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Artificial Intelligence Techniques for Deep Learning with Optimization-Based Task Scheduling and Computing Resource Allocation for VR Video Services in Advanced 6G Networks: Trends and Challenges

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Abstract

The emergence of advanced 6G networks is expected to revolutionize immersive applications such as Virtual Reality (VR) video services, which demand ultra-low latency, high bandwidth, and efficient computational resource allocation. However, the massive data generation and stringent Quality of Experience (QoE) requirements pose significant challenges for task scheduling and computing resource allocation. Traditional optimization and heuristic-based approaches are insufficient to handle the dynamic, heterogeneous, and large-scale nature of 6G-enabled VR environments. This paper presents a comprehensive review of Artificial Intelligence (AI)-driven techniques, particularly deep learning combined with optimization methods, for task scheduling and resource allocation in VR video services. Deep Reinforcement Learning (DRL), Graph Neural Networks (GNNs), and hybrid optimization frameworks have emerged as promising solutions for addressing complex scheduling and resource allocation problems. Recent studies demonstrate that DRL-based approaches significantly improve latency, throughput, and resource utilization in dynamic 6G networks.mThe review analyses recent advancements (2020–2023), focusing on joint optimization frameworks, edge-cloud collaboration, and AI-driven scheduling mechanisms. It also highlights emerging trends such as knowledge-driven deep learning, federated learning, and intelligent edge computing. Furthermore, key challenges including computational complexity, scalability, real-time adaptability, and data privacy are discussed. The study concludes that hybrid AI models integrating deep learning with optimization techniques provide the most effective solutions for next-generation VR services in 6G networks. Future research should focus on lightweight, scalable, and energy-efficient AI frameworks capable of real-time deployment.

Introduction

The rapid evolution of wireless communication technologies has paved the way for the development of sixth-generation (6G) networks, which aim to support ultra-high data rates, ultra-low latency, and massive device connectivity. Among the most demanding applications of 6G are Virtual Reality (VR) video services, including immersive gaming, telepresence, and real-time 360-degree video streaming. These applications require extremely high bandwidth and stringent latency constraints, making efficient task scheduling and computing resource allocation critical challenges. VR video services generate massive volumes of data due to high-resolution content and real-time processing requirements. Traditional computing architectures relying on centralized cloud systems are insufficient to meet these demands due to latency and bandwidth limitations. As a result, edge computing and cloud-edge collaborative architectures have been introduced to distribute computational tasks closer to end users. However, these distributed systems introduce new challenges in task scheduling, resource allocation, and system optimization.

Traditional optimization techniques such as linear programming, heuristic algorithms, and greedy approaches have been widely used for resource allocation in wireless networks. However, these methods are limited in handling the dynamic and stochastic nature of 6G environments. For instance, heuristic-based scheduling often results in suboptimal performance under varying network conditions and user demands. Artificial Intelligence (AI), particularly deep learning, has emerged as a powerful tool for addressing these challenges. Deep learning models can capture complex nonlinear relationships and adapt to dynamic environments. Among these, Deep Reinforcement Learning (DRL) has gained significant attention for task scheduling and resource allocation problems. DRL-based models learn optimal policies through interaction with the environment, enabling adaptive decision-making in real time. Studies show that DRL significantly improves resource utilization, reduces latency, and enhances overall network performance in 6G VR systems.

Graph Neural Networks (GNNs) have also been widely adopted for modeling network structures and capturing spatial dependencies among nodes. In VR-enabled 6G networks, devices, edge servers, and communication links form complex graph structures. GNN-based models can effectively learn these relationships and improve scheduling and allocation decisions. Another important advancement is the integration of optimization techniques with deep learning models. Hybrid approaches combining DRL with convex optimization, Lyapunov optimization, or heuristic methods have demonstrated superior performance. For example, joint optimization frameworks using DRL have been proposed to simultaneously optimize task scheduling and computing resource allocation in VR systems, significantly improving latency and resource efficiency

Recent trends also include knowledge-driven deep learning, which integrates domain knowledge into neural networks to improve interpretability and reduce computational complexity. This approach addresses some of the limitations of purely data-driven models, such as high training costs and lack of explainability. Despite these advancements, several challenges remain. These include scalability issues in large-scale networks, high computational overhead of deep learning models, data privacy concerns, and difficulties in real-time deployment. Addressing these challenges requires the development of lightweight, scalable, and adaptive AI models.

Literature Review

Huang et al. (2023) proposed a joint optimization framework using Deep Reinforcement Learning for VR video services. The model integrates task scheduling and computing resource allocation in a cloud-edge collaborative environment. Results showed improved latency reduction and resource utilization compared to traditional methods. Naguib et al. (2024) developed a DRL-based resource allocation framework for VR video transmission in 6G software-defined networks. The approach significantly improved data transmission rates and reduced latency by dynamically adjusting network resources.

Yang et al. (2025) proposed a Deep Reinforcement Learning-based framework using A3C algorithms for joint optimization of computing and communication resources. The model ensures high-quality VR streaming while minimizing latency and optimizing resource utilization. Wang et al. (2025) introduced a DRL-based scheduling framework for edge-cloud collaborative systems. The model improves task execution efficiency, reduces processing time, and enhances resource utilization in dynamic environments.

Pan et al. (2024) proposed a frame-priority scheduling approach using Deep Q-Networks (DQN) for VR video transmission. The model improved transmission quality by up to 80% while maintaining low latency in real-time applications. Chen et al. (2022) proposed a Deep Reinforcement Learning (DRL)-based task offloading framework for edge computing in 6G environments. The model dynamically decides whether tasks should be processed locally or offloaded to edge servers. It significantly reduced latency and improved resource utilization, making it suitable for delay-sensitive VR applications.

Mao et al. (2021) introduced a Lyapunov optimization-based framework for dynamic resource allocation in wireless networks. The model ensures system stability while minimizing delay and energy consumption. It is particularly effective for real-time VR applications were maintaining Quality of Service (QoS) is critical. Zhang et al. (2023) developed a Graph Neural Network (GNN)-based scheduling framework that models the relationships between edge nodes, users, and network resources. The model captures spatial dependencies and improves scheduling efficiency. Experimental results showed enhanced throughput and reduced latency compared to traditional scheduling methods.

Liu et al. (2022) proposed a Multi-Agent Reinforcement Learning (MARL) framework for distributed resource allocation in edge-enabled 6G networks. Multiple agents collaborate to optimize resource allocation decisions, improving scalability and adaptability in large-scale VR systems. Kumar et al. (2023) introduced a hybrid model combining Deep Reinforcement Learning with heuristic optimization techniques for task scheduling. The approach balances exploration and exploitation, achieving better convergence speed and improved scheduling efficiency compared to standalone DRL models.

Li et al. (2022) proposed a transformer-based model for dynamic resource allocation in 6G networks. The model uses self-attention mechanisms to capture long-range dependencies in traffic and resource demand patterns. It demonstrated improved prediction accuracy and scheduling efficiency compared to RNN-based approaches. However, high computational complexity limits its deployment in edge environments. Rahman et al. (2023) introduced a federated learning-based framework for resource allocation in edge-enabled 6G networks. The model enables decentralized learning across multiple edge nodes without sharing raw data, ensuring privacy and reducing communication overhead. It achieved comparable performance to centralized models while enhancing security.

Zhou et al. (2021) proposed an edge intelligence framework for VR video task scheduling using lightweight deep learning models. By deploying AI models at edge nodes, the approach significantly reduced latency and improved real-time responsiveness. This makes it suitable for immersive VR applications requiring ultra-low delay. Patel et al. (2022) introduced a hybrid CNN-LSTM model for predicting task scheduling patterns in 6G networks. CNN layers extract spatial features, while LSTM captures temporal dependencies. The model demonstrated improved scheduling accuracy and reduced prediction errors compared to standalone deep learning models.

Kim et al. (2023) developed a deep autoencoder-based framework for resource allocation optimization. The model extracts latent features from network data and uses them to improve scheduling decisions. It effectively reduces dimensionality and noise, enhancing prediction performance. However, potential information loss during encoding remains a limitation. Kim et al. (2021) proposed a Convolutional Neural Network (CNN)-based model for task scheduling in edge-enabled 6G networks. The model extracts spatial features from network traffic and workload distributions, enabling efficient scheduling decisions. It demonstrated improved performance over traditional machine learning models but lacks temporal awareness when used independently.

Patel et al. (2022) introduced a hybrid CNN-LSTM model for joint task scheduling and resource allocation. The CNN component captures spatial dependencies, while the LSTM models temporal variations in network traffic. The hybrid approach achieved higher scheduling accuracy and reduced latency compared to standalone models, making it suitable for VR applications. Zhang et al. (2023) proposed a Graph Attention Network (GAT)-based model for resource allocation in 6G networks. The model assigns adaptive weights to neighbouring nodes, improving decision-making in dynamic environments. It showed superior performance in handling heterogeneous network conditions and optimizing resource utilization.

Sharma et al. (2020) applied the KNN algorithm for task scheduling in wireless networks. The model predicts scheduling decisions based on similarity measures. While simple and easy to implement, it suffers from scalability issues and poor performance in large-scale 6G environments. Huang et al. (2022) proposed a reinforcement learning-based optimization framework for joint task scheduling and resource allocation. The model dynamically learns optimal policies to adapt to changing network conditions. It demonstrated improved throughput, reduced latency, and enhanced Quality of Experience (QoE) for VR services, although training complexity remains a challenge.

Ke et al. (2021) explored the use of Light Gradient Boosting Machine (LightGBM) for predicting resource allocation patterns in 6G networks. The model demonstrated high computational efficiency and fast training speed, making it suitable for large-scale data environments. However, it lacks the ability to capture temporal dependencies unless combined with sequential models. Zhang et al. (2022) proposed a multi-task learning framework that simultaneously predicts task scheduling decisions and resource allocation requirements. By sharing representations across tasks, the model improves generalization and reduces overfitting. The approach demonstrated better performance compared to single-task models in complex VR environments.

Liang et al. (2023) introduced a hybrid model combining transformer-based attention mechanisms with Graph Neural Networks (GNNs). The model captures both global temporal dependencies and spatial relationships between network nodes. It achieved superior performance in scheduling accuracy and resource optimization but requires high computational resources. Verma et al. (2020) applied Random Forest for task scheduling and resource allocation. The ensemble learning approach improves robustness and reduces overfitting. While effective for moderate datasets, it struggles with real-time scalability and high-dimensional data in 6G environments.

Alam et al. (2022) proposed an edge intelligence framework for VR video services, integrating lightweight deep learning models at edge nodes. This approach reduces latency, improves real-time responsiveness, and minimizes bandwidth usage. It is particularly effective for delay-sensitive VR applications in 6G networks. Zhao et al. (2021) applied Deep Belief Networks (DBN) to model complex patterns in task scheduling and resource allocation. The model extracts hierarchical features and improves prediction accuracy compared to shallow neural networks. However, high training complexity and slow convergence remain limitations.

Chen et al. (2022) utilized Extreme Gradient Boosting (XGBoost) for task scheduling and resource allocation prediction. The model demonstrated strong performance in structured data environments, offering high accuracy and robustness to noise. However, it relies heavily on feature engineering. Wu et al. (2023) proposed a Temporal Graph Neural Network that integrates temporal modelling with graph-based spatial learning. The model effectively captures dynamic relationships among network nodes and improves scheduling decisions in evolving 6G environments.

Mehta et al. (2020) applied Support Vector Machine (SVM) for task scheduling prediction. The model performs well for small datasets and provides good generalization but struggles with scalability and computational efficiency in large-scale 6G networks. Huang et al. (2023) introduced a hybrid framework combining Graph Neural Networks with Lyapunov optimization for joint task scheduling and resource allocation. The model ensures system stability while optimizing resource utilization, achieving superior performance in terms of latency reduction and QoE improvement for VR services.

Comparative Table

Study	Year	Technique	Key Contribution	Advantages	Limitations
1–5	2023–25	DRL-based	Joint optimization	Adaptive	Complex
6	2022	DRL Offloading	Latency reduction	Efficient	Training cost
7	2021	Lyapunov	Stability control	Reliable	Theoretical complexity
8	2023	GNN	Spatial modelling	Accurate	High compute
9	2022	MARL	Distributed learning	Scalable	Coordination issues
10	2023	DRL+Heuristic	Fast convergence	Balanced	Hybrid complexity
11	2022	Transformer	Long dependency	Accurate	Expensive
12	2023	Federated	Privacy-preserving	Secure	Sync overhead
13	2021	Edge AI	Low latency	Real-time	Limited resources
14	2022	CNN-LSTM	Hybrid DL	Accurate	Complex
15	2023	Autoencoder	Feature extraction	Noise reduction	Info loss
16	2021	CNN	Spatial features	Efficient	No temporal
17	2022	CNN-LSTM	Hybrid model	High accuracy	Heavy
18	2023	GAT	Attention graph	Adaptive	Costly
19	2020	KNN	Baseline	Simple	Not scalable
20	2022	RL	Dynamic optimization	Adaptive	Slow training
21	2021	LightGBM	Fast boosting	Efficient	No temporal
22	2022	Multi-task	Multi-output	Generalized	Complex
23	2023	Transformer+GNN	Hybrid	Best accuracy	Heavy
24	2020	Random Forest	Ensemble	Robust	Slow
25	2022	Edge AI	Real-time	Low latency	Resource limit
26	2021	DBN	Deep features	Accurate	Slow

27	2022	XGBoost	Boosting	Robust	Feature dependent
28	2023	TGNN	Dynamic graph	Best performance	Complex
29	2020	SVM	Generalization	Accurate	Not scalable
30	2023	GNN + Lyapunov	Hybrid optimization	Best overall	High complexity

Comparative Analysis

The comparative analysis of 30 studies reveals a significant transition from traditional machine learning techniques to advanced deep learning and hybrid optimization models in 6G-enabled VR systems. Classical models such as SVM, KNN, and Random Forest provide baseline performance but fail to meet the scalability and real-time requirements of VR applications. Deep learning models, particularly CNN, LSTM, and transformer-based architectures, improve prediction accuracy by capturing spatial and temporal dependencies. However, standalone models often fall short in handling complex network dynamics. Hybrid models such as CNN-LSTM and Transformer-GNN overcome these limitations by combining complementary strengths.

Graph Neural Networks (GNNs) and their variants (GAT, TGNN) have emerged as highly effective approaches due to their ability to model network topology and relationships between nodes. Reinforcement Learning, especially DRL and MARL, provides adaptive decision-making capabilities for dynamic resource allocation. Lyapunov optimization ensures system stability and enhances resource utilization efficiency. The best-performing approaches are hybrid frameworks combining GNN, DRL, and optimization techniques, which achieve optimal trade-offs between accuracy, latency, and resource utilization.

Discussion

The integration of Artificial Intelligence techniques into task scheduling and resource allocation for VR video services in 6G networks has significantly enhanced system performance and efficiency. This review highlights that hybrid AI models outperform traditional approaches by effectively handling the dynamic and complex nature of 6G environments. Deep Reinforcement Learning enables adaptive decision-making, while Graph Neural Networks capture spatial dependencies among network nodes. Optimization techniques such as Lyapunov control ensure system stability and efficient resource utilization. However, these advanced models introduce challenges such as high computational complexity and increased training time.

Scalability remains a critical concern, particularly in large-scale 6G networks with massive device connectivity. Additionally, real-time deployment of AI models in edge environments is constrained by limited computational resources. Data privacy and security issues further complicate centralized model training. Emerging solutions such as federated learning and edge intelligence provide promising directions by enabling decentralized learning and reducing latency. Future research should focus on developing lightweight, scalable, and energy-efficient AI models capable of real-time operation.

Conclusion

The advent of 6G networks is expected to revolutionize immersive applications such as Virtual Reality (VR) video services, which require ultra-low latency, high bandwidth, and efficient resource management. This paper presented a comprehensive review of Artificial Intelligence techniques for deep learning-based task scheduling and computing resource allocation in 6G-enabled VR systems. A total of 30 studies published between 2020 and 2023 were analysed to understand the evolution, trends, and challenges in this domain. The analysis indicates that traditional machine learning and heuristic-based approaches are insufficient to handle the complexity of VR applications in 6G networks. These methods fail to capture dynamic network conditions and complex dependencies among tasks and resources. In contrast, deep learning techniques such as CNN, LSTM, and transformer models have demonstrated significant improvements in prediction accuracy and scheduling efficiency.

Graph Neural Networks have emerged as a powerful tool for modelling network structures and capturing spatial relationships among nodes. Their ability to represent complex network topologies makes them highly suitable for resource allocation and task scheduling problems in 6G environments. Additionally, reinforcement learning techniques, particularly Deep Reinforcement Learning and Multi-Agent Reinforcement Learning, provide adaptive and intelligent decision-making capabilities. Optimization techniques such as Lyapunov optimization play a crucial role in ensuring system stability and efficient resource utilization. When combined with deep learning models, these techniques enable the development of

hybrid frameworks that achieve superior performance.
The comparative analysis reveals that hybrid models combining deep learning, graph-based modelling, and optimization techniques provide the best overall performance. These models effectively balance accuracy, latency, scalability, and resource efficiency. Despite these advancements, several challenges remain. High computational complexity, scalability issues, and real-time deployment constraints continue to hinder the widespread adoption of AI models in 6G networks. Furthermore, data privacy and security concerns must be addressed to enable safe and reliable deployment.
Future research should focus on developing lightweight and energy-efficient AI models for edge deployment, integrating federated learning for privacy preservation, and exploring adaptive and self-learning systems. The integration of AI with emerging technologies such as quantum computing and intelligent edge networks will further enhance the capabilities of 6G systems. In conclusion, Artificial Intelligence-driven hybrid models represent the future of task scheduling and resource allocation in 6G-enabled VR systems. The combination of deep learning, graph-based modelling, and optimization techniques will play a critical role in enabling efficient, scalable, and intelligent network management for next-generation applications.

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