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Deep Learning and Optimization Approaches in Task Scheduling and Computing Resource Allocation for VR Video Services in Advanced 6G Networks: A Review

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Abstract

The rapid advancement of sixth-generation (6G) wireless networks is expected to enable immersive applications such as Virtual Reality (VR) video services, which require ultra-low latency, high bandwidth, and efficient resource utilization. Traditional cloud-centric architectures struggle to meet these stringent requirements due to communication delays and limited scalability. As a result, integrating deep learning with optimization techniques in edge computing environments has emerged as a promising solution for efficient task scheduling and computing resource allocation. Deep learning models, particularly Deep Reinforcement Learning (DRL), have demonstrated strong capabilities in handling dynamic and complex decision-making problems. These models enable intelligent task offloading and adaptive resource allocation by learning optimal policies in uncertain environments. Recent studies show that DRL-based scheduling frameworks outperform traditional heuristic and greedy algorithms, significantly reducing task completion time and improving system efficiency. Optimization techniques such as Lyapunov optimization and convex optimization further enhance system performance by providing theoretical guarantees for stability and resource efficiency. These approaches enable balancing multiple objectives, including latency, energy consumption, and throughput. Moreover, hybrid models combining deep learning and optimization techniques have been shown to improve scalability and adaptability in edge-cloud environments. VR video services introduce unique challenges such as real-time rendering, high data transmission rates, and strict Quality of Experience (QoE) requirements. Efficient task scheduling and resource allocation are therefore critical for ensuring seamless service delivery. This review systematically analyses recent advancements in deep learning and optimization-based approaches, compares their effectiveness, and identifies key research challenges.

Introduction

The evolution of wireless communication technologies toward sixth-generation (6G) networks is expected to revolutionize digital services by enabling ultra-reliable, low-latency, and high-capacity communication. Among the most promising applications of 6G are Virtual Reality (VR) video services, which require real-time interaction, high-resolution rendering, and seamless data transmission. These requirements impose significant challenges on existing network infrastructures, particularly in terms of latency, bandwidth, and computational resource management. Traditional cloud computing architectures are not well-suited for VR applications due to their inherent limitations in handling latency-sensitive workloads. The physical distance between users and centralized cloud servers introduces communication delays, negatively impacting the Quality of Experience (QoE). To address these challenges, Mobile Edge Computing (MEC) has emerged as a key enabling technology that brings computation closer to end users. However, MEC environments are characterized by limited resources, dynamic workloads, and heterogeneous network conditions, making efficient task scheduling and resource allocation highly complex problems.

Task scheduling and resource allocation are critical components in edge computing systems. Task scheduling determines how computational tasks are distributed among available resources, while resource allocation ensures optimal utilization of computing, storage, and communication resources. These problems are inherently complex and often modelled as stochastic optimization problems due to dynamic system conditions. In such environments, traditional heuristic and rule-based approaches fail to deliver optimal performance. Recent advancements in deep learning, particularly Deep Reinforcement Learning (DRL), have provided powerful tools for addressing these challenges. DRL enables systems to learn optimal decision-making policies through interaction with the environment, making it highly suitable for dynamic and uncertain scenarios. Studies show that DRL-based approaches can effectively optimize task scheduling and resource allocation by minimizing latency and energy consumption while maximizing system efficiency.

Furthermore, task scheduling in edge computing is influenced by multiple factors such as network latency, resource availability, and task dependencies. These complexities require adaptive and scalable solutions. Research indicates that deep learning-based scheduling algorithms can dynamically adjust to changing conditions, improving responsiveness and system performance. In addition to deep learning, optimization techniques play a crucial role in ensuring efficient resource utilization. Approaches such as Lyapunov optimization and multi-objective optimization provide mathematical frameworks for balancing conflicting objectives, including latency, energy consumption, and throughput. These techniques are particularly useful in real-time applications such as VR video streaming, where maintaining system stability is essential.

Recent studies have also explored hybrid approaches that combine deep learning with optimization techniques. These approaches leverage the strengths of both methodologies, enabling efficient decision-making and improved system performance. For example, DRL-based frameworks integrated with adaptive optimization strategies have demonstrated superior performance in dynamic edge-cloud environments, achieving better load balancing and reduced response times. Despite these advancements, several challenges remain. These include scalability issues, high computational overhead, data privacy concerns, and the need for real-time decision-making. Addressing these challenges requires the development of lightweight, adaptive, and privacy-preserving models.

This review aims to provide a comprehensive analysis of deep learning and optimization-based approaches for task scheduling and computing resource allocation in VR video services within advanced 6G networks. It systematically reviews recent literature, compares different methodologies, and identifies future research directions.

Literature Review

Jiang et al. proposed a stacked autoencoder-based Deep Reinforcement Learning (DRL) framework for resource scheduling in large-scale MEC networks. The model reduces latency and optimizes resource allocation by learning efficient offloading strategies. Liu et al. developed a DQN-based task scheduling and resource allocation model for edge computing. The approach minimizes task completion time under energy constraints and outperforms traditional scheduling algorithms.

Anand et al. introduced an adaptive DRL-based scheduling framework (EADRL) that dynamically adjusts learning parameters and improves load balancing, response time, and system efficiency.

Li et al. presented a comprehensive survey on DRL-based task scheduling and resource allocation in vehicular edge computing, highlighting the importance of joint optimization strategies for minimizing energy consumption and delay. Avan et al. conducted a state-of-the-art review on task scheduling algorithms in edge computing, emphasizing the importance of distributed scheduling and optimization techniques in improving system performance.

Mao et al. proposed a Deep Reinforcement Learning (DRL)-based computation offloading and resource allocation framework for mobile edge computing (MEC). The model dynamically learns optimal policies to minimize latency and energy consumption. Their results demonstrate significant improvements in system performance compared to traditional heuristic approaches. Chen et al. introduced a deep learning-based task scheduling model integrated with optimization techniques for edge computing environments. The model balances workload distribution across edge nodes and reduces processing delays, making it suitable for VR video services.

Wang et al. developed a multi-agent deep reinforcement learning (MADRL) framework for distributed task scheduling and computing resource allocation. The approach enables cooperative decision-making among edge devices, improving scalability and resource utilization. Zhang et al. proposed a Lyapunov optimization-based framework for resource allocation in MEC systems. The model ensures system stability while minimizing delay and energy consumption, making it effective for real-time VR applications.

Liu et al. introduced a transformer-based deep learning model for task scheduling and resource allocation in edge computing. The model captures long-range dependencies in network traffic and improves scheduling efficiency in dynamic environments. He et al. proposed a Deep Q-Network (DQN)-based task scheduling mechanism for mobile edge computing systems. The model dynamically selects optimal offloading strategies to minimize latency and energy consumption. The study demonstrates improved Quality of Experience (QoE) for VR services in dynamic network environments.

Xu et al. introduced a joint optimization framework combining deep neural networks with heuristic optimization for task scheduling and resource allocation. The approach reduces computational overhead and improves task execution efficiency in large-scale edge networks. Tang et al. developed a Graph Neural Network (GNN)-based scheduling model for distributed edge computing systems. The model captures relationships among edge nodes and improves task allocation efficiency, particularly for VR video streaming.

Huang et al. proposed a CNN-LSTM hybrid model for workload prediction in edge computing. The predicted workload information is used to optimize task scheduling and resource allocation, resulting in reduced latency and improved system performance. Sun et al. introduced a Lyapunov drift-plus-penalty optimization approach for joint task scheduling and energy-efficient resource allocation. The model ensures system stability while minimizing latency and energy consumption in VR-enabled IoT systems.

Zhao et al. proposed an attention-based Deep Reinforcement Learning framework for task scheduling in mobile edge computing. By assigning dynamic importance to tasks, the model improves latency performance and enhances resource utilization in VR service environments.Kim et al. developed an autoencoder-based model for efficient resource allocation in edge computing systems. The model reduces dimensionality of system states and improves decision-making efficiency in scheduling VR workloads.

Ahmed et al. introduced a hybrid deep learning and evolutionary optimization framework for task scheduling. The approach enhances convergence speed and improves system efficiency in dynamic 6G edge environments. Zhou et al. proposed a dynamic Graph Neural Network-based scheduling model that adapts to changing network conditions. The model significantly improves task allocation efficiency for VR video services.

Kumar et al. developed a Lyapunov optimization-based framework for real-time task scheduling and energy-efficient resource allocation. The model ensures system stability while minimizing latency and energy consumption. Li et al. proposed an LSTM-based workload prediction model for task scheduling in edge computing. The model improves latency performance by predicting future workloads and enabling proactive resource allocation.

Gao et al. introduced a Graph Convolutional Network (GCN)-based framework for resource allocation in MEC systems. The model captures spatial dependencies among edge nodes and enhances scheduling efficiency. Patel et al. developed an ensemble learning-based scheduling model combining Random Forest and Gradient Boosting. The approach improves robustness and prediction accuracy in heterogeneous environments.

Ren et al. proposed an Auto-Metric Graph Neural Network for adaptive resource allocation. The model dynamically adjusts network topology and improves task scheduling performance in VR systems. Sharma et al. introduced a CNN-LSTM hybrid model for workload prediction and task scheduling. The model effectively captures spatiotemporal features and improves decision-making accuracy. Alshammari et al. proposed a Lyapunov optimization-based framework for energy-efficient resource allocation in MEC systems supporting VR applications.

Tang et al. developed a transformer-based scheduling model integrated with edge computing. The model captures long-range dependencies and improves scheduling efficiency. Verma et al. introduced a Support

Vector Regression (SVR)-based scheduling model as a baseline approach. While simpler, it provides comparative insights against deep learning models. Hassan et al. proposed a federated deep learning framework for distributed task scheduling and resource allocation. The model enhances privacy while maintaining system performance. Xu et al. introduced a multi-task learning-based deep neural network for joint scheduling and resource allocation. The model optimizes multiple objectives simultaneously, improving system efficiency.

Comparative Table and Analysis

Study	Year	Method	Technique	Advantages	Limitations
Jiang	2020	DRL	Autoencoder + RL	Low latency	High training cost
Liu	2025	DQN	RL scheduling	Efficient	Future-based
Anand	2025	DRL	Adaptive RL	Improved QoE	Complex
Li	2025	Survey	DRL review	Insightful	Not experimental
Avan	2023	Review	Scheduling survey	Comprehensive	No model
Mao	2020	DRL	Offloading	Efficient	Complexity
Chen	2021	DL + Opt	Hybrid	Balanced	Overhead
Wang	2022	MADRL	Multi-agent	Scalable	Training cost
Zhang	2021	Lyapunov	Optimization	Stable	Complex math
Liu	2023	Transformer	Scheduling	Accurate	Heavy
He	2021	DQN	RL scheduling	Adaptive	Convergence issues
Xu	2022	DL + Heuristic	Hybrid	Efficient	Complexity
Tang	2023	GNN	Graph learning	Accurate	Cost
Huang	2020	CNN-LSTM	Prediction	Good accuracy	Training heavy
Sun	2022	Lyapunov	Energy optimization	Stable	Complex
Zhao	2021	Attention RL	Scheduling	Accurate	Heavy
Kim	2020	Autoencoder	Feature reduction	Efficient	Info loss
Ahmed	2022	Hybrid DL	Optimization	Fast convergence	Complex
Zhou	2023	GNN	Dynamic graph	Adaptive	Cost
Kumar	2021	Lyapunov	Scheduling	Stable	Complex
Li	2020	LSTM	Prediction	Efficient	Limited spatial
Gao	2021	GCN	Spatial learning	Accurate	Complex
Patel	2022	Ensemble	RF + GB	Robust	Less deep
Ren	2023	Auto-GNN	Adaptive graph	Flexible	Cost
Sharma	2021	CNN-LSTM	Hybrid	Accurate	Heavy
Alshammari	2022	Lyapunov	Resource mgmt	Efficient	Math complexity
Tang	2023	Transformer	Scheduling	Powerful	Heavy
Verma	2020	SVR	ML baseline	Simple	Low accuracy
Hassan	2022	Federated DL	Privacy	Secure	Communication cost
Xu	2023	Multi-task DL	Joint optimization	Efficient	Complex

Analysis

The analysis reveals that Deep Reinforcement Learning (DRL) and Graph Neural Networks (GNNs) are the most dominant approaches for task scheduling and resource allocation in VR-enabled 6G networks. DRL provides adaptive decision-making capabilities, while GNNs effectively model distributed edge environments. Hybrid approaches combining deep learning and optimization outperform traditional models by improving latency, scalability, and resource utilization. Lyapunov optimization ensures system stability but introduces mathematical complexity. Emerging techniques such as federated learning and transformers enhance privacy and long-range dependency modeling, making them promising for future research.

Discussion

Deep learning and optimization techniques have significantly transformed task scheduling and resource allocation in VR video services within 6G networks. The use of Deep Reinforcement Learning enables intelligent decision-making in dynamic environments, making it highly effective for real-time VR applications. Graph Neural Networks further enhance system performance by modelling spatial relationships among distributed edge nodes. Optimization techniques such as Lyapunov optimization provide strong theoretical guarantees for system stability and efficient resource utilization. However, their complexity poses challenges for real-world implementation. Hybrid approaches combining deep learning with optimization techniques offer a balanced solution by leveraging the strengths of both methods. Despite these advancements, several challenges remain. These include computational overhead, scalability issues, and energy efficiency constraints. VR applications require ultra-low latency and high reliability, which necessitate lightweight and efficient models. Federated learning and transformer-based models are emerging as promising solutions to address privacy and long-range dependency challenges. Future research should focus on developing integrated frameworks that combine deep learning, optimization, and edge computing to enable efficient and scalable VR service delivery in 6G networks.

Conclusion

The emergence of 6G networks is expected to revolutionize immersive technologies such as Virtual Reality (VR), enabling applications that demand ultra-low latency, high bandwidth, and real-time processing. However, these requirements pose significant challenges for task scheduling and computing resource allocation, particularly in edge computing environments where resources are constrained and network conditions are highly dynamic. This review has provided a comprehensive analysis of deep learning and optimization-based approaches for addressing these challenges. Deep learning techniques, particularly Deep Reinforcement Learning (DRL), have demonstrated strong capabilities in handling complex and dynamic decision-making problems. DRL-based models can learn optimal scheduling policies through interaction with the environment, enabling efficient task offloading and resource allocation. These models are highly adaptive and can respond to changing network conditions, making them suitable for VR applications in 6G networks. Graph Neural Networks (GNNs) have also emerged as powerful tools for modeling relationships among distributed edge nodes. By capturing spatial dependencies, GNN-based models improve task scheduling efficiency and resource allocation accuracy. Advanced architectures such as Auto-Metric GNNs further enhance adaptability by dynamically learning network structures. Optimization techniques, particularly Lyapunov optimization, provide a robust mathematical framework for ensuring system stability and efficient resource utilization. These approaches enable balancing multiple objectives, including latency, energy consumption, and throughput. However, their complexity can limit practical implementation. ybrid approaches that integrate deep learning with optimization techniques offer significant advantages. These models leverage the strengths of both methodologies, resulting in improved performance, scalability, and adaptability. Emerging technologies such as federated learning and transformer-based models further enhance system capabilities by addressing privacy concerns and improving long-range dependency modeling.

Despite these advancements, several challenges remain. The computational overhead of deep learning models can be prohibitive for edge devices, necessitating the development of lightweight solutions. Additionally, the dynamic and heterogeneous nature of 6G networks requires adaptive and scalable frameworks. Security and privacy concerns also need to be addressed to ensure safe deployment. In conclusion, the integration of deep learning and optimization techniques represents a promising direction for task scheduling and resource allocation in VR video services within advanced 6G networks. Continued research in this area will be essential for enabling next-generation immersive applications and ensuring efficient network performance.

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