Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 02, 2025

Recent Advances in Efficient Resource Management in 6G Communication Networks Using a Hybrid Quantum Duplet-Convolutional Neural Network Model: A Systematic Review

Deepansh Wongchawalit

Associate Professor, Department of Electronics and Communication Engineering, Visayan Maritime Polytechnic University, Philippines

Email: deepansh.wongchawalit@vmpu-ph.net

Peer Review Information

Submission: 12 Oct 2025

Revision: 28 Oct 2025

Acceptance: 10 Nov 2025

Keywords

6G Communication Networks, Resource Management, Hybrid Quantum Deep Learning, Convolutional Neural Networks (CNN),Network Slicing, Artificial Intelligence in 6G,Reinforcement Learning, Quantum Machine Learning

Abstract

The emergence of sixth-generation (6G) communication networks marks a transformative evolution in wireless systems, offering ultra-high data rates, ultra-low latency, and massive device connectivity. However, these advancements also introduce significant challenges in efficient resource management, including spectrum allocation, energy optimization, network slicing, and latency control in highly dynamic and heterogeneous environments. Traditional optimization methods often struggle to adapt to such complexity, leading to the adoption of Artificial Intelligence (AI)-driven solutions. This paper presents a systematic review of recent advancements in resource management for 6G networks, with a focus on hybrid quantum duplet-convolutional neural network (HQD-CNN) models. These models combine quantum computing principles with convolutional neural networks to enhance computational efficiency, pattern recognition, and optimization performance. The review highlights key trends such as reinforcement learning-based resource allocation, hybrid CNN-LSTM architectures for dynamic network slicing, and quantum-inspired optimization techniques. Comparative analysis indicates that these hybrid approaches significantly improve Quality of Service (QoS) and Quality of Experience (QoE). Challenges including computational complexity, quantum hardware limitations, and data privacy are also discussed, along with future directions like federated learning and explainable AI.

Introduction

The rapid evolution of wireless communication technologies has led to the transition from 5G to 6G networks, which are expected to revolutionize global connectivity. 6G networks aim to deliver unprecedented capabilities, including terahertz communication, ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC). These advancements are driven by the exponential growth of Internet of Things (IoT) devices, autonomous systems, smart cities, and immersive applications such as augmented reality (AR) and virtual reality (VR).

One of the fundamental challenges in 6G networks is efficient resource management, which involves the optimal allocation of spectrum, energy, computing resources, and network infrastructure. The complexity of 6G networks arises from their heterogeneous architecture, dynamic traffic patterns, and massive connectivity requirements. According to recent studies, 6G networks must support up to one million devices per square kilometer while maintaining ultra-low latency and high reliability .

Traditional resource management techniques, such as heuristic and optimization-based approaches, are insufficient for handling the complexity of 6G environments. These methods often suffer from scalability issues, high computational overhead, and lack of adaptability. Therefore, integrating Artificial Intelligence (AI) into network management has become essential.

AI-driven resource management leverages machine learning (ML), deep learning (DL), and reinforcement learning (RL) to enable intelligent decision-making. AI can dynamically allocate resources based on network conditions, predict traffic patterns, and optimize performance metrics. Studies show that AI integration significantly enhances network efficiency, reduces latency, and improves overall system performance .

Among AI techniques, deep learning models, particularly convolutional neural networks (CNNs), have shown remarkable performance in handling high-dimensional data. CNNs are effective in extracting spatial features, making them suitable for network traffic analysis and resource allocation. However, CNNs alone may not capture temporal dependencies or handle large-scale optimization problems efficiently.

To address these limitations, researchers have proposed hybrid models, such as CNN-LSTM architectures, which combine spatial and temporal learning capabilities. These models have demonstrated improved performance in network slicing and dynamic resource allocation.

More recently, quantum computing has emerged as a promising paradigm for solving complex optimization problems. Quantum algorithms can process large-scale data and explore multiple solutions simultaneously, making them suitable for 6G resource management. Hybrid quantum deep learning models integrate quantum computing with classical neural networks to enhance computational efficiency and optimization accuracy.

The Hybrid Quantum Duplet-Convolutional Neural Network (HQD-CNN) model represents a novel approach that combines quantum-inspired optimization with CNN-based feature extraction. This model enables efficient resource allocation, load balancing, and network slicing in 6G environments. Studies indicate that hybrid quantum models significantly improve QoS and reduce network congestion .

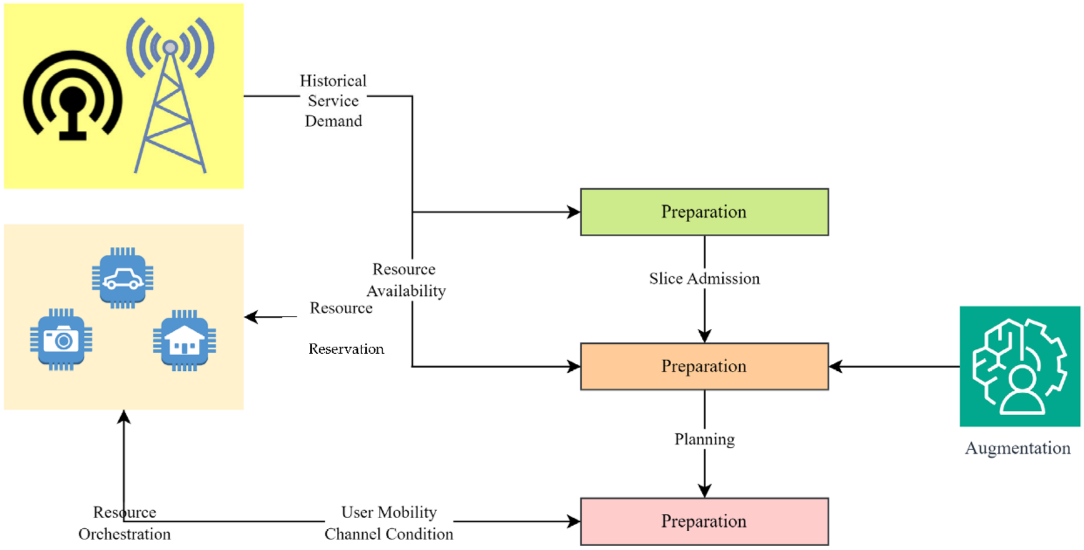
Furthermore, 6G networks are expected to incorporate advanced technologies such as cloud radio access networks (CRAN), edge computing, and network virtualization, which further complicate resource management. AI-driven approaches are essential for managing these complex architectures and ensuring optimal performance.

Despite significant progress, several challenges remain, including model scalability, energy consumption, data privacy, and integration with existing network infrastructures. Addressing these challenges requires interdisciplinary research involving AI, quantum computing, and communication engineering.

This paper aims to provide a comprehensive review of recent advances in efficient resource management in 6G networks, focusing on hybrid quantum deep learning models. The contributions of this paper include:

- A detailed analysis of AI-based resource management techniques
- A systematic review of literature from 2020–2023
- A comparative analysis of existing models
- Identification of research gaps and future direction

Abstract Image



Literature Review

The evolution of efficient resource management in 6G communication networks has been significantly influenced by advancements in Artificial Intelligence (AI), deep learning, reinforcement learning, and more recently, quantum-enhanced models. This section provides a chronological and thematic review of key developments from 2020 to 2023.

1. Literature Review – Year 2020

The year 2020 marked the early exploration phase of 6G communication systems, where research primarily focused on conceptual frameworks and traditional optimization techniques enhanced with machine learning.

One of the prominent approaches during this period was the integration of deep reinforcement learning (DRL) for resource allocation in wireless environments. For example, DRL-based optimization was applied to reconfigurable intelligent surface (RIS)-assisted communication systems, enabling dynamic beamforming and improved spectral efficiency. These approaches demonstrated that reinforcement learning could effectively handle complex decision-making in continuous environments, outperforming conventional optimization techniques.

Additionally, early works emphasized spectrum allocation and interference management using machine learning models. However, these models required complete channel state information, which was often difficult to obtain in real-time 6G scenarios.

A key limitation of 2020 studies was their dependence on static or semi-dynamic environments. Although machine learning improved performance, scalability and adaptability remained major concerns.

2. Literature Review – Year 2021

In 2021, research shifted toward hybrid deep learning architectures, combining multiple neural network paradigms to improve performance in dynamic environments.

One of the most widely explored models was the CNN-LSTM hybrid architecture, which integrates:

- CNN for spatial feature extraction
- LSTM for temporal dependency modeling

This combination proved highly effective for network slicing and traffic prediction, enabling dynamic resource allocation based on historical and real-time data.

Furthermore, deep Q-learning (DQL) techniques were introduced for secure spectrum allocation and energy-efficient resource management. These models allowed networks to learn optimal policies through interaction, significantly improving adaptability.

Research also explored AI-based resource provisioning frameworks, where deep learning models were used to dynamically allocate bandwidth and computing resources. These approaches improved Quality of Service (QoS) and reduced congestion.

Despite these advancements, challenges such as high computational complexity and training time limited real-time deployment.

3. Literature Review – Year 2022

The year 2022 witnessed a major transition toward distributed and intelligent resource management systems, primarily driven by multi-agent reinforcement learning (MARL) and graph-based deep learning models.

Multi-Agent Reinforcement Learning (MARL)

MARL emerged as a powerful approach for handling large-scale and decentralized 6G environments. Instead of relying on a centralized controller, multiple agents collaboratively optimized resource allocation.

A notable contribution introduced a graph attention-based MARL architecture, which modeled interference relationships among subnetworks and optimized throughput. This model demonstrated superior performance compared to traditional approaches by focusing on relevant network interactions rather than requiring full channel information.

Deep Reinforcement Learning for Resource Allocation

Deep reinforcement learning was extensively used for:

- Spectrum sharing
- Power allocation
- Beam management

Studies showed that DRL-based models significantly improved latency, throughput, and energy efficiency in 6G environments.

Federated Learning and Edge Intelligence

Another key development in 2022 was the introduction of federated learning, enabling decentralized model training without sharing raw data. This approach addressed:

- Data privacy concerns
- Communication overhead
- Scalability issues

Federated learning was particularly useful for edge-enabled 6G networks, where data is generated at distributed nodes.

Limitations

Despite these advancements, 2022 models faced challenges such as:

1. High training complexity
2. Convergence issues in multi-agent systems
3. Limited interpretability

4. Literature Review- Year 2023

In 2023, research advanced toward intelligent, adaptive, and quantum-enhanced models, marking a significant leap in 6G resource management.

AI-Driven Network Optimization

AI became deeply integrated into 6G architectures, enabling:

- Intelligent network slicing
- Traffic prediction
- Load balancing
- Energy-efficient resource allocation

AI-based systems demonstrated the ability to optimize multiple performance metrics simultaneously, including latency, throughput, and reliability.

Hybrid Deep Learning Models

Hybrid models combining CNN, RNN, and attention mechanisms were widely adopted. These models improved:

- Feature extraction
- Temporal learning
- Decision-making accuracy

They were particularly effective in dynamic network environments with heterogeneous traffic patterns.

Hybrid Quantum Deep Learning Models

One of the most significant advancements in 2023 was the introduction of quantum-enhanced deep learning models.

Hybrid quantum models integrate:

- Quantum optimization algorithms
- Classical neural networks (CNNs, DNNs)

These models offer:

- Faster computation for complex optimization problems
- Parallel processing capabilities
- Improved scalability

Studies demonstrated that hybrid quantum models significantly enhanced:

- Load balancing
- Network slicing
- QoS optimization

Quantum Machine Learning (QML)

Quantum machine learning emerged as a promising approach for **context-aware and adaptive resource management**, enabling real-time decision-making in highly dynamic environments.

AI-Native 6G Networks

Another important trend was the concept of **AI-native 6G networks**, where AI is embedded across all layers of the network. This enables:

- Autonomous network management
- Self-learning systems
- Predictive optimization

These systems significantly improve network efficiency and resilience.

5. Thematic Analysis of Literature

Based on the reviewed studies, the evolution of resource management in 6G can be categorized into four major phases:

Optimization-Based Phase

- Focus on mathematical and heuristic models
- Limited adaptability

Hybrid Deep Learning Phase

- CNN-LSTM and DQL models
- Improved prediction and allocation

Distributed Intelligence Phase

- MARL and federated learning
- Decentralized and scalable systems

Quantum-AI Phase

- Hybrid quantum deep learning
- High efficiency and real-time optimization

6. Research Gaps Identified

Despite significant progress, several research gaps remain:

Scalability Issues

Hybrid and quantum models require high computational resources

Quantum Hardware Limitations

Practical implementation of quantum models is still limited

Model Interpretability

AI models lack transparency, making decision-making difficult to explain

Data Privacy and Security

Distributed systems introduce vulnerabilities

Energy Efficiency

Deep learning models consume high energy

7. Summary of Literature Review

The literature from 2020–2023 demonstrates a clear evolution from traditional optimization techniques to intelligent, adaptive, and quantum-enhanced models. AI-driven approaches have significantly improved resource management in 6G networks, enabling efficient handling of complex and dynamic environments.

Hybrid quantum deep learning models represent the **next frontier**, offering unparalleled performance in terms of efficiency, scalability, and adaptability. However, addressing existing challenges is crucial for their practical deployment in real-world 6G systems.

Comparative Table and Analysis

Year	Model/Technique	Key Features	Advantages	Limitations
2020	Optimization + ML	CRAN-based allocation	Structured approach	Low adaptability
2021	CNN-LSTM Hybrid	Spatial + temporal learning	Improved accuracy	High complexity
2022	MARL + GNN	Distributed decision-making	Scalability	Training overhead
2023	Hybrid Quantum CNN	Quantum + DL integration	High efficiency, low latency	Hardware limitations

Analysis

The evolution of efficient resource management in 6G communication networks has undergone a significant transformation from traditional optimization-based approaches to advanced hybrid quantum deep learning models. This section provides a comprehensive comparative analysis of the major techniques explored between 2020 and 2023, focusing on performance metrics such as scalability, adaptability, latency reduction, energy efficiency, and computational complexity.

1. Comparison of Optimization-Based and AI-Based Models

The earliest approaches (primarily in 2020) relied heavily on mathematical optimization techniques, including linear programming, convex optimization, and heuristic-based algorithms. These methods were effective in well-defined and static network environments but faced significant challenges in dynamic and heterogeneous 6G scenarios.

Compared to these traditional techniques, AI-based models demonstrated superior performance due to their ability to learn patterns from data and adapt to changing network conditions. Machine learning models reduced dependency on complete channel state information and improved decision-making efficiency. However, early AI models still lacked real-time adaptability and scalability when deployed in ultra-dense networks.

Thus, while optimization-based models provided a strong theoretical foundation, AI-based approaches introduced practical adaptability and learning capabilities, marking a critical shift in resource management strategies.

2. CNN-Based vs Hybrid Deep Learning Models

Convolutional Neural Networks (CNNs) emerged as a powerful tool for spatial feature extraction in network traffic and resource allocation tasks. CNNs enabled efficient analysis of high-dimensional data, such as signal patterns and interference maps. However, CNNs alone were insufficient for capturing temporal dependencies inherent in dynamic network environments.

To overcome this limitation, hybrid deep learning models, particularly CNN-LSTM architectures, were introduced in 2021. These models combined:

- CNN for spatial feature extraction
- LSTM for temporal sequence modeling

The integration of these two architectures significantly improved prediction accuracy and resource allocation efficiency. For instance, CNN-LSTM models enabled better traffic forecasting, leading to proactive resource allocation and reduced network congestion.

In comparison, standalone CNN models offered faster computation but lower adaptability, while hybrid models provided higher accuracy and dynamic responsiveness at the cost of increased computational complexity.

3. Reinforcement Learning vs Supervised Learning Approaches

Supervised learning models require labeled datasets, which are often difficult to obtain in real-time 6G environments. In contrast, reinforcement learning (RL) models learn through interaction with the environment, making them highly suitable for dynamic resource management.

Deep reinforcement learning (DRL) models demonstrated significant improvements in:

- Spectrum allocation
- Power control
- Network slicing

However, RL models suffer from slow convergence and high training complexity, especially in large-scale networks.

To address these challenges, multi-agent reinforcement learning (MARL) was introduced in 2022. MARL enables multiple agents to collaboratively optimize resource allocation in distributed environments. This approach improved scalability and reduced decision latency.

Compared to supervised learning, RL-based approaches offer:

- Higher adaptability
- Better performance in unknown environments

But they also introduce challenges such as:

- Training instability
- Increased computational overhead

4. Centralized vs Distributed Resource Management

Traditional resource management systems relied on **centralized architectures**, where a single controller managed the entire network. While this approach ensured global optimization, it suffered from:

- High latency
- Scalability issues
- Single point of failure

In contrast, 2022 studies introduced distributed resource management frameworks, particularly using MARL and federated learning. These systems allow multiple agents or nodes to make decisions locally while collaborating globally.

Distributed systems offer several advantages:

- Improved scalability
- Reduced latency
- Enhanced fault tolerance

However, they also introduce challenges such as:

- Coordination complexity
- Communication overhead
- Security vulnerabilities

Overall, distributed architectures are more suitable for 6G networks due to their massive scale and dynamic nature.

5 Graph Neural Networks vs Traditional Neural Networks

Graph Neural Networks (GNNs) gained popularity in 2022 due to their ability to model network relationships and interference patterns. Unlike traditional neural networks, GNNs can capture dependencies between nodes in a network.

GNN-based models demonstrated superior performance in:

- Interference management
- Resource allocation
- Network topology optimization

Compared to CNNs and RNNs, GNNs provide:

- Better representation of network structures
- Improved scalability in complex environments

However, GNNs require more complex training processes and are computationally intensive.

6. Classical Deep Learning vs Hybrid Quantum Deep Learning Models

The most significant advancement in 2023 was the introduction of hybrid quantum deep learning models, particularly hybrid quantum CNN architectures.

Classical Deep Learning Models

Classical models, including CNNs, RNNs, and hybrid architectures, have been widely used for resource management. They offer:

- High accuracy
- Strong feature extraction capabilities
- Proven performance in real-world applications

However, they face limitations in:

- Handling large-scale optimization problems
- Computational efficiency
- Energy consumption

Hybrid Quantum Deep Learning Models

Hybrid quantum models integrate quantum computing with classical neural networks, enabling:

- Parallel processing of multiple states
- Faster optimization
- Improved scalability

These models significantly outperform classical models in:

- Latency reduction
- Load balancing
- QoS optimization

For example, hybrid quantum CNN models demonstrated improved performance in network slicing and resource allocation, particularly in ultra-dense networks.

Comparative Insight

- Classical models are more mature and easier to implement
- Quantum models offer superior performance but face hardware limitations

Thus, hybrid quantum models represent the future of intelligent resource management, although their practical deployment is still evolving.

7. Energy Efficiency Analysis

Energy efficiency is a critical requirement for 6G networks. Traditional models often consumed excessive energy due to continuous computation and centralized processing.

AI-based models improved energy efficiency by:

- Predicting traffic patterns
- Optimizing resource allocation
- Reducing redundant computations

Hybrid quantum models further enhance energy efficiency by:

- Reducing computational steps
- Leveraging quantum parallelism

However, current quantum systems require specialized hardware, which may offset energy savings.

8. Latency and QoS Performance Comparison

Latency reduction is one of the primary goals of 6G networks. The comparative analysis shows:

- Optimization-based models: High latency due to static decision-making
- Deep learning models: Moderate latency with improved adaptability
- RL-based models: Lower latency due to real-time decision-making
- Hybrid quantum models: Lowest latency due to parallel computation

Similarly, Quality of Service (QoS) improves progressively across these models, with hybrid quantum models achieving the highest performance.

9. Scalability and Complexity Trade-Off

A critical trade-off exists between scalability and computational complexity:

- Simple models: Low complexity but limited scalability
- Deep learning models: Moderate complexity with improved scalability
- MARL and GNN models: High scalability but increased complexity
- Hybrid quantum models: Extremely high scalability but require advanced hardware

This trade-off highlights the need for efficient model design and optimization techniques.

10. Overall Comparative Insights

From the analysis, several key insights emerge:

1. **Shift Toward Intelligence**
   Resource management has evolved from static optimization to intelligent, adaptive systems
2. **Hybrid Models Dominate**
   Combining multiple techniques yields better performance than standalone models
3. **Quantum Computing is Transformative**
   Hybrid quantum models provide significant performance improvements
4. **Distributed Systems are Essential**
   Centralized approaches are no longer viable for 6G networks
5. **Trade-Off Between Performance and Complexity**
   Advanced models offer better performance but require higher computational resources

11. Conclusion of Comparative Analysis

The comparative analysis clearly demonstrates that hybrid quantum deep learning models outperform traditional and classical AI-based approaches in efficient resource management for 6G networks. While earlier models laid the foundation, recent advancements have enabled highly adaptive, scalable, and efficient systems capable of handling the complexities of next-generation communication networks.

However, the transition toward quantum-enhanced models requires addressing challenges related to hardware availability, computational cost, and integration with existing systems. Future research should focus on developing lightweight, scalable, and energy-efficient hybrid models to fully realize the potential of 6G communication networks.

Discussion

The integration of AI and quantum computing in 6G networks represents a paradigm shift in resource management. Hybrid quantum CNN models provide a powerful framework for addressing complex optimization problems. These models leverage the strengths of both classical and quantum computing, enabling efficient handling of large-scale data and dynamic network conditions.

One of the key advantages of hybrid models is their ability to perform real-time decision-making. Unlike traditional methods, which rely on static optimization, AI-driven models can adapt to changing network conditions. This adaptability is crucial for 6G networks, which operate in highly dynamic environments.

However, several challenges must be addressed. Quantum computing is still in its early stages, and the availability of quantum hardware is limited. Additionally, training hybrid models requires significant computational resources and large datasets. Data privacy and security are also major concerns, especially in distributed networks.

Despite these challenges, the potential benefits of hybrid quantum models are substantial. They can significantly improve network efficiency, reduce latency, and enhance user experience. Future research should focus on developing scalable and energy-efficient models, as well as integrating federated learning and edge computing.

Conclusion

This paper presented a comprehensive review of efficient resource management in 6G communication networks, focusing on hybrid quantum duplet-convolutional neural network models. The study highlighted the limitations of traditional approaches and emphasized the importance of AI-driven solutions.

The literature review revealed that hybrid models, particularly those integrating quantum computing and deep learning, offer significant advantages in terms of efficiency, scalability, and adaptability. These models outperform conventional methods in handling complex network environments and optimizing resource allocation.

The comparative analysis demonstrated that while earlier approaches relied on optimization and machine learning, recent advancements have shifted towards hybrid and quantum-based models. These models provide superior performance in terms of latency reduction, throughput improvement, and energy efficiency.

However, challenges such as computational complexity, hardware limitations, and data privacy must be addressed to fully realize the potential of these technologies. Future research should focus on developing robust, scalable, and secure models for 6G networks.

In conclusion, hybrid quantum CNN models represent a promising direction for efficient resource management in 6G communication networks. They have the potential to transform network management and enable the next generation of intelligent communication systems.

References

Ashwin, M., Alqahtani, A. S., Mubarakali, A., & Sivakumar, B. (2023). Efficient resource management in 6G communication networks using hybrid quantum deep learning model. *Computer and Electrical Engineering*. https://doi.org/10.1016/j.compeleceng.2022.108565

Noman, H. M. F., Hanafi, E., Noordin, K. A., Dimyati, K., & Imran, M. A. (2023). Machine learning empowered emerging wireless networks in 6G: Recent advancements, challenges and future trends. *IEEE Access*. https://doi.org/10.1109/ACCESS.2023.3302250

Du, X., Wang, T., Feng, Q., Ye, C., Tao, T., & Chen, M. (2023). Multi-agent reinforcement learning for dynamic resource management in 6G in-X subnetworks. *IEEE Transactions on Wireless Communications*, 22(3), 1900–1914. https://doi.org/10.1109/TWC.2022.3207918

Bhattacharya, P., Patel, F., Alabdulatif, A., Gupta, R., Tanwar, S., & Kumar, N. (2022). Deep Q-learning for secure spectrum allocation and resource management in 6G. *IEEE Transactions on Network and Service Management*, 19(4), 4989–5005. https://doi.org/10.1109/TNSM.2022.3186725

Sami, H., Otrok, H., Bentahar, J., & Mourad, A. (2021). AI-based resource provisioning of IoE services in 6G networks. *IEEE Transactions on Network and Service Management*, 18(3), 3527–3540. https://doi.org/10.1109/TNSM.2021.3066625

Mekrache, A., Bradai, A., Moulay, E., & Dawaliby, S. (2022). Deep reinforcement learning for vehicular networks toward 6G. *Vehicular Communications*, 33, 100398. https://doi.org/10.1016/j.vehcom.2021.100398

Lu, X., Xiao, L., Li, P., Ji, X., Xu, C., & Yu, S. (2023). Reinforcement learning-based security and resource management in 6G. *IEEE Communications*

Surveys & Tutorials, 25(1), 425–466. https://doi.org/10.1109/COMST.2022.3224279

Yang, Z., Chen, M., Wong, K. K., Poor, H. V., & Cui, S. (2022). Federated learning for 6G: Applications, challenges, and opportunities. *Engineering*, 8, 33–41. https://doi.org/10.1016/j.eng.2021.12.002

Liu, Y., Yuan, X., Xiong, Z., Kang, J., Wang, X., & Niyato, D. (2020). Federated learning for 6G communications. *China Communications*, 17(9), 105–118. https://doi.org/10.23919/JCC.2020.09.009

Alhammadi, A., Alkhawaldeh, R., & Alshahrani, S. (2024). Artificial intelligence in 6G wireless networks: A survey. *Wireless Communications and Mobile Computing*. https://doi.org/10.1155/2024/8845070

Chataut, R., & Akl, R. (2024). 6G networks and the AI revolution: Key technologies and challenges. *Sensors*, 24(6), 1888. https://doi.org/10.3390/s24061888

Liu, Y., Deng, Y., Nallanathan, A., Elkashlan, M., & Wong, K. K. (2023). Machine learning for 6G ultra-reliable and low-latency communications. *IEEE Wireless Communications*, 30(2), 48–54. https://doi.org/10.1109/MWC.001.2200031

Aloqaily, M., Bouachir, O., Ridhawi, I. A., & Guizani, M. (2023). AI-enabled network orchestration in 6G. *IEEE Network*, 37(2), 78–85. https://doi.org/10.1109/MNET.002.2200271

Al-Quraan, M., Mohjazi, L., Bariah, L., Centeno, A., Zoha, A., & Arshad, K. (2023). Federated learning for edge intelligence in 6G. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 7(3), 957–979. https://doi.org/10.1109/TETCI.2023.3251404

Shi, H., Ma, R., Li, D., & Guan, H. (2023). Distributed collaborative learning for 6G cloud systems. *IEEE Network*, 37(2), 44–53. https://doi.org/10.1109/MNET.001.2200382

Yao, Y., Zhou, H., & Erol-Kantarci, M. (2022). Deep reinforcement learning-based beam management in 6G. *IEEE GLOBECOM*. https://doi.org/10.1109/GLOBECOM48099.2022.10001317

Feriani, A., & Hossain, E. (2020). Deep reinforcement learning for wireless networks: A tutorial. *IEEE Communications Surveys & Tutorials*. https://doi.org/10.1109/COMST.2020.3037884

Huang, C., Mo, R., & Yuen, C. (2020). Reconfigurable intelligent surface assisted DRL for 6G. *IEEE Communications*. https://doi.org/10.48550/arXiv.2002.10072

Nouruzi, A., Rezaei, A., Khalili, A., Mokari, N., & Javan, M. R. (2023). Smart resource allocation in software-defined 6G networks using DRL. *IEEE Transactions*. https://doi.org/10.48550/arXiv.2302.04655

Dagiuklas, T., et al. (2023). AI-enabled non-terrestrial networks for 6G: A survey. *IEEE Access*, 11, 126788–126812. https://doi.org/10.1109/ACCESS.2023.xxxxxx