

Original Research Article

Artificial intelligence in 6G communication networks: Physical-layer integration, intelligent scheduling, and deployment challenges

Zekai Li

Fuzhou University of International Studies and Trade, Putian, Fujian, 351100, China

Abstract: As sixth-generation (6G) networks evolve toward integrated space–air–ground connectivity and the convergence of communication, sensing, and computing, artificial intelligence (AI) is shifting from an auxiliary tool to a native network capability. This paper adopts a three-part analytical framework that covers protocol-layer integration, scheduling optimization, and deployment constraints. At the physical layer, it compares the operating boundaries of several deep-learning models for channel estimation and identifies the main obstacles to their practical use. At the network layer, it examines intelligent scheduling through multi-agent reinforcement learning, network-slice orchestration, federated learning, and an endogenous-intelligence architecture with closed-loop network autonomy. It then discusses three barriers to industrial deployment: The AI-native redesign of semantic communications, cross-vendor standardization, and the combined requirements of trustworthiness, security, and environmental sustainability. The analysis provides a structured account of how AI may be integrated into 6G networks and where further technical and institutional work is required.

Keywords: 6G; artificial intelligence; physical-layer integration; resource scheduling; semantic communications; standardization

1. Introduction

Sixth-generation networks are expected to support emerging services such as holographic communications, the industrial metaverse, and ubiquitous Internet of Things applications. These services will involve extremely dense connectivity, rapidly varying channels, and highly differentiated quality-of-service requirements. The envisioned integration of terrestrial, satellite, and aerial networks further increases this complexity^[1-2]. Conventional communication methods built around static models and fixed optimization rules are therefore unlikely to be sufficient. AI, with its capacity for data-driven adaptation and optimization, offers a promising means of managing the complexity of 6G systems.

Using the communication protocol stack as its organizing structure, this paper combines cross-model comparison with an examination of deployment constraints. It reviews the value of AI at the physical and network-scheduling layers, clarifies the operating conditions under which different models are useful, and identifies the technical and institutional barriers that continue to limit large-scale deployment.

2. Key mechanisms for AI integration at the physical layer

2.1. Comparison of deep-learning models for channel estimation

Traditional LS and MMSE channel estimation methods rely too much on accurate channel models and cannot adapt to 6 G high-speed mobile and ultra-large antenna environments. Although methods such as CNN, LSTM, Transformer, and hybrid deep learning have gradually become research hotspots, there are significant differences in computational overhead, feature extraction dimensions, and application scenarios.

Relying on local convolution operators, CNN is good at mining local features of channel frequency domain and spatial domain. In the low-speed static macro-cell environment, its computational cost is about 30 % lower than that of conventional MMSE. However, due to the lack of the ability to capture temporal features, the channel tracking accuracy of high-speed motion scenes (such as high-speed rail,

low-altitude UAV, etc.) is greatly improved. Long short-term memory relies on the gating loop structure and can capture continuous changes in the time domain. Compared with CNN, its estimation accuracy for high-speed scenes is improved by 15 %. However, due to the existence of multi-layer loops, the inference delay is multiplied, making it difficult to deploy at the terminal with limited computing power. Transformer performs joint modeling of spatial-temporal-frequency 3D features based on autofocus technology, and has the best performance in the scenario of ultra-large-scale arrays. However, due to the dependence on a large number of measured channel data, its generalization ability under small sample conditions drops sharply. The lightweight hybrid model of CNN-LSTM and Transformer compromises accuracy and computational overhead, and has become the first choice for 6G test network landing at this stage. In the specific network selection, based on the light convolution, the LSTM hybrid structure is used as the high-speed communication in the vehicle, taking the large base station as an example.

2.2. Challenges in end-to-end physical-layer autoencoder design

Firstly, the traditional neural network training relies on the ideal channel, ignoring the influence of physical factors such as real phase noise and carrier frequency offset, which makes the bit error rate in practical application increase by about 40 % compared with simulation, but also increases the training difficulty of the model. Second, there are deficiencies in interpretability. The neural network based on black box is difficult to trace, and can not meet the reliability maintenance requirements of 5 categories and 9 types of communication systems. Thirdly, facing the problem of backward compatibility, it breaks through the traditional wireless communication hierarchy and is not compatible with 5 G NR signals and protocols. The industry generally adopts the transition structure of ' traditional protocol stack + AI adapter plug-in ', taking into account the smooth evolution of existing devices and the iteration of new technologies.

3. AI-driven intelligent network scheduling

3.1. Multi-agent reinforcement learning for resource allocation

URLLC service focuses on delay and reliability, while eMBB service focuses on throughput and energy efficiency. This project intends to use the COMA inverse fact gradient algorithm to optimize the credibility of multi-agent, reduce the amount of interactive data through model quantization, sparse pruning and other methods, and combine with the scene pre-training model to speed up the convergence rate of heterogeneous networks, so as to achieve efficient distributed resource collaborative configuration.

3.2. Decision optimization for network-slice orchestration

Using LSTM and time converter, the resources required for slicing can be predicted according to the historical data of the business, and the accuracy rate can reach more than 90 %. By using NSGA-II multi-objective optimization method, the hierarchical intelligent matching of user fees and service quality at different levels is carried out, the resource competition among multi-tenants is simulated, and the conflict resolution mechanism is established, which reduces the conflict rate of on-chip resources by 35 %. In order to solve the privacy of multi-tenant data, this project intends to use differential privacy and joint learning technology to retain data locally, update parameters interactively, and continuously optimize the slice scheduling strategy to ensure data security.

3.3. Distributed federated-learning scheduling

According to the terminal 's computing power, data quality and online status, the nodes in the network are trained to improve the learning efficiency by 30 %. By using the reinforcement learning method, the communication and computing resources of the terminal are dynamically configured to reduce the energy consumption of the edge. In order to solve the problem of reduced modeling accuracy caused by heterogeneous multi-source data, the joint mean algorithm is improved to reduce the heterogeneity of data. At present, joint learning still has problems such as large iterative communication overhead and large differences in terminal computing capabilities. Hierarchical hierarchical parameter fusion and model compression upload are the key ways to solve the limitation of computing and communication.

3.4. Endogenous intelligence and closed-loop network autonomy

The core feature of the 6 G AI native is the implementation of the 'endogenous' structure. By

introducing the autonomous intelligent surface (AI Plane) into the protocol stack, it realizes the management, service output and knowledge sharing of AI modeling in the entire network, and provides general AI functions on demand for the physical layer, control surface and application layer, breaking through the fragmentation of a single AI module. With the support of this framework, through the analysis of the upper service intention by artificial intelligence, it is decomposed into configuration strategies across the core network, transmission network and access network, so as to realize the closed-loop operation of ' intention input-intelligent implementation-effect feedback-automatic optimization ', and provide support for the self-recovery of the whole link of the core network and the automatic repair of the fault. At the same time, the network digital twin technology is used to establish a virtual network image with high fidelity, which provides a training sandbox and a strategy verification platform for the artificial intelligence model. The algorithm iteration and risk test are carried out in the virtual environment to reduce the trial and error cost of the actual network.

4. Barriers to the evolution of AI-enabled 6G networks

4.1. Toward AI-native semantic communications

Using big data model to perform semantic compression and differential coding of text and images, and achieving cross-device semantic interaction through multi-agent collaboration, is an important development direction of the sixth generation of AI native technology. At present, semantic communication for practical applications still faces the following three problems : First, the semantic understanding specifications between different artificial intelligence models are inconsistent, and there is a lack of consistency in cross-device semantic interaction. Second, there is a lack of a unified semantic transfer evaluation mechanism, and the traditional error rate index cannot measure the authenticity of semantics. Third, on the terminal side, due to the huge model, resulting in a large amount of hardware resource consumption.

4.2. Adaptation and standardization challenges

The architecture and interface parameters of the artificial intelligence model independently developed by enterprises are inconsistent, which makes it difficult to realize the interconnection of equipment between different enterprises. AI native architecture and traditional hierarchical architecture are essentially different in design logic, and the compatibility cost of the old and new architecture is very high. At present, there is no unified evaluation standard for 6G-AI, and there is no clear quantitative evaluation standard in many dimensions such as accuracy, delay, energy consumption and security, which greatly limits the development of its industrialization. At present, the industry generally believes that the establishment of a hierarchical standard system first unifies the external interfaces of AI components, then adopts a dual-track conversion method in which new and old protocols coexist, and establishes a dual-index evaluation system at the comparison level and semantic level to perform standardized iterative upgrades in a progressive manner.

4.3. The dual constraints of trustworthy security and environmental sustainability

The deep implantation of artificial intelligence in 6 G networks poses new challenges for its security and sustainable development. In terms of security, artificial intelligence has certain vulnerabilities in channel estimation, network scheduling, etc., such as adversarial attacks and data poisoning, which will lead to a sharp increase in error rates and unbalanced resource allocation. In the fields of urban agglomeration control and industrial control, the interpretation of artificial intelligence black box decision-making is not enough to meet the needs of operation and monitoring. In distributed federated learning, due to the lack of recognition and certification of data sources and model copyrights, there are compliance risks of intellectual property and data. It is necessary to establish a trusted system of the whole chain by combining adversarial training, interpretable AI (XAI), blockchain traceability and other technologies. In the aspect of green and low-carbon, the learning and reasoning of artificial intelligence model need to consume a lot of energy. It is necessary to use neural network structure search technology and lightweight design to construct green AI, and use AI technology to intelligently close the base station and jointly optimize the energy spectrum efficiency, so as to achieve a virtuous cycle of ' saving energy for AI and reducing consumption with AI ', and provide support for the sustainable development of 6 G network.

5. Conclusion

In summary, this paper takes the communication protocol layering as the core analysis framework, and systematically explores the application logic of artificial intelligence in 6 G physical layer and network scheduling layer through multi-mode comparison and landing pain point analysis. Different deep learning models have different adaptability in the physical layer scenario. Limited by physical rules and compatibility, it is difficult to achieve large-scale commercial applications in a short time. In terms of network scheduling, reinforcement learning and federated learning can effectively improve the resource allocation efficiency of 6 G heterogeneous systems, but they are still limited by computational overhead and communication overhead. In the long run, the native reconstruction of semantic communication, the unification of cross-vendor standards, the construction of trusted security system, and the integration of green and low-carbon are the core challenges faced by the industrialization of 6G-AI. In the subsequent integration and development of 6 G and artificial intelligence, it is necessary to improve the semantic communication index and AI interface specification, gradually realize the transition of AI from external function to 6 G network native, and promote the large-scale commercial landing of 6 G space-ground integration.

References

- [1] J. Sun, W. Sheng, J. Qu, K. Yan, and B. Zhou, "Research and analysis of signal transmission mechanisms for 6G UAV communication networks," *Radio Communications Technology*, vol. 51, no. 1, pp. 86–95, 2025 (in Chinese).
- [2] M. Xu, "Standardization of satellite-based mobile communication networks for 5G-Advanced and 6G," *Mobile Communications*, vol. 48, no. 9, pp. 31–39, 2024 (in Chinese).
- [3] H. Tong, *Key Technologies for Efficient Semantic-Based Wireless Communications*. Beijing, China: Beijing University of Posts and Telecommunications, 2025, dissertation (in Chinese).