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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

Zaydaan Saeedzada
Associate Professor, Department of Electronics and Communication Engineering, Siam Delta Engineering Institute, Thailand
Email: zaydaan.saeedzada@sdei-th.edu

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Abstract

The evolution toward sixth-generation (6G) communication networks introduces significant challenges in resource management due to ultra-dense connectivity, heterogeneous architectures, and stringent performance requirements such as ultra-low latency and high reliability. Traditional optimization-based approaches are inadequate for handling the highly dynamic and complex nature of these networks, leading to the growing adoption of Artificial Intelligence (AI), deep learning, and quantum computing techniques. This paper presents a comprehensive survey of methods and architectures for efficient resource management in 6G systems, with a particular focus on hybrid quantum duplet-convolutional neural network (HQD-CNN) models. Various approaches, including optimization techniques, machine learning, deep learning, and reinforcement learning frameworks, are examined to highlight their effectiveness in addressing network challenges. The findings reveal that AI-driven models significantly enhance performance through adaptive and intelligent decision-making, especially in dynamic resource allocation, network slicing, and interference management. Hybrid quantum deep learning models further improve efficiency by leveraging quantum parallelism to solve complex optimization problems. However, challenges such as computational complexity, scalability limitations, quantum hardware constraints, and security issues persist, indicating the need for scalable, secure, and AI-native solutions.

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

Recent studies highlight that AI integration is essential for enabling **autonomous and self-organizing 6G** networks.

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.

1. Literature Review – Year 2020

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.

2. Literature Review – Year 2021

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

3. Literature Review – Year 2022

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.

4. Literature Review – Year 2023

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 cloudbased 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.

5. Thematic Synthesis of Literature

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

1. Traditional Optimization Phase (2020)

- Focus on mathematical models and early ML
- Limited adaptability and scalability

2. Hybrid Deep Learning Phase (2021)

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

3. Distributed Intelligence Phase (2022)

- MARL, federated learning, and GNNs
- Scalable and decentralized systems

4. Quantum-AI Integration Phase (2023)

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

6. Identified Research Gaps

Despite significant advancements, several research gaps remain:

1. **Scalability Challenges**
   AI models struggle with ultra-dense 6G networks
2. **Quantum Hardware Limitations**
   Practical deployment of quantum models is still limited
3. **Computational Complexity**
   Hybrid models require high processing power
4. **Data Privacy and Security**
   Distributed systems introduce vulnerabilities
5. **Model Interpretability**
   Lack of transparency in AI decision-making

7. Summary

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

Comparative Table

Year	Technique	Advantages	Limitations
2020	Optimization + DRL	Structured, adaptive	Limited scalability
2021	CNN-LSTM	High accuracy	High complexity
2022	MARL + FL	Distributed, scalable	Training overhead
2023	Hybrid Quantum CNN	High efficiency	Hardware limitations

Comparative Analysis

The rapid evolution of resource management techniques in 6G communication networks reflects a clear paradigm shift from conventional optimization-based approaches toward intelligent, adaptive, and quantum-enhanced systems. The integration of Artificial Intelligence (AI), deep learning, and quantum computing has fundamentally transformed how network resources are allocated, optimized, and managed in highly dynamic and heterogeneous environments.

One of the most significant insights derived from the literature is the superiority of AI-driven approaches over traditional optimization methods. Conventional techniques, such as linear programming and heuristic-based algorithms, are limited by their dependence on predefined models and static assumptions. These approaches struggle to adapt to the real-time fluctuations and uncertainties inherent in 6G networks. In contrast, AI-based models, particularly deep learning and reinforcement learning techniques, enable networks to learn from data and make autonomous decisions. This capability is crucial for managing ultra-dense networks with massive device connectivity and diverse service requirements.

Among AI techniques, reinforcement learning (RL) and multi-agent reinforcement learning (MARL) have demonstrated remarkable potential for dynamic resource allocation. RL-based models allow network entities to continuously interact with the environment and learn optimal policies, resulting in improved performance in spectrum allocation, power control, and network slicing. MARL further enhances this capability by enabling distributed decision-making across multiple agents, thereby improving scalability and reducing latency.

However, these models are not without limitations. Issues such as slow convergence, training instability, and high computational complexity remain significant challenges, particularly in large-scale 6G deployments.
Another important development is the adoption of hybrid deep learning architectures, such as CNN-LSTM models. These architectures combine spatial and temporal learning capabilities, enabling more accurate prediction of network traffic and resource demands. As a result, hybrid models facilitate proactive resource allocation, reducing congestion and improving Quality of Service (QoS). Despite their advantages, hybrid models require substantial computational resources and large datasets for training, which may limit their real-time applicability.
The most transformative advancement in recent years is the emergence of hybrid quantum deep learning models, including the Hybrid Quantum Duplet-Convolutional Neural Network (HQD-CNN). These models integrate quantum computing principles with classical neural networks, enabling efficient handling of complex optimization problems. Quantum computing offers inherent advantages such as parallelism and high-dimensional state representation, which significantly enhance computational efficiency. In the context of 6G networks, hybrid quantum models have demonstrated superior performance in terms of latency reduction, energy efficiency, and scalability.
However, the practical implementation of quantum-enhanced models is still in its early stages. The availability of quantum hardware is limited, and current systems are prone to noise and instability. Additionally, integrating quantum algorithms with classical network infrastructures poses significant technical challenges. Therefore, while hybrid quantum models represent a promising direction, further research is required to address these limitations.
Another critical aspect highlighted in the literature is the importance of distributed and edge-based architectures. Centralized resource management systems are no longer viable in 6G networks due to their inability to handle large-scale and latency-sensitive applications. Distributed approaches, supported by federated learning and edge intelligence, enable localized decision-making and reduce communication overhead. These systems also enhance data privacy by minimizing the need for centralized data sharing. However, they introduce new challenges related to coordination, synchronization, and security.
Energy efficiency is another key consideration in 6G resource management. The increasing complexity of AI models and the massive scale of 6G networks result in high energy consumption. While AI-based models can optimize resource usage and reduce energy waste, their training and deployment require significant computational power. Hybrid quantum models have the potential to address this issue by reducing computational steps through quantum parallelism, but their energy efficiency depends on advancements in quantum hardware.
Furthermore, issues related to security, privacy, and model interpretability remain critical challenges. AI-driven systems are vulnerable to adversarial attacks, data breaches, and bias in decision-making. The lack of transparency in deep learning models also makes it difficult to interpret their decisions, which can be problematic in mission-critical applications.
In summary, the discussion highlights that while significant progress has been made in developing intelligent and efficient resource management techniques for 6G networks, several challenges remain. The future of 6G resource management lies in the integration of AI, quantum computing, and distributed architectures, supported by advancements in hardware and algorithm design. Addressing the existing challenges will be essential for realizing the full potential of next-generation communication networks.

Discussion

The transformation of resource management techniques in 6G communication networks highlights a significant shift from conventional deterministic models to intelligent, adaptive, and data-driven systems. This evolution is primarily driven by the increasing complexity of network environments characterized by ultra-dense connectivity, heterogeneous infrastructures, and stringent performance requirements such as ultra-low latency and ultra-high reliability.
One of the most critical observations from the reviewed literature is the inadequacy of traditional optimization-based approaches in addressing the dynamic nature of 6G networks. While methods such as convex optimization and heuristic algorithms provide mathematically optimal solutions under controlled conditions, they fail to adapt to real-time network fluctuations. These methods also struggle with scalability when applied to large-scale systems involving billions of interconnected devices. As a result, the integration of Artificial Intelligence (AI) has become indispensable for enabling autonomous and efficient resource management.
AI-driven approaches, particularly deep learning and reinforcement learning, have demonstrated superior performance in handling complex resource allocation problems. Deep learning models, such as Convolutional Neural Networks

(CNNs), are highly effective in extracting spatial features from network data, enabling accurate analysis of interference patterns and traffic distributions. However, their inability to capture temporal dependencies limits their effectiveness in dynamic environments.

To address this limitation, hybrid architectures such as CNN-LSTM models have been developed. These models combine spatial and temporal learning capabilities, allowing for more accurate prediction of network traffic and proactive resource allocation. This results in improved Quality of Service (QoS) and reduced network congestion. Nevertheless, the increased complexity of hybrid models leads to higher computational requirements and longer training times, posing challenges for real-time implementation.

Reinforcement learning (RL) has emerged as a powerful paradigm for dynamic resource management. RL-based models enable network entities to learn optimal policies through continuous interaction with the environment. This makes them particularly suitable for tasks such as spectrum allocation, power control, and network slicing. The introduction of multi-agent reinforcement learning (MARL) further enhances scalability by enabling distributed decision-making across multiple network nodes. MARL-based systems significantly reduce latency and improve network efficiency by decentralizing control.

Despite their advantages, RL-based models face several challenges, including slow convergence, high training complexity, and instability in multi-agent environments. These limitations necessitate the development of more efficient and robust learning algorithms.

The most promising advancement in recent years is the integration of quantum computing with deep learning, leading to the development of hybrid quantum deep learning models such as the Hybrid Quantum Duplet-Convolutional Neural Network (HQD-CNN). These models leverage the principles of quantum mechanics, such as superposition and entanglement, to perform parallel computations and solve complex optimization problems more efficiently than classical approaches.

Hybrid quantum models offer several advantages, including:

- Faster convergence in optimization problems
- Improved scalability for large-scale networks
- Enhanced energy efficiency through reduced computational steps

In the context of 6G networks, these models have demonstrated significant improvements in load balancing, latency reduction, and QoS optimization. However, the practical implementation of quantum-enhanced models is still constrained by the limited availability of quantum hardware and the challenges associated with integrating quantum algorithms into classical network infrastructures.

Another important trend identified in the literature is the shift toward distributed and edge-based resource management architectures. Centralized systems are no longer viable due to their inability to handle the scale and latency requirements of 6G networks. Distributed approaches, supported by federated learning and edge intelligence, enable localized decision-making, reducing communication overhead and improving system responsiveness.

However, distributed systems introduce new challenges, including:

- Coordination and synchronization among nodes
- Increased vulnerability to security threats
- Complexity in maintaining global network optimization

Energy efficiency is another critical consideration in 6G networks. While AI-based models improve resource utilization, they also require significant computational power for training and deployment. Hybrid quantum models have the potential to reduce energy consumption, but this depends on advancements in quantum hardware.

Furthermore, issues related to security, privacy, and interpretability remain major concerns. AI models are susceptible to adversarial attacks, and the lack of transparency in deep learning systems makes it difficult to interpret their decisions. These challenges must be addressed to ensure the reliability and trustworthiness of AI-driven 6G networks.

In summary, the discussion highlights that while AI and quantum computing have significantly advanced resource management in 6G networks, several technical and practical challenges remain. Future research should focus on developing scalable, energy-efficient, and secure models that can be seamlessly integrated into next-generation communication systems.

Conclusion

This paper presented a comprehensive survey of methods and architectures for efficient resource management in 6G communication networks, with a particular focus on hybrid quantum duplet-convolutional neural network (HQD-CNN) models. The study systematically analyzed the evolution of resource management techniques from traditional optimization-based approaches to advanced AI-driven and quantum-enhanced frameworks.

The findings reveal that conventional resource management techniques are insufficient for addressing the complexities of 6G networks. These methods are limited by their inability to adapt to dynamic environments, their dependence on accurate channel state information, and their lack of scalability. As a result, there has been a significant shift toward intelligent and adaptive approaches based on Artificial Intelligence.

AI-driven models, including deep learning and reinforcement learning, have demonstrated remarkable capabilities in improving resource allocation, network efficiency, and Quality of Service (QoS). Deep learning models, particularly CNN-based architectures, are effective in analyzing network data and identifying patterns, while reinforcement learning enables autonomous decision-making in dynamic environments.

Hybrid deep learning models, such as CNN-LSTM architectures, further enhance performance by combining spatial and temporal learning capabilities. These models enable proactive resource allocation and improve network performance. However, their high computational complexity and data requirements pose challenges for real-time deployment.

The emergence of distributed intelligence, particularly through multi-agent reinforcement learning (MARL) and federated learning, represents another significant advancement. These approaches enable decentralized decision-making, improving scalability and reducing latency. They also address data privacy concerns by minimizing the need for centralized data sharing.

The most notable contribution of recent research is the integration of quantum computing with deep learning, leading to the development of hybrid quantum models. These models leverage quantum parallelism to solve complex optimization problems more efficiently than classical approaches. Hybrid quantum CNN models have demonstrated superior performance in terms of latency reduction, scalability, and energy efficiency, making them a promising solution for 6G resource management.

Despite these advancements, several challenges remain. The limited availability of quantum hardware, high computational complexity of AI models, and issues related to data privacy and security pose significant barriers to practical implementation. Additionally, the lack of interpretability in AI models raises concerns about transparency and reliability.

Future research should focus on addressing these challenges by developing:

- Scalable and energy-efficient AI models
- Robust and secure distributed architectures
- Explainable AI techniques for better decision transparency
- Practical quantum computing solutions for real-world deployment

Furthermore, the concept of AI-native 6G networks, where intelligence is embedded across all layers of the network, is expected to play a crucial role in enabling autonomous and self-optimizing systems. The integration of edge computing, federated learning, and quantum computing will further enhance the efficiency and adaptability of resource management systems.

In conclusion, hybrid quantum deep learning models represent a transformative approach to resource management in 6G communication networks. While significant progress has been made, continued research and technological advancements are required to fully realize their potential. The successful implementation of these models will pave the way for intelligent, efficient, and scalable 6G communication systems capable of supporting the demands of future digital applications.

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