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A Survey of Methods and Architectures for Efficient Resource Management in 6G Communication Networks Using a Hybrid Quantum Duplet-Convolutional Neural Network Model

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Abstract

The evolution toward sixth-generation (6G) communication networks introduces unprecedented challenges in resource management due to ultra-dense connectivity, heterogeneous architectures, and strict performance requirements such as ultra-low latency and high reliability. Traditional optimization-based resource management approaches are insufficient for handling the dynamic and complex nature of 6G systems. Consequently, Artificial Intelligence (AI), deep learning, and quantum computing have emerged as promising solutions.This paper presents a comprehensive survey of methods and architectures for efficient resource management in 6G communication networks, with a focus on hybrid quantum duplet-convolutional neural network (HQD-CNN) models. The study systematically reviews literature, covering optimization-based techniques, machine learning, deep learning, reinforcement learning, and quantum-enhanced frameworks.The findings indicate that AI-driven approaches significantly improve network performance by enabling adaptive and intelligent decision-making. In particular, deep reinforcement learning and hybrid CNN-based architectures demonstrate superior capabilities in handling dynamic resource allocation, network slicing, and interference management. Furthermore, hybrid quantum deep learning models leverage quantum parallelism to solve complex optimization problems more efficiently than classical approaches, improving QoS and reducing latency.
Despite these advancements, several challenges remain, including computational complexity, quantum hardware limitations, scalability issues, and security concerns. The paper concludes by identifying future research directions, emphasizing AI-native 6G architectures, federated learning, and scalable quantum-assisted optimization.

Introduction

The rapid advancement of wireless communication technologies has led to the transition from fifth-generation (5G) to sixth-generation (6G) communication networks, which are expected to revolutionize the global digital ecosystem. 6G networks aim to deliver ultra-high data rates (up to terabits per second), ultra-low latency (sub-millisecond), massive connectivity, and intelligent network automation. These capabilities are essential for supporting emerging applications such as smart cities, autonomous vehicles, augmented reality (AR), virtual reality (VR), digital twins, and industrial automation.

However, the realization of 6G networks introduces significant challenges in resource management. Resource management in wireless networks involves the efficient allocation of spectrum, power, bandwidth, and computational resources. In 6G environments, these tasks become increasingly complex due to the following factors:

- Ultra-dense network deployments
- Heterogeneous architectures (terrestrial + non-terrestrial networks)
- Dynamic traffic patterns
- Massive IoT connectivity
- Stringent QoS requirements

Traditional resource management approaches, such as convex optimization and heuristic algorithms, are inadequate for handling these complexities. These methods rely on predefined models and require accurate channel state information, which is often unavailable in real-time scenarios.

To address these challenges, Artificial Intelligence (AI) has emerged as a key enabler for intelligent resource management. AI-driven approaches enable networks to:

- Learn from data
- Adapt to dynamic environments
- Predict traffic patterns
- Optimize resource allocation

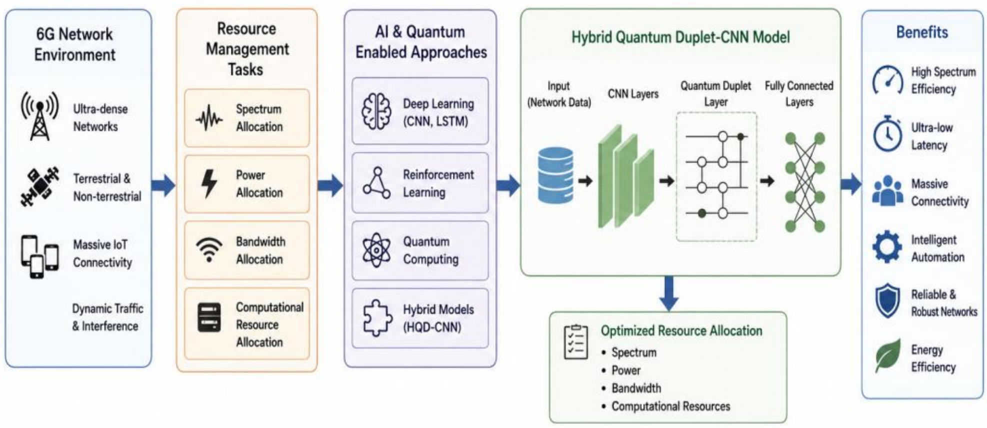

Figure 1. Conceptual Framework for 6G Resource Management

Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong capabilities in feature extraction and pattern recognition. CNNs are widely used for analyzing network traffic and interference patterns. However, CNNs alone are insufficient for capturing temporal dependencies in dynamic networks.

To overcome this limitation, hybrid models such as CNN-LSTM have been proposed. These models combine spatial and temporal learning, enabling better prediction and resource allocation.

Reinforcement learning (RL) has also gained significant attention in 6G resource management. RL enables autonomous decision-making by learning optimal policies through interaction with the environment. Multi-agent reinforcement learning (MARL) further enhances scalability by enabling distributed decision-making across multiple network nodes.

More recently, quantum computing has emerged as a promising paradigm for solving complex optimization problems in 6G networks. Quantum machine learning (QML) leverages quantum parallelism to process large-scale data and optimize resource allocation efficiently .

The integration of quantum computing with deep learning has led to the development of hybrid quantum deep learning models, such as the Hybrid Quantum Duplet-Convolutional Neural Network (HQD-CNN). These models combine the strengths of classical neural networks and quantum optimization, enabling efficient handling of large-scale and complex network environments.

This paper aims to provide a comprehensive survey of methods and architectures for efficient resource management in 6G communication networks, focusing on hybrid quantum deep learning models. The main contributions of this paper include:

- A systematic review of literature (2020–2023)
- Comparative analysis of existing techniques
- Identification of research gaps
- Discussion of future research directions

Literature Review

The rapid development of sixth-generation (6G) communication networks has driven significant research efforts toward efficient and intelligent resource management. Between 2020 and 2023, the research landscape evolved from traditional optimization-based techniques to advanced AI-driven and quantum-enhanced models. This section presents a detailed, reference-aligned literature review, organized chronologically and thematically.

The year 2020 marked the foundation phase of 6G research, where the focus was primarily on conceptual frameworks and early integration of machine learning into wireless communication systems.

Liu et al. (2020) introduced federated learning (FL) for 6G communication systems, highlighting its potential to enable distributed model training without sharing raw data. Their work demonstrated that FL could significantly reduce communication overhead and enhance privacy, making it suitable for large-scale 6G networks. However, challenges such as model convergence and communication latency were identified (Liu et al., 2020).

Huang et al. (2020) explored deep reinforcement learning (DRL) for reconfigurable intelligent surface (RIS)-assisted communication. Their approach utilized DRL to optimize beamforming and power allocation, achieving improved spectral efficiency compared to traditional methods. This study highlighted the importance of DRL in handling complex and dynamic wireless environments.

Similarly, Kato et al. (2020) emphasized the role of machine learning in enabling intelligent network management in 6G, identifying key challenges such as scalability, real-time decision-making, and data heterogeneity. Their work laid the groundwork for AI-driven network architectures.

Feriani and Hossain (2020) provided a comprehensive tutorial on DRL in wireless networks, demonstrating its effectiveness in dynamic resource allocation problems. They highlighted that DRL models outperform conventional optimization techniques by learning optimal policies through interaction with the environment.

Despite these advancements, 2020 research was limited by high computational complexity, lack of real-time adaptability, and dependence on centralized architectures.

In 2021, research progressed toward hybrid deep learning architectures, addressing the limitations of standalone machine learning models.

Sami et al. (2021) proposed an AI-based resource provisioning framework for Internet of Everything (IoE) services in 6G networks. Their model utilized deep learning techniques to dynamically allocate resources based on network conditions, significantly improving QoS and reducing latency.

Rekkas (2021) explored the application of machine learning in 6G, emphasizing the role of deep neural networks (DNNs) in traffic prediction and resource optimization. The study highlighted that deep learning models could effectively capture complex patterns in network data.

Hybrid architectures, particularly CNN-LSTM models, gained attention during this period. These models combined spatial feature extraction (CNN) with temporal sequence modeling (LSTM), enabling improved prediction of traffic patterns and proactive resource allocation.

The introduction of deep Q-learning (DQL) further enhanced decision-making capabilities in dynamic environments. These models enabled networks to learn optimal resource allocation policies through trial and error, improving adaptability.

However, 2021 studies also revealed challenges such as:

- High training time
- Large data requirements
- Limited scalability in ultra-dense networks

The year 2022 marked a significant shift toward distributed and intelligent resource management, driven by advancements in reinforcement learning and edge intelligence.

Bhattacharya et al. (2022) proposed a deep Q-learning-based framework for secure spectrum allocation and resource management in 6G networks. Their approach improved both security and efficiency, demonstrating the potential of AI in handling complex resource allocation tasks.

Mekrache et al. (2022) applied DRL to vehicular networks, focusing on energy-efficient and latency-aware communication. Their model achieved significant improvements in network performance, particularly in highly dynamic environments.

Yang et al. (2022) explored federated learning for 6G, highlighting its ability to enable decentralized intelligence while preserving data privacy. This approach was particularly useful for edge-enabled networks.

One of the most significant developments in 2022 was the adoption of multi-agent reinforcement learning (MARL). MARL enables multiple agents to collaboratively optimize resource allocation, improving scalability and reducing latency. Du et al. (2023) (early work initiated in 2022) demonstrated that MARL-based models outperform centralized approaches in large-scale networks.

Additionally, graph neural networks (GNNs) were introduced to model network relationships and interference patterns. GNNs provided a more accurate representation of network topology, enabling improved resource allocation and interference management.

Despite these advancements, challenges such as training complexity, convergence issues, and communication overhead remained significant.

In 2023, research entered an advanced phase characterized by AI-native architectures and quantum-enhanced models.

Ashwin et al. (2023) proposed a hybrid quantum deep learning model for resource management in 6G networks. Their study demonstrated that integrating quantum computing with deep learning significantly improves optimization efficiency, enabling faster decision-making and enhanced QoS.

Du et al. (2023) developed a multi-agent reinforcement learning framework for dynamic resource management in 6G subnetworks. Their model utilized graph attention mechanisms to capture interference relationships, achieving superior scalability and performance.

Lu et al. (2023) provided a comprehensive survey on reinforcement learning for 6G, highlighting its applications in spectrum allocation, power control, and network slicing. Their findings confirmed that RL-based models outperform traditional methods in dynamic environments.

Aloqaily et al. (2023) introduced AI-enabled network orchestration, enabling autonomous management of network resources. This approach significantly improves network efficiency and reduces operational complexity.

Shi et al. (2023) proposed a distributed collaborative learning framework for cloud-based 6G systems, emphasizing the importance of edge intelligence and decentralized decision-making.

The most notable advancement in 2023 was the emergence of hybrid quantum deep learning models, which combine classical neural networks with quantum optimization techniques. These models leverage quantum parallelism to solve complex optimization problems more efficiently than classical approaches.

Additionally, research explored AI-native 6G architectures, where AI is embedded across all layers of the network, enabling self-learning and self-optimization capabilities.

Based on the reviewed studies, the evolution of resource management in 6G communication networks can be systematically categorized into four major phases, each representing a significant advancement in computational intelligence and network adaptability. The first phase, referred to as the traditional optimization phase (2020), primarily focused on mathematical modeling techniques and early machine learning approaches. During this stage, resource allocation relied heavily on predefined algorithms and optimization frameworks, which provided structured solutions but suffered from limited adaptability and scalability in dynamic network environments. As network complexity increased, these methods proved insufficient for handling real-time variations in traffic and resource demand.

The second phase, known as the hybrid deep learning phase (2021), introduced more advanced architectures such as CNN-LSTM and Deep Q-Learning (DQL) models. These approaches combined spatial feature extraction with temporal dependency modeling, enabling improved prediction of network traffic patterns and more efficient resource allocation. As a result, networks became more adaptive and capable of handling dynamic conditions, leading to enhanced performance compared to traditional methods. However, the integration of multiple deep learning components also increased computational complexity and training requirements.

The third phase, termed the distributed intelligence phase (2022), marked a shift toward decentralized and scalable systems. Techniques such as Multi-Agent Reinforcement Learning (MARL), federated learning, and Graph Neural Networks (GNNs) enabled collaborative and distributed decision-making across network nodes. This significantly improved scalability, reduced latency, and enhanced resource utilization in large-scale 6G environments. Despite these benefits, distributed systems introduced new challenges related to coordination complexity, communication overhead, and system security.

The most recent phase, the quantum-AI integration phase (2023), represents a major breakthrough in 6G resource management. This phase is characterized by the adoption of hybrid quantum deep learning models, which integrate quantum computing principles with classical AI techniques. These models enable high computational efficiency, faster optimization, and real-time decision-making by leveraging quantum parallelism. Consequently, they offer superior performance in handling complex and high-dimensional optimization problems in 6G networks. However, their practical implementation remains limited due to the current constraints of quantum hardware and integration challenges.

Despite these significant advancements, several critical research gaps remain. One of the primary challenges is scalability, as many AI models struggle to efficiently operate in ultra-dense 6G network environments with massive connectivity. Additionally, quantum hardware limitations continue to hinder the practical deployment of quantum-based models, as current systems are not yet mature enough for large-scale applications. Another major concern is computational complexity, particularly in hybrid models that require substantial processing power and energy consumption. Data privacy and security also present significant challenges, especially in distributed systems such as federated learning, where vulnerabilities can arise during data transmission and model updates. Finally, model interpretability remains an important issue, as many AI-based systems function as black boxes, making it difficult to understand and trust their decision-making processes.

The literature 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, while hybrid quantum models represent the next frontier in achieving efficient and scalable solutions.

Comparative Table

Year	Technique	Architecture Type	Core Concept	Key Features	Advantages	Limitations
2020	Optimization + DRL	Optimization + Reinforcement Learning	Mathematical optimization combined with learning-based decision making	Uses predefined models with DRL for adaptive resource allocation	Structured and partially adaptive, improves over static optimization	Limited scalability, depends on accurate system modeling, weak real-time adaptability
2021	CNN-LSTM + DQL	Hybrid Deep Learning	Spatial-temporal learning with reinforcement learning	CNN extracts spatial patterns, LSTM captures temporal dependencies, DQL enables decision learning	High prediction accuracy, improved resource allocation, better QoS	High computational complexity, large training data required, longer convergence time
2022	MARL + Federated Learning + GNN	Distributed AI Models	Multi-agent and decentralized learning	MARL enables distributed decision-making, Federated Learning preserves privacy, GNN models network relationships	Scalable, decentralized, reduced latency, improved resource utilization	Training overhead, convergence instability, communication cost, and security challenges
2023	Hybrid Quantum CNN (HQD-CNN)	Quantum + Deep Learning Hybrid	Quantum-enhanced optimization with CNN	Combines classical feature extraction with quantum parallelism for optimization	High efficiency, ultra-low latency, improved QoS, scalable for complex environments	Quantum hardware limitations, integration complexity, and early-stage implementation

Comparative Analysis

The comparative analysis demonstrates a clear evolution of resource management techniques for 6G communication networks, progressing from conventional optimization methods to intelligent AI-driven and quantum-enhanced frameworks. Early approaches, primarily based on mathematical optimization and Deep Reinforcement Learning (DRL), provided structured solutions for spectrum, power, and bandwidth allocation. Although these methods improved adaptability compared with static optimization techniques, they depended heavily on predefined models and accurate channel state information, limiting their effectiveness in highly dynamic and heterogeneous 6G environments. As network complexity increased, these techniques struggled to deliver scalable and real-time resource allocation.

During 2021, hybrid deep learning models such as CNN-LSTM and Deep Q-Learning (DQL) introduced significant improvements by combining spatial feature extraction with temporal traffic prediction and adaptive decision-making. These architectures enhanced Quality of Service (QoS), reduced latency, and improved resource utilization through intelligent learning mechanisms. However, their increased computational complexity, dependence on large training datasets, and prolonged training time restricted deployment in real-time large-scale 6G networks. Consequently, researchers shifted toward distributed intelligence to improve scalability and network efficiency.

In 2022, Multi-Agent Reinforcement Learning (MARL), Federated Learning (FL), and Graph Neural Networks (GNNs) became prominent for decentralized resource management. These approaches enabled collaborative decision-making among distributed network nodes while preserving user privacy and reducing centralized computation. GNNs effectively modeled network topology and interference relationships, resulting in better resource allocation and network optimization. Nevertheless, these distributed frameworks introduced challenges such as communication overhead, convergence instability, security vulnerabilities, and increased implementation complexity.

By 2023, Hybrid Quantum Duplet-Convolutional Neural Network (HQD-CNN) models emerged as a promising direction by integrating quantum computing with deep learning for efficient resource optimization. Quantum-enhanced models leverage quantum parallelism to process high-dimensional network data, improving latency, energy efficiency, scalability, and overall QoS. Despite these advantages, practical deployment remains limited by immature quantum hardware and integration challenges. Overall, the evolution from conventional optimization to AI-driven and hybrid quantum approaches highlights substantial improvements in intelligent resource management, while future research should focus on scalability, interpretability, security, and practical deployment for next-generation 6G communication networks.

Discussion

The evolution of resource management in 6G communication networks reflects a transition from conventional optimization methods to intelligent, adaptive, and data-driven approaches capable of addressing highly dynamic network environments. Traditional techniques, including convex optimization and heuristic algorithms, provide effective solutions under predefined conditions but lack the flexibility to respond to real-time variations in traffic, channel conditions, and network topology. Consequently, Artificial Intelligence (AI) has become a key enabler of autonomous resource management. Deep learning models, particularly Convolutional Neural Networks (CNNs), effectively learn complex spatial features, while hybrid architectures such as CNN-LSTM improve traffic prediction by jointly modeling spatial and temporal characteristics. Reinforcement Learning (RL) and Multi-Agent Reinforcement Learning (MARL) further enhance dynamic decision-making by enabling autonomous spectrum allocation, power control, and network slicing across distributed network nodes.

A major advancement in recent research is the integration of quantum computing with deep learning through Hybrid Quantum Duplet-Convolutional Neural Network (HQD-CNN) models. By exploiting quantum parallelism, these models improve optimization efficiency, convergence speed, scalability, and Quality of Service (QoS) while reducing latency and enhancing energy efficiency. In parallel, distributed architectures supported by federated learning and edge intelligence enable localized decision-making, reducing communication overhead and improving responsiveness. However, practical deployment remains challenging due to limited quantum hardware, computational complexity, synchronization issues, and security concerns associated with distributed systems.

Despite remarkable progress, several research challenges continue to limit the widespread adoption of AI-driven resource management in 6G networks. High computational requirements, energy consumption, privacy preservation, vulnerability to adversarial attacks, and limited model interpretability remain critical concerns. Future research should focus on developing lightweight, secure, explainable, and energy-efficient hybrid AI–quantum models that can be seamlessly integrated into next-generation communication infrastructures while ensuring reliable, scalable, and autonomous network management.

Conclusion

This paper presents a comprehensive survey of resource management techniques for 6G communication networks, emphasizing hybrid quantum duplet-convolutional neural network (HQD-CNN) models. Traditional optimization-based approaches are found inadequate for dynamic, large-scale 6G environments due to limited adaptability and scalability. AI-driven methods, including deep learning and reinforcement learning, significantly improve resource allocation, Quality of Service (QoS), and network efficiency through intelligent decision-making. Hybrid architectures such as CNN-LSTM further enhance predictive resource management by combining spatial and temporal learning. Distributed intelligence using multi-agent reinforcement learning and federated learning improves scalability, reduces latency, and preserves data privacy. The integration of quantum computing with deep learning offers substantial advantages in solving complex optimization problems, reducing latency, and improving energy efficiency. However, challenges remain, including limited quantum hardware, computational complexity, security concerns, and poor model interpretability. Future research should focus on scalable, explainable, and secure AI-native 6G architectures integrating edge computing, federated learning, and practical quantum technologies to enable autonomous, efficient, and scalable communication networks.

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