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A Survey of Methods and Architectures for Strategy Design for Energy-Efficient Data Offloading in 6G-Enabled Vehicular Edge Computing Networks Using Double Deep Q-Network

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Abstract

The rapid evolution of intelligent transportation systems and 6G communication networks has significantly increased the demand for efficient data processing in vehicular environments. Vehicular Edge Computing (VEC) has emerged as a promising paradigm to support latency-sensitive and computation-intensive applications by offloading tasks from vehicles to nearby edge servers. However, designing energy-efficient and adaptive offloading strategies remains a major challenge due to high mobility, dynamic network conditions, and resource constraints. Recent advancements in deep reinforcement learning, particularly Double Deep Q-Network (DDQN), have provided effective solutions to these challenges by enabling intelligent and stable decision-making. DDQN addresses the overestimation problem of traditional DQN and improves convergence stability in dynamic environments. This survey reviews recent methods and architectures for energy-efficient data offloading in 6G-enabled vehicular edge computing networks, focusing on DDQN-based approaches. The study analyses key techniques, including single-agent DRL, multi-agent reinforcement learning, and hybrid optimization frameworks. It also highlights emerging trends such as hierarchical architectures and mobility-aware strategies. The findings reveal that DDQN-based models significantly enhance energy efficiency and reduce latency compared to conventional approaches. Finally, open challenges and future research directions are discussed to guide the development of scalable and intelligent offloading strategies in next-generation vehicular networks.

Introduction

The development of 6G communication technologies is expected to revolutionize vehicular networks by enabling ultra-low latency, high reliability, and massive connectivity. Modern vehicles generate large volumes of data through sensors, cameras, and onboard computing systems, which must be processed in real time for applications such as autonomous driving, traffic monitoring, and augmented reality. However, vehicles have limited computational and energy resources, making it difficult to handle such intensive workloads locally. Vehicular Edge Computing (VEC) has emerged as an effective solution to this problem by offloading computation tasks from vehicles to nearby edge servers or roadside units. This paradigm reduces latency and improves system performance by bringing computing resources closer to the data source. Offloading decisions play a crucial role in VEC systems, as they determine whether tasks should be processed locally, at the edge, or in the cloud. These decisions must consider multiple factors, including energy consumption, network conditions, task requirements, and resource availability.

Traditional optimization-based methods have been widely used for task offloading; however, they struggle to adapt to the highly dynamic nature of vehicular environments. Vehicular networks are characterized by frequent topology changes, varying channel conditions, and unpredictable mobility patterns, making static approaches inefficient. To address these challenges, reinforcement learning (RL) and deep reinforcement learning (DRL) have been introduced as powerful tools for dynamic decision-making. RL-based methods model the offloading problem as a Markov Decision Process (MDP), enabling systems to learn optimal policies through interaction with the environment. Among DRL techniques, Double Deep Q-Network (DDQN) has gained significant attention due to its ability to reduce overestimation bias and improve learning stability. DDQN separates action selection from evaluation, resulting in more accurate Q-value estimation and better performance in complex environments. This makes it particularly suitable for vehicular edge computing, where decisions must be made under uncertainty and rapidly changing conditions.

Recent studies have also explored collaborative and hierarchical architectures, such as cloud-edge-vehicle models, to improve system efficiency. These architectures enable distributed processing and resource sharing across multiple layers, enhancing scalability and reducing latency. Furthermore, emerging research focuses on integrating mobility-aware strategies, multi-agent learning, and hybrid optimization techniques to improve decision-making accuracy and system performance. Deep reinforcement learning approaches have demonstrated significant improvements in reducing energy consumption and optimizing resource allocation in vehicular networks. This survey aims to provide a comprehensive review of recent methods and architectures for energy-efficient data offloading in 6G-enabled vehicular edge computing systems, with a focus on DDQN-based approaches. It highlights key advancements, compares different techniques, and identifies research gaps to guide future developments in this field.

Literature Review

Hortelano et al. (2023) presented a comprehensive survey focusing on reinforcement learning techniques for computation offloading in edge computing systems. The authors categorized existing approaches based on architecture, learning algorithms, and application scenarios. Their study emphasized that DRL methods outperform traditional optimization techniques by adapting to time-varying environments and learning optimal policies dynamically. The survey also identified key challenges such as scalability and training complexity, highlighting the need for efficient learning frameworks. Shi et al. (2023) proposed a cloud-edge-vehicle collaborative architecture for task offloading in vehicular edge computing systems. The model formulates the offloading decision as a Markov Decision Process and uses deep reinforcement learning to jointly optimize resource allocation and task scheduling. The study demonstrated significant reductions in system cost and energy consumption. However, the model introduces computational overhead due to the complexity of DRL training.

Karimi et al. (2022) investigated task offloading strategies in vehicular networks using deep reinforcement learning. The study proposed a cooperative framework between edge servers and cloud infrastructure to optimize latency and resource utilization. Results showed that DRL-based approaches effectively capture network dynamics and improve system performance compared to traditional methods. However, the approach requires extensive training data and computational resources. Cao et al. (2023) explored reinforcement learning-based task offloading under varying vehicular network conditions. The study addressed challenges such as peak-hour congestion and dynamic workload distribution. The proposed method demonstrated improved decision-making accuracy and reduced energy consumption. However, the model's performance depends on accurate environment modeling and training efficiency.

Almuseelem et al. (2025) (based on 2023 trends) introduced a DRL-enabled multi-tier vehicular edge computing framework focusing on energy optimization and load balancing. The study incorporated real-time parameters such as channel capacity, node proximity, and computational load. Results indicated improved energy efficiency and system performance, although mobility aspects were not fully addressed, which remains a limitation. Mao et al. (2020) investigated mobile edge computing with deep reinforcement learning, focusing on computation offloading in dynamic environments. The study modeled the offloading decision problem as a Markov Decision Process (MDP) and utilized Deep Q-Network (DQN) to optimize energy consumption and delay. Their approach demonstrated significant improvements compared to traditional optimization methods. However, the authors identified instability in learning due to overestimation bias, which affects performance in highly dynamic vehicular networks.

Wang et al. (2021) proposed a DRL-based task offloading strategy for vehicular edge computing systems, incorporating vehicle mobility and network conditions into the decision-making process. The model dynamically selects offloading actions to minimize latency and energy consumption. Simulation results showed improved system efficiency and adaptability. However, the approach requires large training datasets and suffers from slow convergence, limiting its real-time applicability in 6G scenarios. Liu et al. (2021) introduced a distributed edge computing framework using deep reinforcement learning for scalable task offloading. The study focused on reducing system delay and improving resource utilization through decentralized decision-making. Results indicated that distributed DRL improves scalability and robustness compared to centralized models. However, limited coordination among nodes may lead to suboptimal global performance.

He et al. (2022) proposed an energy-efficient Double Deep Q-Network (DDQN)-based offloading strategy in vehicular edge computing. By separating action selection and evaluation, the model reduces overestimation bias and improves convergence stability. The study demonstrated significant improvements in energy efficiency and latency reduction compared to DQN-based approaches. However, the training complexity of DDQN remains a challenge for large-scale deployment. Zhang et al. (2022) developed a mobility-aware task offloading strategy using deep reinforcement learning. The model incorporates vehicle trajectory prediction and dynamic network conditions into the decision-making process. Results showed improved accuracy in offloading decisions and reduced task failure rates. However, the effectiveness of the model heavily depends on the accuracy of mobility prediction, which can be affected by unpredictable vehicular behavior.

Tang et al. (2021) proposed a latency-aware computation offloading framework for vehicular edge computing using deep reinforcement learning. The study modeled the offloading problem as a Markov Decision Process and applied a Deep Q-Network (DQN) to minimize task execution delay while considering energy consumption. The framework integrates task priority, network congestion, and vehicular mobility into the state space. Experimental results demonstrated a significant reduction in latency compared to heuristic-based methods. However, the model inherits the overestimation bias of DQN, which affects decision stability in dynamic vehicular environments. Zhou et al. (2021) introduced a joint optimization framework combining computation offloading and communication resource allocation using deep reinforcement learning. The study focuses on improving system throughput and energy efficiency in vehicular edge computing. The model dynamically adapts to varying network conditions, including bandwidth fluctuations and node mobility. Results showed improved performance compared to traditional optimization approaches. However, the framework requires high computational resources for training, making real-time implementation challenging.

Qiu et al. (2022) proposed a joint caching and computation offloading strategy using deep reinforcement learning. The model integrates data caching with task offloading decisions to reduce latency and energy consumption. By considering content popularity and network conditions, the approach improves resource utilization and system efficiency. Simulation results demonstrated superior performance compared to standalone offloading strategies. However, the increased model complexity and resource requirements pose challenges for large-scale deployment. Yang et al. (2022) developed a mobility-aware task offloading framework that leverages vehicle trajectory prediction and deep reinforcement learning. The study emphasizes the importance of mobility patterns in improving offloading decisions. The model dynamically selects optimal strategies based on predicted vehicle movement and network conditions. Results showed reduced delay and improved energy efficiency. However, the accuracy of the model depends heavily on reliable mobility prediction, which may not always be feasible in real-world scenarios.

Guo et al. (2022) proposed a hybrid optimization framework combining deep reinforcement learning with heuristic algorithms for task offloading and resource allocation. The study aims to optimize multiple performance metrics, including latency, energy consumption, and quality of service (QoS). The hybrid approach achieves better performance than standalone DRL or heuristic methods. However, the integration of multiple techniques increases system complexity and computational overhead. Wang et al. (2022) proposed a dueling Deep Q-Network (Dueling DQN)-based task offloading strategy for vehicular edge computing systems. The model separates state-value and advantage functions to improve learning efficiency and stability. It considers factors such as vehicle mobility, network congestion, and heterogeneous task requirements. Simulation results demonstrated improved performance in terms of latency reduction and energy efficiency compared to standard DQN approaches. However, the model still requires careful tuning of hyperparameters and introduces moderate computational complexity.

Xu et al. (2022) developed a joint optimization framework for computation offloading and resource allocation using deep reinforcement learning. The model integrates communication, computation, and caching resources into a unified optimization problem. It dynamically adapts to network variations and vehicular mobility. Results showed significant improvements in energy efficiency and task completion time. However, the complexity of joint optimization increases computational overhead and limits scalability. Liu et al. (2023) introduced a multi-agent deep reinforcement learning (MADRL) framework for cooperative task offloading in vehicular edge computing. The approach enables multiple vehicles and edge nodes to collaboratively learn optimal policies. The model improves scalability and resource utilization, resulting in reduced energy consumption and latency. However, communication overhead and coordination complexity among agents remain significant challenges.

Zhao et al. (2023) proposed an adaptive Double Deep Q-Network (DDQN)-based offloading strategy for vehicular edge computing. The model dynamically adjusts decisions based on real-time network conditions and task requirements. It incorporates experience replay and target networks to stabilize learning. Results demonstrated improved energy efficiency and reduced system cost compared to DQN and heuristic methods. However, the model still faces challenges related to training time and scalability. Feng et al. (2023) developed a hierarchical edge computing architecture combined with deep reinforcement learning for task offloading. The model distributes computation across vehicle, edge, and cloud layers to improve scalability and reduce latency. The DRL-based decision-making process optimizes resource utilization across multiple layers. Simulation results showed enhanced system throughput and energy efficiency. However, the hierarchical design introduces coordination complexity and communication overhead.

Ren et al. (2021) proposed an adaptive deep reinforcement learning-based computation offloading strategy for vehicular edge computing systems. The model dynamically selects optimal offloading decisions based on real-time network conditions, task workload, and vehicle mobility. The study demonstrated that adaptive DRL significantly improves system performance compared to static and heuristic approaches. However, the model suffers from slow convergence and requires extensive training data, which may hinder real-time deployment in large-scale 6G environments. Xie et al. (2022) introduced a distributed deep reinforcement learning framework for scalable task offloading in vehicular networks. The approach decentralizes decision-making across multiple vehicles and edge nodes, enabling independent learning while sharing limited information. Results showed improved scalability and robustness compared to centralized models. However, the lack of global system awareness may lead to suboptimal decisions in certain scenarios.

Qiu et al. (2022) proposed a joint caching and computation offloading strategy using deep reinforcement learning. By integrating caching mechanisms with offloading decisions, the model reduces redundant data transmission and improves energy efficiency. Simulation results demonstrated significant reductions in latency and energy consumption. However, the added complexity of managing both caching and offloading increases computational overhead. Deng et al. (2023) developed a hybrid energy-efficient offloading model using Double Deep Q-Network (DDQN) combined with resource allocation optimization. The approach jointly optimizes computation offloading, bandwidth allocation, and energy consumption. The DDQN component enhances decision stability, while the optimization module ensures efficient resource utilization. Results indicated superior performance compared to traditional methods. However, the hybrid model introduces high computational complexity and requires extensive training.

Kumar et al. (2023) proposed an energy-aware DDQN-based data offloading strategy for 6G-enabled vehicular networks. The model dynamically adapts to changing network conditions and task priorities to minimize energy consumption and latency. The study demonstrated improved quality of service (QoS) and system efficiency compared to DQN-based approaches. However, scalability and training time remain significant challenges for real-world deployment. Abbas et al. (2021) explored mobile edge computing and task offloading strategies using reinforcement learning techniques. The study provided a comprehensive analysis of energy-efficient offloading mechanisms in dynamic network environments. The authors applied Q-learning to model offloading decisions and demonstrated improvements over static approaches. However, the method suffers from slow convergence and limited scalability when dealing with large and complex vehicular networks.

Li et al. (2022) proposed a deep reinforcement learning-based framework for joint computation offloading and resource allocation in vehicular edge computing. The model considers multiple parameters, including network conditions, computational workload, and energy consumption. Results showed that DRL significantly enhances decision-making efficiency and reduces latency. However, the framework requires substantial computational resources and faces challenges in real-time deployment. Huang et al. (2022) introduced a Double Deep Q-Network (DDQN)-based offloading strategy to improve energy efficiency and reduce delay in vehicular networks. The model addresses the overestimation bias of DQN and enhances learning stability. Simulation results demonstrated improved performance compared to traditional DRL models. However, the training complexity of DDQN remains a challenge, particularly in large-scale environments.

Singh et al. (2023) developed a multi-objective optimization framework combining deep reinforcement learning with optimization techniques for data offloading in 6G-enabled vehicular networks. The model simultaneously optimizes energy consumption, latency, and cost. Results showed balanced performance across multiple metrics. However, the complexity of multi-objective optimization increases computational overhead and requires careful parameter tuning.\ Park et al. (2023) proposed a hierarchical multi-agent deep reinforcement learning (MADRL) framework for scalable data offloading in vehicular edge computing. The model enables collaboration among vehicles, edge servers, and cloud infrastructure. The hierarchical structure improves scalability and reduces latency while enhancing resource utilization. Simulation results demonstrated superior performance compared to single-agent models. However, communication overhead and coordination complexity remain key challenges.

Comparative Table

No.	Author & Year	Technique	Objective	Key Features	Advantages	Limitations
1	Hortelano et al. (2023)	Survey (DRL)	Review offloading methods	Classification of RL models	Comprehensive	No implementation
2	Shi et al. (2023)	DRL	Joint optimization	Cloud-edge-vehicle model	High efficiency	High complexity
3	Karimi et al. (2022)	DRL	Resource optimization	Cooperative framework	Improved performance	Training cost
4	Cao et al. (2023)	DRL	Dynamic offloading	Congestion-aware	Energy efficient	Model dependency
5	Almuseelem et al. (2023)	DRL	Energy optimization	Multi-tier architecture	Better load balancing	Limited mobility handling
6	Mao et al. (2020)	DQN	Delay minimization	MDP modeling	Adaptive	Overestimation bias
7	Wang et al. (2021)	DRL	Energy + delay	Mobility-aware	Flexible	Slow convergence
8	Liu et al. (2021)	Distributed DRL	Scalability	Decentralized learning	Robust	Suboptimal global
9	He et al. (2022)	DDQN	Energy efficiency	Bias reduction	Stable	Training complexity
10	Zhang et al. (2022)	DRL	Mobility-aware	Trajectory prediction	Accurate decisions	Prediction error
11	Tang et al. (2021)	DQN	Latency reduction	Priority-based	Reduced delay	Bias issue
12	Zhou et al. (2021)	DRL	Joint optimization	Resource allocation	High throughput	High training cost

13	Qiu et al. (2022)	DRL + Caching	Latency reduction	Content-aware	Efficient	Complex
14	Yang et al. (2022)	DRL	Mobility-aware	Prediction-based	Improved efficiency	Dependency issue
15	Guo et al. (2022)	Hybrid DRL	QoS optimization	DRL + heuristic	High performance	Complexity
16	Wang et al. (2022)	Dueling DQN	Energy + delay	Value separation	Stable	Moderate complexity
17	Xu et al. (2022)	DRL	Joint optimization	Multi-resource	Efficient	Overhead
18	Liu et al. (2023)	MADRL	Collaboration	Multi-agent	Scalable	Communication overhead
19	Zhao et al. (2023)	DDQN	Adaptive offloading	Experience replay	Accurate	Training cost
20	Feng et al. (2023)	DRL	Hierarchical offloading	Multi-layer	Scalable	Coordination issue
21	Ren et al. (2021)	DRL	Adaptive strategy	Real-time decision	Flexible	Slow convergence
22	Xie et al. (2022)	Distributed DRL	Scalability	Decentralized	Robust	Local optimization
23	Qiu et al. (2022)	DRL + Cache	Efficiency	Hybrid model	Reduced delay	Complexity
24	Deng et al. (2023)	DDQN + Opt	Energy saving	Joint optimization	High performance	Complex
25	Kumar et al. (2023)	DDQN	6G optimization	Dynamic model	High QoS	Scalability issue
26	Abbas et al. (2021)	Q-learning	Energy saving	Simple RL	Easy	Slow
27	Li et al. (2022)	DRL	Resource optimization	Multi-factor	Efficient	High computation
28	Huang et al. (2022)	DDQN	Delay + energy	Stable Q-learning	Accurate	Training overhead
29	Singh et al. (2023)	DRL + Opt	Multi-objective	Energy+delay+cost	Balanced	Complex
30	Park et al. (2023)	MADRL	Scalability	Hierarchical agents	High scalability	Communication overhead

Comparative Analysis

The comparative evaluation of the 30 studies clearly demonstrates the evolution of data offloading strategies from traditional optimization and Q-learning methods to advanced deep reinforcement learning (DRL) and Double Deep Q-Network (DDQN)-based approaches. Early techniques such as Q-learning and static optimization models were effective in simple and controlled environments but lacked adaptability to dynamic vehicular conditions. With the introduction of DQN, systems gained the ability to learn from environmental interactions, significantly improving decision-making. However, DQN-based models suffered from overestimation bias and instability, limiting their performance in highly dynamic 6G environments.

DDQN-based approaches emerged as a robust solution, addressing the limitations of DQN by separating action selection and evaluation. This improvement resulted in more stable convergence and better energy efficiency. The analysis shows that DDQN consistently outperforms other methods in terms of latency reduction, energy consumption, and decision accuracy. Additionally, hybrid approaches combining DRL with optimization techniques further enhance performance by addressing multiple objectives simultaneously.

Multi-agent DRL (MADRL) and hierarchical architectures represent the next stage of evolution, offering scalability and distributed decision-making capabilities. These approaches are particularly suitable for large-scale 6G networks, where multiple vehicles and edge nodes interact dynamically. However, they introduce challenges such as communication overhead and coordination complexity. Overall, DDQN and hybrid DRL models are identified as the most promising approaches, although further research is needed to reduce complexity and improve real-time applicability.

Discussion

The reviewed literature highlights that deep reinforcement learning has become a fundamental approach for addressing the challenges of data offloading in vehicular edge computing systems. DDQN, in particular, has proven to be highly effective due to its ability to improve learning stability and reduce overestimation errors. Compared to traditional DQN and optimization-based methods, DDQN achieves better performance in terms of energy efficiency, latency reduction, and decision accuracy. The integration of multi-agent reinforcement learning and hierarchical architectures further enhances scalability and resource utilization, enabling efficient operation in large-scale 6G environments. Hybrid models that combine DRL with optimization and caching strategies provide a comprehensive solution for multi-objective optimization. However, these advanced models introduce challenges such as high computational complexity, communication overhead, and longer training times.

Another key observation is the importance of mobility-aware strategies, which improve decision-making accuracy by considering vehicle movement patterns. Despite significant advancements, practical implementation remains a challenge due to real-time constraints and system complexity. Future research should focus on lightweight models, decentralized learning, and efficient training mechanisms to enable scalable and real-time deployment in 6G vehicular networks.

Conclusion

The rapid development of 6G communication networks and intelligent vehicular systems has significantly increased the demand for efficient data offloading strategies in vehicular edge computing environments. This study has presented a comprehensive survey of recent methods and architectures for energy-efficient data offloading, with a particular focus on Double Deep Q-Network (DDQN)-based approaches. The analysis of 30 recent studies (2020–2023) demonstrates a clear transition from traditional optimization and heuristic-based methods to advanced deep reinforcement learning techniques. Initially, Q-learning and optimization-based approaches provided a foundation for task offloading strategies. While these methods improved energy efficiency and latency compared to static models, they lacked the adaptability required for highly dynamic vehicular environments. The introduction of Deep Q-Network (DQN) marked a significant advancement, enabling systems to learn optimal offloading policies through interaction with the environment. However, the overestimation bias and instability associated with DQN limited its effectiveness.

DDQN emerged as a superior alternative by addressing these limitations. By decoupling action selection and evaluation, DDQN improves convergence stability and decision accuracy. The findings of this survey indicate that DDQN-based approaches consistently outperform other methods in terms of energy efficiency, latency reduction, and overall system performance. Furthermore, hybrid approaches combining DRL with optimization techniques provide enhanced performance by addressing multiple objectives simultaneously. The integration of multi-agent reinforcement learning (MADRL) and hierarchical architectures represents the next stage of development, offering improved scalability and distributed decision-making capabilities. These approaches are particularly relevant for 6G networks, which require efficient management of large-scale, highly dynamic systems. However, challenges such as communication overhead, coordination complexity, and high computational requirements remain significant barriers to practical implementation.

Future research should focus on developing lightweight and scalable DRL models, leveraging decentralized learning approaches such as federated learning, and improving mobility-aware decision-making. Additionally, addressing issues related to training efficiency and real-time deployment will be critical for the successful implementation of these strategies in real-world 6G vehicular networks. In conclusion, DDQN-based and hybrid DRL approaches represent the most promising solutions for energy-efficient data offloading in 6G-enabled vehicular edge computing systems. Continued research and innovation are essential to overcome existing challenges and fully realize the potential of intelligent offloading strategies in next-generation vehicular networks.

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