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Artificial Intelligence-Driven Integration of Terrestrial and Non-Terrestrial Networks: A Perspective

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ABSTRACT

As sixth-generation (6G) mobile communication accelerates its evolution towards the vision of a satellite-terrestrial integrated network, the deep integration of terrestrial networks (TNs) and non-terrestrial networks (NTNs) has become an inevitable trend for achieving seamless, ubiquitous, and ultra-reliable global communication services. From the perspective of artificial intelligence (AI) technology development, this paper systematically elucidates the application potential of key technologies such as machine learning (ML), deep learning (DL), and large language models (LLMs) in satellite communication networks. This paper first outlines the evolutionary trend of AI technology and analyzes its unique advantages in handling challenges such as highly dynamic topologies, resource constraints, and massive access in low Earth orbit (LEO) satellite networks. Then, from the three dimensions of the physical layer, the network layer, and the service layer, it delves into the application of AI in core scenarios such as channel estimation, anti-interference, transmission optimization, network topology design, intelligent routing, beam resource management, and satellite edge computing. Finally, addressing key challenges such as large-scale node deployment, highly dynamic topology changes, and wide-area seamless coverage, it proposes a systematic solution based on game theory, deep learning, network slicing, and network simulation, and looks forward to future research directions for AI-driven satellite-terrestrial integrated networks, providing important references for building a fully covered, low-latency, highly reliable, and intelligent next-generation mobile communication architecture.

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1. Introduction

The rapid growth of wireless communication technologies, driven by the continuous evolution toward the sixth-generation (6G) mobile communication system, is profoundly reshaping the landscape of global connectivity, especially for those unconnected three billion people [1]. As a consensus in both the academic and industrial circles, a prominent trend in this evolution is the deep integration of terrestrial networks (TNs) and non-terrestrial networks (NTNs), which aims to realize seamless, ubiquitous, and ultra-reliable communication services across space, air, ground, and ocean [2]. Due to economic constraints, terrestrial networks have not fully covered all inhabited areas [3].

As the societal demand for high-speed transmission, ultra-low latency, massive connectivity, and ubiquitous coverage continues to surge, traditional terrestrial communication networks are increasingly insufficient to satisfy these comprehensive requirements [4]. Especially in remote areas, rural regions, deserts, oceans, and other sparsely populated or geographically challenging environments, the deployment and maintenance of ground-based infrastructure face high costs, technical difficulties, and low efficiency, making it difficult to achieve full signal coverage and stable service performance [5].

NTNs, which mainly include satellite communication systems, high-altitude platforms (HAPs), unmanned aerial vehicles (UAVs), and other aerial communication platforms, provide a highly promising solution to bridge the coverage and performance gap left by terrestrial networks [6]. With the reduced cost of deploying NTNs, they become feasible in some cases, e.g., emergency communication [7]. Among these NTN facilities, low-earth orbit (LEO) satellite communication systems stand out with distinctive advantages such as wide-area coverage, low propagation delay, large system capacity, strong anti-destruction capability, and flexible networking [8]. Represented by Starlink and OneWeb, large-scale LEO satellite communication systems have proven effective in a global market, especially in battlefield areas [9].

As 6G communication accelerates its evolution towards the satellite-terrestrial integrated network vision, LEO satellite communication systems, with their outstanding advantages of wide coverage, low latency, and large capacity, will become a core component of the future 6G satellite-terrestrial integrated network, effectively compensating for the coverage shortcomings of terrestrial communication in typical scenarios such as oceans, deserts, and remote areas without a good mobile communication coverage [10]. Facing challenges including massive connections, dynamic topologies, and complex service demands, intelligent technologies, represented by artificial intelligence, are integrated throughout the entire process of signal processing, waveform design, network planning, resource scheduling, link management, and operation and maintenance optimization, becoming a key means to improve the capacity, reliability, and service efficiency of LEO satellite communication systems [11].

Intelligent approaches are widely applied throughout the entire life cycle of satellite communication systems, including network architecture design, constellation planning, radio resource allocation, dynamic link management, handover control, interference suppression, fault diagnosis, and autonomous operation and maintenance [12]. By realizing real-time perception, intelligent decision-making, and adaptive optimization, intelligent technologies effectively improve the spectral efficiency, transmission capacity, system reliability, service quality, and overall operational efficiency of LEO satellite communication systems, laying a solid technical foundation for the efficient, stable, and intelligent operation of future 6G satellite-terrestrial integrated networks [13].

In this paper, we present a perspective for AI-driven integration of TNs and NTNs. Our main contributions are summarized as follows:

- This paper presents an updated overview of AI development in both TNs and NTNs.
- This paper summarizes key applications in AI-driven integration of TNs and NTNs.

- This paper addresses the core challenges of large-scale, highly dynamic, and wide-coverage satellite-terrestrial integrated networks, and proposes a research direction based on game theory and deep learning, using network slicing and simulation as technical means.

The rest of this paper are organized as follows. Section 2 gives a concise overview of trends in AI development. Section 3 presents an updated discussion for integration of terrestrial and non-terrestrial networks. Section 4 discusses the AI-driven research directions for integration of terrestrial and non-terrestrial networks. Section 5 concludes this paper.

The abbreviations used in this paper are summarized in Table 1.

Table 1
 The abbreviations and their full names.

Abbreviation	Full Name
artificial intelligence	AI
artificial neural network	ANN
channel state information	CSI
convolutional neural network	CNN
deep learning	DL
deep neural network	DNN
deep reinforcement learning	DRL
general artificial intelligence	GAI
graphics processing unit	GPU
high-altitude platform	HAP
Internet of Things	IoT
large language model	LLM
low-Earth orbit	LEO
machine learning	ML
mixed-integer nonlinear programming	MINLP
non-terrestrial network	NTN
recurrent neural network	RNN
reinforcement learning	RL
Observe-Orient-Decide-Act	OODA
Quality of Service	QoS
signal-to-interference-plus-noise ratio	SINR
terrestrial network	TN
unmanned aerial vehicle	UAV

2. Trends in AI Development

2.1 Overview of AI Development

Fig. 1 gives an overview of AI models, which acts as a technical hierarchy and core paradigm diagram [14]. The key component of modern AI techniques is machine learning (ML), which is represented by a series of data-driven and algorithm-driven models [15]. ML can be further divided into three categories, including supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning (RL) [16].

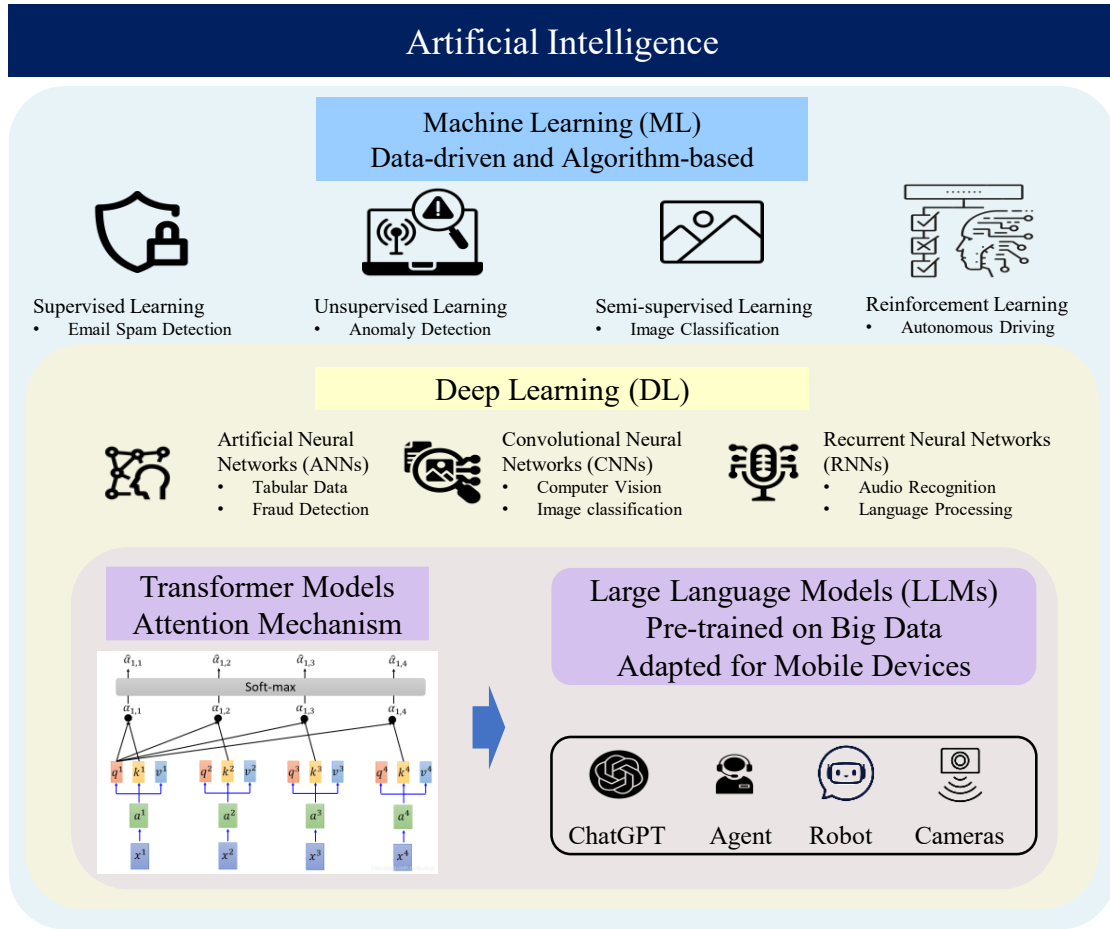


Fig. 1. An overview of AI models.

As the most important subfield of ML, deep learning (DL) uses deep neural networks (DNNs) for automatic feature extraction, which avoids manual feature engineering and complex hyperparameter trials [17]. Typical DL models include artificial neural networks (ANNs), convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [18]. ANNs are designed for processing tabular data, in which all features can be combined into a vector as the input. Before the success of deep learning driven by efficient training on graphics processing units (GPUs), tree models, including XGBoost and LightGBM, are dominant in relevant fields. However, with the well-designed network structures and the appearance of foundation models, ANNs are becoming more effective than XGBoost and LightGBM, e.g., TabNet and TabPFN. The success of CNNs for computer vision is a widely known story, when AlexNet achieves the lowest classification error for the first time as a DL model and ResNet outperforms human-level performance on the ImageNet dataset [19]. RNNs are also widely used for sequence data, including audio recognition and natural language processing [20].

As the most cutting-edge direction in DL, large language models (LLMs) based on the Transformer architecture have achieved milestone progress and widespread success in recent years, e.g., ChatGPT, DeepSeek, and Gemini. Leveraging self-attention mechanisms and large-scale pre-training paradigms, LLMs can efficiently model long-distance dependencies, significantly outperforming traditional models in several core tasks such as natural language understanding, text generation, machine translation, and question answering, even approaching or reaching human-level performance. Simultaneously, the continuous evolution of multimodal learning, general artificial intelligence (GAI) systems, and lightweight deployment technologies based on LLMs has further propelled the leapfrog develop-

ment of deep learning in academic research, industrial applications, and social applications, making it one of the most influential technological systems in the field of AI today [21].

2.2 AI Development for NTN

Typical AI schemes, including ML, DL and RL technologies, with their powerful data modeling capabilities, real-time decision-making advantages, and adaptive learning characteristics, can effectively address typical challenges in LEO satellite networks, such as highly dynamic and time-varying topologies, limited heterogeneous network resources, massive concurrent terminal access, and unstable satellite-to-ground links. Through real-time perception and intelligent optimization of network status, service requirements, and environmental interference, they achieve efficient routing planning, resource scheduling, access control, and fault self-healing. Building upon this, these AI technologies can provide crucial intelligent support for the future 6G satellite-terrestrial integrated communication system, promoting the deep integration and collaborative scheduling of heterogeneous air, space, ground, and sea networks, improving system coverage, transmission reliability, and service quality, and contributing to the construction of a next-generation mobile communication architecture with full coverage, low latency, high reliability, and intelligence. Some key enablers for the growing AI trend in both TNs and NTNs are considered as follows.

First, in 6G-oriented NTN architectures, the complexity of various tasks carried by satellite communication networks will significantly increase, including mobile communication, space edge computing and in-orbit processing for remote sensing data. These tasks cover multi-layered intelligent decision-making scenarios, mainly including key aspects such as dynamic resource allocation, high-precision channel estimation, adaptive modulation and coding, on-board collaborative processing, and autonomous management of the satellite network [22]. If the traditional centralized terrestrial processing mode is still used, it will be difficult to meet the system performance requirements in actual deployment due to limitations such as satellite-to-ground transmission latency, link intermittency, and the high-dimensional optimization problems brought about by large-scale LEO satellite networking. In particular, it cannot adapt to the real-time requirements of dense, highly dynamic satellite networks [23]. At the same time, the execution of satellite communication tasks places more stringent demands on decision-making accuracy and response timeliness to ensure the continuity, reliability, and security of communication services and reduce potential risks caused by latency or decision-making errors. With the rapid development of artificial intelligence technology, intelligent algorithms based on ML and DL can effectively address the above challenges [24]. This type of method can not only achieve higher precision in perception, prediction and optimization operations, but also build an end-to-end automated execution link based on a lightweight machine learning framework, enabling on-board autonomous decision-making, online iteration and model self-updating, thereby significantly reducing dependence on ground centers and providing efficient, adaptive and intelligent technical support for 6G NTN networks [25].

Second, due to their multi-layered architecture, the design and deployment of next-generation NTNs are more complex than traditional terrestrial cellular networks. The introduction of satellite networks brings additional communication performance metrics and constraints, typically requiring the integration of more system parameters to achieve globally optimal network performance. However, the significant increase in parameter dimensionality and problem scale often makes the corresponding network optimization models computationally difficult to solve, or computationally inefficient [26]. Taking resource management in NTNs as an example, its resource optimization problem typically exhibits non-convex optimization characteristics, and traditional optimization methods usually only yield suboptimal solutions or rely on heuristic strategies with performance lacking theoretical guarantees. In contrast, the DL technology, with its powerful nonlinear fitting capabilities of neural networks, can

efficiently approximate complex functions containing a large number of input variables [27]. Through a well-designed network structure, DL can accurately represent the highly dynamic and heterogeneous NTN environment, thereby achieving near-optimal solutions to integrated satellite-terrestrial resource management problems in a controllable and efficient manner [28].

Third, while probabilistic and deterministic models can be used to model and simulate the characteristics of nonlinear networks, these analytical methods typically rely on strong idealizations to derive universal mathematical expressions. This makes them difficult to adapt to the dynamic characteristics and random disturbances of real-world mobile networks, leading to significant discrepancies between simulation results and actual network operation. In contrast, ML models learn patterns and mapping relationships directly from massive amounts of real-world data, without imposing prior assumptions about the system environment and channel characteristics. They can fully cover diverse scenarios and uncertainties during the training phase, resulting in stronger generalization capabilities and higher fitting accuracy. In NTNs, the high dynamic mobility of LEO satellites, the time-varying wireless propagation environment, and the instability of satellite-to-ground links further amplify the negative impact of model errors. Deviations in calculation results and response delays not only reduce system performance but may also trigger more serious problems such as service interruptions and scheduling failures. Against this backdrop, data-driven AI technology has shown significant advantages. Through feature learning, it can effectively reduce the dimensionality of high-dimensional data and extract key information. Various DL frameworks can automatically mine hidden patterns and inherent laws from the perception data of complex systems and directly output end-to-end optimization decision-making schemes, thereby more accurately approximating the real network environment and providing reliable support for the dynamic optimization and intelligent management of NTN.

In addition, AI-based intelligent solutions possess adaptive capabilities to dynamic network environments, enabling continuous iteration and autonomous learning through historical data and real-time interaction. ML technology leverages massive amounts of network operational data to continuously improve perception and decision-making accuracy, dynamically optimizing resource scheduling, routing, and transmission strategies to adapt to diverse and time-varying user service needs. Utilizing advanced algorithms such as RL and DL, NTNs can achieve adaptive allocation of satellite-to-ground link resources, real-time optimization of network parameters, and proactive fault detection, accurate diagnosis, and rapid mitigation through online learning and environmental interaction, effectively improving system robustness and reliability [29]. This autonomous learning and online iteration capability allows NTNs to respond agilely to complex scenarios such as highly dynamic topologies, time-varying channels, and sudden traffic surges, significantly improving the utilization efficiency of scarce resources such as spectrum, power, and orbits, reducing operational overhead and manual intervention costs, and ultimately providing continuous, stable, and high-quality service guarantees for full-coverage, low-latency, and highly reliable 6G NTNs [30].

Finally, in NTNs, network optimization and management decisions typically need to be executed in real time under strict time constraints, with tolerable processing latency generally ranging from a few milliseconds to tens of milliseconds [31]. However, traditional model-based optimization algorithms often have high computational complexity, making them computationally intensive methods. When faced with highly dynamic topologies, large-scale nodes, and multiple constraints, they struggle to meet the low-latency, high-real-time decision-making requirements and are difficult to deploy directly on satellite or edge computing platforms [32]. In contrast, artificial intelligence technologies with online adaptive capabilities offer a more promising technical path to address these issues [33]. For example, online learning methods based on deep reinforcement learning can quickly output decision results through real-time interaction with the network environment. After training convergence, they can achieve low-latency inference, thereby efficiently completing resource management tasks such as resource allocation and power control, ensuring the rational and efficient utilization of limited

communication resources in NTN. This advantage is particularly crucial in latency-sensitive decision-making scenarios such as beam scheduling, satellite switching, and route planning, providing important support for NTNs to achieve highly reliable, low-latency, and adaptive intelligent operation and maintenance and resource scheduling [34].

3. Integration of Terrestrial and Non-Terrestrial Networks

3.1 Integrated Scenario

Fig. 2 illustrates a typical satellite-terrestrial integrated network scenario, achieving comprehensive coverage and interconnectivity across air, space, and ground:

- **Space Segment:** Composed of a constellation of multiple LEO satellites, these satellites exchange data at high speed via inter-satellite links, forming an autonomous and controllable space backbone transmission network.
- **Ground Segment:** Deployed infrastructure such as ground satellite stations and 5G/6G base stations, serving as the key interface between the TNs and NTNs, ensuring seamless integration of satellite signals with terrestrial cellular networks.
- **User Segment:** Covering diverse terminals and scenarios, including intelligent connected vehicles on roads, public transportation, handheld mobile terminals, and drone swarms performing missions. These devices can access the network via ground base stations or directly via satellite when terrestrial network coverage is insufficient, achieving comprehensive communication.

Through efficient collaboration of space-ground links, the entire system provides continuous, reliable, and wide-coverage communication services to ground and low-altitude users, effectively supporting diverse application scenarios such as intelligent transportation, emergency communication, and the Internet of Things (IoT) [35].

3.2 Physical-Layer Applications

3.2.1 Channel Estimation

In satellite-terrestrial integrated networks, channel state information (CSI) is the core foundation for achieving efficient and reliable communication. By accurately acquiring CSI, the system can dynamically adjust transmission parameters such as modulation and coding schemes, power allocation, and beamforming weights based on time-varying channel conditions. This is crucial for overcoming inherent challenges in satellite communication, such as long-distance transmission, Doppler shift, and atmospheric attenuation, and for ensuring link stability.

In traditional terrestrial cellular networks, classic channel estimation algorithms such as maximum likelihood and minimum mean square error have been widely used. However, in LEO satellite communication scenarios, due to the characteristics of space-ground links, such as high-speed relative motion, large time delay spread, time-varying topology, and limited onboard computing resources, these model-driven traditional methods face problems such as high computational complexity, slow convergence speed, and insufficient robustness, making it difficult to directly meet the stringent real-time and reliability requirements of satellite-terrestrial integrated networks [36].

Therefore, data-driven ML channel estimation and decision-making methods are becoming a research hotspot in both academia and industry. By using high-dimensional, heterogeneous channel

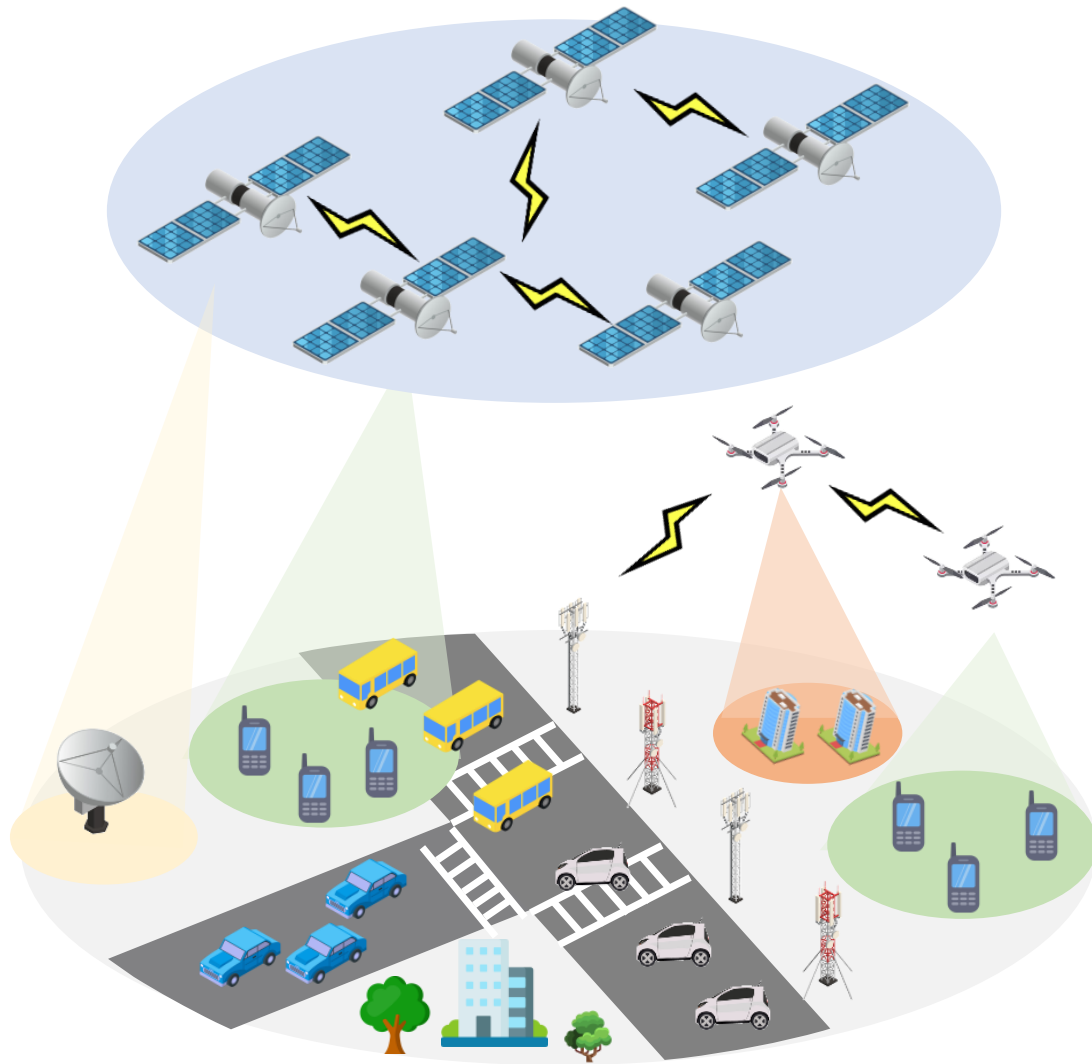


Fig. 2. The integration of terrestrial and non-terrestrial networks.

characteristics (such as transmission distance, propagation delay, received power, azimuth angle, departure angle, signal bandwidth, and carrier frequency) as input and the CSI to be estimated as the output label for supervised learning, the channel estimation problem can be effectively transformed into a regression fitting or classification task that ML models excel at handling. This paradigm shift not only leverages the powerful feature extraction and nonlinear mapping capabilities of deep neural networks to learn complex channel statistical characteristics from massive amounts of historical data, but also significantly reduces online inference latency while ensuring estimation accuracy, providing a new technical path for efficient and intelligent transmission control in satellite-terrestrial integrated networks [37].

3.2.2 Anti-interference

Satellite communication networks, with their wide-area coverage, high mobility, and resilience, have become a key component of 6G and next-generation satellite-terrestrial integrated networks. However, the predictability of satellite orbits and the periodic visibility of beam coverage make them highly susceptible to both intentional interference, e.g., malicious electronic countermeasures, and

unintentional interference, e.g., spectrum congestion and interstellar interference, seriously threatening the reliability and transmission effectiveness of communication links. Therefore, developing efficient and adaptive anti-jamming technologies is crucial for ensuring the safe and stable operation of satellite-terrestrial integrated networks [38].

Traditional satellite communication anti-jamming technologies primarily rely on broadband high-speed frequency hopping and direct sequence spread spectrum, combined with power control and diversity reception, forming a blind anti-jamming mechanism. While these technologies can guarantee minimum communication connectivity in worst-case scenarios, they suffer from inherent limitations such as low spectrum utilization, slow response, and difficulty adapting to dynamic interference environments, making them unsuitable for increasingly complex electromagnetic countermeasures requirements [39].

In recent years, the rapid development of AI technologies has provided a revolutionary approach to constructing an intelligent anti-interference cognitive loop, driving the evolution of communication anti-interference from traditional passive defense to a closed-loop paradigm of proactive cognition and intelligent decision-making. Specifically, an intelligent anti-interference system aims to construct a complete Observe-Orient-Decide-Act (OODA) loop, i.e., using intelligent interference cognition as the sensor to perceive the type, intensity, and spectral characteristics of interference in real time, using intelligent anti-interference decision-making as the brain to generate optimal anti-interference strategies based on RL, using intelligent anti-interference waveform reconstruction as the execution unit to dynamically adjust modulation methods, coding schemes, and beamforming parameters, and finally, using intelligent anti-interference effectiveness evaluation to generate feedback and continuously optimize system performance.

Early cutting-edge research has deployed AI-based cognitive engines to efficiently acquire spectral knowledge and learn interference characteristics within the spectrum of satellite communication, and collaboratively utilizes deep reinforcement learning (DRL) for real-time decision-making to effectively avoid or combat various intentional and unintentional interferences [40].

3.2.3 *Transmission Optimization*

In satellite-terrestrial integrated networks, satellite payload power and available spectrum are core, scarce resources supporting wide-area coverage and high-speed transmission. With the emergence of massive terminal access and diverse service demands, achieving efficient power and spectrum allocation under the constraint of limited on-board resources has become a key challenge for improving system throughput and ensuring Quality of Service (QoS). Traditional resource management methods rely on mathematical tools such as convex optimization and game theory. However, in satellite communication scenarios, these methods face fundamental bottlenecks.

First, objective functions, e.g., maximizing system throughput and energy efficiency, typically exhibit highly nonlinear characteristics, while constraints such as signal-to-interference-plus-noise ratio (SINR) and user fairness further introduce non-convexity, causing the problem to fall into local optima rather than global optima. Second, decisions such as carrier allocation and beam selection are essentially discrete integer variables, intertwined with continuous power allocation variables, forming a complex mixed-integer nonlinear programming (MINLP) problem. Traditional convex optimization methods (such as Lagrange duality) either require linear approximations leading to performance loss or exhibit computational complexity that grows exponentially with problem size when dealing with such problems, making them unsuitable for the stringent requirements of real-time onboard decision-making.

Therefore, data-driven RL frameworks are becoming the mainstream paradigm for solving satellite communication transmission resource optimization problems. In these methods, the complex net-

work scenario is first abstracted into a high-dimensional state vector, which typically contains multi-dimensional information such as user location, channel quality, service type, and remaining resources. Subsequently, DNNs are used to extract features from the high-dimensional state and reduce its dimensionality, mapping it to a low-dimensional feature space to reduce the learning difficulty. The agent, taking the current state as input, learns and outputs the optimal resource allocation strategy (such as power allocation matrix and carrier allocation scheme) through continuous interaction with the environment, aiming to maximize long-term cumulative rewards (such as long-term throughput, energy efficiency, or user satisfaction). This end-to-end learning approach not only avoids complex mathematical modeling and solving processes, but also enables adaptive optimization in dynamically changing channel and service environments, providing a highly promising technical path for intelligent resource management in satellite-terrestrial integrated networks [41].

3.3 Network-Layer Applications

3.3.1 Network Topology Design

As core nodes of space-based information networks, LEO communication satellite constellations experience continuous and dynamic changes in their inter-satellite link and satellite-ground link connections during their high-speed orbit around the Earth. This results in a highly time-varying network characterized by frequent topology reconfiguration. Topology planning, a crucial step in ensuring network connectivity, reducing transmission latency, and improving resource utilization, aims to maximize the use of limited communication resources by optimizing the configuration strategies of ISL and SGL, while meeting constraints such as service latency, throughput, and reliability. However, traditional topology optimization methods based on graph theory or linear programming generally suffer from inherent drawbacks when facing the massive number of nodes, strong time-varying nature, and multiple constraints of LEO constellations. These drawbacks include high computational complexity, slow response, and difficulty in adapting to dynamic environments, making them unsuitable for the stringent real-time and robustness requirements of next-generation satellite-terrestrial integrated networks. In recent years, AI technologies, represented by DRL, have provided a revolutionary technical path for solving topology planning problems in highly dynamic environments, and have achieved a series of breakthroughs in the field of LEO constellation topology optimization [42].

3.3.2 Network Routing

In satellite-terrestrial integrated networks, the network routing problem is typically formulated as a shortest path optimization problem with graph theory, and classical graph algorithms such as the Dijkstra algorithm are widely used for solving this problem. In this modeling paradigm, satellite nodes, ground gateways, and terminal devices can be uniformly modeled as vertices in a topology graph, while inter-satellite links, space-ground links, and other communication connections correspond to edges. The weights of these edges can be flexibly defined based on key performance indicators such as end-to-end latency, transmission jitter, system throughput, and packet loss rate, thus transforming routing decisions into a constrained optimal path search problem.

However, in multi-layered integrated architectures composed of LEO satellites, geostationary satellites, and heterogeneous ground networks, the network topology exhibits highly dynamic, time-varying, and complex characteristics. On the one hand, the high-speed motion of LEO satellites leads to continuous topology reconstruction, with link connectivity and propagation delays constantly changing. On the other hand, the cross-layer routing constraints, the randomness of channel conditions, and the spatiotemporal unevenness of service traffic brought about by the multi-layered network architecture

collectively result in a routing environment with strong uncertainty and non-stationarity. Against this backdrop, the inherent limitations of the traditional Dijkstra algorithm, which relies on fixed topology, static weights, and global information, are significantly amplified. Its computational real-time performance, environmental adaptability, and routing performance are insufficient to meet the quality of service requirements of large-scale dynamic satellite networks.

To address these challenges, AI-based routing optimization methods have received widespread attention from academia and industry in recent years. Some studies employ fuzzy logic systems to comprehensively evaluate diverse routing tasks and dynamic performance indicators, transforming multi-objective, fuzzy routing requirements into quantifiable decision-making criteria. They also combine this with improved convolutional neural networks to achieve supervised learning of routing strategies, improving path selection accuracy in complex environments through data-driven approaches. Meanwhile, another type of research builds intelligent routing models based on reinforcement learning frameworks. These models treat dynamic networks as interactive environments, using real-time topology status, traffic distribution, and link quality as observation inputs. Through continuous trial and error and iterative optimization between the agent and the network environment, they achieve a synergistic improvement in end-to-end latency, load balancing, and robustness. These methods do not require pre-established precise network models and can adaptively adjust routing strategies under dynamic topology and traffic fluctuations, providing an efficient and scalable intelligent routing solution for next-generation satellite-terrestrial integrated networks [43].

3.4 *Service-Layer Applications*

3.4.1 *Beam Resource Management*

Currently, modern communication satellites generally employ phased array antenna technology. Through electronically controlled beamforming and flexible pointing, they can dynamically allocate beam resources across multiple dimensions, including space, time, and frequency, providing hardware support for concurrent services from multiple users and services. However, in LEO satellite communication systems, due to the high-speed orbit of satellites, the visible arc time of any coverage area on the ground is extremely short, resulting in highly time-varying and fast-switching characteristics for the satellite-to-ground link. Simultaneously, the distribution density, service types, and traffic demands of user terminals in different areas exhibit significant spatiotemporal inhomogeneity, further exacerbating the difficulty of onboard resource allocation. Against this backdrop, designing efficient and adaptive beam scheduling strategies to achieve precise matching between beam coverage, resource allocation, and dynamic service demands within the constraints of limited onboard payload, power, and spectrum resources has become a key scientific and technological challenge for improving the throughput, service quality, and system fairness of LEO satellite networks.

In recent years, DRL has been widely researched and applied in the field of LEO satellite beam resource scheduling due to their unique advantages in autonomous decision-making, online optimization, and long-term benefit maximization in complex dynamic environments. The beam resource allocation strategy based on deep reinforcement learning models time-varying traffic distribution, dynamic topology, and on-board resource constraints into a unified reinforcement learning environment. Using deep neural networks as policy function approximators, it jointly optimizes beam pointing, beam shape, and bandwidth allocation schemes across three degrees of freedom, including time, space, and frequency. This enables real-time response to non-uniform, time-varying traffic requests. This strategy not only quickly adapts to service fluctuations, achieving synergistic optimization of system throughput and user fairness, but also maintains good generalization ability and robustness even in scenarios with increased traffic demand and denser network topologies. It provides an effective and

feasible technical solution for intelligent beam resource management of next-generation dynamic LEO satellite networks.

3.4.2 *Satellite Edge Computing*

With the continuous expansion of LEO satellite constellations and the ongoing improvement of onboard processing capabilities, satellite edge computing has become a key technology for improving service response speed and reducing transmission load in satellite-terrestrial integrated networks. Traditional satellite communication systems typically transmit data back to a ground-based central cloud for processing, which suffers from problems such as long transmission distances, high link latency, high bandwidth consumption, and excessive pressure on the ground core network, making it difficult to meet the low-latency requirements of high-real-time, large-scale access services such as IoT, emergency communications, and vehicle-mounted terminals. Deploying edge computing nodes on satellites allows for data storage, task offloading, distributed computing, and local decision-making close to user data sources, effectively shortening end-to-end processing latency, reducing data transmission pressure on space-ground links, and improving the overall operational efficiency and service reliability.

However, satellite edge computing faces numerous stringent challenges in resource scheduling and task allocation. The computing, storage, and energy resources of satellite nodes are highly limited. The dynamic topology changes caused by the high-speed movement of LEO satellites, intermittent link connectivity, and the spatiotemporal uneven distribution of user services result in strong randomness and non-stationarity in task offloading decisions and resource allocation. Meanwhile, mechanisms such as multi-satellite collaborative computing, space-ground collaborative processing, and cross-orbit mission migration further increase the complexity of system modeling. Traditional methods based on convex optimization, heuristic algorithms, or centralized scheduling struggle to achieve real-time and efficient resource allocation in dynamic environments.

Therefore, AI-based distributed edge computing scheduling strategies have gradually become a research hotspot. Deep reinforcement learning and distributed reinforcement learning methods can take dynamic network states, task requirements, and remaining computing resources as inputs. Through continuous interaction between agents and the environment, they learn the optimal task offloading ratio, computing node selection, and resource allocation scheme. Some studies model satellite edge computing as a Markov decision process, using neural networks to fit complex environmental and reward functions to achieve multi-objective optimization of latency, energy consumption, and system utility. Other studies employ distributed multi-agent architectures to achieve inter-satellite collaborative computing and dynamic load balancing, improving overall network computing efficiency while ensuring service quality. These AI-based intelligent edge computing paradigms can effectively adapt to the highly dynamic characteristics of satellite-terrestrial networks, providing efficient and scalable computing support capabilities for the next generation of satellite-terrestrial integrated networks [44].

4. AI-Driven Research Directions

Fig. 3 presents an overview of research challenges and applications in AI-driven integration of TNs and NTN. The research and development of satellite-terrestrial integrated networks has always revolved around addressing core challenges such as large-scale node deployment, highly dynamic topology changes, and wide-area seamless coverage. These challenges stem not only from the high-speed movement of the satellite constellation itself and the access requirements of massive numbers of terminals, but also from the urgent expectation of global, seamless communication coverage. Together,

they constitute the core driving force for theoretical innovation and technological breakthroughs. To effectively address these challenges, the research community is building a support system from two dimensions, including fundamental theory and key technologies. At the theoretical level, game theory is widely used to model resource competition and collaborative decision-making among multiple agents, while deep learning, with its powerful nonlinear fitting and feature extraction capabilities, provides a new paradigm for prediction, optimization, and intelligent management in highly dynamic network environments. At the technological level, network slicing technology, by virtualizing logically isolated differentiated service networks on a unified physical infrastructure, can simultaneously meet the diverse service requirements, while network simulation platforms provide an indispensable experimental environment for algorithm verification and performance evaluation in large-scale, highly dynamic scenarios.

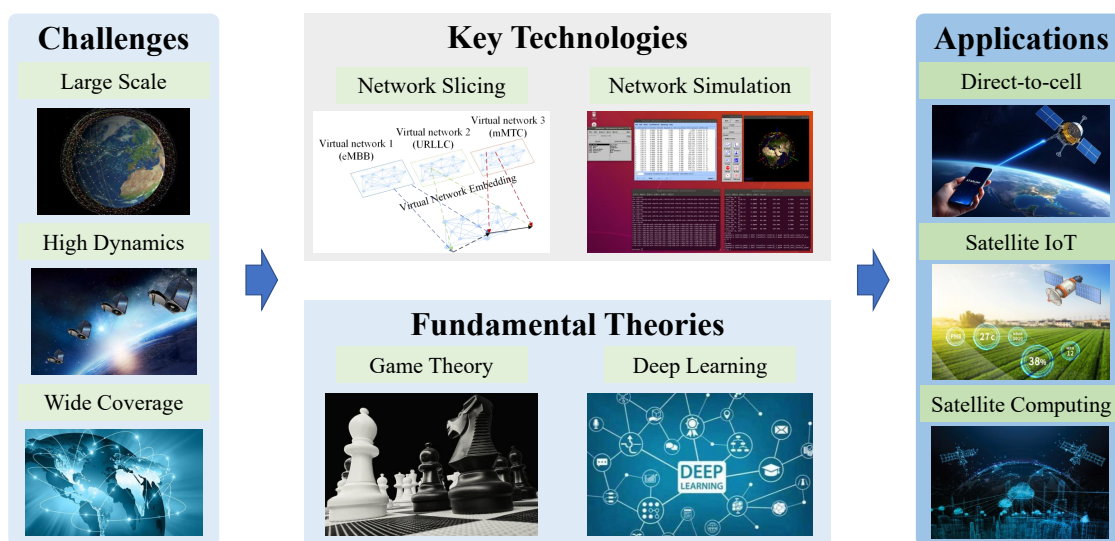


Fig. 3. Research challenges and applications in AI-driven integration of TNs and NTNs.

The value of technological innovation ultimately needs to be demonstrated through practical verification. For intelligent satellite communication systems, the robustness of the AI algorithms, the adaptability of the system architecture, and the reliability of the service capabilities all rely on a systematic, end-to-end testing and verification system. However, the research community is still lack of a comprehensive ground-based testing, simulation and verification platform for intelligent satellite communication systems. Through high-fidelity channel simulation, topology dynamic simulation, and business scenario reproduction, this future platform should be able to accurately recreate real-world constraints such as the time-varying characteristics of satellite-to-ground links, multi-user access conflicts, and cross-layer protocol interactions. This allows for the quantitative evaluation of the convergence speed, decision-making accuracy, and anti-interference capabilities of core modules such as AI-driven resource scheduling algorithms, intelligent routing strategies, and anomaly detection models. Simultaneously, it comprehensively verifies the stability, fault tolerance, and scalability under high-concurrency and high-dynamic scenarios. Based on this, pilot deployments should be actively promoted across different scenarios and industries. Small-scale implementations should be conducted in typical application scenarios such as emergency communication in remote areas, marine IoT data backhaul, and aircraft cabin interconnection. Through real business flows and user feedback data, a closed-loop evaluation of algorithm performance, system compatibility, and operational costs can be formed, thereby driving model iteration, architecture optimization, and strategy upgrades.

5. Conclusion

This paper systematically elucidates the key role and development prospects of AI in promoting the deep integration of terrestrial and non-terrestrial networks. With the accelerated evolution of 6G communication towards the satellite-terrestrial integrated network architecture, LEO satellite communication systems, with their advantages of wide coverage, low latency, and large capacity, have become the core infrastructure for filling coverage gaps in terrestrial networks and building seamless global connectivity. Facing challenges such as the highly dynamic topology, resource constraints, massive access, and complex service requirements of satellite networks, AI technologies, represented by machine learning, deep learning, and reinforcement learning, have demonstrated powerful data modeling, real-time decision-making, and adaptive optimization capabilities, providing innovative solutions for the entire lifecycle management of channel estimation, anti-interference, transmission optimization, topology design, intelligent routing, beam scheduling, and edge computing.

In the future, AI-driven research on satellite-terrestrial integrated networks should focus on the following directions. First, constructing a fusion theoretical framework based on game theory and deep learning to support multi-agent collaborative decision-making and resource optimization. Second, developing network slicing and intelligent simulation technologies to achieve precise adaptation to differentiated service requirements and efficient algorithm verification. Third, promoting the deployment of ground testing platforms and pilot projects in typical scenarios to form a complete closed loop from algorithm development to application implementation. Through the deep integration of theoretical innovation and technological breakthroughs, artificial intelligence will lay a solid foundation for the full coverage, low latency, high reliability and intelligent development of the next generation of mobile communication networks, and ultimately help realize the 6G vision.

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Conflicts of Interest

The authors declare no conflicts of interest.

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