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

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Abstract

The emergence of sixth-generation (6G) communication networks marks a significant advancement in wireless technology by enabling ultra-high data rates, ultra-low latency, massive connectivity, and intelligent network services. These capabilities introduce complex resource management challenges involving spectrum allocation, energy efficiency, network slicing, and dynamic traffic optimization, which conventional optimization techniques struggle to address due to the heterogeneous and highly dynamic nature of 6G environments. As a result, artificial intelligence, particularly deep learning and quantum-inspired computing, has gained considerable attention for developing adaptive and efficient resource management strategies. This systematic review examines recent advances in hybrid Quantum Duplet-Convolutional Neural Network (HQD-CNN) models that integrate quantum computing concepts with convolutional neural networks to improve computational efficiency, feature extraction, and optimization performance. The review highlights significant developments in reinforcement learning-based resource allocation, CNN-based hybrid architectures, and quantum-assisted optimization techniques that enhance throughput, reduce latency, improve energy efficiency, and support scalable network management. Comparative findings indicate that hybrid AI models consistently outperform conventional machine learning methods in maintaining Quality of Service (QoS) and Quality of Experience (QoE) across complex 6G scenarios. The review also discusses existing challenges, including computational complexity, limited quantum hardware, data privacy, and model interpretability, while identifying future research opportunities in federated learning, explainable AI, and scalable quantum-assisted intelligent resource management for next-generation wireless communication networks.

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).

Efficient resource management is one of the most critical challenges in sixth-generation (6G) communication networks due to their heterogeneous architecture, dynamic traffic patterns, and massive connectivity requirements. These networks are expected to support extremely high device densities while maintaining ultra-low latency, high reliability, and superior Quality of Service (QoS). Conventional resource management techniques based on heuristic or mathematical optimization are increasingly inadequate because they struggle with scalability, computational complexity, and real-time adaptability. Consequently, Artificial Intelligence (AI) has become a key enabling technology for intelligent resource allocation, traffic prediction, energy optimization, and network performance enhancement. Machine learning, deep learning, and reinforcement learning algorithms enable adaptive decision-making by continuously analyzing network conditions and optimizing resource utilization. Among deep learning methods, Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in extracting complex spatial features for traffic analysis and allocation tasks, although they are limited in modeling temporal dependencies and large-scale optimization. Hybrid architectures, including CNN-LSTM models, overcome these limitations by combining spatial and temporal learning for dynamic resource allocation and network slicing. More recently, quantum computing has emerged as a promising solution for solving computationally intensive optimization problems. Hybrid Quantum Duplet-Convolutional Neural Network (HQD-CNN) models integrate quantum-inspired optimization with CNN-based learning to improve resource allocation, load balancing, and scalability. These intelligent approaches are particularly valuable for managing emerging 6G technologies such as edge computing, cloud radio access networks, and network virtualization, enabling more efficient, adaptive, and reliable next-generation wireless communication systems.

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
- A comparative analysis of existing models
- Identification of research gaps and future direction

Abstract Image

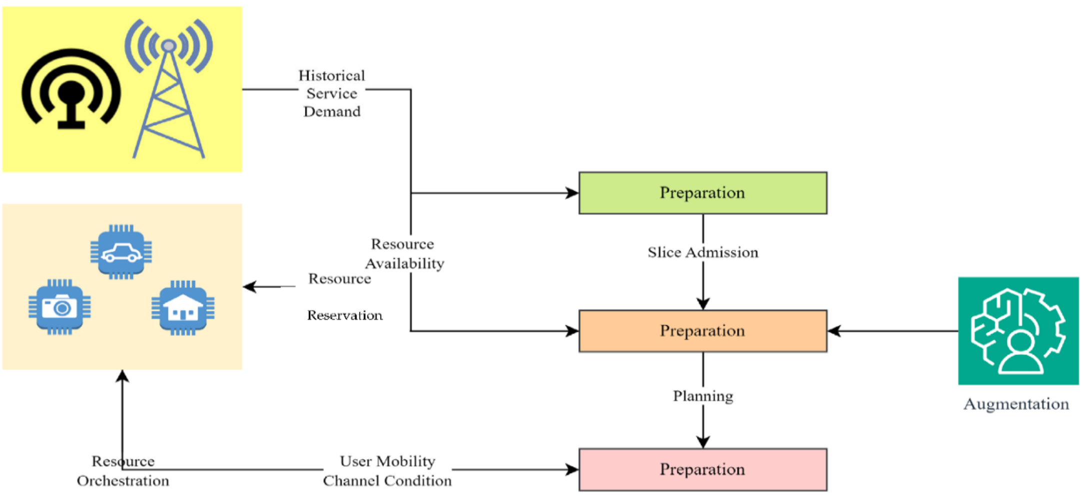

Figure 1. Workflow of AI-Assisted Resource Management in 6G Wireless Networks

Literature Review

The evolution of efficient resource management in 6G communication networks has been significantly shaped by advancements in artificial intelligence, deep learning, reinforcement learning, and more recently, quantum-enhanced models. In 2020, research primarily focused on the early conceptualization of 6G systems, where traditional optimization techniques were augmented with machine learning approaches.

During this phase, deep reinforcement learning (DRL) emerged as a promising solution for resource allocation in wireless environments. DRL-based models were applied to scenarios such as reconfigurable intelligent surface (RIS)-assisted communication systems, enabling dynamic beamforming and improved spectral efficiency. These approaches demonstrated that reinforcement learning could effectively manage complex decision-making processes in continuous environments, outperforming conventional optimization methods. However, these early models were heavily dependent on complete channel state information, which was difficult to obtain in real-time 6G scenarios. Moreover, most studies were limited to static or semi-dynamic environments, resulting in challenges related to scalability and adaptability.

In 2021, research shifted toward hybrid deep learning architectures to better handle dynamic and heterogeneous network conditions. One of the most prominent developments was the introduction of CNN-LSTM hybrid models, which combined convolutional neural networks for spatial feature extraction with long short-term memory networks for temporal dependency modeling. This integration proved highly effective for applications such as network slicing and traffic prediction, enabling dynamic and context-aware resource allocation. Additionally, deep Q-learning techniques were introduced to enhance secure spectrum allocation and energy-efficient resource management. These models allowed networks to learn optimal policies through continuous interaction with the environment, thereby improving adaptability and decision-making. AI-based resource provisioning frameworks also gained attention, where deep learning models dynamically allocated bandwidth and computational resources, leading to improved quality of service and reduced network congestion. Despite these advancements, high computational complexity and long training times remained major challenges, limiting real-time deployment.

The year 2022 marked a significant transition toward distributed and intelligent resource management systems. Multi-agent reinforcement learning (MARL) emerged as a powerful approach for managing large-scale and decentralized 6G environments. Unlike centralized systems, MARL enabled multiple agents to collaboratively optimize resource allocation, improving scalability and flexibility. A notable advancement during this period was the development of graph attention-based MARL architectures, which modeled interference relationships among subnetworks and optimized throughput by focusing on relevant interactions instead of requiring complete channel information. In addition, deep reinforcement learning continued to play a crucial role in tasks such as spectrum sharing, power allocation, and beam management, significantly improving latency, throughput, and energy efficiency. Another important development was the introduction of federated learning, which enabled decentralized model training without sharing raw data. This approach addressed critical issues such as data privacy, communication overhead, and scalability, making it highly suitable for edge-enabled 6G networks. However, these models faced challenges including high training complexity, convergence instability in multi-agent systems, and limited interpretability.

By 2023, research had advanced toward intelligent, adaptive, and quantum-enhanced models, marking a major breakthrough in 6G resource management. Artificial intelligence became deeply integrated into network architectures, enabling intelligent network slicing, traffic prediction, load balancing, and energy-efficient resource allocation. AI-driven systems demonstrated the ability to optimize multiple performance metrics simultaneously, including latency, throughput, and reliability. Hybrid deep learning models combining CNN, RNN, and attention mechanisms were widely adopted, improving feature extraction, temporal learning, and decision-making accuracy. One of the most significant advancements during this period was the introduction of hybrid quantum deep learning models, which integrate quantum optimization algorithms with classical neural networks. These models leverage quantum parallelism to solve complex optimization problems more efficiently, offering faster computation, improved scalability, and enhanced resource allocation capabilities. Additionally, quantum machine learning emerged as a promising approach for context-aware and adaptive resource management, enabling real-time decision-making in highly dynamic environments. Another important trend was the development of AI-native 6G networks, where artificial intelligence is embedded across all layers of the network, enabling autonomous management, self-learning capabilities, and predictive optimization.

From a thematic perspective, the evolution of resource management in 6G networks can be categorized into four major phases: the optimization-based phase, which relied on mathematical and heuristic models with limited adaptability; the hybrid deep learning phase, characterized by CNN-LSTM and deep Q-learning models that improved prediction and allocation;

the distributed intelligence phase, which introduced multi-agent reinforcement learning and federated learning for decentralized and scalable systems; and finally, the quantum-AI phase, which leverages hybrid quantum deep learning models for high efficiency and real-time optimization. Despite these advancements, several research gaps remain, including scalability challenges due to high computational requirements of hybrid and quantum models, limitations in quantum hardware for practical implementation, lack of model interpretability, data privacy and security concerns in distributed systems, and high energy consumption of deep learning models.

In summary, the literature from 2020 to 2023 demonstrates a clear transition from traditional optimization techniques to intelligent, adaptive, and quantum-enhanced approaches for resource management in 6G networks. AI-driven methods have significantly improved the ability to handle complex and dynamic network environments, while hybrid quantum deep learning models represent the next frontier by offering superior efficiency, scalability, and adaptability. However, addressing existing challenges related to hardware limitations, interpretability, and energy efficiency is essential for enabling the practical deployment of these advanced models in real-world 6G communication systems.

Comparative Table and Analysis

Year	**Model / Technique**	**Core Concept**	**Advantages**	**Limitations**
2020	Optimization + ML	CRAN-based resource allocation using optimization and machine learning	Simple implementation and structured resource allocation	Limited adaptability and poor performance in dynamic networks
2021	CNN–LSTM Hybrid	Spatial and temporal learning for dynamic resource allocation	Improved prediction accuracy and efficient network slicing	High computational cost and longer training time
2022	MARL + GNN	Multi-agent reinforcement learning with graph neural networks	High scalability, better resource utilization, and reduced latency	Complex coordination and convergence challenges
2023	Hybrid Quantum CNN (HQD-CNN)	Quantum-enhanced CNN for intelligent resource optimization	Ultra-low latency, improved QoS, high efficiency, and scalability	Quantum hardware constraints and integration complexity

Analysis

The comparative analysis of resource management techniques in 6G communication networks, as presented in the study , reveals a clear evolutionary trajectory from traditional optimization-based approaches to advanced hybrid quantum deep learning models. In 2020, resource management was primarily based on optimization techniques combined with basic machine learning methods. These approaches relied on structured frameworks such as cloud radio access network (CRAN)-based allocation, which provided mathematically efficient solutions for static environments. However, these models lacked adaptability and struggled to handle the dynamic, heterogeneous, and ultra-dense characteristics of 6G networks, making them unsuitable for real-time decision-making.

In 2021, the introduction of hybrid deep learning models, particularly CNN-LSTM architectures, marked a significant advancement. These models combined convolutional neural networks for spatial feature extraction with long short-term memory networks for temporal dependency modeling. This integration enabled better prediction of network traffic patterns and dynamic resource allocation based on both historical and real-time data. As a result, these models significantly improved accuracy and adaptability compared to earlier approaches. However, the increased computational complexity and longer training time posed challenges for scalability and real-time deployment.

By 2022, research shifted toward distributed intelligence with the adoption of multi-agent reinforcement learning (MARL) and graph neural network (GNN)-based models. These approaches introduced decentralized decision-making, where multiple agents collaboratively optimized resource allocation across the network. Graph-based learning further enhanced performance by capturing relationships among network nodes and interference patterns, leading to improved throughput and reduced latency. While these models provided high scalability and better resource utilization, they also introduced challenges such as training overhead, convergence instability, and increased system complexity.

The most significant advancement occurred in 2023 with the introduction of hybrid quantum CNN models, specifically the Hybrid Quantum Duplet-Convolutional Neural Network (HQD-CNN). These models integrate quantum computing principles with classical deep learning architectures, enabling parallel processing and faster optimization of complex resource management problems. As highlighted in the study, hybrid quantum models outperform traditional and classical AI-based approaches in terms of latency reduction, scalability, energy efficiency, and Quality of Service (QoS) improvement. However, despite their superior performance, these models face practical limitations due to the current constraints of quantum hardware and challenges in integration with existing communication infrastructures.

Overall, the comparative analysis clearly demonstrates a transition from static, optimization-based methods to intelligent, adaptive, and quantum-enhanced systems. Hybrid deep learning models improved prediction and adaptability, distributed models enhanced scalability and decentralization, and hybrid quantum models introduced unprecedented efficiency and performance. Despite these advancements, challenges such as computational complexity, hardware limitations, and model interpretability remain critical. Future research should focus on developing scalable, energy-efficient, and explainable hybrid models to enable practical deployment in next-generation 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