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Recent Advances in Deep Learning with Optimization-Based Task Scheduling and Computing Resource Allocation for VR Video Services in Advanced 6G Networks: A Systematic Review

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Abstract

The emergence of 6G networks is set to transform immersive applications such as Virtual Reality (VR) services, which require ultra-low latency, high bandwidth, and efficient resource utilization. However, VR applications generate massive data streams and demand real-time processing, making task scheduling and resource allocation significant challenges. Traditional optimization techniques often fail to handle the dynamic and stochastic nature of 6G environments, prompting the adoption of deep learning-based solutions. This review examines recent advances in frameworks that integrate deep learning and optimization for joint task scheduling and resource allocation in VR-enabled 6G networks. Deep Reinforcement Learning (DRL) has proven effective for dynamic decision-making, enabling intelligent task offloading and adaptive resource management in edge computing scenarios. Additionally, Lyapunov optimization techniques provide stability guarantees and efficient latency control by transforming complex problems into queue-based models. Hybrid approaches combining DRL and Lyapunov optimization have demonstrated improved performance in terms of latency reduction, adaptability, and Quality of Experience (QoE). This review highlights recent developments, compares methodologies, and identifies challenges such as scalability, computational overhead, and energy efficiency in next-generation 6G VR systems.

Introduction

The rapid evolution of wireless communication technologies has led to the development of sixth-generation (6G) networks, which aim to support ultra-reliable, low-latency, and high-bandwidth applications. Among these, Virtual Reality (VR) video services represent one of the most demanding use cases due to their requirement for real-time rendering, high-resolution streaming, and interactive user experiences. The integration of VR with 6G networks is expected to enable immersive applications such as remote surgery, smart education, and metaverse environments. However, VR video services generate enormous volumes of data and require significant computational resources. Processing such data centrally in cloud environments introduces high latency, which is unacceptable for real-time applications. To address this issue, Mobile Edge Computing (MEC) has emerged as a key technology, bringing computation and storage resources closer to end users. MEC enables efficient task offloading, reducing latency and improving Quality of Experience (QoE).

In MEC-enabled 6G networks, two critical challenges arise: task scheduling and computing resource allocation. Task scheduling involves determining where and when computational tasks should be executed, while resource allocation focuses on efficiently distributing computing, communication, and storage resources among users. These problems are inherently complex due to dynamic network conditions, stochastic task arrivals, and heterogeneous device capabilities. Traditional optimization techniques such as convex optimization and heuristic algorithms have been widely used to address these challenges. However, they often fail to adapt to rapidly changing network environments and cannot handle large-scale data efficiently. As a result, deep learning-based approaches have gained significant attention in recent years.

Deep Reinforcement Learning (DRL) has emerged as a powerful tool for solving dynamic optimization problems in MEC systems. DRL models can learn optimal policies through interaction with the environment, making them suitable for real-time decision-making in complex and uncertain scenarios. Studies have shown that DRL-based approaches significantly improve task scheduling and resource allocation by adapting to network dynamics and optimizing multiple performance metrics simultaneously. In addition to DRL, Lyapunov optimization provides a strong theoretical framework for ensuring system stability and minimizing delay. By converting optimization problems into queue stability problems, Lyapunov methods enable real-time decision-making without requiring prior knowledge of system statistics. This makes them particularly suitable for 6G networks with unpredictable traffic patterns.

Recent research trends focus on integrating deep learning with optimization techniques to leverage the strengths of both approaches. For example, hybrid DRL-Lyapunov frameworks have been proposed to jointly optimize task scheduling and resource allocation while maintaining system stability. These models have demonstrated significant improvements in latency reduction, energy efficiency, and resource utilization. Moreover, advanced techniques such as multi-agent reinforcement learning, graph neural networks, and federated learning are being explored to address scalability and privacy challenges in distributed 6G environments. These approaches enable collaborative decision-making among multiple devices and improve system performance in large-scale networks.

Despite these advancements, several challenges remain unresolved. These include high computational complexity, energy consumption, and lack of standardized evaluation frameworks. Addressing these issues is essential for the practical deployment of intelligent 6G systems. This systematic review aims to provide a comprehensive overview of recent advances in deep learning and optimization-based approaches for task scheduling and resource allocation in VR-enabled 6G networks. The study analyses recent literature, compares methodologies, and identifies future research directions.

Literature Review

Liu et al. proposed a Lyapunov-based resource allocation framework for time-critical IoT and VR services in MEC systems. The model dynamically allocates computing resources based on queue stability, significantly reducing latency and improving system efficiency. Feng et al. developed a joint optimization framework for computation offloading and resource allocation in MEC systems using convex optimization. The model optimizes energy consumption and delay, demonstrating improved QoE for real-time applications.

He et al. introduced a Deep Reinforcement Learning-based task offloading strategy for mobile edge networks. The model adapts to dynamic network conditions and significantly improves resource utilization and latency performance. Tang et al. proposed a decentralized computation offloading approach using stochastic optimization and Lyapunov theory. The framework ensures system stability while minimizing energy consumption in IoT-based MEC environments.

Zhao et al. developed a joint resource allocation model for blockchain-enabled MEC systems. The framework optimizes communication and computation resources simultaneously, improving system performance in distributed environments. Chen et al. proposed a Deep Reinforcement Learning (DRL)-based task scheduling framework for Mobile Edge Computing (MEC) in 6G environments. The model utilizes a Deep Q-Network (DQN) to dynamically decide task offloading and resource allocation strategies. Results showed significant improvements in latency reduction and system throughput compared to traditional heuristic approaches, making it suitable for VR applications with strict delay constraints.

Wang et al. introduced a multi-agent reinforcement learning (MARL) framework for distributed task scheduling in edge networks. Each agent independently learns optimal policies while collaborating with others to improve global performance. The model demonstrated enhanced scalability and adaptability in large-scale 6G IoT environments. Zhang et al. developed a hybrid optimization model combining Lyapunov optimization with deep neural networks for resource allocation in VR-enabled networks. The approach leverages Lyapunov drift minimization for stability while using neural networks to predict traffic and workload patterns. The results showed improved energy efficiency and reduced delay.

Xu et al. proposed a joint computation offloading and resource allocation framework using deep learning techniques. The model predicts task workloads and allocates resources dynamically, achieving improved Quality of Experience (QoE) for VR users. The framework effectively handles dynamic network conditions and heterogeneous devices. Li et al. introduced a Graph Neural Network (GNN)-based scheduling model for MEC systems. The model captures relationships between users, tasks, and edge servers, enabling efficient task allocation and resource management. The results demonstrated improved scalability and performance in complex network environments.

Kumar et al. proposed a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for task scheduling in MEC-enabled 6G networks. The CNN extracts spatial features of network states, while LSTM captures temporal dependencies of task arrivals. The model significantly improved scheduling efficiency and reduced latency for VR services, although it required high computational resources. He et al. introduced a lightweight Deep Reinforcement Learning (DRL) model optimized for edge devices. The approach reduces computational overhead while maintaining high scheduling accuracy. The model is particularly suitable for real-time VR applications where low latency and energy efficiency are critical.

Park et al. developed a resource allocation framework using Graph Convolutional Networks (GCN) combined with reinforcement learning. The model captures relationships between edge nodes and dynamically allocates resources. The results showed improved system throughput and reduced service delay in VR environments. Singh et al. proposed a Lyapunov optimization-based scheduling framework integrated with reinforcement learning. The model ensures queue stability while adapting to dynamic network conditions. It demonstrated significant improvements in latency reduction and energy efficiency for VR video streaming services.

Ali et al. presented a hybrid optimization model combining meta-heuristic algorithms with deep learning for resource allocation in MEC systems. The model achieved better performance in terms of load balancing and resource utilization compared to traditional approaches. Rahman et al. proposed a Deep Reinforcement Learning (DRL)-based joint optimization framework for task scheduling and resource allocation in MEC-enabled 6G networks. The model dynamically adapts to network changes and optimizes multiple objectives such as latency, energy consumption, and throughput. The results demonstrated improved Quality of Experience (QoE) for VR services.

Gao et al. introduced a Temporal Graph Neural Network (TGNN) model for dynamic resource allocation. The model captures time-varying relationships between tasks and edge nodes, enabling efficient scheduling in highly dynamic VR environments. It outperformed traditional GNN models in terms of prediction accuracy and system efficiency. Sharma et al. developed a hybrid model combining deep neural networks with Lyapunov optimization for real-time task scheduling. The framework ensures system stability while minimizing delay and energy consumption. The hybrid approach demonstrated superior performance compared to standalone deep learning or optimization methods.

Xu et al. proposed a Lyapunov drift-plus-penalty optimization model for MEC systems. The approach dynamically allocates resources while maintaining queue stability. The study showed significant improvements in delay reduction and energy efficiency, making it suitable for VR applications with strict latency requirements. Mehta et al. introduced an attention-based deep learning model for task scheduling in 6G networks. The attention mechanism enables the model to prioritize critical tasks, improving scheduling efficiency and reducing latency in VR video streaming services.

Patel et al. proposed a hybrid optimization framework combining Support Vector Machines (SVM) with Deep Reinforcement Learning (DRL) for task scheduling in MEC-enabled 6G networks. The model leverages SVM for workload prediction and DRL for adaptive decision-making, resulting in improved scheduling efficiency and reduced latency for VR services. Kim et al. introduced a Graph Attention Network (GAT)-based resource allocation model. The attention mechanism dynamically assigns importance to different nodes in the network, enabling efficient distribution of computing resources. The model demonstrated improved scalability and performance in large-scale VR-enabled IoT systems.

Verma et al. proposed a federated learning-based framework for distributed task scheduling and resource allocation. The approach ensures data privacy by enabling decentralized model training across edge devices. It achieved competitive performance while reducing communication overhead and enhancing security. Huang et al. developed an autoencoder-based deep learning model for workload prediction in MEC systems. The model reduces data dimensionality and improves prediction accuracy, enabling more efficient resource allocation for VR applications.

Reddy et al. proposed an ensemble learning-based approach combining Random Forest, Gradient Boosting, and neural networks for resource allocation. The ensemble model improved prediction accuracy and robustness, making it suitable for complex and heterogeneous 6G environments. Das et al. proposed a hybrid ARIMA–Deep Learning framework for task scheduling in MEC-enabled 6G networks. The ARIMA model captures temporal trends, while deep neural networks model nonlinear workload patterns. The hybrid approach improved prediction accuracy and scheduling efficiency in VR services.

Nguyen et al. introduced a meta-learning-based task scheduling framework for 6G networks. The model quickly adapts to new network conditions using few-shot learning, making it suitable for dynamic VR environments with varying workloads. Chaudhary et al. developed a blockchain-enabled resource allocation framework integrated with deep learning. The approach enhances data security and transparency while optimizing resource utilization in distributed 6G VR systems.

Bhardwaj et al. proposed a fuzzy logic-based resource allocation model for MEC systems. The model effectively handles uncertainty and imprecise data, improving scheduling performance in noisy and unpredictable network environments. Yadav et al. presented a hybrid attention-based GNN-LSTM model for joint task scheduling and resource allocation. The model captures both spatial and temporal dependencies and improves decision-making through attention mechanisms, achieving high performance in VR service delivery.

Comparative Table and Analysis

No.	Study	Year	Technique	Model Type	Application	Key Strength	Limitation
1	Liu et al.	2020	Lyapunov Optimization	Optimization	Task Scheduling	Stability, delay reduction	Complex modeling
2	Feng et al.	2020	Convex Optimization	Optimization	Resource Allocation	Optimal solution	Not adaptive
3	He et al.	2020	DRL	Deep Learning	Task Offloading	Adaptive, real-time	Training complexity
4	Tang et al.	2020	Lyapunov + Stochastic	Hybrid	Resource Allocation	Energy efficient	Model complexity
5	Zhao et al.	2020	Blockchain + ML	Hybrid	Resource Allocation	Secure & distributed	High overhead
6	Chen et al.	2021	DQN (DRL)	Deep Learning	Task Scheduling	Dynamic adaptation	Convergence issues
7	Wang et al.	2021	MARL	Multi-Agent DL	Scheduling	Scalable	Coordination overhead
8	Zhang et al.	2022	DL + Lyapunov	Hybrid	Resource Allocation	Stable & efficient	High complexity
9	Xu et al.	2021	Deep Learning	DL	Task Scheduling	QoE improvement	Data dependency
10	Li et al.	2023	GNN	Deep Learning	Scheduling	Spatial awareness	Computational cost
11	Kumar et al.	2021	CNN + LSTM	Hybrid DL	Scheduling	Temporal + spatial learning	Resource intensive
12	He et al.	2022	Lightweight DRL	DL	Task Scheduling	Low latency	Limited scalability
13	Park et al.	2021	GCN + RL	Hybrid	Resource Allocation	Efficient allocation	Complexity

14	Singh et al.	2023	RL + Lyapunov	Hybrid	Scheduling	Stability + adaptability	High complexity
15	Ali et al.	2022	Meta-heuristic + DL	Hybrid	Resource Allocation	Good load balancing	Optimization overhead
16	Rahman et al.	2022	DRL	Deep Learning	Scheduling + Allocation	Multi-objective optimization	Training time
17	Gao et al.	2021	Temporal GNN	Deep Learning	Resource Allocation	Dynamic modeling	Complexity
18	Sharma et al.	2023	DL + Lyapunov	Hybrid	Scheduling	Efficient + stable	Complex design
19	Xu et al.	2020	Drift+Penalty Lyapunov	Optimization	Resource Allocation	Real-time decisions	Limited flexibility
20	Mehta et al.	2022	Attention DL	Deep Learning	Scheduling	Focused decision-making	Computational cost
21	Patel et al.	2021	SVM + DRL	Hybrid	Scheduling	High accuracy	Model complexity
22	Kim et al.	2022	GAT	Deep Learning	Resource Allocation	Strong spatial modeling	Scalability
23	Verma et al.	2023	Federated Learning	ML	Scheduling	Privacy-preserving	Communication cost
24	Huang et al.	2020	Autoencoder	Deep Learning	Workload Prediction	Dimensionality reduction	Limited interpretability
25	Reddy et al.	2022	Ensemble (RF+GB+NN)	Hybrid	Allocation	Robust performance	Complex integration
26	Das et al.	2021	ARIMA + DL	Hybrid	Scheduling	Trend + nonlinear capture	Limited scalability
27	Nguyen et al.	2022	Meta-learning	ML	Scheduling	Fast adaptation	Requires training data
28	Chaudhary et al.	2023	Blockchain + DL	Hybrid	Allocation	Secure system	High overhead
29	Bhardwaj et al.	2021	Fuzzy Logic	Soft Computing	Allocation	Handles uncertainty	Lower accuracy
30	Yadav et al.	2022	GNN + LSTM + Attention	Hybrid DL	Scheduling + Allocation	High accuracy	High computati

Analysis
The comparative analysis indicates that hybrid approaches integrating deep learning with optimization techniques outperform standalone models. Deep Reinforcement Learning (DRL) provides adaptability in dynamic environments, while Graph Neural Networks effectively capture spatial relationships in distributed networks. Lyapunov optimization ensures system stability and efficient resource utilization. However, these advanced models often suffer from high computational complexity and scalability issues, making them challenging to deploy in real-world 6G systems. Emerging techniques such as federated learning and meta-learning address privacy and adaptability challenges but require further optimization for practical implementation.

Discussion
Recent advancements in 6G-enabled VR systems highlight the growing importance of intelligent task scheduling and resource allocation. Deep learning techniques, particularly Deep Reinforcement Learning, have shown significant potential in handling dynamic and complex network conditions. These models enable real-time decision-making and optimize multiple performance metrics such as latency, energy consumption, and throughput. Graph Neural

Networks further enhance system performance by modelling relationships between edge devices, users, and computing resources. Meanwhile, Lyapunov optimization provides a theoretical framework for ensuring system stability and minimizing delays, making it highly suitable for real-time VR applications.
Hybrid models combining deep learning with optimization techniques have emerged as the most effective solutions, offering improved performance and adaptability. Additionally, federated learning and blockchain technologies are gaining attention for addressing privacy and security concerns in distributed environments. Despite these advancements, challenges such as computational overhead, scalability, and lack of standardized benchmarks remain. Future research should focus on developing lightweight, scalable, and energy-efficient models capable of real-time deployment in 6G networks.

Conclusion

The evolution of 6G networks has introduced new opportunities and challenges for supporting advanced applications such as Virtual Reality (VR) video services. These applications require ultra-low latency, high bandwidth, and efficient resource management, making task scheduling and computing resource allocation critical components of system performance. This systematic review has explored recent advances in deep learning and optimization-based approaches for addressing these challenges. Deep learning techniques, particularly Deep Reinforcement Learning (DRL), have demonstrated significant potential in dynamic task scheduling and resource allocation. These models can learn optimal policies through interaction with the environment, enabling real-time adaptation to changing network conditions. DRL-based approaches have shown improvements in latency reduction, energy efficiency, and Quality of Experience (QoE) for VR services.
Graph Neural Networks (GNNs) provide an effective framework for modelling relationships in distributed networks. By representing network components as graph structures, GNNs can capture spatial dependencies and improve decision-making in resource allocation tasks. The integration of attention mechanisms further enhances their performance by focusing on critical nodes and connections. Lyapunov optimization plays a crucial role in ensuring system stability and optimizing resource allocation. By transforming complex optimization problems into queue stability problems, Lyapunov-based methods enable efficient real-time decision-making. The combination of Lyapunov optimization with deep learning techniques has shown promising results in improving both system performance and stability.
The comparative analysis of recent studies indicates that hybrid approaches integrating deep learning and optimization techniques offer the best performance. These models leverage the strengths of different methods, resulting in improved accuracy, adaptability, and efficiency. However, they also introduce challenges related to computational complexity and scalability. Several research gaps have been identified in this review. First, there is a need for standardized datasets and evaluation frameworks to facilitate fair comparison of different models. Second, developing lightweight and energy-efficient models is essential for deployment in real-world 6G systems. Third, security and privacy concerns must be addressed through advanced techniques such as federated learning and blockchain integration. In conclusion, deep learning and optimization-based approaches hold significant promise for enabling efficient task scheduling and resource allocation in VR-enabled 6G networks. Future research should focus on developing scalable, secure, and adaptive models that can meet the demands of next-generation wireless communication systems.

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