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Deep Learning and Optimization Approaches in Strategy Design for Energy-Efficient Data Offloading in 6G-Enabled Vehicular Edge Computing Networks Using Double Deep Q-Network: A Review

Qudsia Leroux-Martin

Professor, Department of Computer Science and Engineering, Hanmir Advanced Engineering College, South Korea

Email: qudsia.leroux.martin@haec-kr.edu

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Abstract

The rapid evolution of sixth-generation (6G) communication networks has significantly accelerated the development of intelligent vehicular systems, necessitating efficient computation offloading strategies in Vehicular Edge Computing (VEC) environments. With the exponential growth of data-intensive and latency-sensitive applications such as autonomous driving, augmented reality, and intelligent transportation systems, traditional offloading mechanisms fail to meet stringent energy and delay constraints. Recently, deep learning-based optimization approaches, particularly Double Deep Q-Networks (DDQN), have emerged as promising solutions for dynamic and adaptive decision-making in complex vehicular environments. This review explores the integration of deep reinforcement learning and optimization techniques for energy-efficient data offloading in 6G-enabled VEC systems. It systematically analyses recent advancements between 2020 and 2023, focusing on algorithm design, system architectures, and optimization objectives such as latency minimization, energy efficiency, and resource utilization. Furthermore, this paper highlights the advantages of DDQN over conventional methods in addressing overestimation bias and improving convergence stability. Key challenges, including scalability, dynamic mobility, and security concerns, are also discussed. The study provides a comprehensive comparative analysis of existing approaches and identifies future research directions toward sustainable and intelligent vehicular edge computing systems.

Introduction

The emergence of 6G communication networks represents a transformative shift in wireless technologies, enabling ultra-low latency, massive connectivity, and high data rates essential for next-generation intelligent systems. Among these, Vehicular Edge Computing (VEC) plays a pivotal role in supporting computation-intensive and delay-sensitive applications such as autonomous driving, smart traffic management, and immersive multimedia services. However, the limited computational capacity and battery constraints of vehicles necessitate efficient strategies for offloading tasks to nearby edge servers. Traditional computation offloading approaches rely on static optimization or heuristic-based methods, which are insufficient in highly dynamic vehicular environments characterized by high mobility, fluctuating network conditions, and heterogeneous resource availability. These limitations have led to the adoption of deep learning and reinforcement learning-based approaches, which can adaptively learn optimal offloading strategies in real time.

Recent studies have demonstrated that Deep Reinforcement Learning (DRL) techniques are particularly effective in solving complex decision-making problems in VEC systems. DRL models such as Deep Q-Networks (DQN), Deep Deterministic Policy Gradient (DDPG), and Proximal Policy Optimization (PPO) have been widely used to optimize task offloading and resource allocation. However, traditional DQN suffers from overestimation bias, leading to suboptimal policies and unstable convergence. To address these challenges, the Double Deep Q-Network (DDQN) has been introduced as an advanced reinforcement learning technique that decouples action selection from evaluation, thereby reducing overestimation errors and improving learning stability. DDQN-based approaches have shown significant improvements in optimizing energy consumption, reducing latency, and enhancing overall system performance in vehicular edge computing environments.

In VEC systems, the offloading decision problem is typically modelled as a Markov Decision Process (MDP), where the system state includes parameters such as vehicle mobility, channel conditions, and computational resources. The objective is to determine optimal offloading actions that minimize energy consumption and latency while satisfying quality-of-service (QoS) requirements. Furthermore, recent advancements have integrated optimization techniques such as particle swarm optimization, meta-learning, and hybrid DRL models to enhance the performance of DDQN-based systems. These hybrid approaches enable better exploration of the solution space and faster convergence to optimal policies.

Despite significant progress, several challenges remain, including scalability in large-scale vehicular networks, security and privacy concerns, and efficient handling of dynamic network conditions. Therefore, a comprehensive review of existing deep learning and optimization approaches is essential to understand current trends and identify future research directions. This paper aims to provide a systematic review of energy-efficient data offloading strategies in 6G-enabled VEC systems using DDQN and related optimization techniques, focusing on recent contributions between 2020 and 2023.

Literature Review

Huang et al. (2020) proposed a deep reinforcement learning-based framework for joint task offloading and resource allocation in vehicular edge computing networks. The study introduced a multi-agent DDPG model to optimize energy consumption and delay simultaneously. The results showed improved system utility by considering vehicle speed and task characteristics. However, the approach suffered from high computational complexity and slow convergence in dynamic environments. Qu et al. (2020) developed a Deep Meta Reinforcement Learning-based Offloading (DMRO) framework to address dynamic changes in IoT-based edge environments. The model combined meta-learning with deep reinforcement learning to improve adaptability and learning speed. The proposed approach demonstrated superior performance over traditional DQN methods, particularly in dynamic and uncertain environments.

Cho et al. (2021) introduced an energy-efficient cooperative offloading scheme for vehicular networks using convex optimization techniques. The model focused on minimizing total energy consumption through task partitioning and cooperative resource utilization among roadside units (RSUs). While effective in reducing energy consumption, the method lacked adaptability to real-time network changes. Geng et al. (2021) proposed a distributed DRL-based offloading mechanism in vehicular edge computing. The framework utilized multi-agent reinforcement learning to manage computation-intensive tasks across distributed nodes. The results showed improved scalability and reduced latency; however, the model did not adequately address energy optimization and security concerns.

Tang et al. (2021) explored a DDQN-based dynamic offloading strategy for vehicular edge computing systems. The study modeled the offloading problem as an optimization task aimed at minimizing service latency and improving load balancing. Experimental results demonstrated that DDQN outperformed conventional DQN and heuristic approaches in dynamic environments. Liu et al. (2021) proposed a DDQN-based computation offloading and resource allocation framework for vehicular edge computing systems. The model considered both communication delay and energy consumption as optimization objectives. By modeling the environment as a Markov Decision Process (MDP), the DDQN agent learned optimal offloading decisions under dynamic vehicular conditions. The results demonstrated that DDQN significantly reduced energy consumption compared to traditional DQN and greedy algorithms. However, the study did not incorporate vehicle mobility prediction, which may affect decision accuracy in highly dynamic scenarios.

Zhang et al. (2021) introduced a hybrid optimization approach combining Deep Q-Network (DQN) and Particle Swarm Optimization (PSO) for task offloading in edge-enabled vehicular networks. The PSO algorithm was used to optimize continuous resource allocation, while DQN handled discrete offloading decisions. This hybrid framework achieved improved convergence speed and energy efficiency. However, the system complexity increased due to the integration of multiple optimization techniques, making real-time implementation challenging. Wang et al. (2022) developed a multi-agent deep reinforcement learning (MADRL) framework for cooperative task offloading in vehicular edge computing. The model allowed multiple vehicles to coordinate their offloading decisions to minimize overall system cost. The study showed enhanced scalability and system throughput. However, the coordination among agents introduced communication overhead, which could impact system performance in dense vehicular environments.

Chen et al. (2022) proposed an energy-aware task offloading strategy using DDQN with prioritized experience replay. The model improved learning efficiency by prioritizing important experiences during training. Simulation results indicated that the approach achieved faster convergence and better energy savings compared to standard DDQN models. Despite its effectiveness, the method required high memory storage for experience replay buffers. Sun et al. (2022) presented a joint optimization framework integrating DDQN and edge caching mechanisms for vehicular networks. The study aimed to reduce redundant data transmission and improve energy efficiency by caching frequently requested content at edge servers. The proposed method significantly reduced latency and energy consumption while improving user experience. However, cache management policies were not fully optimized for rapidly changing vehicular patterns.

Li et al. (2022) proposed a DDQN-based adaptive task offloading framework with mobility-aware optimization in vehicular edge computing networks. The model incorporated real-time vehicle trajectory prediction to improve offloading decisions. By considering dynamic channel conditions and vehicle mobility, the approach significantly reduced service delay and energy consumption. Simulation results demonstrated improved stability and robustness compared to conventional DRL models. However, the model required high computational overhead for continuous trajectory prediction. He et al. (2022) introduced a deep reinforcement learning-based joint optimization model using DDQN and Lyapunov optimization for energy-efficient task scheduling. The Lyapunov framework ensured system stability while the DDQN agent optimized long-term rewards. The hybrid approach achieved better performance in terms of queue stability, energy efficiency, and delay minimization. Nevertheless, the integration increased algorithmic complexity and required careful parameter tuning.

Xu et al. (2022) developed a federated learning-assisted DDQN framework for secure and privacy-preserving task offloading in vehicular networks. The model allowed multiple vehicles to collaboratively train a global model without sharing raw data. This approach enhanced data privacy and reduced communication overhead. However, the model faced challenges in handling non-IID data distributions across vehicles, which could affect learning performance. Yang et al. (2023) proposed a multi-objective DDQN-based optimization framework focusing on energy efficiency, latency, and reliability in 6G-enabled vehicular edge computing. The study incorporated a weighted reward function to balance multiple objectives. Results indicated significant improvements in Quality of Service (QoS) metrics compared to single-objective models. However, determining appropriate weight parameters remained a challenge.

Zhao et al. (2023) introduced a hierarchical deep reinforcement learning (HDRL) model integrated with DDQN for large-scale vehicular networks. The hierarchical structure divided decision-making into high-level and low-level policies, improving scalability and reducing decision complexity. The proposed approach achieved better performance in dense vehicular environments. However, training hierarchical models required more time and computational resources. Kumar et al. (2022) proposed a hybrid Deep Q-Network (DQN) with Genetic Algorithm (GA) for optimizing computation offloading and resource allocation in vehicular edge computing. The GA component was used to optimize action selection and improve global search capability, while DQN handled dynamic decision-making. The results demonstrated improved energy efficiency and reduced latency compared to standalone DQN models. However, the hybridization increased computational overhead and reduced real-time applicability in fast-changing vehicular scenarios.

Park et al. (2022) introduced a context-aware DDQN framework for energy-efficient offloading in 6G vehicular networks. The model incorporated contextual information such as traffic density, network congestion, and vehicle mobility patterns into the state space. This enhanced the adaptability of the offloading decisions. Simulation results showed improved performance in terms of energy savings and latency reduction. However, the increased state-space complexity required more training data and longer convergence time. Ren et al. (2023) developed a multi-objective optimization model combining DDQN with Ant Colony Optimization (ACO) for vehicular edge computing. The ACO component optimized routing paths, while DDQN handled offloading decisions. This hybrid model achieved better load balancing and reduced network congestion. Nevertheless, the integration of ACO introduced additional computational complexity, making scalability a concern for large-scale networks.

Gupta et al. (2023) proposed a transfer learning-based DDQN framework to accelerate learning in dynamic vehicular environments. By leveraging previously learned policies, the model reduced training time and improved adaptability to new scenarios. The results showed faster convergence and improved energy efficiency. However, transfer learning performance depended heavily on the similarity between source and target environments. Alnoman et al. (2023) introduced an AI-driven edge intelligence framework integrating DDQN with blockchain technology for secure and energy-efficient offloading. The blockchain layer ensured data integrity and secure transactions between vehicles and edge servers. The approach improved system security while maintaining energy efficiency. However, blockchain integration introduced latency overhead and scalability challenges.

Singh et al. (2023) proposed a deep reinforcement learning-based dynamic offloading model using DDQN with adaptive reward tuning. The model dynamically adjusted reward weights based on network conditions, improving decision-making efficiency. The results showed enhanced adaptability and energy savings in highly dynamic vehicular environments. Chen and Liu (2023) introduced a DDQN-based joint computation and communication resource optimization framework. The model minimized both transmission delay and energy consumption by jointly optimizing bandwidth and computing resources. However, the framework required extensive training data for optimal performance.

Verma et al. (2023) developed a lightweight DDQN model for low-power vehicular devices. The model reduced neural network complexity while maintaining performance, making it suitable for resource-constrained environments. However, slight accuracy trade-offs were observed. Abbas et al. (2023) proposed a cloud-edge collaborative DDQN framework for large-scale vehicular networks. The model distributed computation between cloud and edge layers, improving scalability and reducing processing delays. However, dependency on cloud infrastructure introduced additional latency.

Feng et al. (2023) introduced a graph neural network (GNN)-enhanced DDQN model for capturing spatial relationships among vehicles. The integration of GNN improved decision-making in dense vehicular networks. However, the model complexity increased significantly. Raza et al. (2023) proposed a secure DDQN-based offloading strategy with intrusion detection mechanisms. The model enhanced system security while optimizing energy efficiency. However, security mechanisms added computational overhead.

Kim et al. (2023) developed a multi-agent DDQN framework for cooperative vehicular offloading. The approach enabled coordination among vehicles to optimize global performance. However, communication overhead among agents remained a challenge. Zhou et al. (2023) proposed a DDQN with edge intelligence and predictive analytics to anticipate network conditions. This predictive capability improved decision-making efficiency and reduced latency. However, prediction errors could affect performance.

Patel et al. (2023) introduced a hybrid DDQN and fuzzy logic-based optimization framework for handling uncertainty in vehicular networks. The fuzzy system improved decision robustness. However, parameter tuning complexity increased. Ahmed et al. (2023) proposed a deep learning-driven holistic optimization framework combining DDQN with multi-objective evolutionary algorithms. The model achieved superior performance in energy efficiency, latency reduction, and load balancing. However, computational complexity remained a limitation.

Comparative Table

Study	Year	Method	Key Focus	Advantages	Limitations
Huang	2020	DDPG	Resource allocation	High accuracy	Slow convergence
Qu	2020	Meta-RL	Adaptability	Fast learning	Complexity
Cho	2021	Convex Opt.	Energy minimization	Low energy	Static model
Geng	2021	Multi-agent RL	Scalability	Reduced delay	No energy focus

Tang	2021	DDQN	Offloading	Better than DQN	Limited scope
Liu	2021	DDQN	Energy-delay	Efficient	No mobility
Zhang	2021	DQN+PSO	Hybrid optimization	Fast convergence	Complex
Wang	2022	MADRL	Cooperation	Scalable	Overhead
Chen	2022	DDQN+PER	Learning efficiency	Fast convergence	Memory cost
Sun	2022	DDQN+Caching	Latency reduction	Efficient	Cache issue
Li	2022	DDQN	Mobility-aware	Robust	High cost
He	2022	DDQN+Lyapunov	Stability	Balanced	Complex
Xu	2022	FL+DDQN	Privacy	Secure	Non-IID issue
Yang	2023	Multi-objective DDQN	QoS	Balanced	Weight tuning
Zhao	2023	HDRL	Scalability	Efficient	Training time
Kumar	2022	DQN+GA	Optimization	Global search	Overhead
Park	2022	Context-DDQN	Adaptability	Efficient	State complexity
Ren	2023	DDQN+ACO	Routing	Load balance	Complexity
Gupta	2023	Transfer-DDQN	Fast learning	Adaptive	Dependency
Alnoman	2023	DDQN+Blockchain	Security	Secure	Latency
Singh	2023	Adaptive DDQN	Dynamic reward	Flexible	Complexity
Chen	2023	Joint optimization	Efficiency	Balanced	Data need
Verma	2023	Lightweight DDQN	Low power	Efficient	Accuracy drop
Abbas	2023	Cloud-edge DDQN	Scalability	Fast	Cloud delay
Feng	2023	GNN+DDQN	Spatial learning	Accurate	Heavy
Raza	2023	Secure DDQN	Security	Safe	Overhead
Kim	2023	Multi-agent DDQN	Cooperation	Efficient	Comm cost
Zhou	2023	Predictive DDQN	Forecasting	Low delay	Errors
Patel	2023	Fuzzy+DDQN	Uncertainty	Robust	Tuning
Ahmed	2023	Hybrid AI	Multi-objective	High performance	Complex

Comparative Analysis

The comparative analysis of the 30 studies reveals a clear evolution from traditional optimization techniques toward advanced deep reinforcement learning-based approaches. Early works (2020–2021) primarily focused on DQN and DDPG models, which provided foundational frameworks for task offloading but suffered from issues such as overestimation bias and slow convergence. The introduction of DDQN significantly improved learning stability and decision accuracy, making it a preferred approach in later studies. From 2022 onwards, research shifted toward hybrid models combining DDQN with optimization techniques such as PSO, GA, ACO, and Lyapunov optimization. These hybrid approaches enhanced performance by improving exploration capabilities and convergence speed. Additionally, the integration of emerging technologies such as federated learning, blockchain, and graph neural networks addressed critical challenges related to privacy, security, and scalability.

Multi-agent and hierarchical reinforcement learning models further improved system scalability and coordination among vehicles. However, these approaches introduced communication overhead and increased system complexity. Lightweight and transfer learning-based models attempted to address computational constraints, making them suitable for real-world deployment. Overall, DDQN-based approaches demonstrated superior performance in terms of energy efficiency, latency reduction, and adaptability. However, challenges such as computational complexity, scalability, and dynamic network conditions remain open research issues.

Discussion

The integration of deep learning and optimization techniques in vehicular edge computing has significantly enhanced energy-efficient data offloading strategies. DDQN-based models have emerged as a powerful solution due to their ability to handle dynamic environments and reduce overestimation bias. The reviewed studies highlight the effectiveness of combining reinforcement learning with optimization algorithms to achieve better system performance. Hybrid approaches, such as DDQN with PSO, GA, and ACO, provide improved exploration and convergence but introduce additional computational overhead. Similarly, the adoption of federated learning and blockchain enhances privacy and security but may impact latency and scalability. Multi-agent systems enable cooperative decision-making but require efficient communication mechanisms to avoid overhead.

Despite these advancements, several challenges remain unresolved. These include handling highly dynamic vehicular mobility, ensuring real-time decision-making, and reducing computational complexity for deployment in resource-constrained environments. Future research should focus on developing lightweight, scalable, and secure frameworks that can adapt to rapidly changing network conditions while maintaining energy efficiency.

Conclusion

The rapid advancement of 6G communication technologies has revolutionized vehicular edge computing, enabling the deployment of intelligent and energy-efficient systems for next-generation applications. This review comprehensively analyzed deep learning and optimization approaches for strategy design in energy-efficient data offloading using Double Deep Q-Networks (DDQN). The findings indicate that DDQN-based approaches outperform traditional optimization and reinforcement learning techniques by addressing overestimation bias and improving learning stability. The integration of hybrid optimization methods, including particle swarm optimization, genetic algorithms, and ant colony optimization, further enhances system performance by improving convergence speed and solution quality.

Moreover, the incorporation of advanced technologies such as federated learning, blockchain, and graph neural networks has addressed critical challenges related to privacy, security, and scalability. Multi-agent and hierarchical reinforcement learning models have improved coordination and decision-making in large-scale vehicular networks. However, the review also highlights several limitations and challenges. The increased complexity of hybrid models poses difficulties in real-time implementation, particularly in highly dynamic vehicular environments. Communication overhead in multi-agent systems and latency introduced by blockchain technologies remain significant concerns. Additionally, the need for large-scale training data and computational resources limits the practical deployment of these models.

Future research should focus on developing lightweight and efficient models that can operate under resource constraints while maintaining high performance. The integration of explainable AI and adaptive learning techniques could further enhance model transparency and adaptability. Furthermore, addressing security vulnerabilities and ensuring robust performance under diverse network conditions will be critical for real-world deployment. In conclusion, DDQN-based deep learning and optimization approaches offer a promising direction for energy-efficient data offloading in 6G-enabled vehicular edge computing networks. Continued research and innovation in this domain will play a vital role in enabling sustainable and intelligent transportation systems.

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