction of AI algorithms becomes another open issue. Additionally, emerging innovations such as digital twins, blockchain, and quantum communications could be leveraged and combined with virtualization technologies to enhance the efficiency and security of next-generation networks.

A. COPING WITH THE CHARACTERISTICS OF NTNs

Due to the unique characteristics of NTNs, the implementation of virtualization technologies in next-generation networks faces several difficulties. These features mainly include the dynamic environment, the large-scale topology, and the limited resources on board NTN platforms. On the one hand, the high mobility of network nodes increases the complexity of network management and operation. These mobile nodes can follow either predictable patterns, such as satellites moving according to their predefined orbits, or unpredictable patterns, such as UAVs, which can exhibit varying flying trajectories. This results in unstable connectivity, frequent handovers, and service interruption. Hence, novel mobility and handover management strategies are crucial to guarantee QoS requirements and seamless connectivity [28], [265], [272]. In SDN/NFV-enabled networks, continuous flow rules computation, forwarding tables updates, and NFV service reconfiguration are necessary to avoid disruptions and assure service continuity. Besides, the high mobility and frequent handovers yield variations in network resource availability. This affects the provisioning of network slices where the resources reserved for one slice may no longer be accessible, causing failure to meet QoS constraints. Therefore, adaptive NS schemes are needed, and developing dynamic resource reservation and orchestration is imperative [186], [257], [273]. On the other hand, scalability issues emerge as the number of network nodes and end-users grows. Mega-constellations of NGEO satellites and HAPS, as well as large UAV swarms, can cause network performance degradation. Hence, efficient scalable network management procedures and hierarchical architectures should be designed to alleviate the scalability problem [18], [265]. In particular, the physically centralized single controller structure is inadequate for SDN-enabled integrated TN-NTNs. This is due not only to the single controller's restricted computing powers in comparison to the network's scale but also to the high latency and increased control overhead caused by this type of control structure. As a result, a logically distributed hierarchical control structure is required to satisfy the growing service demands of these large-scale networks [28], [263], [274]. Another scalability challenge involves the placement of VNFs and the embedding of SFCs in NFV-based networks. Specifically, the complexity of these optimization problems escalates because of the large size of the network and the limited resources of NTN platforms [223]. Therefore, designing suitable network architectures and effective network operation and management algorithms is important to overcome the scalability obstacles. Furthermore, the limited resources on board NTN platforms introduce constraints on the network's ability to cope with its dynamic large-scale topology. The restricted communication, computing, and caching resources can impose limitations on the NTN nodes' functionalities, such as collecting network information, processing data, and executing complex algorithms. In addition, multiple connectivity interruptions and limited service duration can be caused by the energy depletion of satellite and aerial nodes, relying on batteries and solar power [220], [272]. The energy constraints can result in service discontinuity and network failure, especially in UAV-assisted networks, where the energy supplies are used for connectivity and flight purposes. Thus, it is critical to develop energy-efficient lightweight schemes taking into account the limited resources and characteristics of the different nodes in integrated TN-NTNs.

B. DEALING WITH MULTI-DOMAIN NETWORK ARCHITECTURE

A multi-domain multi-tenant architecture is created by virtualizing integrated terrestrial and non-terrestrial networks using SDN, NFV, and NS. This introduces a number of challenges stemming from the essential seamless orchestration and management of multi-dimensional resources across multiple network domains, while catering to the needs of diverse tenants. In this multi-domain architecture, network resources are owned by numerous service and infrastructure providers across different administrative domains [41]. For instance, space, airborne, and terrestrial platforms are managed and operated by different entities, including traditional terrestrial telecommunication companies, and aerospace agencies. Cloud services and edge computing infrastructure providers are also major stakeholders, as next-generation networks rely significantly on technologies requiring unprecedented computational capabilities. Besides, the heterogeneity of the underlying network equipment supported by a variety of communication standards and technologies further complicates the issue and limits the network interoperability [25], [265]. Consequently, it becomes necessary not only to provide a unified methodology to abstract the network resources offered by various providers but also to promote the standardization of the protocols and interfaces. This facilitate the exchange of these resources and the seamless integration of different network components in virtualized integrated 6G networks [41], [109], [257], [275]. The next challenge imposed by such architecture is the design of efficient cross-domain coordination and collaboration mechanisms between the different entities. Developing efficient and cost-effective schemes to share and orchestrate resources across various domains, while meeting the stringent requirements of diverse services is necessary to create customized network slices in multi-domain networks. Moreover, the availability of network resources is directly affected by the dynamic topology of 6G networks, necessitating a dynamic SLA decomposition across the different domains [257]. However, ensuring the SLA in this multi-domain architecture is difficult. It demands the implementation of innovative cross-domain orchestration and coordination approaches capable of adapting to the characteristics of NTNs. Furthermore, through NS, the multi-domain integrated TN-NTN architectures offer tailored services to multiple tenants, by enabling the creation of various network slices on top of the shared infrastructure. This raises a number of obstacles; notably in terms of the properties of slice isolation, elasticity, and scalability [109], [276]. It is challenging to ensure an isolated, elastic, and scalable allocation of network resources for each tenant, due to the large-scale topology, the high mobility, and the constantly changing user demands. Thus, it is essential to design NS strategies capable of maintaining high levels of QoS satisfaction for each network slice, while dealing with 6G network features.

C. ENSURING NETWORK SECURITY AND RESILIENCY

Compared to terrestrial networks, the unique characteristics of integrated TN-NTNs complicate the task of ensuring network security, resiliency, and data privacy. In fact, the large-scale, dynamic, and heterogeneous topology combined with the limited onboard resources imposes numerous challenges. First, a crucial security challenge is the vulnerability of data transmission, due to the wireless and broadcast nature of communication links in integrated TN-NTNs. Jamming, eavesdropping, disruption, and falsification of data are potential threats in this scenario [18], [113], [265]. Notably, in SDN-enabled networks, the communications between the data and control planes can be susceptible to such menaces, which can compromise the network nodes [18], [113]. Additionally, hijacking and unauthorized access to non-terrestrial platforms, including satellites, HAPS, and UAVs are other significant vulnerabilities [218], [265], [277]. Hence, lightweight, low-complexity solutions for physical layer security are of paramount importance. Novel techniques for anti-jamming, encryption, authentication, and intrusion detection are necessary to safeguard data transmission in highly dynamic networks. Also, blockchain and quantum communication can be leveraged to protect the data and secure satellites' optical links, respectively. Second, since the SDN paradigm offers the centralization of the control logic, the security of SDN controllers is another important concern [112], [274], [278]. On the level of the control plane, cyber-attacks and malicious activities, such as controllers' unauthorized access and hijacking, DDoS and target selection attacks, and software vulnerabilities, can be fatal where the attacker can gain access to the entire network. Thus, it is necessary to design security protocols to ensure the protection of SDN controllers, especially if they are deployed on NTN nodes. AI models can be employed for attack detection and mitigation, while blockchain techniques can be used to ensure the trustworthiness and integrity of the network entities. Besides, the optimal orchestration and placement of security VNFs, such as virtual IDSs, firewalls, and proxies can aid in the mitigation of cyber-attacks on the network [106], [221]. However, the virtualization of network functions as VNFs in NFV-enabled networks can increase their vulnerability because of software flaws [113]. Moreover, the slicing of a shared underlying infrastructure introduces other security and data privacy challenges, in NS-based integrated TN-NTNs. Since multiple tenants can share the same physical network node to deploy their virtual networks, an attacker can exploit one slice to gain access to another slice and exhaust its resources [41], [256]. Another security concern in sliced networks is data leakage during the communication between end-users and network slices. This type of communication involves the exchange of sensitive user information such as location, device type, and user demands. The interception and tampering of such data can result in the users' association with an exposed network slice. Therefore, efficient security policies should be enforced including traditional and AI-enabled authentication and slice access control measures. In addition, the multi-domain architecture of integrated networks requires the development of efficient mechanisms to seamlessly orchestrate security protocols across the different domains in [274]. Furthermore, network resiliency is a major issue in integrated TN-NTNs due to the network characteristics. The large communication ranges of satellites and the high dynamicity of UAV-assisted networks, in particular, render the TN-NTNs more susceptible to failures and interruptions [257]. For sliced networks, robust NS solutions that can countermeasure various types of network failures are necessary to sustain network performance and ensure service continuity during the slices' life cycles.

D. DESIGNING DEDICATED SIMULATIONS TOOLS

The network performance evaluation phase is mandatory before deploying new network architectures and implementing novel protocols in a real-world environment. As a result, it is vital to test and validate communication systems using simulation tools and experimental implementations. However, this can be a challenging task in integrated TN-NTNs because existing network simulators lack the adaptability to NTNs characteristics. Also, real-life experimental evaluation of NTN platforms is difficult [18], [113], [222]. Field trials using NTN platforms such as satellites, HAPS, and UAVs can involve significant expenses, safety risks, and regulatory constraints. This limits scale and frequency of these trials. In addition, existing simulation tools are not suitable for these networks since they are built for terrestrial networks and do not capture the specificities of NT nodes. In particular, the current simulation tools that incorporate virtualization technologies and protocols need to be extended. Additionally, novel tools need to be built to include the constraints imposed by the use of satellites, HAPS, and UAVs. For example, the well-known OpenFlow protocol used in SDN-enabled networks should be extended. The development of novel extensions capable of dealing with the NTN features is also required [273], [274]. Nonetheless, few efforts have recently been directed at the design of specialized simulation tools for next-generation networks. For instance, a virtualized environment emulation framework (VENUE) is introduced in [222] to facilitate the validation and prototyping of NFV-enabled UAV-assisted networks. In addition, extensions for the network simulator NS3 and the OpenFlow protocol are proposed in [110] and [28] to implement SDN-based S-T networks architectures and evaluate routing algorithms and network management strategies. However, such studies are still in their early stages, and further research is necessary. Meanwhile, theoretical modeling can be utilized to understand the network behavior and evaluate the performance of the proposed architectures and algorithms [274].

E. APPLYING AI ALGORITHMS

AI will play a critical role in the development of 6G networks. Particularly, it can solve multiple complex problems in network virtualization as discussed before. It can also enhance network performance through prediction and pattern recognition, as well as enable autonomous network planning and operation [17]. Nonetheless, using AI algorithms in next-generation networks raises a number of issues that can be observed from two aspects. On the one hand, issues caused by the inherent characteristics of AI models can complicate its implementation in 6G networks. Supervised and unsupervised learning, used for prediction and classification problems, require large realistic training datasets, causing data collection and analysis challenges. Meanwhile, RL algorithms, used for decision-making tasks, struggle to solve complex optimization problems with numerous constraints [186]. Another concern with using AI in 6G networks is algorithm selection, as there is no one-size-fits-all solution. Different factors should be considered in choosing a suitable AI technique to address a particular network problem [257]. This includes the type of problem, the needed resources to execute the algorithm, and the desired level of performance. Thus, it is necessary to conduct an analysis that examines the cost-benefit trade-off between the selected AI model and its anticipated performance. On the other hand, applying AI in integrated TN-NTNs is a challenging task due to the unique features of SAGIN including the highly dynamic environment, the large-scale topology, and the limited on-board resources. The high mobility of NT platforms introduces increased dynamicity to the network topology. This results in the need for designing adaptive algorithms with continuous updating capable of obtaining optimized strategies at different time slots for resource allocation, device/user association, routing, controller placement, etc. Supervised and unsupervised ML techniques lack the resilience to adapt to such a dynamic environment [18], [186], [257]. This is mainly due to their dependence on the training dataset, where the real dataset may be statistically different and constantly changing. Consequently, it causes degradation in the ML algorithm performance. RL can be a solution for this issue, since the RL agents can continuously learn new optimal policies adapting to the dynamic environment in a dataset-free fashion [58]. Nevertheless, the use of RL in integrated TN-NTNs raises multiple challenges [279]–[282]. This includes the sample efficiency issue, which refers to the algorithm's ability to achieve good performance with a minimal number of interactions with the environment. Specifically, in the TN-NTNs dynamic environment, RL agents require a greater number of trials to learn effectively, impacting the sample efficiency. Consequently, the model convergence and learning speed are affected. Another issue involves the use of distributed multi-agent RL, which is typically employed to combat scalability problems in TN-NTNs. However, the coordination between different agents is crucial for the effective implementation of these techniques, leading to additional obstacles. Furthermore, the large-scale topology of 6G networks increases the dimensionality of the state space for RL agents, imposing another challenge on the learning and optimization process of these AI models. This network characteristic brings additional obstacles in the application of AI methods regarding algorithmic complexity, feature extraction, and massive data collection and analysis [257]. Moreover, AI models are expected to deliver high performance in order to satisfy the needs of this expanding network with increased demands, diverse services, and stringent QoS requirements. Nevertheless, the limited resources on board NT nodes further complicate this task where the satellites, HAPS, and UAVs may not have sufficient resources in terms of energy, computing, and storage necessary for the implementation of powerful AI solutions [18], [186], [283], [284]. Therefore, the development of low-complexity, lightweight, and energy-efficient AI algorithms is required in 6G networks.

F. LEVERAGING OTHER EMERGING TECHNOLOGIES

Virtualization technologies can be combined with other emerging innovations — such as digital twins, blockchain, and quantum communications — to improve the performance and security of next-generation networks.

Multiple definitions can be found in the literature describing the Digital Twin (DT) paradigm. One way to characterize DT is by viewing them as replications of physical entities (objects, people, environments, etc.). Specifically, virtual representations of the physical assets are accurately created, and uni/bi-directional communication links are established, enabling the interaction between the two sides [285]. Powered by AI, digital twins can optimize and enhance the performance of next-generation networks. DTs can monitor the network status, analyze its operation, and predict failures in a real-time manner, using a closed loop between the physical and digital versions of the network [285]. In the context of SDN/NFV-enabled integrated TN-NTNs, DTs can further enable network virtualization, and improve the adaptability to highly dynamic topologies. Additionally, DTs can provide network operators with real-time insights into their network performance. They can be built in the SDN controller to enable proactive dynamic and intelligent network control [286]. Moreover, DTs can be used to create simulation and emulation environments, especially for networks incorporating NT platforms, to test and validate different applications instead of relying on the physical infrastructure, which can either be costly and/or dangerous [18]. For instance, using physical satellites to design, optimize, and test satellite-assisted networks can be very expensive and require interactions with satellite infrastructure providers. Meanwhile, DTs of such networks can be built, allowing researchers to flexibly and easily conduct their experiments and apply their modifications.

Similarly, deploying actual UAVs during the development and optimization stages of UAV-based networks can be both dangerous and costly. Hence, DTs can aid in designing, validating, and ensuring the safety of UAV-assisted networks. End-user virtualization is another approach for implementing DTs in virtualized networks where it can be utilized to describe the state and service requirements of end-users [6]. While technologies such as SDN, NFV, and NS focus on the virtualization of network infrastructure and resources, DTs of end-users enable the virtualization of end-users providing significant real-time end-user data that can boost the network's decision-making, management, and simulation capabilities. Furthermore, NS and DT technologies can enable service-centric and user-centric networking, respectively. While NS creates customized slices for different services, enabling service-centric management in 6G networks, DTs could be used to characterize end-users, allowing user-centric management in 6G networks [6]. In fact, after the creation of service-tailored slices, the data provided by the DT of individual end-users in each slice can be exploited to enable user-oriented decision-making. This improves intra-slice network management, thereby increasing the granularity and adaptability of network management, particularly in highly dynamic environments with diverse end-users.

Blockchain is a groundbreaking innovation that has revolutionized data storage, sharing, and verification. Originally developed for crypto-currencies, it is defined as a distributed and transparent ledger that ensures secure recording of transactions and assets [18], [287]. Blockchain can play a pivotal role in improving the security, privacy, and reliability of next-generation networks. In particular, for integrated TN-NTNs that use NT platforms, it is crucial to ensure the security and privacy of the exchanged critical data between network nodes, especially that it is wirelessly transmitted. In addition, the decentralized consensus mechanism of blockchain can enhance the trustworthiness of the network entities across different domains. It can verify the integrity of network data and node access control, and aid in cyber-attacks and malicious activity detection [17], [18], [277]. Moreover, SDN-enabled integrated TN-NTNs can benefit from blockchain by securing distributed SDN controllers and verifying OpenFlow tables [22]. Sliced networks also can employ blockchain to support authenticated slice brokering and trustworthy infrastructure sharing between the MNOs. This can be realized by offering traceable and transparent slice ledgers that can autonomously track the slice sharing and leasing behaviors [22].

Quantum technologies, including communication, computing, and sensing, are reshaping multiple fields, such as cyber-security, high-performance computing, and networking. In particular, quantum communication is transforming the way information is transmitted [288]. While classical communications rely on the classical zero and one bits, quantum communications leverage the principle of quantum physics to transmit quantum bits, known as qubits [27]. This would inherently result in secure and efficient data transmission where cyber-attacks and malicious activities can be effortlessly detected and mitigated, rendering it appropriate for integrated TN-NTNs [12], [17]. Moreover, the SDN paradigm can be combined with quantum communications in future networks to enhance quantum resource management and task administration [27]. The SDN controller can continuously monitor the quantum parameters, including the secret key rate of the Quantum key Distribution (QKD) protocol and the quantum bit error rate.

XI. CONCLUSION

To support the large variety of applications and satisfy the target KPIs of 6G networks, integrated TN-NTNs are envisioned as 6G key enabling technologies. However, the TN-NTNs integration faces several issues that can be solved using network virtualization technologies such as SDN, NFV, and NS. This survey provided a comprehensive review on the adaptation of these networking paradigms in next-generation networks. We commenced by covering the fundamentals of NTNs and virtualization techniques. Then, we brought attention to the intersection of AI and network virtualization, summarizing the major research areas where AI models play a pivotal role in enhancing SDN, NFV, and NS. After that, the survey highlighted the prevalent problems emerging from the adaptation of these techniques in integrated TN-NTNs. We proposed a taxonomy of integrated TN-NTNs virtualization based on a four-level classification. This taxonomy offers a structured and comprehensive review of relevant contributions, providing a synthesis of virtualization in integrated networks from different perspectives. Moreover, we summarized the insights acquired through the review and analysis of the documented works. Particularly, we discussed how research works focused on virtualization in the S-T segment, with limited efforts in the other segments. Additionally, we highlighted how SDN technology gained more attention compared to NFV and NS. We also explained how researchers tended to employ conventional methods such as heuristics, whereas AI-based approaches are scarce. Lastly, we identified several open issues and explored future research directions for the advancement of integrated TN-NTNs virtualization in the 6G era. We conclude that adopting network virtualization technologies in 6G integrated TN-NTNs offers efficient network management and improved network performance. Nonetheless, numerous research gaps should be addressed and further investigations are required to realize the full potential of these technologies.

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