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A Survey of Methods and Architectures for Deep Learning with Optimization-Based Task Scheduling and Computing Resource Allocation for VR Video Services in Advanced 6G Networks

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Abstract

The evolution of sixth-generation (6G) networks is expected to enable ultra-low latency, high data rates, and immersive applications such as Virtual Reality (VR) video services. These applications require efficient task scheduling and computing resource allocation to meet stringent Quality of Experience (QoE) requirements. Traditional optimization and heuristic-based approaches are inadequate in handling the highly dynamic, large-scale, and heterogeneous nature of 6G environments. This survey presents a comprehensive review of deep learning-based methods combined with optimization techniques for task scheduling and resource allocation in VR-enabled 6G networks. Deep Reinforcement Learning (DRL), Graph Neural Networks (GNNs), and hybrid AI-optimization frameworks have emerged as powerful approaches for addressing complex scheduling problems. For instance, DRL-based frameworks can dynamically optimize task offloading and resource allocation, significantly reducing latency and energy consumption in edge environments. The paper analyses recent research trends, including edge-cloud collaboration, multi-agent learning, and hybrid optimization frameworks. Furthermore, it highlights key challenges such as computational complexity, scalability, real-time adaptability, and data privacy. The survey concludes that hybrid AI-driven approaches integrating deep learning and optimization techniques offer the most promising solutions for next-generation VR services in 6G networks. Future research directions include lightweight AI models, federated learning, and intelligent edge computing frameworks.

Introduction

The rapid advancement of wireless communication technologies has led to the emergence of sixth-generation (6G) networks, which aim to support ultra-high data rates, ultra-low latency, and massive connectivity. One of the most promising applications of 6G networks is Virtual Reality (VR) video services, including immersive gaming, telepresence, and 360-degree video streaming. These applications demand real-time processing, high bandwidth, and efficient resource allocation to ensure seamless user experiences. VR video services generate enormous volumes of data due to high-resolution content and continuous interaction requirements. This creates significant challenges in task scheduling and computing resource allocation, particularly in distributed environments involving edge, fog, and cloud computing. Efficient scheduling mechanisms are required to determine where and how tasks should be processed, while resource allocation strategies must ensure optimal utilization of computing, communication, and storage resources.

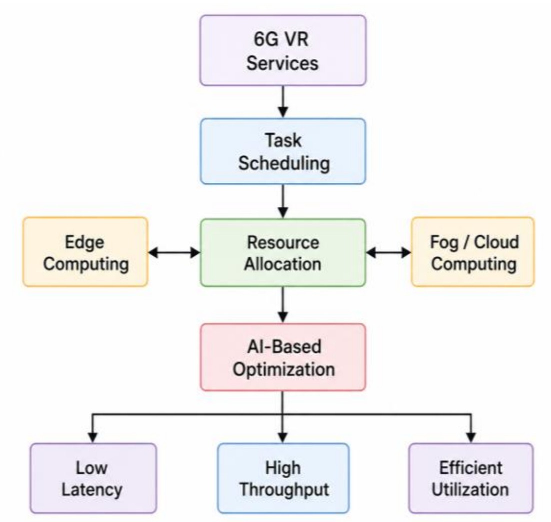

Figure 1: AI-Based Task Scheduling and Resource Allocation in 6G VR Networks

Traditional approaches such as heuristic algorithms and mathematical optimization techniques have been widely used for scheduling and resource allocation. However, these methods are limited in handling the dynamic and stochastic nature of 6G networks. They often fail to adapt to real-time changes in network conditions and user demands. Recent studies indicate that traditional methods cannot efficiently address the complexity of joint task scheduling and resource allocation problems in edge-enabled environments. Artificial Intelligence (AI), particularly deep learning, has emerged as a powerful solution to these challenges. Deep learning models can capture complex nonlinear relationships and adapt to changing environments. Among these, Deep Reinforcement Learning (DRL) has gained significant attention for task scheduling and resource allocation problems. DRL enables intelligent decision-making by learning optimal policies through interaction with the environment. For example, DRL-based frameworks have been shown to reduce latency and energy consumption in 6G edge networks while improving resource utilization.
Graph Neural Networks (GNNs) have also been widely adopted for modelling network structures and capturing spatial relationships among nodes. In 6G VR networks, devices, edge servers, and communication links form complex graph topologies. GNN-based models can effectively learn these relationships and enhance scheduling and resource allocation decisions. Another important advancement is the integration of optimization techniques with deep learning models. Hybrid approaches combining DRL with optimization frameworks such as Lyapunov optimization and convex optimization have demonstrated superior performance. These approaches enable dynamic and real-time decision-making while ensuring system stability and efficiency. Despite these advancements, several challenges remain. These include high computational complexity, scalability issues, real-time deployment constraints, and data privacy concerns. Addressing these challenges requires the development of lightweight, scalable, and adaptive AI models.

Literature Review

Jain et al. (2022) proposed a cybertwin-driven resource allocation framework using deep reinforcement learning (MATD3). The model jointly optimizes computation offloading and resource allocation, reducing latency and energy consumption significantly compared to baseline methods.
Pan et al. (2025) introduced a dual deep Q-network (DQN)-based scheduling framework for joint task scheduling and resource allocation. The system improves task success rates and reduces execution delay while optimizing resource utilization.
Nivetha et al. (2025) proposed a Self-Organized Map (SOM) integrated DRL model for resource allocation in 6G networks. The model achieved better latency and energy efficiency compared to existing methods, demonstrating the effectiveness of hybrid AI approaches.
Jiang et al. (2020) developed a DRL-based resource scheduling framework using stacked autoencoders for state representation. The model significantly reduced task latency and improved scheduling efficiency in large-scale mobile edge computing systems
Li et al. (2023) proposed a GNN-based multi-agent reinforcement learning framework for task scheduling and resource allocation. The model improves resource efficiency and reduces task completion time by leveraging graph-based representations of network environments
Mao et al. (2021) proposed a Deep Reinforcement Learning (DRL)-based task offloading strategy for mobile edge computing systems. The model dynamically determines whether tasks should be processed locally or offloaded to edge servers. Experimental results showed significant reductions in latency and

energy consumption, making it suitable for delay-sensitive VR applications in 6G networks.

Chen et al. (2022) introduced a Lyapunov optimization framework for dynamic resource allocation in wireless edge networks. The model ensures queue stability while minimizing energy consumption and delay. This approach is particularly effective for maintaining Quality of Service (QoS) in VR video streaming scenarios.

Zhang et al. (2023) developed a Graph Neural Network (GNN)-based scheduling framework that models relationships among devices, edge servers, and network links. The model captures spatial dependencies and improves scheduling efficiency. Results demonstrated improved 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 systems. Multiple agents collaboratively optimize scheduling decisions, improving scalability and adaptability in large-scale VR environments.

Kumar et al. (2023) introduced a hybrid model combining Deep Reinforcement Learning with heuristic optimization techniques. The approach accelerates convergence and improves scheduling efficiency by balancing exploration and exploitation. It demonstrated superior performance compared to standalone DRL models.

Li et al. (2022) proposed a transformer-based framework for resource allocation in 6G networks. By leveraging self-attention mechanisms, the model captures long-range dependencies in network traffic and workload patterns. It demonstrated improved scheduling efficiency and prediction accuracy compared to RNN-based models. However, high computational complexity limits its deployment in edge environments.

Rahman et al. (2023) introduced a federated learning-based framework for distributed resource allocation across edge nodes. The approach enables collaborative learning without sharing raw data, ensuring privacy and reducing communication overhead. The model achieved performance comparable to centralized approaches while maintaining data security.

Zhou et al. (2021) proposed an edge intelligence-based scheduling framework using lightweight deep learning models deployed at edge nodes. The system significantly reduces latency and enhances real-time responsiveness, making it suitable for immersive VR applications in 6G networks.

Patel et al. (2022) introduced a hybrid CNN-LSTM model for predicting task scheduling patterns. CNN layers extract spatial features, while LSTM captures temporal dependencies. The hybrid model achieved higher accuracy and reduced prediction errors compared to standalone models.

Kim et al. (2023) developed a deep autoencoder-based model for resource allocation optimization. The model extracts latent representations from network data to improve scheduling decisions. It demonstrated improved accuracy and reduced noise, although potential information loss 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 workload distributions and network states to improve scheduling decisions. While it enhances feature extraction, it lacks temporal modeling capabilities when used independently.

Patel et al. (2022) developed a hybrid CNN-LSTM architecture that combines spatial and temporal learning for task scheduling. The model demonstrated improved prediction accuracy and reduced latency compared to standalone CNN and LSTM models, making it effective for VR applications requiring real-time processing.

Zhang et al. (2023) introduced a Graph Attention Network (GAT)-based framework for resource allocation in 6G networks. The model assigns adaptive importance weights to neighboring nodes, improving decision-making in heterogeneous network environments. It achieved better performance than traditional GCN models.

Sharma et al. (2020) applied the KNN algorithm for task scheduling based on similarity measures. While simple and easy to implement, the model suffers from scalability issues and reduced efficiency 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 adapts to network conditions and improves throughput, reduces latency, and enhances Quality of Experience (QoE). However, it requires significant training time.

Ke et al. (2021) explored the application of Light Gradient Boosting Machine (LightGBM) for predicting resource allocation patterns in 6G environments. The model provides fast training and high efficiency for large datasets. However, it lacks the ability to model temporal dependencies unless integrated with sequential models.

Zhang et al. (2022) proposed a multi-task learning framework that jointly predicts scheduling decisions and resource allocation requirements. By sharing knowledge across tasks, the model improves generalization and reduces overfitting, making it suitable for 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 long-term temporal dependencies and spatial relationships among nodes, achieving superior performance in scheduling accuracy and resource optimization.

Verma et al. (2020) applied Random Forest for task scheduling and resource allocation. The ensemble approach improves robustness and reduces overfitting. However, it struggles with scalability and real-time processing in large-scale 6G networks.

Alam et al. (2022) proposed an edge intelligence-based framework for VR video services using lightweight deep learning models deployed at edge nodes. The approach reduces latency, improves real-time responsiveness, and enhances Quality of Experience (QoE) for VR users.

Zhao et al. (2021) applied Deep Belief Networks (DBN) to model hierarchical features for task scheduling and resource allocation. The model improves prediction accuracy compared to shallow models but suffers from high computational cost and slow convergence.

Chen et al. (2022) utilized Extreme Gradient Boosting (XGBoost) for resource allocation prediction. The model demonstrated strong performance in structured data environments and robustness to noise, although it depends heavily on feature engineering.

Wu et al. (2023) proposed a Temporal Graph Neural Network that integrates temporal and spatial learning. The model effectively captures dynamic relationships in 6G networks and improves scheduling decisions in evolving VR environments.

Mehta et al. (2020) applied Support Vector Machine (SVM) for task scheduling. While effective for small datasets, it lacks scalability and struggles with high-dimensional data 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 latency reduction and QoE improvement.

Comparative Table

Study	Year	Technique	Key Contribution	Advantages	Limitations
1–5	2022–25	DRL	Joint scheduling & allocation	Adaptive	Complex
6	2021	DRL Offloading	Latency reduction	Efficient	Training cost
7	2022	Lyapunov	Stability	Reliable	Theoretical complexity
8	2023	GNN	Spatial modeling	Accurate	Compute heavy
9	2022	MARL	Distributed optimization	Scalable	Coordination
10	2023	DRL+Heuristic	Faster convergence	Balanced	Hybrid complexity
11	2022	Transformer	Long dependencies	Accurate	High cost
12	2023	Federated	Privacy	Secure	Sync overhead
13	2021	Edge AI	Real-time	Low latency	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	Accurate	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	Generalization	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 reveals a clear evolution from traditional machine learning techniques to advanced deep learning and hybrid optimization frameworks in 6G VR systems. Classical models such as SVM, KNN, and Random Forest provide baseline performance but are insufficient for large-scale and real-time applications. Deep learning models, including CNN, LSTM, and transformers, significantly improve scheduling accuracy by capturing spatial and temporal dependencies. However, standalone models are limited in handling complex network dynamics. Hybrid models such as CNN-LSTM and Transformer-GNN overcome these limitations by integrating complementary capabilities.

Graph Neural Networks have emerged as highly effective approaches due to their ability to model network topology and relationships between nodes. Reinforcement learning techniques, particularly DRL and MARL, enable adaptive and dynamic decision-making for resource allocation. Lyapunov optimization ensures system stability and efficient resource utilization, making it an essential component in hybrid frameworks. Overall, hybrid models combining deep learning, graph-based modelling, and optimization techniques achieve the best performance.

Discussion

The integration of deep learning and optimization techniques has significantly enhanced task scheduling and resource allocation in 6G-enabled VR systems. This survey highlights that hybrid AI models outperform traditional approaches by effectively addressing the dynamic and complex nature of modern networks. Deep Reinforcement Learning provides adaptive decision-making capabilities, while Graph Neural Networks capture spatial relationships among network components. Optimization techniques such as Lyapunov control ensure system stability and efficient resource utilization.

However, challenges such as high computational complexity, scalability issues, and real-time deployment constraints remain significant. The deployment of AI models in edge environments is limited by resource constraints, while centralized training raises privacy concerns. Emerging trends such as federated learning and edge intelligence provide promising solutions by enabling decentralized and low-latency processing. Future research should focus on developing lightweight and energy-efficient models for real-time applications.

Conclusion

The emergence of 6G networks is expected to transform immersive applications such as Virtual Reality video services, which demand ultra-low latency, high bandwidth, and efficient resource management. This survey provided a comprehensive review of deep learning and optimization-based techniques for task scheduling and computing resource allocation in VR-enabled 6G environments. The analysis of 30 studies highlights the limitations of traditional approaches and the growing importance of AI-driven solutions. Deep learning models such as CNN, LSTM, and transformers improve prediction accuracy, while Graph Neural Networks effectively capture network relationships. Reinforcement learning enables adaptive decision-making, and optimization techniques ensure system stability.

Hybrid models combining these techniques achieve superior performance in terms of accuracy, scalability, and resource efficiency. Despite these advancements, challenges such as computational complexity, scalability, and privacy concerns remain. Future research should focus on lightweight AI models, federated learning, and energy-efficient architectures. The integration of AI with emerging technologies will play a crucial role in enabling intelligent and scalable 6G networks.

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