Asia Pacific Academy of Science Pte. Ltd.

Computer and Telecommunication Engineering 2025, 3(1), 3170.
https://doi.org/10.54517/cte3170

Review

A survey on the applications of machine learning, deep learning, and reinforcement learning in wireless communications

Huu Q. Tran[1], Viet-Thanh Pham[1], Sy Ngo[2,*]

[1] Faculty of Electronics Technology (FET), Industrial University of Ho Chi Minh City (IUH), Ho Chi Minh City 70000, Vietnam
[2] Institute of Engineering and Technology, Thu Dau Mot University (TDM), Thu Dau Mot City 75000, Vietnam
*** Corresponding author:** Sy Ngo, syn@tdmu.edu.vn

CITATION

Tran HQ, Pham VT, Ngo S. A survey on the applications of machine learning, deep learning, and reinforcement learning in wireless communications. Computer and Telecommunication Engineering. 2025; 3(1): 3170. https://doi.org/10.54517/cte3170

ARTICLE INFO

Received: 18 December 2024
Accepted: 26 February 2025
Available online: 20 March 2025

Abstract: This survey explores the integration of machine learning (ML), deep learning (DL), and reinforcement learning (RL) within wireless communications. It reviews various methods, algorithms, and applications while addressing the challenges and future research directions in this field. The paper highlights the necessity of intelligent techniques to enhance the performance and management of wireless networks, driven by the increasing complexity and demand for higher efficiency. Key areas of focus include network optimization, resource management, security, signal recognition, channel coding, traffic prediction, access control, and energy optimization. The survey also discusses emerging techniques such as federated learning, transfer learning, and multi-agent reinforcement learning, emphasizing their potential to revolutionize wireless communication systems.

Keywords: DL; edge intelligence; FL; IoT; MARL; ML; RL

1. Introduction

Wireless communications have become a cornerstone of modern society, supporting an ever-expanding range of applications, from mobile communications and autonomous systems to the Internet of Things (IoT) [1], as illustrated in **Figure 1**. The journey of wireless communication began in the late 19th century with the theoretical prediction of electromagnetic waves by James Clerk Maxwell and their experimental validation by Heinrich Hertz [2]. The first practical wireless communication system was developed by Guglielmo Marconi, who successfully transmitted Morse code signals over long distances [2]. This laid the foundation for subsequent advancements, including the development of radio, television, and mobile communications. The evolution of wireless technologies has been marked by significant milestones, such as the introduction of the first-generation (1G) mobile networks in the 1980s, which used analog signals, followed by the digital revolution with 2G, 3G, and 4G networks [3]. Each generation brought improvements in data rates, capacity, and reliability, culminating in the current deployment of 5G networks, which offer unprecedented speeds and low latency [3]. However, these advancements have also led to a significant surge in data traffic and the widespread adoption of connected devices [4]. Despite these advancements, traditional methods of network management and optimization are proving inadequate for the needs of contemporary wireless networks [5]. Conventional approaches often struggle with issues such as limited bandwidth, interference, and the increasing complexity of managing diverse and dynamic network environments [5,6]. These challenges necessitate the adoption of intelligent methods for optimization, resource allocation, and system adaptability [6].

The rapid evolution of technologies like 5G and the anticipated advent of 6G networks have driven unprecedented demands for higher performance, greater scalability, and enhanced reliability in wireless systems. These demands, coupled with increasing complexity, have pushed traditional approaches to their limits, necessitating the adoption of intelligent methods for optimization, resource allocation, and system adaptability [7]. Artificial intelligence (AI) techniques, particularly machine learning (ML), deep learning (DL), and reinforcement learning (RL), have emerged as transformative solutions in this context. ML enables systems to analyze and learn from vast amounts of data, DL excels at uncovering complex patterns, and RL facilitates decision-making in dynamic environments. Together, these approaches empower wireless communication networks to achieve superior performance across a variety of tasks, including channel estimation, interference management, power allocation, and mobility prediction. This paper provides a comprehensive survey of the applications of ML, DL, and RL in wireless communications, detailing their underlying methodologies and showcasing how they address critical challenges in the field. Key applications include optimizing network performance, enabling proactive fault detection, adaptive beamforming, and intelligent spectrum management. Beyond these, AI-driven techniques are central to advancing emerging paradigms such as intelligent edge computing, autonomous networks, and proactive resource orchestration. Additionally, this survey highlights the transformative potential of these methods in shaping future wireless systems, focusing on their ability to support dynamic, scalable, and robust networks. It identifies gaps in current research, such as the need for energy-efficient algorithms, real-time adaptability, and integration with novel architectures like reconfigurable intelligent surfaces (RIS). Future directions are discussed, emphasizing the importance of interdisciplinary approaches and innovative AI models tailored for next-generation wireless systems [8–12].

By synthesizing the state-of-the-art advancements and mapping future opportunities, this paper seeks to inspire further exploration and innovation in applying AI-driven solutions to wireless communications, ultimately paving the way for smarter and more resilient networks.

Figure 1. Wireless communications as an integral part of modern society connecting.

The swift advancement of wireless technologies has resulted in a significant surge in data traffic and the widespread adoption of connected devices [13,14]. Consequently, conventional methods of network management and optimization are proving inadequate for the needs of contemporary wireless networks [15,16]. Intelligent techniques, including ML, DL, and RL, present promising solutions by facilitating adaptive, data-driven strategies for network management [17,18]. These methods can process large volumes of data, detect patterns, and make real-time decisions to improve network performance and efficiency [19,20]. Machine learning includes a wide range of algorithms and models that can be utilized in various facets of wireless communications, such as network optimization, resource management, security, and anomaly detection [21–26]. Deep learning, a branch of ML, uses multi-layered neural networks to capture complex data patterns, making it especially effective for tasks like signal recognition, channel coding, and traffic prediction [27–29]. Conversely, reinforcement learning is centered on training agents to make decisions through trial and error, making it highly appropriate for dynamic and unpredictable wireless environments [30–35]. Beyond the core techniques, emerging methods such as federated learning and transfer learning are becoming increasingly important in wireless communications. Federated learning supports decentralized model training, maintaining data privacy by keeping data on individual devices [36]. Transfer learning, on the other hand, facilitates knowledge transfer across similar environments, thereby reducing the data requirements for new deployments [36]. Multi-agent reinforcement learning (MARL) expands RL capabilities by involving multiple agents that either collaborate or compete within a wireless environment, enabling advanced applications like network slicing in 5G [37]. This survey aims to provide a comprehensive overview of these intelligent techniques, their applications in wireless communications, and the challenges and future research directions in this rapidly evolving field (see **Figure 2**). By examining the potential of ML, DL, and RL, we aim to highlight the transformative impact these technologies can have on the design and operation of next-generation wireless networks. A comparison of various AI technologies in wireless communication is presented in **Table 1**.

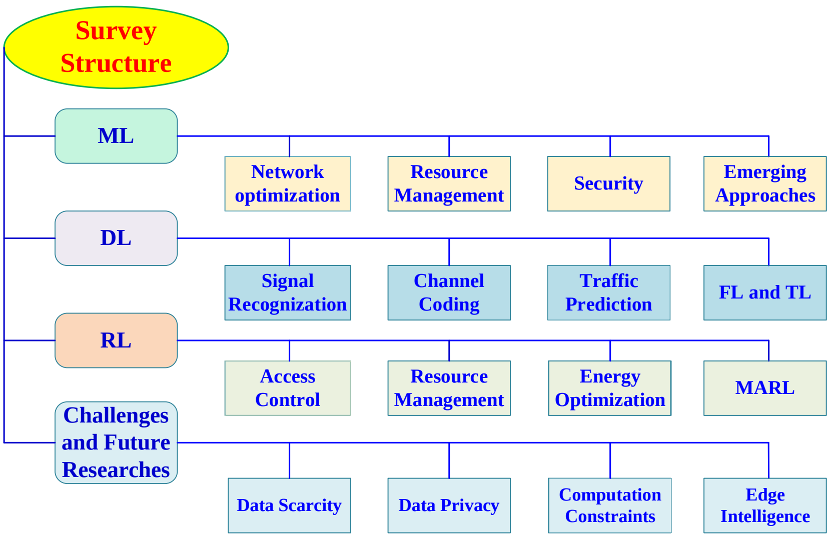

Figure 2. The structure of the survey shows machine learning and its subcategories, in which various algorithms and models can be applied to different aspects of wireless communications.

Table 1. A comparison of different AI technologies in wireless communication.

Technology	Description	Applications	Challenges	References
ML	ML algorithms, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Random Forests, are employed for various tasks in wireless communications. These tasks encompass network optimization, resource management, and security, leveraging the strengths of each algorithm to enhance the performance and reliability of wireless networks.	Network optimization, resource management, security.	Necessitates extensive datasets and significant computational power.	[38–40]
DL	DL models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Generative Adversarial Networks (GANs) are utilized for tasks like signal recognition, channel coding, and traffic prediction.	Signal recognition, channel coding, traffic prediction.	Significant computational demands and the requirement for extensive datasets.	[41–43]
RL	RL focuses on training agents to make decisions by providing rewards for desired actions. Prominent algorithms in this domain include Q-learning, Deep Q-Networks (DQN), and Asynchronous Advantage Actor-Critic (A3C).	Access control, resource management, energy optimization.	The ever-changing nature of wireless environments and the high computational demands.	[44–46]
FL	FL facilitates decentralized model training, ensuring data privacy by retaining data on individual devices.	Determining user location in mobile edge computing.	Ensuring the security of data transmission and the efficiency of model updates.	[47]
TL	TL facilitates the transfer of knowledge across similar environments, thereby minimizing the data needed for new deployments.	Adjusting pre-trained models for new environments using minimal data.	Scarcity of data in new environments.	[47]
MARL	Multi-Agent Reinforcement Learning (MARL) entails training several agents that either collaborate or compete within a wireless environment to handle tasks such as spectrum allocation and network load distribution.	Spectrum allocation, network load distribution, security.	Managing the coordination of multiple agents and addressing computational demands.	[48]
Edge Intelligence	Edge intelligence shifts computation to the network's edge, allowing for real-time processing and minimizing latency and bandwidth requirements.	Real-time video processing, augmented reality (AR), autonomous driving.	Limitations in computational power on edge devices.	[49]

Table 2. A comparison between our survey and other similar works.

Survey	Focus	Comparison with Our Survey
Graph Neural Networks for Routing Optimization: Challenges and Opportunities [50]	Application of GNNs for routing optimization in communication networks, addressing scalability, real-world deployment, explainability, and security challenges.	Our survey covers ML, DL, and RL in wireless communications, including but not limited to routing optimization. We acknowledge GNNs as an emerging technique but extend our discussion to various applications such as resource management, security, and signal recognition.
Cellular Traffic Prediction with Machine Learning: A Survey [51]	Comprehensive analysis of ML models for cellular traffic prediction, particularly in 5G networks.	Our survey considers traffic prediction as one of the key applications of ML/DL while also covering additional areas such as channel coding, access control, and energy optimization. We also discuss RL, federated learning, and transfer learning, which are not the primary focus of this survey.
Graph-based Deep Learning for Communication Networks: A Survey [52]	Application of graph-based deep learning models (e.g., GNNs, GATs) to various communication network problems, including both wired and wireless scenarios.	While this survey focuses on graph-based models, our survey provides a broader perspective on ML, DL, and RL techniques in wireless communications. We include graph-based models but aim to offer a more comprehensive view of intelligent techniques and their applications.

Table 1 presents a comparison of different AI technologies in wireless communication, encompassing Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), Federated Learning (FL), Transfer Learning (TL),

Multi-Agent Reinforcement Learning (MARL), and Edge Intelligence. This comparison highlights the unique features, applications, and advantages of each technology, providing a comprehensive understanding of their roles in enhancing wireless communication systems. **Table 2** shows a comparison between our survey and other similar works mentioned in the surveys.

The primary contributions of this paper are as follows:

1) This survey paper examines the integration of machine learning (ML), deep learning (DL), and reinforcement learning (RL) into wireless communications to tackle the growing complexity and efficiency demands of modern networks. The authors review essential algorithms and applications, emphasizing network optimization, resource management, security, signal recognition, channel coding, traffic prediction, access control, and energy efficiency. They also highlight emerging techniques such as federated learning (FL), transfer learning (TL), and multi-agent reinforcement learning (MARL) for their potential to enhance wireless communication systems.
2) ML significantly contributes to network optimization and dynamic resource allocation. DL is utilized for intricate tasks like signal recognition and traffic prediction. RL, ideal for adaptive environments, is employed to enhance access control and resource management. Emerging methods such as FL enable decentralized model training while preserving privacy, and MARL supports advanced applications like spectrum allocation and network load distribution.
3) The paper addresses the challenges of deploying intelligent methods, such as data scarcity, computational complexity, and privacy concerns. Proposed solutions include synthetic data generation, lightweight neural networks, and edge intelligence to facilitate efficient ML model deployment in wireless systems. The survey concludes by highlighting the need for further research to develop efficient algorithms, tackle privacy issues, and enhance real-time adaptation, paving the way for the next generation of wireless communication applications.

The structure of this paper is as follows: Section 2 discusses machine learning in wireless communications. Next, Section 3 provides an overview of deep learning in wireless communications. In Section 4, we explore reinforcement learning in wireless communications. Section 5 outlines challenges and future research directions. Finally, Section 6 concludes the paper.

2. Machine learning in wireless communications

Machine learning techniques are extensively utilized in wireless communications to improve network performance and efficiency. Algorithms like SVM, KNN, Decision Trees, and Random Forests are commonly employed for tasks such as network optimization, resource management, and security.

2.1. Network optimization

ML algorithms can optimize network parameters to enhance throughput and minimize latency. For example, SVMs have been applied to optimize handover decisions in cellular networks [21].

2.2. Resource management

ML techniques assist in dynamic resource allocation, ensuring efficient use of spectrum and power. Random Forests, for instance, have been used to predict traffic patterns and allocate resources accordingly [22].

2.3. Security

Machine learning algorithms improve security by detecting anomalies and potential threats. Decision Trees, for instance, have been used to identify and mitigate security breaches in wireless networks [23]. Physical layer security (PLS) differs from traditional cryptographic methods that rely on encryption algorithms at higher layers [24]. The physical characteristics of wireless channels, such as high-frequency millimeter-wave signals, are well-suited for PLS [25]. Machine learning can enhance PLS by enabling lightweight and keyless security approaches [26].

2.4. Emerging techniques and hybrid approaches in ML for wireless communications

Recently, hybrid techniques that combine traditional ML algorithms with advanced optimization methods, such as genetic algorithms and particle swarm optimization, have been developed to enhance performance in complex wireless systems. For example, hybrid models that integrate SVM with genetic algorithms show promise in optimizing parameters for interference management in heterogeneous networks. Additionally, combining KNN with deep learning models enables rapid and accurate localization in dense environments, addressing challenges like multipath fading and interference. These hybrid approaches provide a means to tackle the dynamic nature of wireless channels by allowing adaptive and flexible model updates in real-time [35].

3. Deep learning in wireless communications

Deep learning, a subset of machine learning, utilizes neural networks with multiple layers to model complex data patterns. Prominent models like CNNs, RNNs, LSTM networks, and GANs have demonstrated significant potential in wireless communications.

3.1. Signal recognition

CNNs have been employed for automatic modulation classification, enhancing the accuracy of signal recognition in noisy environments [27].

3.2. Channel coding

DL models such as RNNs and LSTM networks have been utilized to design and decode error-correcting codes, thereby improving the reliability of data transmission [28].

3.3. Traffic prediction

GANs have been employed to predict network traffic, facilitating proactive resource management and alleviating congestion [29].

3.4. Federated learning and transfer learning in wireless communications

FL and TL have recently gained popularity in wireless communication applications due to their advantages in privacy preservation and computational efficiency. FL, which supports decentralized model training, is ideal for scenarios where data privacy is critical, such as user localization in mobile edge computing. FL enables devices to collaboratively train a shared model while keeping data locally, thus preserving user privacy and minimizing the risk of data breaches [50]. Conversely, TL facilitates knowledge transfer across similar environments, allowing models trained on one network to be applied to other regions with minimal adjustments. This significantly reduces data requirements for new deployments, making it particularly beneficial in IoT scenarios where devices are resource-constrained and frequently move across networks. TL helps adapt pre-trained models to new environments with limited data, thereby enhancing the efficiency and effectiveness of wireless communication systems [50].

4. Reinforcement learning in wireless communications

RL trains agents to make decisions by incentivizing preferred actions. Prominent algorithms like Q-learning, Deep Q-Networks (DQN), and Asynchronous Advantage Actor-Critic (A3C) have been utilized in different areas of wireless communications.

4.1. Access control

RL algorithms enhance access control mechanisms, promoting fair and efficient utilization of the wireless medium. Q-learning, in particular, has been applied to regulate access in cognitive radio networks [30].

4.2. Resource management

RL techniques allocate resources dynamically according to real-time network conditions, thereby enhancing overall network performance. DQN has been utilized to optimize power allocation in wireless networks [31].

4.3. Energy optimization

RL methods reduce energy consumption in wireless sensor networks, thereby extending the lifespan of battery-powered devices. The A3C algorithm has been employed to create energy-efficient routing protocols [32].

4.4. Multi-agent reinforcement learning (MARL) in cooperative and competitive settings

MARL involves training multiple agents that either collaborate or compete within a wireless environment, enabling advanced applications such as network slicing in 5G. For instance, MARL can handle spectrum allocation by balancing the competing demands of various users and devices. In cooperative scenarios, MARL can optimize network load distribution, enhancing quality of service (QoS) and reducing latency, which is particularly advantageous for low-latency applications like autonomous driving and remote surgery [51]. Furthermore, adversarial MARL scenarios tackle security issues, where agents learn to detect and counteract malicious attempts to disrupt network communications [51].

5. Challenges and future research directions

By mid-2024, practical applications of ML, DL, and RL have been implemented across various fields. Ericsson introduced Radio Access Network (RAN) Intelligence [49], while DL algorithms have been used to dynamically manage network resources, thereby improving QoS based on real-time demand patterns. Nokia developed the Nokia Cognitive Analytics solution to enhance customer satisfaction, applying ML to 300 dimensions, including customer satisfaction and subscriber experience, to improve prediction accuracy and real-time decision-making [53]. Vodafone utilized ML to reduce energy consumption through sleep mode management based on user traffic data [54]. Palo Alto Networks proposed specific DL security solutions to detect and respond to real-time emerging threats within wireless networks [55]. ZTE's prominent product, its 5G base station, combines DL for adaptive modulation and channel estimation, providing widespread 5G coverage for urban environments [56]. Huawei's iMaster NCE uses advanced DL technology to optimize wireless network resources and automatically balance traffic loads based on user demand [57]. Qualcomm, a leader in wireless communications, has focused on ML-enabled processors, RF sensing, and MIMO-GAN solutions, with notable products including the neural-augmented Kalman filter [58,59] and neural RF SLAM [60]. Despite these advancements, applying ML, DL, and RL in wireless communications faces challenges such as the need for large datasets, computational complexity, and the highly dynamic nature of wireless environments [61–63]. The ever-changing and unpredictable characteristics of wireless channels present significant obstacles to real-time learning and adaptation [33]. Additionally, the computational demands of deep learning models pose barriers to deployment in resource-constrained environments like mobile edge computing [34]. Future research should focus on developing more efficient algorithms, leveraging transfer learning, and exploring federated learning to address privacy concerns. Transfer learning can reduce the need for large datasets by transferring knowledge across domains, while federated learning enhances privacy by training models locally on devices without sharing raw data [33].

5.1. Addressing data scarcity and privacy in ML for wireless networks

Data scarcity poses a significant challenge in training ML models for wireless communications, especially when labeled datasets are limited or expensive to acquire. Techniques like data augmentation and GANs have effectively diversified datasets without sacrificing performance [49]. Privacy concerns, another critical issue, can be mitigated through FL, which reduces the need for centralized data storage and minimizes the risk of data breaches by keeping data on individual devices.

Additionally, implementing robust encryption protocols during model transmission and updates in federated systems further protects sensitive information [49].

5.2. Computational constraints and edge intelligence

Deploying ML, DL, and RL models in wireless communications often demands significant computational resources, challenging their feasibility in edge environments. Edge intelligence, which involves offloading computation to the network's edge (e.g., mobile edge computing), offers a promising solution. This approach enables real-time processing by reducing latency and bandwidth requirements, crucial for applications like real-time video processing and augmented reality (AR). Research into lightweight neural network models, such as TinyML, aims to address these computational constraints while maintaining high accuracy [54]. Edge intelligence integrates sensing, communication, and computation at the network's edge, allowing for efficient data processing closer to the source. This not only reduces the load on central servers but also enhances the responsiveness of low-latency applications. For instance, in 6G networks, edge intelligence is expected to support advanced applications such as autonomous driving and smart cities by providing real-time data processing and decision-making capabilities [53].

5.3. Dynamic and unpredictable wireless environments

The ever-changing and unpredictable characteristics of wireless channels present significant obstacles to real-time learning and adaptation [53]. Traditional ML models often struggle to cope with the dynamic nature of wireless environments, leading to suboptimal performance. Future research should focus on developing more robust and adaptive algorithms that can handle the variability and uncertainty inherent in wireless communications. Techniques such as transfer learning can reduce the need for large datasets by transferring knowledge across domains, while federated learning enhances privacy by training models locally on devices without sharing raw data [55].

5.4. Energy efficiency

The computational demands of deep learning models pose barriers to deployment in resource-constrained environments like mobile edge computing [53]. Future research should explore energy-efficient algorithms and hardware accelerators to reduce the power consumption of ML models. This is particularly important for battery-powered devices and IoT applications, where energy efficiency is a critical concern. Techniques such as model compression, quantization, and pruning can help reduce the computational complexity and energy consumption of deep learning models [55].

5.5. Integration with emerging technologies

Integrating ML, DL, and RL with emerging technologies such as reconfigurable intelligent surfaces (RIS), unmanned aerial vehicles (UAVs), and non-orthogonal multiple access (NOMA) presents new opportunities and challenges [55]. These technologies can enhance the performance and scalability of wireless networks, but they also introduce additional complexity. Future research should focus on developing

ML algorithms that can effectively leverage these emerging technologies to optimize network performance and resource allocation [57].

By addressing these challenges and exploring future research directions, the potential of ML, DL, and RL in wireless communications can be fully realized, paving the way for smarter and more resilient networks.

6. Conclusion

This paper has comprehensively examined the applications of ML, DL, and RL in wireless communications, underscoring their transformative impact. Our analysis reveals that these AI-driven techniques significantly enhance network optimization, resource management, security, and signal processing. Specifically, ML-based dynamic resource allocation and spectrum management improve network efficiency, while DL models excel in signal recognition, channel coding, and traffic prediction. RL, particularly MARL, proves instrumental in optimizing spectrum allocation and network load distribution, enabling critical applications such as 5G network slicing, autonomous driving, and remote surgery. Moreover, emerging approaches like federated learning and transfer learning mitigate data privacy and scarcity challenges, while edge intelligence enhances computational efficiency and real-time processing. These advancements collectively pave the way for more adaptive, intelligent, and resilient wireless communication networks. The broader implications of these technologies extend beyond conventional wireless systems, influencing next-generation applications such as smart cities, IoT, and autonomous networks. However, challenges remain, including the need for large datasets, computational complexity, and the dynamic nature of wireless environments. Future research should prioritize developing more efficient AI models, leveraging transfer learning to minimize data requirements, and adopting federated learning to enhance privacy. Additionally, synthetic data generation and edge intelligence will be pivotal in overcoming data scarcity and computational limitations. By addressing these challenges, AI-driven techniques will continue to shape the evolution of wireless networks, ensuring enhanced efficiency, security, and reliability. The integration of ML, DL, and RL will not only revolutionize wireless communications but also drive innovation in broader technological ecosystems, making intelligent and adaptive networks a cornerstone of future digital infrastructure.

This paper has thoroughly surveyed the applications of ML, DL, and RL in wireless communications, highlighting their transformative potential. Key findings include significant enhancements in network optimization, resource management, security, and signal processing through dynamic resource allocation, efficient spectrum management, and proactive fault detection. Advanced ML algorithms improve security by detecting anomalies and mitigating threats, while DL models excel in signal recognition, channel coding, and traffic prediction. RL, particularly MARL, shows promise in managing spectrum allocation and optimizing network load distribution, crucial for applications like 5G network slicing, autonomous driving, and remote surgery. Emerging techniques such as federated learning and transfer learning address data privacy and scarcity issues, while edge intelligence enhances computational efficiency and real-time processing capabilities. These findings underscore the critical role of AI-driven techniques in addressing the growing complexity and performance demands of modern wireless networks. The broader implications for the future of wireless communications include enhanced network efficiency, increased security and reliability, and support for emerging applications such as autonomous systems, IoT, and smart cities. Despite these advancements, challenges remain, including the need for large datasets, computational complexity, and the dynamic nature of wireless environments. Future research should focus on developing more efficient algorithms, leveraging transfer learning to reduce data requirements, and exploring federated learning to address privacy concerns. Addressing data scarcity through synthetic data generation and enhancing computational efficiency through edge intelligence are also critical areas for future exploration. By overcoming these challenges, we can pave the way for more intelligent and adaptive wireless communication systems that support the next generation of applications and services. The continued integration of ML, DL, and RL will be pivotal in shaping the future of wireless communications, driving innovation, and ensuring the efficient, secure, and reliable operation of networks.

Conflict of interest: The authors declare no conflict of interest.

References

1. Bahalul Haque AKM, Zihad OM, Hasan R. 5G and Internet of Things—Integration Trends, Opportunities, and Future Research Avenues. In: 5G and Beyond. Springer; 2023.
2. Rajiv. History of Wireless communication—Morse Code to 5G Technology. Available online: https://www.rfpage.com/history-of-wireless-communication-morse-code-to-5g-technology/ (accessed on 3 December 2024).
3. Rajiv. Evolution of wireless technologies 1G to 5G in mobile communication. Available online: https://www.rfpage.com/evolution-of-wireless-technologies-1g-to-5g-in-mobile-communication/ (accessed on 3 December 2024).
4. Ahmed Solyman AA, Yahya K. Evolution of wireless communication networks: From 1G to 6G and future perspective. International Journal of Electrical and Computer Engineering (IJECE). 2022; 12(4): 3943–3950. doi: 10.11591/ijece.v12i4.pp3943-3950
5. Exploring the Challenges and Limitations of Wireless Communication. Available online: https://www.aal-persona.org/exploring-the-challenges-and-limitations-of-wireless-communication/ (accessed on 3 December 2024).
6. RF Wireless World. Available online: https://www.rfwireless-world.com/Terminology/Advantages-and-Disadvantages-of-wireless-communication.html (accessed on 3 December 2024).
7. Akbar MS, Hussain Z, Ikram M, et al. On Challenges of Sixth Generation (6G) Wireless Networks: A Comprehensive Survey of Requirements, Applications, and Security Issues. Journal of Network and Computer Applications. 2025; 233.
8. Hu S, Chen X, Ni W, et al. Distributed Machine Learning for Wireless Communication Networks: Techniques, Architectures, and Applications. arXiv. 2020.
9. Zhao L, Li S, Tan Z, et al. A Multi-UAV Cooperative Task Scheduling in Dynamic Environments: Throughput Maximization. IEEE Transactions on Computers. 2025; 74(2): 442–454. doi: 10.1109/tc.2024.3483636
10. Zhao L, Li S, Guan Y, et al. Adaptive Multi-UAV Trajectory Planning Leveraging Digital Twin Technology for Urban IIoT Applications. IEEE Transactions on Network Science and Engineering. 2024; 11(6): 5349–5363. doi: 10.1109/tnse.2023.3344428
11. Zhao L, Mao C, Wan S, et al. CAST: Efficient Traffic Scenario Inpainting in Cellular Vehicle-to-Everything Systems. IEEE Transactions on Mobile Computing. 2025; 24(3): 2331–2345. doi: 10.1109/tmc.2024.3492148
12. Mao C, Zhao L, Liu Z, et al. Empowering C-V2X Through Advanced Joint Traffic Prediction in Urban Networks. IEEE Internet of Things Journal. 2024; 11(24): 39780–39793. doi: 10.1109/jiot.2024.3447046
13. Ericsson Mobility Report. Mobile data traffic forecast. Ericsson. 2023.

14. Cisco Annual Internet Report (2018–2023). White Paper. Cisco. 2020.
15. Liu F, Kibalya G, Kumar SVNS, Zhang P. Challenges of Traditional Networks and Development of Programmable Networks. In: Software Defined Internet of Everything. Springer; 2022.
16. Gupta A. Network Management: Current Trends and Future Perspectives. Journal of Network and Systems Management. 2006; 14(4): 483–491. doi: 10.1007/s10922-006-9044-7
17. Li Y. Deep Reinforcement Learning: Opportunities and Challenges. arXiv. 2022.
18. Wong A, Bäck T, Kononova AV, Plaat A. Deep multiagent reinforcement learning: Challenges and directions. Artificial Intelligence Review. 2022; 56(6): 5023–5056. doi: 10.1007/s10462-022-10299-x
19. Umoga UJ, Sodiya EO, Ugwuanyi ED, et al. Exploring the potential of AI-driven optimization in enhancing network performance and efficiency. Magna Scientia Advanced Research and Reviews 2024; 10(1): 368–378.
20. Khoramnejad F, Hossain E. Generative AI for the Optimization of Next-Generation Wireless Networks: Basics, State-of-the Art, and Open Challenges. arXiv. 2024.
21. Piccialli V, Sciandrone M. Nonlinear optimization and support vector machines. Annals of Operations Research. 2022; 314(1): 15–47. doi: 10.1007/s10479-022-04655-x
22. Yang X, Hua Z, Li L, et al. Multi-source information fusion-driven corn yield prediction using the Random Forest from the perspective of Agricultural and Forestry Economic Management. Scientific Reports. 2024; 14(1). doi: 10.1038/s41598-024-54354-9
23. Al-Omari M, Rawashdeh M, Qutaishat F, et al. An Intelligent Tree-Based Intrusion Detection Model for Cyber Security. Journal of Network and Systems Management. 2021; 29(2). doi: 10.1007/s10922-021-09591-y
24. Wang N, Wang P, Alipour-Fanid A, et al. Physical-Layer Security of 5G Wireless Networks for IoT: Challenges and Opportunities. IEEE Internet of Things Journal. 2019; 6(5): 8169–8181. doi: 10.1109/jiot.2019.2927379
25. Wu Y, Khisti A, Xiao C, et al. A Survey of Physical Layer Security Techniques for 5G Wireless Networks and Challenges Ahead. IEEE Journal on Selected Areas in Communications. 2018; 36(4): 679–695. doi: 10.1109/jsac.2018.2825560
26. Melki R, Noura HN, Chehab A, Couturier R. Machine Learning for Physical Layer Security: Limitations, Challenges and Recommendation. 2022 16th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS). 2022; 53–60. doi: 10.1109/sitis57111.2022.00017
27. Zhang H, Yu L, Chen Y, Wei Y. Fast Complex-Valued CNN for Radar Jamming Signal Recognition. Remote Sensing. 2021; 13(15): 2867. doi: 10.3390/rs13152867
28. Donges N, Urwin M. A Guide to Recurrent Neural Networks (RNNs). Built In. 2024.
29. Rossi L, Ajmar A, Paolanti M, Pierdicca R. Vehicle trajectory prediction and generation using LSTM models and GANs. PLOS ONE. 2021; 16(7): e0253868. doi: 10.1371/journal.pone.0253868
30. Seyde T, Werner P, Schwarting W, et al. Solving Continuous Control via Q-learning. arXiv. 2023.
31. Agarwal V, Sharma S. DQN Algorithm for network resource management in vehicular communication network. International Journal of Information Technology. 2023; 15(6): 3371–3379. doi: 10.1007/s41870-023-01399-0
32. Yang Y, Li H, Shen B, et al. Microgrid Energy Management Strategy Base on UCB-A3C Learning. Frontiers in Energy Research. 2022; 10. doi: 10.3389/fenrg.2022.858895
33. Razavi-Far R, Wang B, Taylor ME, Yang Q. In: Federated and Transfer Learning. Springer International Publishing; 2023.
34. Guo W, Zhuang F, Zhang X, Dong J. A comprehensive survey of federated transfer learning: Challenges, methods and applications. Frontiers of Computer Science. 2024; 18(6). doi: 10.1007/s11704-024-40065-x
35. Wei C, Wu G, Barth MJ, et al. KI-GAN: Knowledge-Informed Generative Adversarial Networks for Enhanced Multi-Vehicle Trajectory Forecasting at Signalized Intersections. 2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). 2024; 7115–7124. doi: 10.1109/cvprw63382.2024.00706
36. Pu T, Wang X, Cao Y, et al. Power flow adjustment for smart microgrid based on edge computing and multi-agent deep reinforcement learning. Journal of Cloud Computing. 2021; 10(1). doi: 10.1186/s13677-021-00259-1
37. Rostami SM, Samet S, Kobti Z. A Study of Blockchain-Based Federated Learning. In: Razavi-Far R, Wang B, Taylor ME, Yang Q (editors). Federated and Transfer Learning. Springer; 2023.
38. Luo FL. In: Machine Learning for Future Wireless Communications. Wiley-IEEE Press; 2019.
39. Sun Y, Peng M, Zhou Y, et al. Application of Machine Learning in Wireless Networks: Key Techniques and Open Issues. IEEE Communications Surveys & Tutorials. 2019; 21(4): 3072–3108. doi: 10.1109/comst.2019.2924243
40. Bishop CM. In: Pattern Recognition and Machine Learning. Springer; 2006.

41. Goodfellow I, Bengio Y, Courville A. Deep Learning. MIT Press; 2016.
42. Qin Z, Ye H, Li GY, et al. Deep Learning in Physical Layer Communications. IEEE Wireless Communications. 2019; 26(2): 93–99. doi: 10.1109/mwc.2019.1800601.
43. Ye H, Li GY, Juang BH. Power of Deep Learning for Channel Estimation and Signal Detection in OFDM Systems. IEEE Wireless Communications Letters. 2018; 7(1): 114–117. doi: 10.1109/lwc.2017.2757490.
44. Sutton RS, Barto AG. In: Reinforcement Learning: An Introduction. MIT Press; 2018.
45. Luong NC, Hoang DT, Gong S, et al. Applications of Deep Reinforcement Learning in Communications and Networking: A Survey. IEEE Communications Surveys & Tutorials. 2019; 21(4): 3133–3174. doi: 10.1109/comst.2019.2916583.
46. Di Felice M, Bedogni L, Bononi L. Reinforcement Learning-Based Spectrum Management for Cognitive Radio Networks: A Literature Review and Case Study. Handbook of Cognitive Radio. Springer, Singapore; 2018.
47. Qin Z, Li GY, Ye H. Federated Learning and Wireless Communications. IEEE Wireless Communications. 2021; 28(5): 134–140. doi: 10.1109/mwc.011.2000501
48. Oroojlooy A, Hajinezhad D. A review of cooperative multi-agent deep reinforcement learning. Appl Intell. 2023; 53: 13677–13722. doi: 10.1007/s10489-022-04105-y
49. ERICSSON. Ericsson Intelligent RAN Automation. Available online: https://www.ericsson.com/en/ran/intelligent-ran-automation (accessed on 5 October 2024).
50. Jiang W, Han H, Zhang Y, et al. Graph Neural Networks for Routing Optimization: Challenges and Opportunities. Sustainability. 2024; 16(21): 9239. doi: 10.3390/su16219239.
51. Jiang W. Cellular traffic prediction with machine learning: A survey. Expert Systems with Applications. 2022; 201: 117163. doi: 10.1016/j.eswa.2022.117163.
52. Jiang W. Graph-based Deep Learning for Communication Networks: A Survey. Computer Communications. 2022; 185: 40–54.
53. Available online: https://www.nokia.com/about-us/news/releases/2018/03/27/nokias-new-ai-powered-analytics-software-dramatically-improves customer-experience-and-satisfaction/ (accessed on 5 October 2024).
54. Available online: https://www.ericsson.com/en/cases/2019/augmenting-mimo-energy-management-with-machine-learning-and-ai (accessed on 5 October 2024).
55. Available online: https://www.paloaltonetworks.com/network-security/ngfw-vs-fortinet (accessed on 5 October 2024).
56. ZTE. Industrial 5G Cloud Based Station. Available onlilne: https://www.zte.com.cn/global/solutions_latest/5g-advanced/industrial_cloud_based_station.html (accessed 29 November 2024).
57. HUAWEI. Network Management, Control, and Analysis Software. Available onlilne: https://e.huawei.com/en/products/network-analysis (accessed 29 November 2024).
58. Qualcomm. Available onlilne: https://www.qualcomm.com/news/onq/2022/05/bringing-ai-research-to-wireless-communication-and sensing (accessed 29 November 2024).
59. Pratik K, Amjad RA, Behboodi A, et al. Neural Augmentation of Kalman Filter with Hypernetwork for Channel Tracking. 2021 IEEE Global Communications Conference (GLOBECOM). 2021; 1–6. doi: 10.1109/globecom46510.2021.9685798
60. Kadambi S, Behboodi A, Soriaga JB, et al. Neural RF SLAM for unsupervised positioning and mapping with channel state information. ICC 2022—IEEE International Conference on Communications. 2022; 3238–3244. doi: 10.1109/icc45855.2022.9838367
61. Chen M, Gunduz D, Huang K, et al. Distributed Learning in Wireless Networks: Recent Progress and Future Challenges. IEEE Journal on Selected Areas in Communications. 2021; 39(12): 3579–3605. doi: 10.1109/jsac.2021.3118346
62. Warden P, Situnayake D. TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers. O'Reilly Media; 2019.
63. Letaief KB, Shi Y, Lu J, Lu J. Edge Artificial Intelligence for 6G: Vision, Enabling Technologies, and Applications. IEEE Journal on Selected Areas in Communications. 2022; 40(1): 5–36. doi: 10.1109/jsac.2021.3126076.