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Autonomous 6G Physical Layer Architectures for Space-Air-Ground Integrated Networks

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Abstract

The emergence of sixth generation (6G) wireless systems calls for a significant shift away from conventional deterministic communication models. As communication infrastructures evolve into Space-Air-Ground Integrated Networks (SAGIN), traditional physical layer (PHY) techniques struggle to operate effectively under the severe Doppler effects and long propagation delays associated with space environments. This paper examines the role of artificial intelligence embedded directly within the 6G transceiver architecture to enable ultra-reliable and low-latency communication (URLLC). By replacing conventional signal estimation approaches with AI-driven PHY mechanisms, communication systems can avoid the computational burden of matrix inversion operations that often limit resource-constrained spaceborne platforms. A mathematical framework is developed to illustrate how intelligent edge nodes can autonomously deliver critical Smart Grid telemetry through Low Earth Orbit (LEO) satellite constellations. In addition, complexity analysis shows that deep learning-based modulation techniques exhibit near linear scaling behavior, offering a more efficient and resilient communication foundation for both decentralized energy networks and Spacecraft Internet of Things (IoT) applications. The dynamic channel variability, spectrum utilization issues, and real-time decision-making demands present in varied SAGIN contexts are all addressed by the suggested architecture. Incorporating AI-enhanced transceiver intelligence lowers computing overhead while increasing communication flexibility, dependability, and spectrum efficiency. Performance analysis shows how intelligent communication systems may facilitate large-scale Internet of Things connectivity, autonomous satellite operations, and mission-critical data sharing.

Keywords: 6G, Space-Air-Ground Integrated Networks (SAGIN), URLLC, Deep Reinforcement Learning, Channel Estimation, Internet of Things.

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INTRODUCTION

For decades, the physical layer (PHY) of cellular communication systems has been built around deterministic mathematical models [14]. Although fifth-generation (5G) networks introduced significant improvements in broadband connectivity and network capacity, the underlying transceiver architecture continues to rely heavily on conventional techniques such as Least Squares (LS) and Minimum Mean Square Error (MMSE) estimation. These approaches perform effectively under relatively predictable terrestrial channel conditions. However, the transition toward sixth-generation (6G) networks introduces a substantially more complex communication landscape [3]. The emergence of Space-Air-Ground Integrated Networks (SAGIN) brings highly dynamic and nonlinear propagation environments where the effectiveness of traditional mathematical models becomes increasingly limited [11, 15].

One of the key motivations behind this evolution is the rapid growth of Spacecraft Internet of Things (IoT) technologies together with the ongoing transformation of terrestrial Smart Grid infrastructures [20]. Spacecraft IoT systems, consisting of interconnected sensors, autonomous subsystems, and edge-computing platforms deployed across satellites and orbital habitats, face significant communication challenges. Low Earth Orbit (LEO) satellite constellations operate under severe Doppler effects and frequently encounter intermittent connectivity, making reliable communication difficult to maintain [8, 12]. Processing all telemetry data at terrestrial ground stations further increases latency, which is often unacceptable for time critical mission operations.

At the same time, modern Smart Grids increasingly depend on Ultra-Reliable Low-Latency Communication (URLLC) to support real time monitoring and energy management functions [5]. Tasks such as dynamic load balancing and emergency response during natural disasters require communication infrastructures that remain operational even when terrestrial fiber networks are disrupted. Satellite supported 6G communication offers a promising alternative, provided that the physical layer can adapt autonomously to atmospheric fading, interference, and hardware impairments without continuous human intervention [6, 19].

To address these limitations, recent studies advocate replacing isolated and mathematically driven transceiver blocks with an end-to-end AI-native physical layer architecture [2, 4]. Rather than relying on computationally intensive matrix inversion operations, edge devices can employ lightweight and quantized neural networks to estimate channel conditions in real time [10, 16]. Motivated by these developments, this paper presents a mathematical framework for an AI-driven 6G PHY designed for SAGIN environments, with particular emphasis on hardware efficient implementation and autonomous resource optimization [1, 7].

LITERATURE REVIEW

The evolution toward sixth-generation (6G) wireless communication systems has accelerated research into communication architectures that move beyond traditional mathematical models and incorporate artificial intelligence directly within the network infrastructure [14, 22]. Existing physical layer frameworks often struggle to maintain reliable performance under severe Doppler effects, high propagation delays, and static resource allocation mechanisms, particularly within Space-Air-Ground Integrated Networks (SAGIN). As a result, recent studies increasingly emphasize embedding intelligence directly into the transceiver chain to reduce communication overhead and overcome the limitations of deterministic signal processing.

AI-Driven Channel Estimation and PHY Architecture

Traditional channel estimation techniques such as Least Squares (LS) and Minimum Mean Square Error (MMSE) have demonstrated satisfactory performance under relatively stable communication conditions. However, their effectiveness declines significantly in highly dynamic wireless environments. To address this limitation, researchers have explored deep learning (DL) techniques for physical layer optimization. Convolutional Neural Networks (CNNs) for implicit channel estimation and reported improved accuracy with lower pilot overhead compared to conventional MMSE methods is employed [10]. Likewise, autoencoder-based communication architectures jointly optimize transmitter and receiver operations through end-to-end learning, eliminating the dependence on fixed transceiver blocks [2]. Despite these advantages, such approaches often encounter challenges when exposed to previously unseen channel conditions and generally require computationally intensive offline training.

Edge Intelligence in Spacecraft IoT

The rapid growth of Low Earth Orbit (LEO) satellite constellations has significantly increased the volume of Spacecraft IoT telemetry that must be processed and transmitted. Conventional architecture relies heavily on space-to-ground communication, creating latency and bandwidth bottlenecks. To overcome these limitations, several studies advocate incorporating edge intelligence directly into satellite payloads [12, 16]. By deploying AI models on RISC-V processors and radiation tolerant FPGA platforms, satellites can perform localized signal processing tasks, including channel equalization and interference mitigation, rather than operating solely as communication relays [23]. Additionally, Deep Reinforcement Learning (DRL) can support autonomous resource allocation and maintain stable Inter-Satellite Links (ISLs) despite severe Doppler effects [20]. However, practical deployment remains constrained by the limited computational resources and power budgets available on radiation-hardened spacecraft hardware.

Autonomous Smart Grid Operations

Modern Smart Grids increasingly depend on Ultra-Reliable Low-Latency Communication (URLLC) to support real-time monitoring, load balancing, and emergency response operations [5]. Because terrestrial communication infrastructure is vulnerable to environmental disruptions and natural disasters, satellite-assisted 6G architectures have emerged as a promising solution for maintaining continuous connectivity [6]. Researchers have explored Federated Learning and Deep Reinforcement Learning techniques to enable decentralized grid nodes to autonomously optimize spectrum utilization, transmission parameters, and resource allocation [19]. Although these approaches improve adaptability and resilience, DRL-based systems often require extended training and convergence periods before reaching optimal performance, which may limit their effectiveness during sudden grid disturbances.

The Semantic and Hardware Integration Gap

Semantic Communication has gained considerable attention as a mechanism for transmitting only meaningful information rather than complete raw data streams [18]. By extracting task-relevant features before transmission, semantic communication can significantly reduce bandwidth requirements and improve communication efficiency. Nevertheless, implementing semantic processing at the transmitting edge introduces substantial computational overhead. Current space ground communication platforms typically depend on lightweight TinyML models because of strict hardware limitations, particularly within spaceborne environments. These compact models often struggle to satisfy the stringent timing and processing requirements associated with Terahertz (THz) communication channels. Consequently, a noticeable gap remains between advances in semantic communication and their practical integration into resource constrained communication systems.

Computational Latency and the Proposed Research Gap

One of the most significant limitations of traditional physical layer architectures is their dependence on matrix inversion operations for channel estimation and signal optimization. These computations generally scale with cubic complexity, creating substantial processing delays in ultra-massive MIMO deployments. Within highly dynamic SAGIN environments, such delays can render Channel State Information (CSI) outdated before transmission occurs, reducing overall communication reliability. Although recent studies have proposed localized AI-based alternatives to address these challenges [16], many existing solutions do not adequately consider hardware aware optimization or the strict timing constraints imposed by URLLC applications.

A clear research gap therefore exists in the development of a unified physical layer architecture capable of eliminating reliance on deterministic mathematical solvers while remaining computationally efficient. The framework proposed in this work addresses this challenge by combining a DRL-driven Markov Decision Process with Reconfigurable Intelligent Surfaces (RIS) to create an AI-native physical layer architecture. By distributing intelligence directly across the communication infrastructure, the proposed system achieves near linear computational scaling and supports the sub-millisecond processing requirements necessary for reliable interoperability between autonomous spacecraft networks and terrestrial Smart Grid systems.

SYSTEMS MODEL AND PROBLEM FORMULATION

To model the practical behavior of a Space-Air-Ground Integrated Network (SAGIN), it is first necessary to characterize the propagation conditions that govern communication in orbital environments. In the considered framework, a downlink communication scenario is assumed, where a Low Earth Orbit (LEO) satellite operates not merely as a communication relay but as an intelligent edge-processing node responsible for delivering time-sensitive telemetry to a terrestrial Smart Grid receiver [23].

RIS-Assisted Terahertz Channel Architecture

Communication within the Terahertz (THz) spectrum offers substantial bandwidth advantages but also introduces significant propagation challenges, particularly severe free space path loss and atmospheric molecular absorption [11]. Therefore, establishing a reliable direct Line-of-Sight (LoS) connection between a LEO satellite and a terrestrial receiver becomes increasingly difficult, especially under dynamic environmental conditions. To improve link robustness, the proposed framework incorporates a Reconfigurable Intelligent Surface (RIS) composed of multiple passive reflecting elements capable of adaptively shaping the propagation environment [21].

$$y_k = \left(h_{d,k}^H + h_{r,k}^H \Phi G\right) w_k s_k + n\_k \tag{1}$$

In this model, the received signal at the Smart Grid node depends on both the direct and RIS-assisted propagation paths. The direct THz channel vector originates from the satellite's Ultra-Massive MIMO antenna array, while the reflected component is represented through the RIS-assisted channel matrix. The matrix (Φ) denotes the diagonal phase-shift configuration of the RIS elements. The formulation further incorporates the transmit precoding vector, transmitted symbol, and Additive White Gaussian Noise (AWGN), which inevitably affects signal quality during transmission.

The Matrix Inversion Bottleneck

One of the primary limitations of conventional communication architecture lies in the computational burden associated with obtaining accurate Channel State Information (CSI). To determine an optimal precoding vector, the communication system typically employs a Minimum Mean Square Error (MMSE) estimator, which requires inversion of the channel covariance matrix [10].

The complexity of this matrix inversion operation increases cubically with the number of transmit antennas and is generally expressed as (O(M^3)). Within modern 6G systems utilizing hundreds or even thousands of antenna elements for holographic beamforming, this computational requirement becomes a major obstacle [15]. Radiation hardened processors used in spaceborne platforms do not possess the computational capability required to repeatedly perform such operations within the short coherence intervals associated with high-mobility LEO channels. As a result, communication systems may fail to satisfy the strict timing requirements imposed by Ultra-Reliable Low-Latency Communication (URLLC) applications [12].

Orbital Dynamics and Doppler Impairments

Unlike terrestrial cellular networks, where relative motion between transmitters and receivers is generally moderate, LEO satellites travel at velocities exceeding 7.5 km/s relative to the Earth's surface [12]. These extreme orbital speeds introduce substantial Doppler shifts that significantly reduce channel coherence time. In THz communication systems, even minor variations in relative positioning can trigger rapid phase changes and severe fast fading effects [8].

Conventional synchronization mechanisms, including phase-locked loops and related tracking circuits, often struggle to respond effectively to such rapid channel fluctuations. Consequently, communication reliability degrades, leading to increased packet loss across both Inter-Satellite Links (ISLs) and space-to-ground telemetry channels [20]. Additionally, strict power limitations in spacecraft IoT systems necessitate the use of highly directional pencil beams, which can easily become misaligned because of orbital jitter and platform instability [16]. Under these conditions, relying solely on static mathematical communication models becomes increasingly ineffective. This limitation highlights the need for an adaptive AI-driven physical layer capable of predicting channel variations and compensating for communication impairments in real time.

Orbital Dynamics and Doppler Impairments

The complete physical and functional architecture of the proposed framework is illustrated in **Figure 1**. As shown in **Figure 1(a)**, the communication infrastructure is based on a multi-layered Space-Air-Ground Integrated Network (SAGIN) that combines multiple communication technologies, including Free Space Optical (FSO) links, millimeter-wave (mmWave) communication, Unmanned Aerial Vehicle (UAV) networks, and terrestrial Base Transceiver Station (BTS) connectivity. This heterogeneous architecture enables seamless integration between orbital, aerial, and terrestrial communication assets, creating a unified ecosystem capable of supporting a broad range of applications such as Smart Grids, maritime transportation systems, industrial automation, and autonomous vehicle networks.

The corresponding functional organization of the proposed system is presented in **Figure 1(b)**. The architecture is structured into four primary operational layers, each responsible for a specific set of network functions that collectively enable intelligent communication and resource management across the SAGIN environment.

SAGIN Infrastructure

The foundational layer consists of the physical communication infrastructure. It includes the Space Network, comprising satellites and other orbital communication platforms; the Aerial Network, which incorporates UAVs and High-Altitude Platform Stations (HAPS); and the Ground Network, consisting of IoT devices, autonomous vehicles, ground stations, sensors, and terrestrial base stations. Together, these elements provide continuous end-to-end connectivity across space, air, and ground domains.

Network Protocol Layer

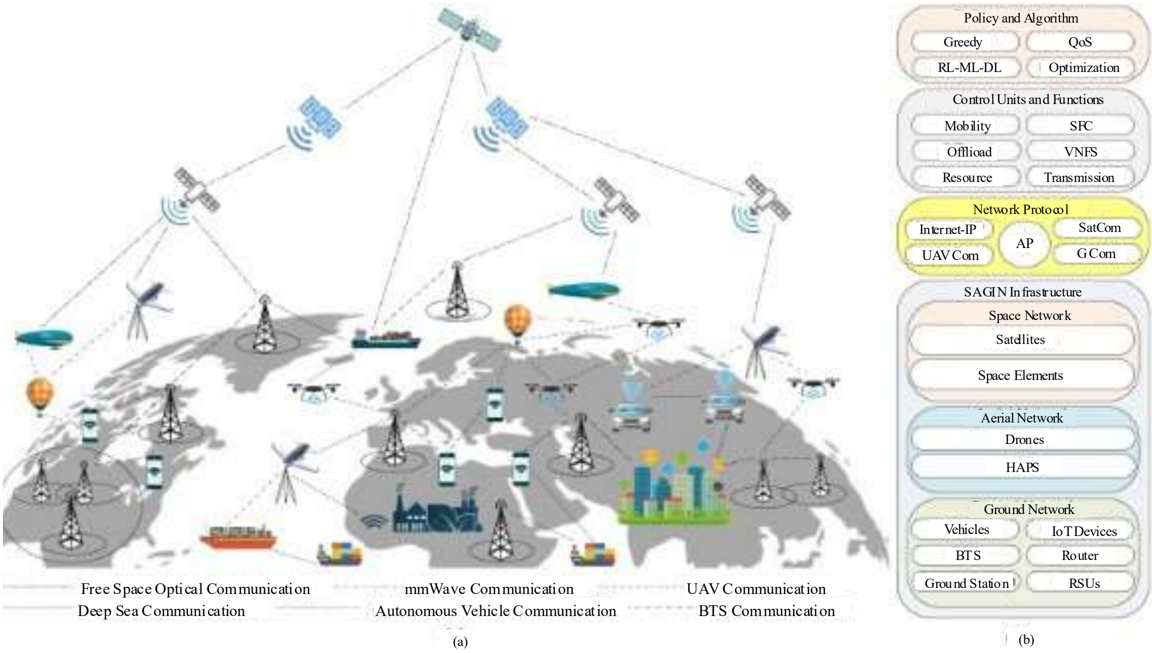
The second layer serves as the communication abstraction framework that enables interoperability among heterogeneous network segments. This layer supports Internet Protocol (IP) services, satellite communication protocols, UAV communication links, and conventional terrestrial networking mechanisms. By providing a unified protocol interface, it ensures seamless information exchange throughout the integrated network architecture.

Control Units and Network Functions

The third layer incorporates distributed control units responsible for real-time network management and optimization. Key functionalities include resource allocation, transmission scheduling, mobility management, service function chaining (SFC), and computational workload offloading. These control mechanisms allow the network to adapt dynamically to changing communication requirements while maintaining efficient utilization of available resources.

State Space Policy and Intelligent Decision Layer

The highest layer functions as the centralized intelligence engine of the proposed framework. Unlike conventional communication systems that primarily rely on static Quality of Service (QoS) policies and heuristic optimization techniques, this layer employs advanced Reinforcement Learning (RL), Machine Learning (ML), and Deep Learning (DL) algorithms. These AI-driven models continuously monitor network conditions and autonomously optimize routing, spectrum allocation, transmission parameters, and resource utilization. Consequently, the framework can maintain reliable, low-latency, and adaptive communication across the entire Space-Air-Ground Integrated Network while supporting the stringent requirements of future 6G applications.



AI-Driven Full-Architecture SAGIN Ecosystem depicting (a) physical multi-tier topology and (b) functional protocol layers.

AI-DRIVEN PHYSICAL LAYER FRAMEWORK

To model the practical behavior of a Space-Air-Ground Integrated Network (SAGIN), it is first necessary to characterize the propagation conditions that govern come to address the computational limitations associated with conventional matrix-based signal processing, the proposed framework replaces deterministic optimization methods with an autonomous AI-native physical layer architecture [2]. In the proposed system, intelligence is deployed directly at the Low Earth Orbit (LEO) satellite edge, enabling real-time communication decisions without dependence on continuous ground-station support. By utilizing quantized TinyML accelerators, inference operations can be executed within the strict sub-millisecond latency constraints required by Ultra-Reliable Low-Latency Communication (URLLC), a target that remains challenging for traditional spaceborne processing platforms [23].

Deep Reinforcement Learning (DRL) Optimization

The adaptive behavior of the proposed physical layer is modeled as a Markov Decision Process (MDP). This formulation allows a Deep Reinforcement Learning (DRL) agent operating onboard the satellite to continuously optimize communication parameters based on changing environmental conditions without requiring external intervention [20]. At each discrete time instant (t), the agent interacts with the communication environment through three primary components.

State Space

The state space contains the key variables that describe the instantaneous operating conditions of the communication system. These variables include the estimated Channel State Information (CSI), the current Smart Grid traffic demand, and the relative orbital velocity responsible for Doppler-induced channel variations [19].

$$s_t = \hat{H}_t, L_t, v_t \in S \tag{2}$$

Here, $\hat{\boldsymbol{H}}_t$ represents the estimated channel conditions, $\boldsymbol{L}_t$ denotes the current communication load, and $\boldsymbol{v}_t$ corresponds to the relative orbital velocity between communicating nodes.

Action Space

Based on the observed system state, the DRL agent selects an action that dynamically reconfigures the physical layer. These actions include selecting an appropriate Modulation and Coding Scheme (MCS), adjusting transmission parameters, and calculating the optimal RIS phase-shift configuration to improve signal propagation under changing channel conditions [21]. Through this process, the communication system can respond autonomously to interference, fading, and spectrum congestion.

Reward Function

The reward function is designed to ensure that communication performance remains aligned with the stringent requirements of 6G networks. Specifically, the objective is to maximize data throughput while penalizing actions that increase processing latency beyond the allowable URLLC threshold. Through repeated interaction with the environment, the agent gradually learns an optimal communication strategy capable of maintaining reliable connectivity across both Inter-Satellite Links (ISLs) and space-to-ground channels despite orbital disturbances [20].

$$R_t = \sum_{k=1}^{K} (\omega_1 C_k - \omega_2 \max(0, \tau_k - \tau_{max}))$$

In this formulation, $\boldsymbol{C_k}$ *denotes the achievable communication capacity, while the second term imposes a penalty whenever the latency* $\boldsymbol{\tau_k}$ *exceeds the maximum allowable threshold* $\boldsymbol{\tau_{max}}$.

Linear Complexity Through Quantized Neural Estimators

A major advantage of the proposed AI-native architecture lies in its ability to eliminate the computational burden associated with conventional MMSE-based processing. Instead of repeatedly performing matrix inversion operations, the framework employs a quantized Convolutional Neural Network (CNN) to estimate channel conditions directly from received pilot signals [10]. Through multiple convolutional layers, the neural network learns the complex nonlinear behavior of highly dynamic THz communication channels using data-driven feature extraction. The most significant improvement comes from the computational scaling characteristics of the trained model. After offline training and weight quantization for edge deployment, the inference complexity grows approximately linearly with the number of antenna elements, represented as (O(M)). This contrasts sharply with the cubic complexity (O(M^3)) associated with conventional deterministic estimators. Such a reduction is particularly important for Ultra-Massive MIMO systems operating in high-mobility LEO environments, where communication decisions must be completed before channel conditions change significantly [15]. By reducing processing latency while maintaining estimation accuracy, the proposed framework enables practical AI deployment within future 6G Space-Air-Ground Integrated Networks [9, 13].

NUMERICAL SIMULATION AND COMPLEXITY ANALYSIS

To verify the computational benefits of the proposed AI-native physical layer, a complexity analysis was conducted by comparing conventional signal processing methods with the proposed neural network-based approach. Within the considered Space-Air-Ground Integrated Network (SAGIN), the Low Earth Orbit (LEO) satellite functions as the primary edge-processing platform responsible for executing physical layer operations in real time.

In conventional communication systems, channel estimation is commonly performed using the Minimum Mean Square Error (MMSE) algorithm. Although MMSE provides reliable estimation accuracy, it requires repeated matrix inversion operations whose computational complexity increases cubically with the number of antenna elements. This complexity can be expressed as (O(M^3), where (M) denotes the size of the antenna array. As Ultra-Massive MIMO (UM-MIMO) deployments continue expanding in 6G systems, the computational burden associated with these matrix operations becomes increasingly difficult to manage, particularly on resource-constrained spaceborne hardware [17].

The proposed AI-native framework adopts a different strategy. Instead of relying on matrix inversion, channel estimation is performed using a quantized Convolutional Neural Network (CNN). Since the network parameters are learned during offline training, real-time execution involves only lightweight inference operations. Consequently, the computational complexity scales approximately linearly with the number of antenna elements and can be represented as (O(M)).

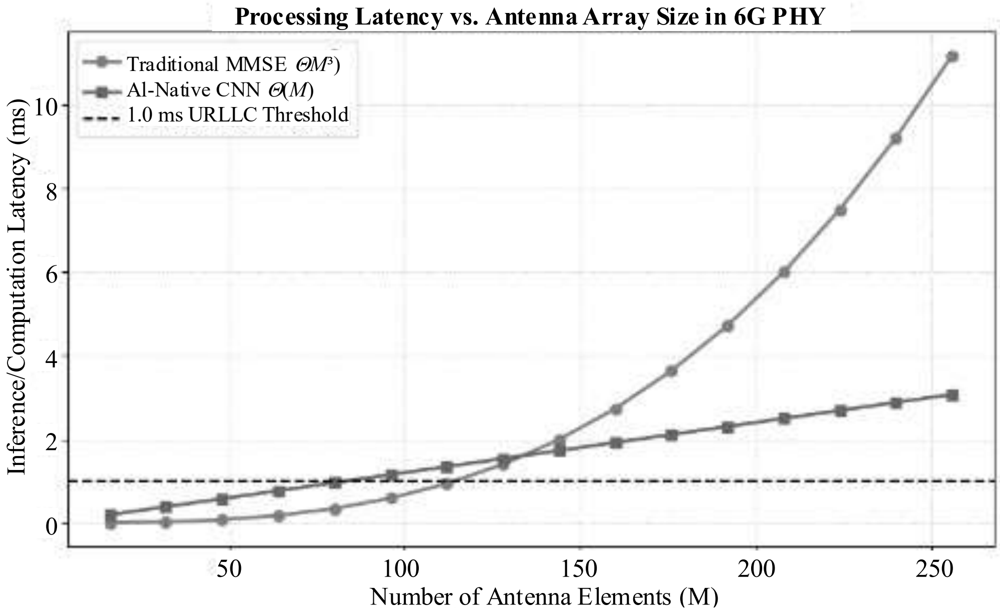


Figure 2. Computational latency comparison between conventional MMSE estimation and the proposed AI-native CNN framework for varying antenna array sizes.

As illustrated in Figure 2, the computational latency associated with conventional MMSE estimation increases rapidly as the antenna array size grows. Once the system exceeds approximately 128 antenna elements a common requirement for high-frequency Terahertz beamforming applications, the processing delay rises beyond the strict 1 ms threshold associated with Ultra-Reliable Low-Latency Communication (URLLC). Such delays can result in outdated channel estimates and potential communication failures.

FUTURE DIRECTIONS: QUANTUM AND NEUROMORPHIC INTEGRATION

Although AI-native physical layer architectures address many of the immediate computational limitations of current communication systems, several challenges remain before fully autonomous space-ground communication networks become a reality [14, 22]. Future research is expected to focus on emerging technologies capable of improving security, efficiency, and long-term operational sustainability.

Quantum Physical Layer Security

As artificial intelligence becomes more deeply integrated into communication systems, attack strategies are also expected to become increasingly sophisticated. Techniques such as intelligent jamming, adversarial learning, and generative radio-frequency spoofing may eventually challenge conventional security mechanisms. For this reason, future 6G architectures should investigate the integration of Quantum Key Distribution (QKD) directly within the physical layer [24].

By utilizing quantum enabled Inter-Satellite Links (ISLs), communication systems could exploit the fundamental properties of quantum mechanics to enhance security. Any attempt to intercept or observe the transmitted quantum information would alter the quantum state itself, making unauthorized access immediately detectable. Integrating AI-assisted communication optimization with quantum-secured transmission therefore represents an important direction for future space-ground communication networks.

Neuromorphic Engineering for Space Environments

Energy efficiency remains one of the most critical constraints affecting autonomous spacecraft and remote sensing systems. Traditional von Neumann processors consume considerable power during continuous computation and AI inference, limiting the operational lifespan of deep-space missions and isolated edge devices [23].

To address this challenge, future physical layer research should explore Neuromorphic Engineering approaches, particularly Spiking Neural Networks (SNNs). Unlike conventional neural architectures, SNNs operate using event-driven computation, activating only when meaningful information is detected [4, 25]. This behavior closely resembles biological neural systems and can significantly reduce energy consumption.

For Spacecraft IoT applications and remote Smart Grid monitoring systems, neuromorphic processors could enable continuous environmental monitoring while operating at extremely low power levels. The ability to perform intelligent signal processing using only microwatts of energy would greatly extend mission duration, improve hardware longevity, and support the deployment of highly autonomous communication nodes in both terrestrial and space environments.

CONCLUSION

The emergence of Space-Air-Ground Integrated Networks (SAGIN) as a core component of future 6G communication systems presents challenges that conventional physical layer architectures are increasingly unable to address. As discussed throughout this work, traditional signal-processing techniques rely heavily on matrix inversion operations whose computational complexity grows cubically with the size of the antenna array. In Ultra-Massive MIMO environments, this processing burden introduces significant latency, making it difficult to satisfy the stringent sub-millisecond requirements associated with mission critical Smart Grid control and Spacecraft IoT communication.

To overcome these limitations, this paper proposed an AI-native physical layer framework that integrates Deep Reinforcement Learning (DRL) and quantized Convolutional Neural Networks (CNNs) directly into the communication process. By transferring the majority of computational effort to an offline training stage, the proposed architecture significantly reduces real-time processing requirements. As a result, onboard inference complexity scales approximately linearly, enabling faster decision-making and more efficient channel estimation within highly dynamic communication environments.

The analysis further demonstrates that AI-driven optimization can maintain reliable communication performance even under severe Doppler effects, rapid channel variations, and atmospheric impairments commonly encountered in Terahertz based satellite links. Such adaptability is particularly important for future SAGIN deployments, where communication systems must operate autonomously across space, air, and terrestrial domains. Ultimately, the integration of artificial intelligence into the physical layer should not be viewed merely as a performance enhancement. Rather, it represents a necessary architectural evolution for supporting resilient, low-latency, and self-optimizing communication infrastructures. As 6G networks continue to expand toward deep-space exploration and decentralized energy ecosystems, AI-native physical layer technologies are expected to play a central role in enabling reliable and autonomous operation across these increasingly complex environments.

REFERENCES

1. OLAWOYIN LA, Oloyede MO, Oloyede AA, Imam-Fulani YO, Mahmoud-Jimoh A. Artificial Intelligence for Physical Layer Security in 6G Wireless Networks: Challenges and Opportunities-A Systematic Review. Nigerian Journal of Technological Development. 2026 Mar 31;23(1):322-31.
2. Christopoulou A, Kosmanos D, Xenakis A, Chaikalis C. AI-Enabled Autoencoder-Based Physical Layer Design for 6G Communication Systems. Electronics. 2026 Jan 26;15(3):538.

3. Shafaei S, Palaios A, Ennaceur Z, Zhang J, Pandit V, Gautam P, Gharouni A, Gajic B, Banerjee B, Mallikarjun SB, Habibi MA. Towards AI in 6G: Concepts, Techniques, and Standards. IEEE access. 2025 Aug 4.
4. Mutescu PM, Petrariu AI, Coca E, Patachia-Sultanoiu C, Mihai RM, Lavric A. AI-Native PHY-Layer in 6G Orchestrated Spectrum-Aware Networks. Sensors. 2025 Nov 26;25(23):7206.
5. Kumar M, Tripathi ND, Reed JH. A Survey of Smart Grid Emerging Use Cases and Relevant 5G and 6G Capabilities and Features. IEEE Access. 2026 Feb 24.
6. Shen Y, Zhou Q, Wen Y, Shuai Z, Shen ZJ. Integrated satellite-terrestrial network framework for next generation smart grid. IEEE Transactions on Smart Grid. 2024 Jul 5;15(5):5249-52.
7. Al Shahrani AM. IoT enabled intelligent receiver synchronization system for long-range 6G consumer technology. IEEE Transactions on Consumer Electronics. 2024 Jun 7;70(3):5747-55.
8. Fontanesi G, Ortíz F, Lagunas E, Garcés-Socarrás LM, Baeza VM, Vázquez MÁ, Vásquez-Peralvo JA, Minardi M, Vu HN, Honnaiah PJ, Lacoste C. Artificial intelligence for satellite communication: A survey. IEEE Communications Surveys & Tutorials. 2025 Feb 13;28:1381-435.
9. Fourati F, Alouini MS. Artificial intelligence for satellite communication: A review. Intelligent and Converged Networks. 2021 Sep;2(3):213-43.
10. Qiao Z, Xue J, Zhang J, Liu G, Ma X, Li R, Khan FA, Thompson JS, Xu Z. Adaptive implicit-based deep learning channel estimation for 6G communications. IEEE Communications Magazine. 2025 Jul 29;63(8):64-70.
11. Long WX, Ye S, Moretti M, Morelli M, Sanguinetti L, Chen R, Wang CX. Channel Estimation for 6G Near-Field Wireless Communications: A Comprehensive Survey. IEEE Communications Surveys & Tutorials. 2026 Mar 23;28:5496-531.
12. Jamshed MA, Haq B, Mohsin MA, Nauman A, Yanikomeroglu H. Artificial intelligence, ambient backscatter communication and non-terrestrial networks: A 6g commixture. IEEE Internet of Things Magazine. 2025 Feb 27;8(2):88-94.
13. Zhang Y, Wu Y, Liu A, Xia X, Pan T, Liu X. Deep learning-based channel prediction for LEO satellite massive MIMO communication system. IEEE Wireless Communications Letters. 2021 May 24;10(8):1835-9.
14. Saad W, Bennis M, Chen M. A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. IEEE network. 2019 Oct 15;34(3):134-42.
15. Chun CJ, Kang JM, Kim IM. Deep learning-based channel estimation for massive MIMO systems. IEEE Wireless Communications Letters. 2019 Apr 19;8(4):1228-31.
16. Zhang P, Chen N, Shen S, Yu S, Kumar N, Hsu CH. AI-enabled space-air-ground integrated networks: Management and optimization. IEEE network. 2023 Apr 17;38(2):186-92.
17. Yang Z, Chen M, Wong KK, Poor HV, Cui S. Federated learning for 6G: Applications, challenges, and opportunities. Engineering. 2022 Jan 1;8:33-41.
18. Wang Y, Gao Z, Zheng D, Chen S, Gündüz D, Poor HV. Transformer-empowered 6G intelligent networks: From massive MIMO processing to semantic communication. IEEE Wireless Communications. 2022 Nov 23;30(6):127-35.
19. AT MR, B B, RR SA, Naidu RC, M RK, Ramachandran P, Rajkumar S, Kumar VN, Aggarwal G, Siddiqui AM. Intelligent energy management across smart grids deploying 6G IoT, AI, and blockchain in sustainable smart cities. IoT. 2024 Aug 31;5(3):560-91.
20. Soleymani M, Bonyani M, Wang C. Simulation of autonomous resource allocation through deep reinforcement learning-based portfolio-project integration. Automation in Construction. 2024 Jun 1;162:105381.
21. Di Renzo M, Zappone A, Debbah M, Alouini MS, Yuen C, De Rosny J, Tretyakov S. Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and the road ahead. IEEE journal on selected areas in communications. 2020 Jul 14;38(11):2450-525.
22. Tariq F, Khandaker MR, Wong KK, Imran MA, Bennis M, Debbah M. A speculative study on 6G. IEEE Wireless communications. 2020 Aug 18;27(4):118-25.
23. Barretta D, Marini L, Razzano F, Guerrisi G, Sandberg S, Del Prete R, Zancan V, Mariotti E, Furano

G, Manovi L, Guo J. Toward real-time earth system intelligence through advancements in onboard ai processing: A review. IEEE Geoscience and Remote Sensing Magazine. 2026 Apr 3.
24. Dang S, Amin O, Shihada B, Alouini MS. What should 6G be?. Nature Electronics. 2020 Jan;3(1):20-9.
25. Shafin R, Liu L, Chandrasekhar V, Chen H, Reed J, Zhang JC. Artificial intelligence-enabled cellular networks: A critical path to beyond-5G and 6G. IEEE Wireless Communications. 2020 Mar 18;27(2):212-7.