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Review article

Machine learning-driven integration of terrestrial and non-terrestrial networks for enhanced 6G connectivity

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ABSTRACT

Non-terrestrial networks (NTN)s are essential for achieving the persistent connectivity goal of sixth-generation networks, especially in areas lacking terrestrial infrastructure. However, integrating NTNs with terrestrial networks presents several challenges. The dynamic and complex nature of NTN communication scenarios makes traditional model-based approaches for resource allocation and parameter optimization computationally intensive and often impractical. Machine learning (ML)-based solutions are critical here because they can efficiently identify patterns in dynamic, multi-dimensional data, offering enhanced performance with reduced complexity. ML algorithms are categorized based on learning style—supervised, unsupervised, and reinforcement learning—and architecture, including centralized, decentralized, and distributed ML. Each approach has advantages and limitations in different contexts, making it crucial to select the most suitable ML strategy for each specific scenario in the integration of terrestrial and non-terrestrial networks (TNTN)s. This paper reviews the integration architectures of TNTNs as outlined in the 3rd Generation Partnership Project, examines ML-based existing work, and discusses suitable ML learning styles and architectures for various TNTN scenarios. Subsequently, it delves into the capabilities and challenges of different ML approaches through a case study in a specific scenario.

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1. Introduction

The conclusion of fifth-generation (5G) standardization and subsequent deployments has driven academic and industry leaders to pursue the sixth-generation (6G) objective: persistent connectivity. This aim addresses the demand for uninterrupted, dependable, high-throughput connectivity everywhere and at all times [1]. Achieving this is particularly challenging in regions with limited cellular infrastructure, situations involving high-speed vehicles, and extremely crowded areas. Non-terrestrial networks (NTNs) are promising facilitators of the 6G vision due to their expansive coverage and minimal dependence on ground-based infrastructure. Consequently, various organizations have identified the requirements for effective terrestrial and NTNs (TNTNs) integration [2]. Additionally, the 3rd Generation Partnership Project (3GPP) has issued multiple technical reports and specifications on NTNs to integrate them into the 5G new radio (NR) standards, beginning with Release (Rel)-15.

Integrating TNTN is a complex task. It involves handling the usual challenges of managing diverse networks, and specific issues like identifying NTN devices and networks, constantly tracking their positions and movements, managing how cells and satellites connect and adjust, and controlling their beam directions. There are several integration requirements. For example, smooth handover mechanisms enable devices to transition between TNTNs without disruption. Ensuring compatibility between communication protocols utilized in both TNTNs is essential for facilitating effective data exchange. Dynamic allocation and management of resources, such as bandwidth (BW) and spectrum, are necessary to optimize network performance based on demand and usage patterns. The network needs to be centrally controlled and orchestrated to manage it properly. Strategies for interference mitigation between TNTN should be implemented to keep the signal quality and reliability high. Robust security measures should be applied to protect data during transitions between terrestrial and non-terrestrial segments of the network. The integrated network should also be scalable to handle the increased number of connected devices and the need to handle more data. Given these multifaceted challenges, traditional model-based solutions often fall short due to the extensive time required to gather relevant parameters and perform calculations [3].

Machine learning (ML) offers a promising alternative, leveraging its capacity to process large datasets quickly and adaptively learn from complex and dynamic environments. It can predict network load, anticipate resource demands, optimize handover processes, and enhance security protocols by identifying patterns and anomalies that do not exist in conventional methods. Therefore, incorporating ML into the management of TNTNs can lead to more efficient and responsive network operations, catering to the complex requirements of integrated TNTN systems. However, they cannot be applied blindly. Their effectiveness depends on factors like the computational complexity, the volume of training data needed, and how well the trained model performs in general situations. Another factor is their learning style and architecture. The data can be processed in a supervised (SL), unsupervised (USL), or reinforcement learning (RL) manner. Also, centralized, decentralized, or distributed control and processing schemes can be considered for their architectures.

1.1. Related work

The overview of the vision, requirements, and challenges of 6G wireless networks are explained in [4,5], and [6]. The current status and future directions of 6G wireless networks are reviewed in [7]. [8] and [9] discuss the key enabling technologies for 6G networks, such as wireless power transfer, terahertz communication, and visible light communication. The technologies, applications, and challenges of 6G wireless networks are explored in [10] and [11]. The opportunities and challenges in 6G networks, including ultra-reliable, low-latency, and massive machine-type communication, are discussed in [12,13], and [14]. A comprehensive 6G wireless communication survey is presented in [15] and [16]. The concept and standardization of 6G networks, including new wireless technologies and spectrum bands, are explained in [17,18]. In [19], the authors explore the challenges and opportunities of 6G networks, including the use of satellite communication. A comprehensive survey of 6G networks, including new radio access technologies and security challenges, is presented in [20,21]. Similarly, [22] presents a comprehensive survey of 6G wireless networks, including network slicing and new antenna technologies. [23] explains the five facets of the new wireless generation, along with its challenges and future directions. Although the primary goal of these papers is not to explain the role of NTN or TNTN integration, they discuss them since they are important and promising for 6G networks.

Numerous studies have investigated the role of NTNs in 6G wireless communications. For example, [24–29] provide a comprehensive look at various NTN applications, including satellite communication, aerial drones, and terrestrial devices. [30] delves into the specific challenges of satellite communication within 6G, such as power constraints, latency issues, and frequency allocation. [31] discusses the space-aerial-terrestrial integrated networks concept, recent research, key technologies, and standardization efforts, identifying future challenges for achieving a fully integrated 5G system. [32] explores multiple access techniques for 6G-enabled NTN-assisted Internet of things (IoT) technologies, detailing the architecture, key features, and challenges of NTNs. [33] highlights the role of NTNs in various environments, particularly transportation, and discusses architectures and standards for this integration based on the ITA-NTN project. [34] discusses the importance of mobility management in integrating satellite-based networks with 5G, focusing on challenges like power and signaling for mobile devices. It highlights recent research [35] reviews the research activities on NTNs. Then, it presents the characteristics and enabling technologies of NTNs in the 6G landscape and sheds light on the challenges. [36] discusses UAV-based wireless networks, including their advancements, challenges, and solutions. [37] examines how 6G will integrate TNTN using NR technology. It analyzes 3GPP specifications, identifies strengths and weaknesses of NR for 6G services on NTNs, and offers research insights for future development. [38] outlines NTN in 5G based on 3GPP Rel-17 and 18. [39,40] provide a comprehensive review of the 3GPP NTN standard, detailing its role in integrating satellite networks with 5G and beyond. [41] examines the challenges and advancements in integrating NTN components into 6G, essential for achieving global connectivity. [42] examines the progression of NTNs, underscoring their significance in 5G technology and illustrating their critical role in shaping the 6G ecosystem. [43] and [44] examine the impact of 6G networks across industries like agriculture, transportation, and healthcare. [45] discusses the technical aspects and integration challenges of various radio access technologies within 6G. [45] presents an overview of the space network entities such as unmanned aerial vehicles (UAVs), Low altitude platform stations (LAPs), and high-altitude platform stations (HAPs). Furthermore, the evolution from interoperable to fully integrated scenarios is summarized. [46] proposes an intelligent platform with an adaptation layer for integrating TN and NTN IoT networks, using distributed ML. It assesses this approach's efficiency and security and explores future research areas like digital twins and semantic communications. Also, the integration of NTN with other promising technologies, quantum technologies, reconfigurable intelligent surfaces, and IoT is discussed in [47,48], and [49], respectively to unveil their synergistic potential.

Most of the ML-based NTN works focus on implementing various ML approaches on a single facet of NTN operations, such as enabling IoT [50], handover optimization [51], trustworthy clash-free surveillance [52], integrating low earth orbit (LEO) satellites and multi-UAVs [53], sustainable maritime networking [54], vehicular networks [55], and coverage optimization [56]. Besides that, [57] presents the use of ML approaches in learning and adapting to complex NTN environments. [58] explores using artificial intelligence (AI) to address the challenges of integrating satellite-based NTN into 6G. It reviews existing research, discusses AI's potential to solve issues like delays and resource management, and offers recommendations for future AI-driven NTN in 6G. [59] examines how RL optimizes satellites and drones in next-generation cellular systems. It reviews RL's role in managing challenges such as resource allocation and control and identifies gaps between simulations and real-world applications, suggesting areas for future research. [60] explores practical approaches that ML offers for TNTN integration. Also, by going through the ML-based solutions that can make it easier for integrated TNTNs, this work shed light on the difficulties and problems associated with this integration. However, none of these works investigates the importance and usage of different ML algorithms for TNTN integration.

Unlike existing works, this paper presents a comprehensive survey of ML approaches, including a case study demonstrating how different ML approaches can be applied to solve integration issues, thereby providing a practical roadmap for future implementations. Thus, we provide a framework that can guide practical implementations and scenario-based optimization. Most related works are summarized in Table 1.

1.2. Paper contribution

In view of the above discussion, a preliminary version of this work [62] showing the capabilities and challenges of ML classes is extended. This paper presents the following contributions.

- Uniquely categorizes and discusses ML algorithms based on their learning styles and architectures, tailored to integrating TNTNs.
- Recommends suitable ML approaches for some integrated TNTN scenarios and architectures with sound reasoning.
- Incorporating a case study that applies the discussed ML approaches in this paper TNTNs, this paper offers practical insights.
- Reviews the use cases and scenarios for integrated TNTN and the properties of the associated devices.

1.3. Paper organization

The structure of this paper is outlined as follows. Section 2 provides foundational knowledge on ML. Section 3 explores NTNs and their role in 6G networks. Section 4 presents ML approaches that enhance the efficiency of NTNs alongside a discussion on recent ML-driven research in this domain for 6G networks. Also, it suggests suitable ML approaches for various TNTN scenarios and architectures. Section 5 demonstrates a practical case study to elucidate the concepts discussed in this paper. Section 6 highlights significant research directions and challenges in this area. Finally, the paper concludes in Section 7. The organization of the paper is depicted in Fig. 1.

2. Machine learning background

ML algorithms exhibit adaptability to new scenarios, proficiency in handling multidimensional and large datasets, robust performance, and learning complex patterns. Various ML algorithms exist based on their learning style and architecture (see Fig. 2). Choosing the most suitable algorithm allows us to leverage its advantages effectively.

In the case of learning style, ML algorithms can be divided into three groups: supervised learning (SL), unsupervised learning (USL), and RL. In SL, the algorithm is presented with a labelled dataset, where each input is paired with its corresponding output, enabling precise mapping

Table 1
Summary of most related works.

Year	Publication	Brief description
[26]	2019	Explores how combining satellite and TNTs can improve mobile communication and outlines key developments and future research needs.
[9]	2020	Proposes a fiber-wireless network architecture exploring scenarios like NR-free space optical backhauling and VLC-aided positioning.
[31]	2020	Examines the integration of space and aerial networks into 5G, discussing benefits, challenges, and future directions for creating a fully integrated 5G system.
[35]	2020	Reviews research activities on NTNs and present the characteristics and enabling technologies of NTNs in the 6G landscape.
[30]	2021	Examines the role of UAVs in beyond 5G and 6G networks, highlighting their potential in cellular support, ML, and NTNs.
[37]	2021	Explores 6G integrated TNTNs via NR, highlighting strengths, weaknesses, and future research directions based on 3GPP standards.
[36]	2022	Explores how UAVs enhance wireless networks, offering better flexibility and coverage. It reviews key challenges, solutions, and future research in this field.
[40]	2022	Introduces 3D networks in 6G, combining TNTN components to achieve immersive connectivity, and discusses TNTN components research and standardization efforts.
[42]	2022	Surveys the evolution of NTNs, highlighting their relevance to 5G networks and, how they will play a pivotal role in the development of the 6G ecosystem.
[45]	2022	Investigates the integrated TNTNs for improved user experience and connecting unserved devices, emphasizing the challenges of a 3D wireless network architecture.
[61]	2022	Examines wireless backhaul in 5G and B5G networks, focusing on integrating technologies like UAV, HAPS, and millimeter wave (mmWave).
[19]	2023	Describes an energy-efficient resource allocation framework for NTNs, optimizing system efficiency through joint UAV deployment and power control.
[29]	2023	Examines the progression from 5G and beyond, focusing on the role of NTN and the evolving network infrastructures and services to meet future performance demands.
[32]	2023	Explores multiple access techniques for NTN-assisted IoT systems, analyzing their architecture, performance, and challenges, based on energy and spectrum efficiency.
[39]	2023	Reviews the 3GPP NTN standard, explores its implications for satellite and 5G integration, and discusses the next steps in its development.
[46]	2023	Presents an intelligent adaptation layer for integrating TN and NTN IoT networks, using distributed ML to improve communication efficiency and security.
[57]	2023	Investigates AI's role in NTNs for 6G networks, covering AI approaches for NTN challenges, AI-driven resource allocation, and future research directions.
[58]	2023	Proposes using AI to address challenges in integrating satellite-based NTN into 6G, emphasizing AI's potential to enhance NTN performance.
[59]	2023	Explores how RL improves NTN focusing on resource management and control challenges while highlighting gaps between simulations and real-world use.
[33]	2024	Discusses integrating TNTNs to boost global 6G connectivity, improve reliability, and enhance service in remote areas, building on 5G advancements.

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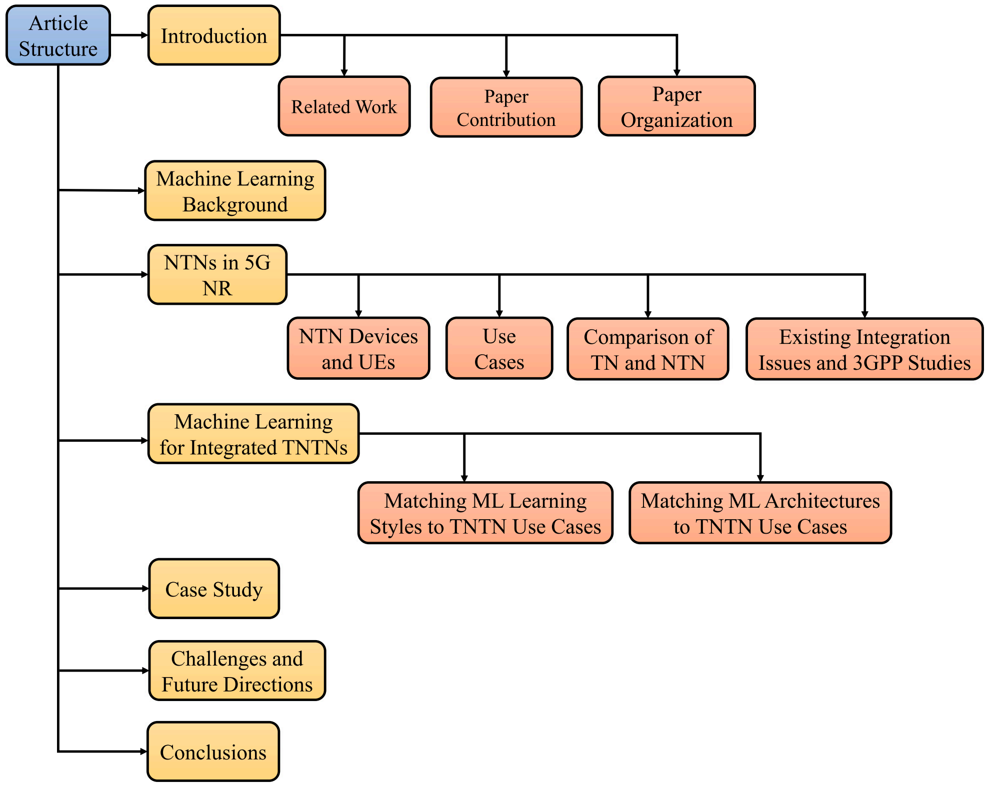

Fig. 1. The article structure.

Table 1 (*continued*).

Year	Publication	Brief description
[34]	2024	Reviews mobility management for integrating satellite-based NTNs with 5G, focusing on challenges like power and signaling, with implications for 6G.
[41]	2024	Explores challenges in integrating NTN components into 6G, focusing on advancements in radio access technologies.
[60]	2024	Discusses the integration of TNTNs, focusing on AI/ML practical solutions to address key challenges in seamless integration and optimization.
This paper		Builds on previous research by categorizing ML algorithms tailored for TNTNs in 6G. It recommends appropriate ML approaches for integrating TNTNs, includes a case study for practical insights, and reviews relevant use cases and device properties.

and prediction; however, its reliance on labelled data can be a limitation, as acquiring and annotating large datasets can be time-consuming and costly. In contrast, USL ventures into unlabelled territories within the data landscape, as algorithms are presented with unlabelled data and tasked with uncovering inherent patterns, structures, or relationships without explicit guidance, offering the advantage of discovering previously unknown insights; nevertheless, the absence of labelled data for guidance can lead to ambiguity and challenges in evaluating the effectiveness of learned patterns. Meanwhile, RL offers a dynamic approach where an agent interacts with an environment, learning to make sequential decisions through trial and error in pursuit of maximizing cumulative rewards, allowing for adaptability in complex and changing environments; however, its reliance on continuous exploration can lead to long learning times and the potential for suboptimal decisions during the learning process. Note that these learning styles can also be used with multiple hidden layers, called deep learning (DL). Usage of multiple layers is especially useful when large amounts of data exist, the problem is complex, and the data is high-dimensional [63].

Similarly, considering the architecture (organization and distribution of ML process) is essential for deploying ML systems effectively, whether it is centralized, decentralized, or distributed. Centralized ML aggregates all data in a single central location for model training. In this setup, organizations collect and store data from various sources in one repository. The training of ML models then takes place using this consolidated dataset. Centralized ML offers simplicity in managing data and training procedures, as everything operates within a unified environment. Decision-making is centralized, allowing clear accountability and control over the training process. This approach is widely employed in several ML setups, where data can be easily accessed and processed from a central server. However, it may pose challenges in scenarios where data privacy regulations restrict the sharing of sensitive information or where BW limitations hinder data transfer to a centralized location.

Decentralized ML disperses data across multiple locations or devices. Each location conducts model training locally using its respective dataset. This decentralized approach is beneficial in scenarios where data cannot be easily centralized or situations where data privacy concerns mandate local processing. By distributing the training process, decentralized ML mitigates some challenges associated with centralized approaches, such as BW constraints and data privacy regulations. However, it requires mechanisms for coordinating and aggregating updates from different sources, which adds extra complexity to the system.

Distributed ML is a broader concept encompassing both centralized and decentralized approaches. In a distributed ML system, data and computational tasks are spread across multiple nodes, which can be centralized or decentralized. This setup enables parallel processing and scalability, as computations can be performed concurrently across distributed resources. Distributed ML offers advantages such as improved fault tolerance and resource utilization compared to centralized approaches. However, it also requires efficient communication and coordination mechanisms to ensure synchronized model training and data consistency across distributed nodes. Recently, federated learning (FL) also took great interest, which is a specific type of

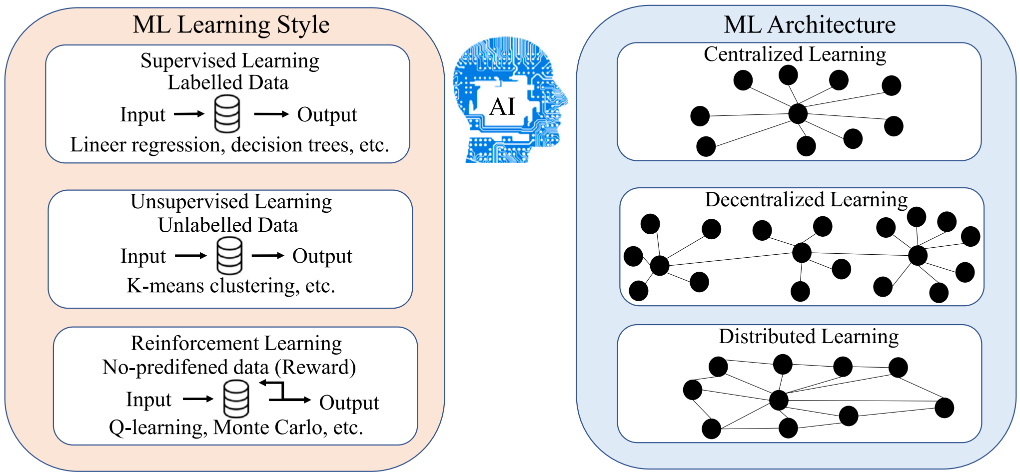

Fig. 2. ML background.

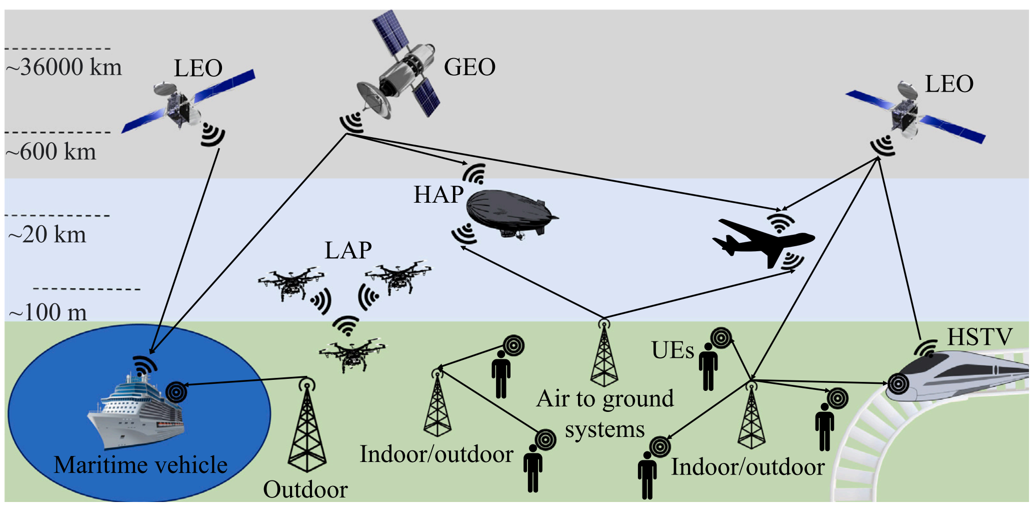

Fig. 3. The devices in integrated TNTNs.

distributed ML that prioritizes data privacy by keeping data decentralized [64]. Instead of sending raw data to a central server, only model updates, such as gradients, are communicated. These updates are aggregated and used to update a global model, which is then returned to the participating devices. FL preserves privacy as raw data never leaves the local device; only model updates are shared. This approach is particularly useful in scenarios where data privacy is paramount. However, FL requires careful management of communication and synchronization between devices to ensure effective model training without compromising privacy or efficiency.

3. NTNs in 5G NR

NTN systems include various non-terrestrial devices such as satellites, HAPs, aircraft, drones, and weather balloons. These systems are structured with an aerial or space station that operates similarly to a ground-based base station (BS) or repeater. They also include a service link that connects ground terminals to the aerial or space station and a gateway that links the non-terrestrial access network to the main network through a feeder link. The equipment on the non-terrestrial device can be either transparent/bent-pipe, performing frequency filtering, conversion, and amplification, or regenerative, handling demodulation, decoding, switching, routing, coding, and modulation tasks.

3.1. NTNs devices and users

The devices in integrated TNTNs can be classified into six groups: satellites, HAPs, LAPs, maritime vehicles, high-speed terrestrial vehicles (HSTVs), and mobile UEs, as depicted in Fig. 3. Some information regarding the operating and channel conditions and connectivity concerns are given in Table 2, and additional information is given below. Here, *connecting devices* are the non-terrestrial platforms and *connected devices* are devices which can achieve ubiquitous connectivity through NTNs or the connecting devices. The common issue for all connected devices and scenarios is the lack of or limited terrestrial architecture.

- *Satellite*: Satellites are categorized into geostationary earth orbits (GEO), medium earth orbit (MEO), and LEO. GEO satellites are stationary relative to a fixed position on Earth, while MEO and LEO satellites maintain a constant orbit. LEO satellite constellations, like OneWeb and Starlink, aim to offer worldwide connectivity.
- *HAPS*: At a lower altitude than satellites, HAPs primarily have limited Terrestrial network (TN) connections and broader secondary satellite connections. The 3GPP has classified them as international mobile BSs.
- *LAPs*: Limited connectivity was provided for communication with control centres in the past, but this is insufficient for the IoT era.

Table 2
Device categories in NTNs use cases.

Device category	Altitude	Mobility	Channel	Connectivity concerns
Connecting devices				
Satellite	GEO: 35786 km MEO: 7000–20000 km LEO: 600–1200 km	GEO: None MEO: High, circular orbit LEO: High, circular orbit	Free space with atmospheric & scintillation losses - Sat2Sat: LoS - Sat2(dense)Urban user equipment (UE): nLoS - Sat2Rural UE: LoS	- Large delay & Doppler spread - Strong fading effects - Satellite mobility - nLoS connections
HAPS	8–50 km	Low	Free space with AWGN, 2-tap model - HAPS2HAPS/Sat: LoS - HAPS2UE: LoS/nLoS	- UE positioning - Trajectory planning
Connected devices				
Low altitude AVs	0.1–6 km	High, known trajectory	Free space - AV2AV: LoS - AV2HAPS/Sat: LoS - AV2UE: nLoS	- Frequent handovers - Doppler shifts - Dynamic channel conditions - May cross national borders
Maritime vehicles	Sea level	Low	Free space with ocean clutter and evaporation duct	- Large distances between UEs - Unique channel conditions
HSTVs	Terrestrial	High	Varies depending on environment - (Dense) Urban: nLoS - Suburban/Rural: LoS	- Doppler spread - Frequent handovers - May cross national borders
Mobile UEs	Terrestrial	Low	Indoor: nLoS Outdoor: nLoS/LoS	- UE positioning - Undeterministic UE trajectory - Limited device capabilities

- *Maritime vehicles*: Maritime operations require open-sea and land-sea communication. [54,65] consider maritime communication services as a use case of TNTNs in 5G NR networks.
- *HSTVs*: These vehicles, such as high-speed trains, are becoming more autonomous with the help of IoT devices. Additionally, on-board customers have become accustomed to continuous connectivity and expect a certain level of communication services. This requires a massive number of secure and sometimes broadband connections.
- *Mobile UE*: The mobile UEs can be pedestrians and UEs in automobiles. Connectivity is possible in urban environments due to the presence of TN infrastructure. However, this infrastructure may be overloaded in times or locations of extreme UE density. Rural or uninhabited locations also necessitate alternative solutions.

3.2. Use cases

While the devices and their operation scenarios effectively give insight into the challenges, the use cases determine the requirements pertaining to communication. The type of service that these users need is explained herein [66].

- *Connectivity*: TNs alone are incapable of providing global, ubiquitous connectivity in the following scenarios:

  1. *Rural/uninhabited locations*: These locations have little to no permanent residents or visitors. As such, installing infrastructure is not feasible for operators.
  2. *Extremely dense populations/crowded events*: Sports matches, concerts, and other events push the limits of cellular networks and significantly degrade the quality of service (QoS).
  3. *High mobility UEs*: These UEs frequently undergo handovers, which reduce their QoS and place additional strain on the networks.

  These scenarios can occur at the same time, such as in high-speed passenger trains or commercial airplanes, which both host numerous UEs and traverse areas with minimal or no cellular infrastructure. Depending on the service, the connectivity can be multi-mode, fixed, mobile, or a combination of mobile and fixed. The categories proposed to enable connectivity are [66]:

  – *Multi/resilient*: In multi-connectivity, a UE has multiple connections to increase data rate or as a backup connection for reliability. Here, the NTN connection can be the backup or main connection. Resilient connectivity aims to prevent a complete network outage. Thus, in outage scenarios, the NTN is expected to provide broadband connectivity between the UEs and the core network.
  – *Fixed/trunking*: In fixed connectivity, NTNs will provide the only connection. Planned to be deployed in rural or ad-hoc areas, broadband connectivity between the core network and nomadic UEs is aimed. Trunking is to provide temporary 5G connectivity in emergency situations.
  – *Mobile cell*: This is the solution for the third scenario where connectivity is compromised. Here, the NTN is expected to provide broadband connectivity between the core network and UEs on board a highly mobile platform.
  – *Mobile-hybrid*: This is for enabling connectivity to UEs on public transport with fixed routes. NTNs will provide a backup or auxiliary connection for routes where the TNs have a limited capacity.
  – *Hot-spot-on-demand*: Here, NTNs are expected to provide temporary 5G connectivity to under-served areas.

- *Broadcasting*: This includes direct-to-node, direct-to-mobile, and edge network delivery broadcasts. In direct-to-node broadcasts, information is sent to an access point and then distributed to the UEs within the network. Direct-to-mobile broadcasts deliver information to multiple UEs at once, which is essential for sending alerts to the community or responders during emergencies, or for distributing global software updates. Edge-network delivery involves transferring popular content or system updates to edge nodes for caching and redistribution, requiring broadband connectivity from the NTN devices.
- *Public safety*: The goal is to ensure connectivity among emergency responders, regardless of their location or the availability of terrestrial infrastructure. This connectivity can be categorized into wide-area, local, and regional public safety networks. NTNs play a crucial role in facilitating this connectivity by linking the emergency responder UEs, tactical cells, and the core network.
- *IoT service*: Based on the mobility and coverage needs, these use cases can be classified into wide-area and local IoT service

connectivity based on the mobility and coverage needs. IoT devices on high-speed transport vehicles HSTVs and similar mobile scenarios over a defined area are likely to be supported by NTNs offering wide-area connectivity. Meanwhile, devices in applications like smart grids are expected to receive support from NTNs providing local area connectivity. In this arrangement, the NTNs will facilitate connectivity between the IoT devices, their central hub or point, and the core network.

3.3. Comparison of TN and NTN

TN and NTN share the common goal of providing wireless connectivity. However, their architecture, operational conditions, and performance characteristics differ due to their deployment environments. Understanding these similarities and differences is crucial for integrating NTNs into 5G NR and beyond.

TNs have been supporting communication for nearly half a century. As a result, compared to NTNs, they have a developed foundation and well-defined, regularly updated standards. Cellular networks, in particular, have a centralized infrastructure with all devices connected to and routed through a core network. Currently, these networks are able to support a variety of services with different performance metrics. They are also able to co-exist with other technologies, allowing multi-connectivity. As the name suggests, TNs is a land-based technology that provides optimal service to urban and high population density areas.

NTNs, on the other hand, are a relatively recent concept which has just begun to provide service on a small scale. These networks are comprised of aerial platforms and/or satellites and dish antennas on the ground serving as a hub for commercial personal devices. Currently, there are only a few providers who have mainly developed their own standards, and direct communication between an NTN BS and UE device is still very limited in capability due to power constraints and BW availability. Despite this, the lack of terrestrial connectivity in rural and maritime regions, along with the increase in communication demands surpassing the technological limitations of TNs has spurred efforts to incorporate NTNs and TNs. The main edge NTNs bring to the table is a wider coverage area, independence on terrestrial infrastructure, and, in general, line-of-sight communication.

While the basic communication principles apply to both TNs and NTNs, certain aspects differ due to different propagation environments, NTN device types and service area sizes. For example, because non-terrestrial devices are often a few kilometers above ground level, there is significant propagation delay and latency. Their altitude comes with the advantage of having large coverage areas. Handover, an issue related to the mobility of devices in TNs, is more complex in NTNs due to the additional mobility of the non-terrestrial base-stations. Additionally, due to the difference in environment, NTNs face different channel characteristics than TNs, such as the added tropospheric and ionospheric effects and significant path loss.

Understanding these distinctions helps guide the design and integration of NTNs into existing TN frameworks. By leveraging the strengths of both systems, a more comprehensive and resilient 6G network can be achieved.

3.4. Existing integration issues and 3GPP studies

Integrated TNTNs need a versatile architecture to efficiently manage traffic between TNs and NTNs. This structure should optimize the use of network resources intelligently. At a minimum, both idle and active UEs should receive consistent, worldwide coverage without experiencing congestion rejections or service degradation.

Meeting these objectives presents several challenges. NTNs experience much longer propagation delays compared to TNs, which can increase service interruption times during service continuity in idle mode or during handovers in active mode. Additionally, the non-GEO satellites' movement leads to frequent handovers in the active mode because, unlike the static coverage of a GEO satellite with its large fixed spot cells, the coverage area of a LEO satellite changes over time based on the satellite's path, requiring frequent updates or handovers. Moreover, there is a significant signal variation from the centre to the edge of the NTN cells, making it impractical to use the same transmission parameters for UEs located at different positions within a cell. Another challenge is the delay caused by the random access procedures, which impacts UE connection setup and time synchronization. Integrated TNTN systems need to support fast UE handovers and continuous service with minimal delays in these random access procedures.

In this regard, NTNs have been a significant focus of the 5G standardization efforts by the 3GPP, with key developments in Rel-15, Rel-16, and Rel-17. Rel-15, which began in 2017, delivered the outcomes of a feasibility study that looked at channel models and deployment scenarios [66]. Following that, Rel-16 outlined the minimal adjustments needed in the current standards to incorporate crucial NTN features [67], while Rel-17, completed in 2022, concentrated on developing a transparent payload architecture with earth-fixed tracking areas and frequency division duplex systems [68]. Additionally, a study phase addressing network-verified NTN UE location was completed, with its normative phase getting approval during the 3GPP Plenary #98e electronic meeting [69].

The upcoming 3GPP Rel-18, Rel-19, and Rel-20, designated for 5G-Advanced, are set to refine the scenarios and utilization of NTNs. Currently, work is ongoing on Rel-18, which focuses on enhancements for NTN IoT [70]. This Rel aims to address the integration of TNTN, improve throughput performance, and optimize the use of the global navigation satellite system to reduce power consumption for sustained connections. Additionally, it aims to enhance machine-type communications with minimal updates using integrated TNTNs. The study items for Rel-18 also include considerations for integrated TNTN mobility, service continuity, and coverage improvements. These discussions explore possible enhancements in low-rate codec performance within a context limited by link budget, including voice services over NR.

4. Machine learning for integrated TNTNs

TNTNs require overcoming compatibility issues, coordinating seamless handovers, efficiently routing traffic, and optimizing resource allocation across diverse infrastructures. This integration is particularly crucial in dynamic environments where signal strengths, user demands, and interference patterns constantly fluctuate. ML is a powerful tool in addressing these challenges, offering intelligent solutions to optimize network interoperability, performance, and resource allocation. ML algorithms can analyse TNTN components' data, learning patterns and behaviours to facilitate smooth handovers, efficient traffic management, and dynamic resource allocation. Moreover, ML enables real-time adaptation of network parameters to account for changes in network topology, user mobility, and environmental conditions. By harnessing ML-driven insights, integrated TNTNs can operate cohesively, maximizing the benefits of both architectures while ensuring reliable and high-performance connectivity for users.

The quality and representativeness of the training data play a crucial role in the performance of ML models. Biased or poor-quality data can result in biased or inaccurate models, decreasing the reliability of predictions. Additionally, without proper tuning of parameters and consideration of model complexity, ML algorithms may suffer from overfitting or underfitting, leading to suboptimal performance on unseen data. Interpretability is another concern, as many ML models are complex 'black boxes' making it challenging to understand their decision-making process. This lack of transparency can hinder trust and validation of results, particularly in critical applications like network optimization. Furthermore, ML models are susceptible to adversarial attacks and may inadvertently perpetuate biases present in the data, raising ethical and legal concerns. Besides, how and where to train the

Table 3
Learning styles and architectures for existing ML-based NTN works.

Paper	Description	Learning style	Architecture
[71]	Uses multi-armed bandit (an RL algorithm) in a central point which is a UAV to optimize various performance aspects of UAV operations in cellular networks.	RL	Centralized ML
[72]	SL approaches consisting of long short-term memory and support vector machine are used to predict radio link failure for UAV trajectory modification. The model training and data handling are managed in a centralized manner.	SL	Centralized ML
[73]	Deep RL algorithm is used to dynamically adjust task allocation based on real-time changes and feedback across multiple UAVs. The architecture of the learning system is distributed, as it involves multiple UAVs operating as mobile-edge computing nodes.	RL	Distributed ML
[74]	SL approaches (multi-layer perceptron and long short-term memory) are trained for UAV positioning and throughput estimation. The learning architecture is centralized as the training and application of the models are conducted on a centralized dataset, processed and evaluated using centralized computing resources.	SL	Centralized ML
[75]	The paper utilizes RL approaches (reward-to-go and drift-plus-penalty) with a central BS that assists in the caching and decision-making process across the network.	RL	Centralized ML
[76]	SL is used, where models are trained with known labels but these labels are kept private and distributed among different participants. The training involves learning from labelled data without directly sharing the labels, so maintains data privacy.	SL	Distributed ML
[77]	SL algorithm (convolutional neural network (CNN)) is trained on labelled data. The labels correspond to different modulation types, and the CNN learns to classify these based on the input data transformed into images. The entire model training and testing process occurs within a single environment, utilizing a centralized data store and computational resources.	SL	Distributed ML
[78]	The artificial neural networks (ANN)s are trained for path loss prediction in urban environments using labelled data, where the inputs are environmental characteristics, and the outputs are the corresponding path loss values. The ANNs are trained within a controlled, single-system environment, which indicates a centralized learning approach.	SL	Centralized ML
[79]	This paper uses an RL algorithm involving agents learning to make decisions by interacting with a dynamic environment to achieve the highest long-term rewards, particularly focusing on access control for wireless networks involving satellites, blimps, and other NTNs. The method incorporates a DL model where each UE acts as an independent RL agent. These agents interact with their local environment and make autonomous decisions based on the policy learned through DRL. The learning parameters are centrally updated at a trainer node.	RL	Centralized ML
[80]	Deep RL algorithm is utilized to make intelligent decisions about resource allocation and task offloading, enabling the network to dynamically adapt to varying conditions and optimize service quality for IoT applications in integrated networks. The proposed network integrates edge intelligence across different layers of network architecture, including terrestrial, airborne, and spaceborne layers. The system features distributed intelligence, where edge nodes across these layers are capable of making autonomous decisions based on locally available data and computational resources.	RL	Distributed ML
[81]	The paper develops a multi-tier deep RL framework using distributed learning for 6G NTNs. It tailors deep RL to the unique capabilities of space, air, and ground stations, allowing each tier to independently optimize tasks like spectrum allocation and trajectory planning. This approach enhances overall network performance by enabling coordinated, scalable optimization across the different tiers.	RL	Distributed ML
[82]	The paper utilizes USL algorithms (K-means and K-medoids) to integrate aerial and satellite segments efficiently. These algorithms are used to determine optimal positions for the aerial BS by clustering user coordinates and minimizing distance metrics. The learning system is decentralized as the integration involves both aerial and satellite segments independently determining the optimal solutions based on local data.	USL	Centralized ML

ML algorithm is also critical. Therefore, it is essential to approach the implementation of ML algorithms judiciously, considering data quality, model interpretability, robustness, and ethical considerations. Along with this line, ML algorithms cannot be used blindly; rather, after we define the problem and corresponding dataset, we should determine their learning style and architecture to get the maximum benefit from the ML algorithms as detailed in Section 2.

In Table 3, we categorize the existing ML-based NTN-related works in the literature based on their learning style and architectures. Then, we propose learning styles and architectures for existing use cases in the literature with sound reasoning, as shown in Table 4 and the following. Note that this is not a definitive categorization, and other classifications are also possible depending on the context and objectives. For example, ML techniques can be categorized based on model complexity, application domains, or data types. However, our focus on learning styles and architectures provides a broad yet practical framework that encompasses many of these other aspects while addressing the key challenges of integrated TNTNs.

The use cases presented in this section are drawn from recognized open problems in the NTN literature and relevant discussions from

Table 4
Mapping of use cases to learning styles and architecture types.

Use case	Learning style and reason	Architecture type and reason
Updating the location of the satellites	RL: Suitable due to its ability to learn adaptively through continuous interaction and adaptation to network conditions.	Decentralized ML: Avoids bottlenecks, reduces delays in data delivery, and handles synchronization across mobile LEO satellites effectively.
Propagation channel and synchronization	SL: Suitable due to the reliance on labelled historical data for predicting synchronization configurations.	Decentralized ML: Enables tailored feature extraction per device for varied delay and Doppler models, improving performance across scenarios.
Cell pattern generation	USL: Suitable for discovering patterns within data without prior knowledge, so proper for cell pattern analysis.	Decentralized ML: Required due to the need for specialized signaling in larger, mobile cells with extended acquisition windows.
Service continuity between TN and NTN	SL: Suitable for predicting handover mechanisms based on labelled historical data of network transitions.	Distributed ML: Offers a balance between centralized control and reduced delay by distributing decision-making for seamless handovers.
Satellite and HAPs-based design	SL: Suitable for optimizing design parameters based on labelled historical data to maximize performance.	Centralized ML: Handles multiple design criteria simultaneously, allowing for optimized decision-making in complex scenarios.
Terminal mobility	RL: Suitable due to its capacity to learn adaptively based on network conditions and users' feedbacks.	Decentralized ML: Effective for managing communication in high-speed environments where latency from centralized approaches is a concern.
Security	RL: Suitable for adapting security mechanisms based on real-time feedback to counter evolving threats.	Decentralized ML: Necessary to comply with privacy concerns and legal restrictions on sharing sensitive information across networks.
Dynamic service deployment	USL: Suitable for discovering patterns and relationships within data without needing labelled examples.	Centralized ML: Aggregates data to identify trends and optimize service deployment policies across integrated networks.
Energy efficiency	RL: Suitable for dynamically optimizing resource allocation and power management based on real-time conditions.	Centralized ML: Facilitates consistent energy management across the network by providing comprehensive data analysis for efficiency.
Radio resource management	USL: Suitable for identifying patterns and optimizing resource allocation based on unstructured network topology data.	Centralized ML: Effective in managing complex and adaptive processes for cross-border cell patterns and varying traffic demands.
Frequency planning and channel BW	RL: Suitable for continuously adapting frequency plans and BW allocations to changing network conditions.	Centralized ML: Learns relationships between diverse challenges, enabling optimized frequency planning and spectrum management.

3GPP standardization meetings [66] and documents. Their timely and practical solutions are vital for the successful integrated TNTN. We have organized these use cases according to the specific challenges they pose for ML-driven optimization in integrated TNTNs, including signal processing, resource management, mobility, and service continuity. This categorization emphasizes their relevance to the broader goals of seamless network operation, efficient resource allocation, and enhanced user experience.

4.1. Matching ML learning styles to TNTN use cases

This part explores which ML learning styles (SL, USL, and RL) are suited to particular TNTN use cases. Note that while we suggest specific ML learning styles, these recommendations may not always be optimal or exclusive. Depending on various real-world scenarios, other ML learning styles might be more suitable, and their applicability should be thoroughly investigated. Furthermore, different ML learning styles may be used in a hybrid manner or adaptively changed to better address the evolving demands of TNTNs.

- *Updating the location of the satellites*: RL can be a suitable choice for this scenario. This is because RL's capacity to learn optimal strategies through interaction with the environment aligns with the dynamic nature of this task. RL agents autonomously adjust satellite positions to optimize network connectivity and coverage by continuously assessing feedback from network performance metrics and user demands. Furthermore, RL's flexibility to adapt to evolving network conditions and explore innovative strategies ensures efficient satellite location updates, enhancing overall network performance and user satisfaction.
- *Propagation channel and synchronization*: SL can be a suitable learning style for this scenario thanks to its reliance on labelled historical data with different delay and Doppler models. By leveraging this labelled data, SL algorithms can effectively predict synchronization configurations, which is crucial for optimizing network performance. With accurate predictions derived from past synchronization configurations, SL enables the network to adapt to varying channel conditions and ensure efficient data transmission. This approach provides a robust foundation for synchronization management, facilitating seamless communication across integrated TNTNs while maximizing spectral efficiency and minimizing latency.
- *Cell pattern generation*: USL is well-suited to this scenario as it does not require labelled examples, making it ideal for discovering patterns and structures within the data related to cell patterns without prior knowledge. By autonomously analyzing the data, USL algorithms can identify hidden relationships and structures, revealing insights that may not be available through manual analysis. This approach allows for exploring the diverse cell patterns and their impact on access channels, facilitating the design and optimization of network layouts to enhance coverage and capacity. Through USL, integrated networks can adaptively evolve their cell patterns to meet changing user demands and environmental conditions, ultimately improving network efficiency and user experience.
- *Service continuity between TN and NTN*: For ensuring service continuity between TNTNs, SL emerges as the most promising learning style. SL's reliance on labelled historical data makes it particularly suited for predicting handover-triggering mechanisms based on past network transitions. By training on labelled examples

of handover events between TNTNs, SL algorithms can effectively identify patterns and decision boundaries, enabling proactive handover management. This approach ensures seamless service continuity for users transitioning between different network types, optimizing network resource allocation and minimizing service disruptions. SL provides a robust framework for enhancing service continuity in integrated networks, ultimately improving overall network reliability and user satisfaction.

- *Satellite and HAPs-based design*: SL is the suitable learning style for satellite and HAP-based design within integrated TNTNs. SL's reliance on labelled historical data allows for the optimization of design criteria based on past performance metrics and configurations. By leveraging this labelled data, SL algorithms can effectively identify optimal design parameters and predict their impact on network performance. This approach enables network planners to make informed decisions regarding satellite and HAP-based infrastructure, maximizing coverage, capacity, and reliability. SL provides a systematic framework for optimizing design criteria, ensuring integrated networks' efficient deployment and operation to meet evolving user demands and technological advancements.
- *Terminal mobility*: RL's ability to learn optimal strategies through interactions with the environment aligns well with the dynamic and complex nature of terminal mobility management. By continuously adapting its strategy based on feedback from network conditions and user movements, RL agents can optimize resource allocation and handover decisions to ensure seamless connectivity for mobile terminals. This adaptive approach enables RL to navigate the challenges of terminal mobility in integrated networks, dynamically adjusting network configurations to meet changing user demands and environmental conditions. RL provides a robust framework for optimizing terminal mobility management, ultimately enhancing network efficiency and user experience in integrated TNTNs.
- *Security*: RL's capacity to learn from feedback and adapt its strategies based on environmental cues aligns well with the dynamic and evolving nature of network security threats. By continuously exploring and exploiting different security actions and their consequences, RL agents can autonomously adapt security mechanisms to mitigate emerging threats and vulnerabilities. This adaptive approach enables RL to adjust security policies dynamically based on real-time feedback from the network environment, enhancing resilience against evolving cyber threats. RL provides a robust framework for implementing adaptive security mechanisms in integrated networks, safeguarding network integrity, confidentiality, and availability while mitigating risks in real-time.
- *Dynamic service deployment*: For dynamic service deployment within integrated TNTNs, USL is a promising learning style. USL's ability to discover patterns and relationships within data without needing labelled examples makes it well-suited for identifying emerging service deployment policies and trends. By autonomously analyzing network data, USL algorithms can uncover hidden patterns in service usage, network traffic, and user behaviour, facilitating the dynamic adaptation of service deployment strategies. This approach enables network operators to efficiently allocate resources, optimize service provisioning, and respond to changing user demands in real-time. USL provides a flexible framework for enhancing dynamic service deployment in integrated networks, fostering agility, scalability, and responsiveness to evolving network requirements and user preferences.
- *Energy efficiency*: RL's ability to learn optimal policies through interactions with the environment aligns well with the dynamic nature of energy management in network operations. By continuously adapting resource allocation strategies based on real-time feedback from changing network conditions and performance goals, RL agents can optimize energy consumption while maintaining service quality. This adaptive approach enables RL to dynamically adjust resource utilization, power management, and network configurations to minimize energy consumption without compromising network performance. RL provides a robust framework for enhancing energy efficiency in integrated networks, promoting sustainability, cost-effectiveness, and environmental stewardship in network operations.
- *Radio resource management*: USL's capacity to discover patterns and relationships within data without needing labelled examples aligns well with the complex and dynamic nature of network topology optimization. By autonomously analyzing network topology data, USL algorithms can uncover hidden correlations between network elements, traffic patterns, and performance metrics. This approach enables network operators to gain insights into the underlying structure of the network topology, facilitating the development of adaptive resource management strategies. USL provides a flexible framework for optimizing radio resource management in integrated networks, fostering efficiency, scalability, and resilience to evolving network dynamics and user demands.
- *Frequency planning and channel BW*: RL's ability to learn optimal strategies through interactions with the environment aligns well with the dynamic and complex nature of frequency planning and BW allocation. By continuously adapting frequency and BW allocation policies based on real-time feedback from changing network conditions and performance requirements, RL agents can optimize spectrum utilization while maximizing network capacity and QoS. This adaptive approach enables RL to dynamically adjust frequency plans and channel BW allocations to accommodate fluctuating traffic demands and mitigate interference, ultimately enhancing network performance and user experience. RL provides a robust framework for optimizing frequency planning and channel BW in integrated networks, promoting efficiency, flexibility, and adaptability to evolving network requirements and environmental conditions.

4.2. Matching ML architectures to TNTN use cases

While ML learning styles are pivotal, the architectural design of ML systems is also important in addressing integrated TNTN challenges. This part examines how different ML architectures are strategically deployed to meet the diverse demands of TNTN applications. These architectures include centralized, decentralized, and distributed ML approaches, each offering unique advantages and challenges.

- *Updating the location of the satellites*: When the locations of multiple LEO satellites require frequent updates, using centralized ML can create issues due to delays in data delivery and challenges in synchronizing various devices. Additionally, this method can lead to bottlenecks and problems with single-point failures for mobile LEO satellites. Thus, a decentralized ML approach could be more effective for addressing these concerns.
- *Propagation channel and synchronization*: Different delay and Doppler models exist for various communication scenarios. For instance, satellite communications typically occur under outdoor and line of sight (LoS) conditions, while indoor and non-LoS (nLoS) conditions can be managed using HAPs. Satellite signals are mainly direct LoS and follow a Ricean distribution with a strong direct signal component, experiencing slow fading due to obstacles like trees and bridges. Conversely, signals in HAP-based systems also follow a Ricean model but include significant multipath components. Consequently, the synchronization settings at both UE and Next Generation NodeB (5G gNB) levels, such as the preamble sequence and aggregation to accommodate specific Doppler and multipath channel models, and the cyclic prefix to offset delay spread, need to differ. Hence, a single ML algorithm

might not be universally effective. A centralized ML system would need to handle feature extraction for various challenges, which could be complex in multiple scenarios. However, a decentralized ML approach allows each device to independently extract features and run tailored algorithms, potentially offering superior performance in such settings.

- *Cell pattern generation*: Compared to cellular networks, satellite and HAPs systems often have larger, possibly mobile, cells. These cells can produce a high differential propagation delay between a UE at the cell centre and a UE at the cell edge, particularly at low operational elevation angles. This affects contention-based access channels when the network does not know where the UEs are. Here, the differential latency caused by the large cell size may cause a near-far effect during the initial access procedure. To boost performance, an extended acquisition window may be required. However, if the UE position is known during a session, the network can correct for the differential latency. As a result, specialized signalling may be required to support these larger, mobile cells for broadcast services. Since specialized signalling is required, a decentralized ML approach is more promising.
- *Service continuity between TN and NTN*: To maintain service continuity, a handover to or from the satellite/HAPs system may be necessary when a UE exits or enters cellular coverage. The criteria for triggering a handover can vary; for example, a satellite connection might be discontinued when a strong cellular signal is detected, whereas a cellular connection might only be dropped when the signal strength is very weak. The handover process should consider the service features, capabilities, and measurement reports from both access technologies. Given the complexity of these factors, a centralized ML approach seems promising for managing this process efficiently. However, the differences in propagation delay between NTNs and cellular networks can cause significant jitter. As previously mentioned, using centralized ML to ensure service continuity might introduce additional delays due to the time needed for data delivery and scheduling. If minimizing delay is critical for the application, a decentralized ML approach might be preferable. Alternatively, distributed ML can be used to use the advantages of both centralized ML and decentralized ML.
- *Satellite and HAPs-based design*: Several design criteria exist for satellite and HAPs-based communication systems. Some of these design criteria are:
  - Maximizing throughput from the uplink UE and the downlink satellite/HAPs for a given transmit power.
  - Maximizing service availability in cases of deep fading.
  - Maximizing the throughput/power ratio; the operation point in the power amplifier at the satellite or the UE should be adjusted as close to the saturation point as possible when needed.
  - Maximizing signal availability with slow and deep fading; vital for UE near the cell edge, modulation, and coding techniques with very low SNR operating points or other options should be studied.
  - The MAC layer should be able to flexibly and dynamically allocate physical resource blocks to maximize spectrum efficiency and accommodate low-power terminals.

  Given that various design criteria need to be considered together, a centralized ML approach could potentially offer improved performance.
- *Terminal mobility*: Facilitating communication for extremely high-speed UE, such as aircraft systems travelling up to 1000 km/h, presents significant challenges [83]. At these speeds, centralized ML approaches are ineffective due to the latency introduced by data sharing among nodes. Therefore, decentralized ML is a more viable solution for managing such high-speed communications.
- *Security*: Integrated TNTNs handle sensitive information, including user mobility, service usage statistics, and operator data. Sharing this information might not be desirable for operators and could even be illegal under certain national laws. In such cases, decentralized ML may be the only viable option.
- *Dynamic service deployment*: The presence of multiple NTNs and varying demands from ground-based UE could influence dynamic service deployment policies. Analyzing their data collectively might enhance system performance. Along with this line, centralized ML can be beneficial in these networks.
- *Energy efficiency*: Centralized ML can be developed as a service that aids mobile network operators in achieving energy efficiency, operational efficiency, and widespread coverage in machine-type communications. This service can facilitate mobility and service continuity for TNTN machine-type communication, offering easy-to-deploy, always-available, secure, and reliable communications. With a centralized ML approach, IoT devices, sensors, or other reduced-capability devices do not require complex computing resources.
- *Radio resource management*: The unique cell patterns of NTNs require effective mobility management. Additionally, NTN cells may cross national borders, impacting cell identification, tracking, location area design, roaming and charging procedures, and location-based services. Consequently, NTNs needs to manage multiple processes simultaneously, which can be efficiently handled using a centralized ML approach. Moreover, the access control mechanism must adapt quickly to varying traffic demands while considering UE mobility needs. These elements are best managed collectively through a centralized ML strategy.
- *Frequency planning and channel BW*: Integrated TNTN encompass several key aspects. For instance, they support frequency reuse and flexible spectrum allocation across different cells. Additionally, techniques are implemented to reduce the risk of inter-cell interference, ensuring efficient use of the spectrum. Carrier numbering is crucial for enabling targeted spectrum use and precise pairing between uplink and downlink bands, including the separation of bands. Carrier aggregation is another strategy used to maintain equal throughput while providing greater flexibility in carrier allocation between cells and adhering to frequency reuse constraints. These aspects necessitate the system's ability to understand and adapt the relationship between various parameters and to adjust the upper layers, such as MAC and network layer signalling, accordingly. Since centralized ML is effective for learning relationships between diverse challenges, it could be particularly useful in this context.

5. Case study: Interference management for integrated TNTNs

The diverse and dynamic nature of integrated TNTNs introduces new interference scenarios, necessitating sophisticated management techniques. These interference management techniques are crucial for the successful deployment and optimization of next-generation wireless networks. For example, the integrated networks utilize hybrid approaches that combine fractional frequency reuse (FFR) with the deployment of LAPs to strategically manage cell-edge interference and improve signal-to-interference ratio (SIR) for edge users. This strategy benefits from UAVs' superior line of sight and reduced path loss, directly addressing the co-channel interference that hampers densely populated network areas. However, the optimum height for the UAVs should be selected for efficient utilization of integrated TNTNs.

Recently, ML has been used to dynamically analyse network conditions, predict interference patterns, and automatically adjust network parameters in real-time. By implementing ML algorithms, networks can become more adaptive and responsive to fluctuating environments and user densities, potentially reducing the need for extensive manual configuration. This does not only streamline the management of complex

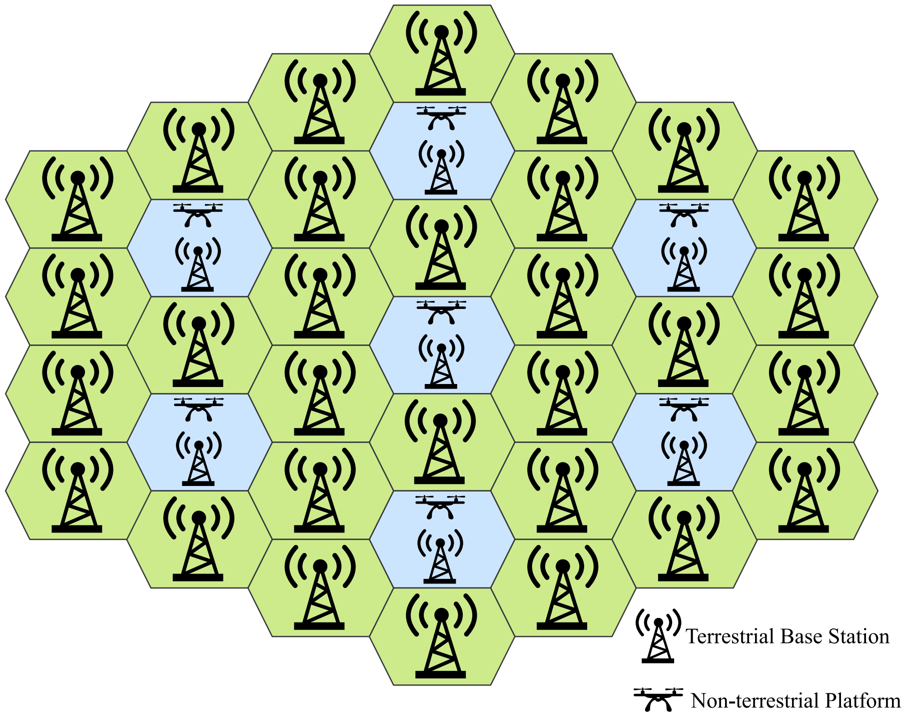

Fig. 4. The case study of the system model shows an area served by terrestrial BSs (green) and integrated terrestrial and non-terrestrial BSs (blue), forming an integrated TNTN. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

integrated networks but also significantly improves their scalability and sustainability as they expand to accommodate an increasing number of devices and data traffic. However, ML has diverse learning styles and architectures, which have different aspects of advantages and disadvantages, as discussed in this paper, and they should be investigated to select the optimum height of UAVs for optimum interference management for integrated TNTNs. Here note that the optimum height is indicated as the height that gives desired SIR values for the UEs. In the following, we compare the previously discussed ML learning styles and the architectures by simulations for UAVs' height optimization.

In the simulations, the dataset was generated using MATLAB, a tool widely preferred for wireless communication simulations due to its specialized libraries and advanced capabilities in modelling complex systems like our scenario, where TBSs and LAPs coordinate to enhance cell-edge user performance. MATLAB handles critical aspects such as path loss models and SIR calculations with precision, making it ideal for our network setup. We implemented the ML models using Keras in Python. Keras was selected for its ease of use, flexibility, and strong integration with TensorFlow, enabling rapid prototyping and efficient training of the ML algorithms in both centralized and distributed setups. To generate the dataset, we consider a network where terrestrial base stations (TBSs) and LAPs collaborate to improve the performance of the cell-edge users. This joint network is coordinated to implement FFR technique with a static BW ratio. The network model layout is shown in Fig. 4. TBSs are responsible for inner-cell users (shown by green region) while LAPs are positioned on top of the TBSs and communicate with the cell-edge users. The starting positions of UEs' are illustrated in Fig. 5. Here note that Fig. 5 is an illustration for one UAV. Also, there are the same number of UEs for each UAV. Besides that, all the UEs are assumed to move to the right or left on their corresponding cell line for each sample time.

We use an altitude-dependent empirical path loss model [84] based on a measurement campaign performed with 800 megahertz LTE networks. The UAV altitude increased from 1.5 to 120 meters (m) as in [85],

$$PL(d) = \beta + \alpha \log_{10}(d) + \chi_{\sigma}, \tag{1}$$

where $d = \sqrt{h^2 + d_H^2}$, d (in m) is 3D distance from the transmitter to the receiver, where h denotes the height of BS and d_H denotes horizontal distances between user and BS. χ_{σ} is zero-mean Gaussian distributed random variable (in dB) with standard deviation σ, which denotes the shadowing, α is path loss exponent, β (in dB) is the intercept point with the line $d = 1$ m [86]. Measurements have shown that at any value of d, the path loss $PL(d)$ at a particular location is random and distributed log-normally (in dB) about the mean distance-dependent value [85]. That means it can serve both TBSs and UAVs. The parameters α, β and σ are as follows.

$$a(h) = max(p_1^{\alpha} + p_2^{\alpha} \log_{10}(h), 2), \tag{2}$$

$$\beta(h) = p_1^{\beta} + p_2^{\beta} \log_{10}(min(h, h_{FSPL})), \tag{3}$$

$$\sigma(h) = p_1^{\sigma} + p_2^{\sigma} \log_{10}(min(h, h_{FSPL})), \tag{4}$$

where $p_1^{\alpha}, p_2^{\alpha}, p_1^{\beta}, p_2^{\beta}, p_1^{\sigma}$, and p_2^{σ} are 3.9, −0.9, −8.5, 20.5, 8.2, and −2.1, respectively [87]. The free space propagation exponent is assumed to be equal to 2 ($\alpha = 2$) and h_{FSPL} denotes the height of free space propagation [85].

The SIR formula is

$$SIR_{d,R,P} = \frac{P_r}{\sum_{TBS} \sum_{UAV} P_I}, \tag{5}$$

where d is the distance, R is radius of cell and P is transmitter power. The desired received signal strength and interfering signal power can be modelled similarly, with the subscript r and I, respectively. The received signal power is calculated by

$$P_r = P_{TBS,UAV} - PL, \tag{6}$$

where $P_{TBS,UAV}$ (in dBm) are transmit powers for terrestrial BS and low altitude platform, respectively. The interference calculation contains undesired signals of all second-tier cells and LAPs interferes as in [87].

All of the models are trained and tested on a Dell G16 7630 computer with Intel® Core™ i7-13700HX central processing unit (CPU) @ 2.1 GHz CPU, 16 GB random access memory (RAM), NVIDIA GeForce RTX 4060 graphical processing unit, and Windows 11 operating system.

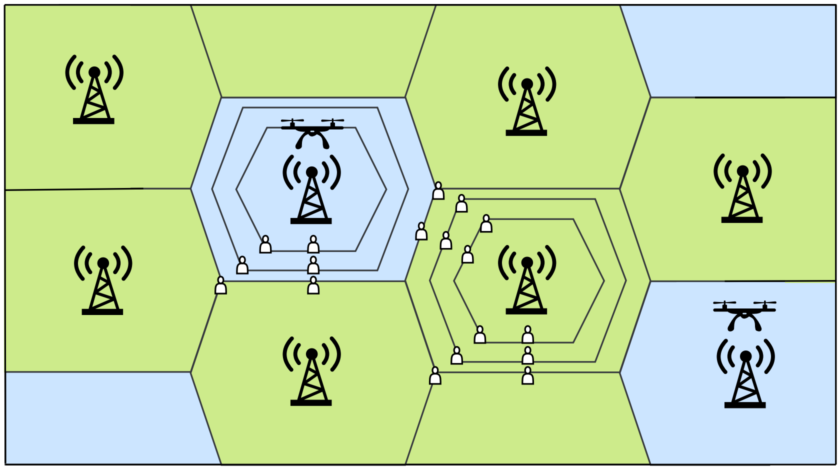

Fig. 5. Example UE positions in the system model.

Table 5
Simulation results for different ML learning styles and architectures.

ML architecture	ML learning style	MSE results
Centralized ML	SL	41,4
	USL	280,3
	RL	40,4
Decentralized ML	SL	44,9
	USL	320,1
	RL	44,4
Distributed ML	SL	43,2
	USL	292,0
	RL	42,7

All parameters of the ML models are empirically set considering the performance and generalization capability of these models.

In SL, SIR values are used as input, while labelled optimum heights are used for output. Ten hidden units are used with a rectified linear unit activation function. In RL, the state is the current height, the action is height changes, and the reward is decided by comparing desired and current SIR values. In USL, we use the data to cluster them together depending on their heights and then create boundaries to find the exact heights. Although USL is not preferred for forecasting, we use it for comparison. All learning styles are also analysed for different learning architectures. For centralized ML, all SIR values are collected and processed in a centralized device (UAV that is in the centre of Fig. 4). For decentralized ML, each UAV optimizes its height according to its corresponding users' SIR values. In distributed ML, the network devices share data and learn collaboratively, enabling them to make decentralized decisions.

For the comparison, the mean-square error (MSE) metric is used. More specifically, based on the desired SIRs, the heights of the UAVs are adjusted, and the difference between optimal heights and ML-based solutions are compared in terms of MSE. The simulation results can be found in Table 5. Simulation shows that in the case of learning style, RL yields the best results, followed by SL, while USL has the highest MSE. In the case of architecture, centralized ML gives the best results, followed by distributed ML, and decentralized ML gives the worst results. However, all these learning styles and architectures have their advantages and disadvantages over each other.

RL tends to perform better in dynamic and adaptive scenarios, resulting in lower MSE values. However, it can take a longer time to converge due to the need for exploration and exploitation. Also, it is more resource-intensive due to the ongoing need for interaction with the environment and the computational demands of learning optimal policies. The SL learning style also performs well since it is guided by clear objectives as it learns from labelled data. This means the model is trained with examples that already have answers, making it easier to measure its accuracy and performance. However, it might not adapt as quickly to changing conditions as RL. For instance, in this case study, SL cannot use previous samples of UEs' positions and the optimal heights of UAVs. In other words, SL algorithms require specific adjustments during their design, such as assigning greater weight to the most recent samples, which helps correlate the last samples more closely with the testing data. Furthermore, SL requires a large amount of labelled data, which can be expensive and time-consuming to acquire. In some real-world integrated TNTN scenarios, labelled data may not be readily available. USL does not require labelled data, but its accuracy performance is limited and it depends on the boundaries to select the optimum height in this case study.

In the case of ML architecture, centralized ML gives the best performance since all data is in one place, it is easier to model tuning, which can lead to more optimized models. However, centralized ML can suffer from scalability issues as the amount of data grows. Large datasets can cause significant delays due to the limitations of a single machine's memory and processing power. Also, centralizing data from multiple sources can lead to significant privacy concerns, especially when sensitive data is involved. Besides that, if the central device fails, the entire ML process can be disrupted if the central device fails. Decentralized ML can operate directly on data sources without the need to share them, reducing privacy and security risks. This is particularly useful in scenarios where data cannot be shared due to confidentiality constraints. Also, decentralized systems are generally more robust against failures. If one node goes down, others can continue to operate without major disruptions, improving the system's reliability. Besides that, nodes in a decentralized system can operate independently and make local decisions, which can be beneficial in real-time applications where sending data to a central device may cause delays. However, its performance is not as good as centralized ML since each device trains only considering its own performance. Also, coordinating between different nodes in a decentralized system can be complex. Distributed learning enhances overall network adaptability and efficiency, leading to competitive MSE values close to centralized approaches. It can handle very large datasets by partitioning them across multiple machines. Also, by distributing the workload across several machines. However, setting up a distributed ML system can be complex due to the need to manage multiple machines, handle data partitioning, and synchronize processes effectively and performance can be heavily influenced by network speed and reliability. High latency or unstable network connections can severely impact the efficiency of distributed training. Therefore, by strategically deploying these learning styles and architectures according to their strengths and the specific needs of the TNTN scenario, network operators can significantly enhance interference management and overall network performance.

6. Challenges and future directions

The integration of ML with TNTNs requires a holistic and adaptable approach due to the complex and dynamic nature of these networks. Key considerations include designing ML models that are flexible and scalable enough to handle the diversity and variability within TNTNs. Multi-objective optimization plays a critical role in balancing performance metrics such as accuracy, computational complexity, and resource management. Given the limited availability of real-world datasets, iterative refinement through simulations is essential for reliable model development. Additionally, standardized protocols and collaborative efforts, guided by organizations like 3GPP, are crucial for ensuring consistency and scalability across different layers of TNTN architecture.

Building upon these insights, several specific challenges should be addressed to implement ML approaches in integrated TNTNs efficiently:

- *Simulation models*: ML algorithms are data hungry. Since the implementation of integrated TNTNs is limited, it is difficult to get a real dataset. Thus, simulation models for integrated TNTNs should be defined.
- *Simulation analysis*: Simulation analysis should be made for different ML learning styles and architectures to compare their accuracy, complexity, security, memory load, etc. Possible scenarios are routing techniques with UAVs, satellites, and HAPs in hierarchical architecture, identification, localization and optimal trajectory design, analyses to ensure privacy, integrity, and secrecy, resource management, network planning, power control, received signal strength prediction, interference management (including the case study that is given in this paper), and transmission parameter tuning.
- *Hybrid ML approaches*: Hybrid ML approaches that combine multiple learning styles and architectures to leverage their respective strengths should be investigated. For instance, a combination of SL for initial deployment and RL for real-time adaptation can be explored.
- *Data*: A TNTNs system regularly generates data that is statistically unique from each other due to varied operation, or surroundings, i.e. in a non-independent identically distributed (i.i.d.) manner. Because ML algorithms rely on the i.i.d. assumption, unique strategies to handle statistical heterogeneity should be created.
- *Privacy*: ML algorithms heavily depend on data. Thus, it is necessary to take precautions to ensure that the data used for training is not manipulated by illegitimate parties. It is also important that sensitive data is not obtained from illegitimate parties.
- *Dynamism*: The storage, computing, and communication capabilities within a TNTN system vary significantly. Therefore, a TNTN training system should be flexible and capable of adapting to the capabilities of the least powerful devices in the system.
- *Theoretical analysis*: Data driven versus model-based algorithms' performance for TNTNs should be investigated.
- *Complexity*: Despite the advantages of ML algorithms, most ML approaches are computationally heavy. Thus, these approaches should be investigated in terms of computational complexity, latency, and delay.
- *Number of updates*: This should be well optimized, along with the update message itself, i.e., the training derivatives, to reduce traffic. The training outcome for each round should be transmitted. Therefore, much research focuses on lowering the number of update rounds and then the update message itself, i.e., the training derivatives.
- *Selection of centralized ML device*: This can be based on the device's processing capability, location, scheduling, and memory, all of which are critical for the performance of the chosen approach, and should be investigated further.
- *Standard effect*: ML protocols for data exchange, data security, model training, and decision-making processes in integrated TNTN should be defined in standards such as 3GPP.

7. Conclusions

The integration of NTNs with TNs poses a complex challenge, especially for achieving seamless 6G connectivity. This paper has critically examined ML learning styles and architectures tailored to address the unique challenges of integrating TNTNs. Through a comprehensive survey and a case study, the paper categorized ML algorithms based on their learning styles—SL, USL, and RL—and architectures—centralized, decentralized, and distributed. It identified suitable approaches for each integration scenario, emphasizing the importance of selecting the right ML strategy to optimize network performance and resource allocation effectively. The case study provided practical insights into applying these ML approaches, demonstrating their potential to improve service continuity and enhance user experience in integrated TNTNs. This study laid a foundational framework for future research and practical implementations, aimed at advancing the integration of TNTNs to meet the emerging demands of 6G technologies. It called for further research into optimizing ML models and architectures to handle the dynamic and diverse requirements of integrated TNTN environments efficiently.

CRediT authorship contribution statement

Mehmet Ali Aygul: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Halise Turkmen:** Writing – review & editing, Writing – original draft, Visualization, Methodology. **Hakan Ali Cirpan:** Validation, Supervision, Investigation, Conceptualization. **Huseyin Arslan:** Visualization, Validation, Supervision, Project administration, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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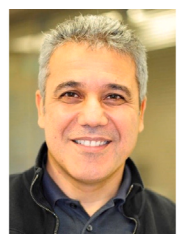

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