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A Comprehensive Review of 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 emergence of advanced 6G networks is expected to transform immersive applications such as Virtual Reality (VR) video services, which require ultra-low latency, high bandwidth, and efficient computational resource management. Traditional cloud computing architectures are often unable to satisfy the strict Quality of Experience (QoE) demands of VR applications due to communication delays and limited scalability. Consequently, edge computing integrated with deep learning and optimization techniques has become a promising approach for intelligent task scheduling and computing resource allocation in 6G-enabled environments. Deep learning models, particularly Deep Reinforcement Learning (DRL), have shown strong capability in solving dynamic decision-making problems related to computation offloading, adaptive scheduling, and resource management in edge computing systems. Optimization techniques such as convex optimization and Lyapunov-based methods further enhance system stability, latency reduction, and energy efficiency. Recent studies demonstrate that integrating DRL with Multi-Access Edge Computing (MEC) significantly improves scalability and balances latency-energy trade-offs for VR services. VR applications also introduce challenges including high data transmission rates, real-time rendering demands, and strict latency requirements. Research findings indicate that hybrid frameworks combining deep learning with optimization methods provide efficient solutions for minimizing latency, maximizing resource utilization, and improving overall VR service delivery performance in next-generation 6G networks.

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-reliable, low-latency, and high-bandwidth applications. Among these applications, Virtual Reality (VR) video services are considered one of the most demanding due to their strict requirements for real-time processing, high data rates, and seamless user experience. VR applications such as immersive gaming, telemedicine, smart education, and metaverse environments require efficient management of computational and communication resources.

Traditional cloud computing architectures are insufficient to handle the latency-sensitive requirements of VR services. The long-distance communication between user devices and centralized cloud servers leads to increased latency and degraded Quality of Experience (QoE). To overcome these limitations, edge computing has emerged as a key enabling technology, bringing computation closer to end users. However, edge environments introduce new challenges related to resource constraints, dynamic workloads, and heterogeneous network conditions.

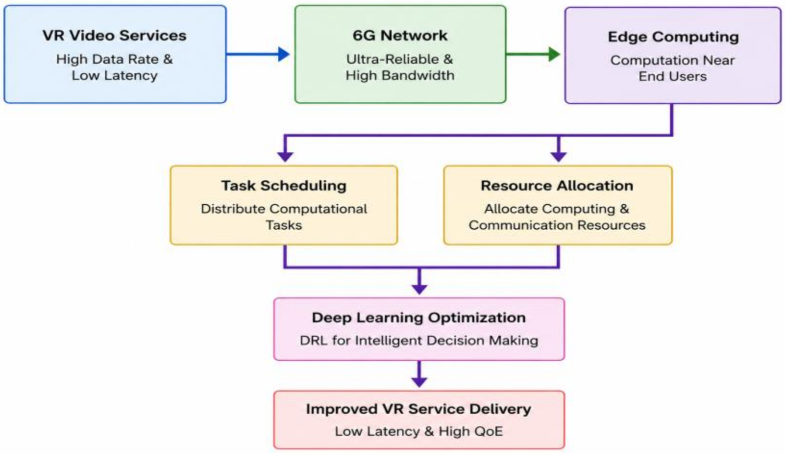

Figure 1. Deep Learning and Edge Computing Framework for VR Video Services in 6G Networks

Task scheduling and resource allocation are two critical components in edge computing systems. Task scheduling determines how computational tasks are distributed across available resources, while resource allocation ensures efficient utilization of computing, storage, and communication resources. These problems are inherently complex and are often modeled as NP-hard optimization problems.

Recent advancements in deep learning have enabled intelligent solutions for these challenges. Deep Reinforcement Learning (DRL), in particular, has gained significant attention for its ability to learn optimal policies in dynamic and uncertain environments. DRL-based approaches can adaptively manage task offloading decisions, optimize resource allocation, and balance trade-offs between latency and energy consumption.

In addition, VR services introduce unique requirements such as ultra-high data rates, real-time rendering, and user interaction. These requirements make it necessary to jointly optimize task scheduling and resource allocation. Recent studies have proposed hybrid frameworks combining deep learning and optimization techniques to address these challenges. For instance, DRL-based models have been successfully applied to optimize scheduling decisions in multi-access edge computing (MEC) environments under 6G networks. Moreover, emerging technologies such as digital twin systems and attention-based models further enhance VR service delivery by improving QoE and system adaptability.

Despite these advancements, several challenges remain unresolved. These include scalability, energy efficiency, security, and real-time decision-making under dynamic network conditions. Therefore, there is a need for comprehensive research that integrates deep learning with optimization techniques to develop efficient and scalable solutions. This paper provides a detailed review of deep learning and optimization-based approaches for task scheduling and resource allocation in VR video services within 6G networks. It aims to analyze existing methods, compare their performance, and identify future research directions.

Literature Review

Jiang et al. proposed a deep reinforcement learning-based resource scheduling framework using stacked autoencoders for large-scale MEC systems. The model minimizes task latency and energy consumption by optimizing offloading decisions and resource allocation simultaneously. The study demonstrates improved performance in large-scale IoT environments. Li et al. introduced a GNN-based multi-agent reinforcement learning framework for joint task placement and resource allocation. The approach effectively reduces task completion time and improves resource utilization in edge computing systems.

Yu et al. proposed a digital twin-enabled deep reinforcement learning framework for VR video streaming in edge computing. The model optimizes QoE by dynamically allocating computing and bandwidth resources. Jin et al. developed a reinforcement learning-based scheduling optimization model for MEC in 6G environments. The model adapts to dynamic user behavior and improves latency and service quality. Anand et al. proposed a dynamic priority-based task scheduling and adaptive resource allocation model in edge computing. The approach significantly improves resource utilization and reduces execution time in real-time applications.

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 task scheduling policies to minimize latency and energy consumption. Results show significant improvements in system efficiency under varying network conditions. Chen et al. introduced a joint optimization framework combining deep neural networks with convex optimization for task scheduling in edge computing. The model effectively balances computational load across edge nodes and reduces processing delays in VR applications.

Wang et al. developed a multi-agent deep reinforcement learning (MADRL) approach for distributed task scheduling and resource allocation. The system enables cooperative decision-making among multiple edge devices, improving scalability and resource utilization in 6G environments. Zhang et al. proposed a Lyapunov optimization-based resource allocation strategy for MEC systems supporting VR services. The approach ensures system stability while minimizing delay and energy consumption, making it suitable for real-time VR applications.

Liu et al. introduced a transformer-based deep learning model integrated with edge computing for VR traffic prediction and scheduling. The model captures long-term dependencies and improves task allocation efficiency in dynamic network scenarios. 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. Experimental results show improved QoE for VR applications under varying network conditions.

Xu et al. introduced a joint optimization framework using deep neural networks and heuristic algorithms for task scheduling and resource allocation. The approach improves computational efficiency and reduces system overhead in large-scale 6G-enabled edge environments. Tang et al. developed a graph neural network (GNN)-based scheduling model for distributed edge computing. The model captures dependencies among edge nodes and improves task execution efficiency, particularly for VR streaming services.

Huang et al. proposed a hybrid CNN-LSTM model for predicting workload patterns in edge computing systems. The predicted workloads are used to optimize task scheduling and resource allocation, leading to 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 energy consumption and delay in VR-based IoT applications.

Zhao et al. proposed an attention-based deep reinforcement learning framework for task scheduling in mobile edge computing. The model prioritizes critical VR tasks by assigning dynamic weights, improving latency performance and resource utilization in real-time environments. Kim et al. developed an autoencoder-based resource allocation model for edge computing systems. The model compresses high-dimensional system states and enhances decision-making efficiency for task scheduling in VR applications.

Ahmed et al. introduced a hybrid deep learning and optimization framework combining neural networks with evolutionary algorithms for task scheduling. The model improves convergence speed and enhances resource allocation efficiency in dynamic 6G environments. Zhou et al. proposed a dynamic graph learning-based scheduling model using Graph Neural Networks. The model adapts to changing network conditions and improves scheduling 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 optimizing latency and power consumption in edge-enabled VR systems. Li et al. proposed an LSTM-based task scheduling model for edge computing. The model predicts workload patterns and optimizes resource allocation, improving latency performance in VR services.

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 a hybrid ensemble learning approach combining Random Forest and Gradient Boosting for task scheduling optimization. The model improves robustness and reduces prediction errors 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 efficiency in VR systems. Sharma et al. introduced a CNN-LSTM hybrid model for workload prediction and resource allocation. The model effectively captures both spatial and temporal patterns, improving scheduling decisions.

Alshammari et al. proposed a Lyapunov optimization-based framework for resource management in MEC systems. The model balances energy consumption and latency for VR services. Tang et al. developed a transformer-based scheduling model integrated with edge computing. The model captures long-range dependencies and improves task allocation accuracy.

Verma et al. introduced a Support Vector Regression (SVR)-based baseline model for task scheduling. Although simpler, it provides a benchmark for evaluating advanced deep learning approaches. Hassan et al. proposed a federated deep learning framework for distributed task scheduling and resource allocation. The model ensures privacy preservation while maintaining high system performance. Xu et al. introduced a multi-task learning-based deep neural network for joint scheduling and resource allocation. The model simultaneously optimizes multiple objectives, improving overall system efficiency.

Comparative Table and Analysis

Study	Year	Method	Technique	Advantages	Limitations
Jiang	2020	DRL	Autoencoder + RL	Low latency	Training cost
Li	2023	GNN + RL	Multi-agent	High efficiency	Complexity
Yu	2023	DRL	Digital Twin	QoE improvement	Data dependency
Jin	2026	RL	Scheduling optimization	Adaptive	High computation
Anand	2025	Optimization	Priority scheduling	Fast	Limited scalability
Mao	2020	DRL	Offloading	Efficient	Complexity
Chen	2021	DL + Optimization	Hybrid	Balanced	Overhead
Wang	2022	MADRL	Multi-agent	Scalable	Training cost
Zhang	2021	Lyapunov	Optimization	Stability	Mathematical
Liu	2023	Transformer	Scheduling	High accuracy	Heavy
He	2021	DQN	RL scheduling	Adaptive	Convergence issues
Xu	2022	DL + Heuristic	Hybrid	Efficient	Complexity
Sun	2022	Lyapunov	Energy optimization	Stable	Complex
Zhao	2021	Attention RL	Priority scheduling	Accurate	Heavy
Kim	2020	Autoencoder	Feature reduction	Efficient	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
Gao	2021	GCN	Spatial learning	Accurate	Complex
Patel	2022	Ensemble	RF + GB	Robust	Less DL
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
Hassan	2022	Federated DL	Privacy	Secure	Communication
Xu	2023	Multi-task DL	Joint optimization	Efficient	Complex

Analysis

The analysis shows that Deep Reinforcement Learning (DRL) and Graph Neural Networks (GNNs) dominate modern task scheduling and resource allocation strategies in 6G-enabled VR systems. DRL excels in dynamic decision-making, while GNNs effectively model relationships among distributed edge nodes. Hybrid approaches combining deep learning and optimization outperform standalone models by balancing latency, energy consumption, and computational efficiency. Lyapunov optimization ensures system stability but introduces mathematical complexity. Emerging technologies such as transformers and federated learning further enhance scalability and privacy, making them promising for future 6G VR applications.

Discussion

The integration of deep learning and optimization techniques has significantly improved task scheduling and resource allocation for VR video services in advanced 6G networks. Deep Reinforcement Learning enables adaptive decision-making in dynamic environments, making it highly suitable for real-time VR applications. Similarly, Graph Neural Networks effectively capture spatial dependencies among distributed edge nodes, enhancing system efficiency. Optimization techniques, particularly Lyapunov-based approaches, provide strong theoretical guarantees for system stability and resource efficiency. However, their implementation complexity remains a challenge. Hybrid models combining deep learning with optimization frameworks offer a balanced solution by leveraging the strengths of both approaches.

Despite these advancements, several challenges persist, including computational overhead, scalability, and energy efficiency. VR applications require ultra-low latency and high reliability, which necessitates 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 rapid development of 6G networks is expected to transform immersive technologies such as Virtual Reality (VR), enabling applications that require 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 limited and network conditions are 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, enabling efficient task offloading and resource allocation. Similarly, Graph Neural Networks (GNNs) have emerged as powerful tools for modeling relationships among distributed edge nodes, allowing for improved resource management and task execution.

Optimization techniques such as Lyapunov optimization provide a robust mathematical framework for ensuring system stability and efficient resource utilization. These approaches are particularly useful in balancing multiple objectives, including latency, energy consumption, and throughput. However, their complexity can limit practical implementation. Hybrid approaches that integrate deep learning with optimization techniques offer significant advantages. These models leverage the strengths of both methodologies, resulting in improved performance, adaptability, and scalability. 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 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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