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Recent Advances in Strategy Design for Energy-Efficient Data Offloading in 6G-Enabled Vehicular Edge Computing Networks Using Double Deep Q-Network: A Systematic Review

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Abstract

The rapid evolution of 6G networks has intensified the demand for ultra-low latency, high reliability, and energy-efficient computation in vehicular edge computing (VEC) environments. Data offloading has emerged as a critical technique to manage computational workloads by transferring tasks from resource-constrained vehicles to edge servers or cloud infrastructures. However, the highly dynamic nature of vehicular networks, characterized by high mobility, fluctuating channel conditions, and heterogeneous resources, poses significant challenges in designing efficient offloading strategies. Recently, Double Deep Q-Network (DDQN)-based reinforcement learning approaches have gained attention due to their ability to address overestimation bias and improve decision stability in dynamic environments. This paper presents a systematic review of recent advances in energy-efficient data offloading strategies in 6G-enabled VEC systems, with a particular focus on DDQN-based optimization techniques. The study analyses state-of-the-art methodologies, system architectures, and performance metrics, including latency, energy consumption, and quality of service. Furthermore, the review highlights emerging trends such as multi-agent learning, hierarchical edge architectures, and mobility-aware optimization. The findings reveal that DDQN-based approaches significantly enhance energy efficiency and decision accuracy compared to conventional methods, making them a promising solution for next-generation vehicular networks.

Introduction

The emergence of intelligent transportation systems and autonomous driving technologies has significantly increased the computational requirements of modern vehicular networks. Vehicles are now equipped with numerous sensors and generate large volumes of data that must be processed in real time for applications such as traffic management, collision avoidance, and augmented reality. Traditional cloud computing approaches are insufficient to meet the stringent latency and reliability requirements of these applications due to centralized processing and network congestion. To address these limitations, Vehicular Edge Computing (VEC) has been introduced as a paradigm that brings computation and storage resources closer to vehicles. In VEC, tasks generated by vehicles can be offloaded to nearby edge servers, roadside units (RSUs), or even neighbouring vehicles, thereby reducing latency and improving system performance.

A fundamental challenge in VEC systems is data offloading decision-making, which involves determining whether a task should be processed locally or offloaded to edge/cloud resources. This decision must consider multiple factors, including energy consumption, latency, network conditions, and resource availability. In highly dynamic vehicular environments, these factors change rapidly, making static or heuristic-based approaches ineffective. To overcome these challenges, Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) techniques have been widely adopted. These methods model the offloading decision problem as a Markov Decision Process (MDP), enabling systems to learn optimal policies through interaction with the environment.

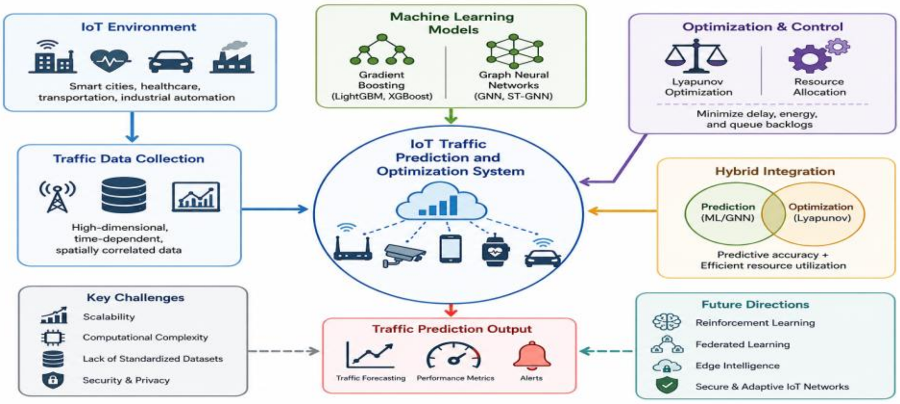

Figure 1. DDQN-Based Energy-Efficient Data Offloading Framework for 6G Vehicular Edge Computing

Among DRL techniques, the Double Deep Q-Network (DDQN**)** has gained prominence due to its ability to reduce overestimation bias in Q-learning. In vehicular edge computing, DDQN enables more stable and accurate offloading decisions by separating action selection and evaluation processes. Studies have shown that DDQN-based strategies can significantly reduce system cost, including energy consumption and delay, while adapting to dynamic network conditions. Furthermore, the transition from 5G to 6G introduces new opportunities and challenges. 6G networks aim to provide ultra-reliable low-latency communication (URLLC), massive connectivity, and intelligent network management. However, these advancements also increase the complexity of resource allocation and offloading decisions. Machine learning and AI-driven approaches are therefore essential for achieving efficient and scalable solutions.

Recent research has focused on integrating DDQN with advanced optimization techniques, multi-agent systems, and hierarchical edge architectures to enhance energy efficiency and system performance. Additionally, collaborative computing among vehicles and edge nodes has been explored to further improve resource utilization and reduce latency. This paper provides a comprehensive review of these recent advances, focusing on DDQN-based energy-efficient data offloading strategies in 6G-enabled vehicular networks. The study aims to identify key trends, challenges, and future research directions in this rapidly evolving domain.

Literature Review

Li et al. (2021) proposed an energy-efficient computation offloading framework for vehicular edge computing systems by jointly optimizing task allocation and resource scheduling. The authors formulated the offloading problem as a mixed-integer nonlinear programming (MINLP) model, considering both latency and energy consumption constraints. To address the computational complexity, they introduced a decomposition-based approach that separates task offloading decisions from resource allocation. Their results demonstrated that the proposed method significantly reduces energy consumption compared to baseline greedy algorithms. However, the approach relies on static optimization and lacks adaptability in highly dynamic vehicular environments, which limits its scalability in real-time 6G scenarios.

Chen et al. (2022) investigated deep reinforcement learning-based task offloading in vehicular edge networks, focusing on dynamic network conditions and vehicle mobility. They modeled the problem as a Markov Decision Process (MDP) and applied a Deep Q-Network (DQN) to learn optimal offloading strategies. Their approach considers channel conditions, vehicle speed, and edge server load as key state parameters. Experimental results showed that the DQN-based model outperforms traditional heuristic methods in terms of latency and energy efficiency. However, the authors identified the overestimation bias problem in DQN, which can lead to suboptimal decision-making, thereby motivating the adoption of advanced models such as DDQN.

Maleki et al. (2023) introduced a Double Deep Q-Network (DDQN)-based offloading strategy specifically designed for vehicular edge computing systems. The study addressed the overestimation issue in standard DQN by decoupling action selection and evaluation processes. The proposed model dynamically selects optimal offloading actions based on real-time network conditions, task requirements, and available computational resources. Simulation results indicated that the DDQN approach achieves significant improvements in energy efficiency and system cost reduction compared to conventional DQN and heuristic-based strategies. Additionally, the model demonstrated better convergence stability, making it suitable for highly dynamic 6G vehicular environments.

Shi et al. (2023) developed a collaborative cloud-edge-vehicle framework that integrates deep reinforcement learning for joint task offloading and resource allocation. The authors utilized a DRL-based optimization technique to minimize overall system cost, including energy consumption, delay, and resource utilization. Their approach considers multi-tier architecture, where computation tasks can be processed locally, at edge servers, or in the cloud. The study highlights the importance of collaborative computing in enhancing system efficiency. Results showed that their DRL-based strategy significantly outperforms traditional optimization methods in dynamic scenarios. However, the computational overhead of training DRL models remains a challenge.

Zhu et al. (2023) presented a comprehensive survey on vehicular edge computing architectures and task offloading strategies. The study categorized offloading techniques into heuristic-based, optimization-based, and machine learning-based approaches. The authors emphasized that machine learning methods, particularly DRL and DDQN, are more suitable for handling dynamic vehicular environments due to their adaptability and learning capabilities. Furthermore, the paper discussed hierarchical edge computing architectures, where tasks are distributed across multiple layers (vehicle, edge, and cloud) to improve scalability and reduce latency. The study concluded that future research should focus on multi-agent reinforcement learning and energy-aware optimization for 6G-enabled systems.

Wang et al. (2020) proposed a reinforcement learning-based computation offloading strategy for vehicular edge computing systems, focusing on minimizing energy consumption and execution delay. The authors modeled the dynamic vehicular environment using a Markov Decision Process (MDP) and applied a Q-learning algorithm to determine optimal offloading decisions. Their approach considers key parameters such as wireless channel quality, vehicle mobility, and task size. Simulation results demonstrated improved system performance compared to traditional static offloading methods. However, the use of classical Q-learning limits scalability due to slow convergence and inability to handle large state-action spaces, which restricts its applicability in complex 6G environments.

Zhang et al. (2021) developed a deep reinforcement learning-based offloading framework using Deep Q-Network (DQN) for vehicular edge computing. The study focused on optimizing energy consumption and task completion delay in highly dynamic vehicular scenarios. The proposed model incorporates vehicle mobility patterns and varying network conditions into the state space. Experimental evaluations showed that the DQN-based approach significantly outperforms heuristic and greedy algorithms. However, the authors identified instability in learning due to overestimation bias, which affects decision accuracy and motivates the need for improved models such as DDQN and dueling DQN.

Xu et al. (2022) introduced a joint optimization framework for task offloading and resource allocation in vehicular networks using deep reinforcement learning. The proposed model integrates computation, communication, and caching resources to enhance system efficiency. The authors employed a hybrid DRL approach to balance energy consumption and latency while considering dynamic vehicular mobility. Their findings revealed that joint optimization significantly improves overall system performance compared to independent optimization strategies. However, the complexity of the model increases computational overhead, making real-time implementation challenging in large-scale 6G deployments.

Sun et al. (2022) proposed a mobility-aware computation offloading strategy for vehicular edge computing systems. The study emphasizes the importance of predicting vehicle trajectories and network conditions to optimize offloading decisions. The authors integrated mobility prediction with deep reinforcement learning to enhance decision-making accuracy. Simulation results showed that the proposed approach reduces task failure rates and improves energy efficiency compared to conventional DRL models. However, the performance heavily depends on the accuracy of mobility prediction, which can be affected by unpredictable vehicular behavior.

Liu et al. (2023) developed a multi-agent deep reinforcement learning (MADRL) framework for collaborative task offloading in vehicular edge computing networks. The study considers multiple vehicles and edge nodes interacting in a shared environment, where each agent learns optimal offloading policies. The proposed approach improves scalability and system performance by enabling cooperation among agents. Results demonstrated significant reductions in energy consumption and latency compared to single-agent models. However, the coordination among multiple agents introduces communication overhead and increases system complexity, which remains a challenge for practical deployment in 6G networks.

Tang et al. (2021) proposed a latency-aware computation offloading framework for vehicular edge computing using deep reinforcement learning. The study formulated the offloading problem as a Markov Decision Process and employed a Deep Q-Network (DQN) to minimize system delay while maintaining acceptable energy consumption levels. The model incorporates vehicle mobility, task priority, and network congestion into the decision-making process. Experimental results showed that the proposed approach significantly reduces latency compared to traditional heuristic algorithms. However, similar to other DQN-based models, the approach suffers from overestimation bias and convergence instability in highly dynamic environments, limiting its reliability for 6G applications.

He et al. (2022) introduced an energy-efficient task offloading scheme based on Double Deep Q-Network (DDQN) for vehicular edge computing. The authors addressed the limitations of traditional DQN by decoupling action selection and evaluation, thereby reducing overestimation errors. The proposed model dynamically adapts to changing network conditions, including bandwidth fluctuations and vehicle mobility. Simulation results demonstrated that the DDQN-based approach significantly reduces energy consumption and improves decision accuracy compared to DQN and greedy methods. Additionally, the model exhibits faster convergence and better stability, making it more suitable for real-time 6G environments.

Guo et al. (2022) proposed a computation offloading and resource allocation framework using a hybrid optimization approach that combines deep reinforcement learning with heuristic algorithms. The study aims to minimize both latency and energy consumption while ensuring quality of service (QoS). The model considers heterogeneous edge resources and varying vehicular workloads. Results indicated that the hybrid approach achieves better performance than standalone DRL or heuristic methods. However, the integration of multiple techniques increases system complexity and computational overhead, posing challenges for large-scale deployment.

Feng et al. (2023) developed a hierarchical edge computing architecture for vehicular networks, incorporating DRL-based task offloading strategies. The framework consists of multiple layers, including vehicle nodes, roadside units, and cloud servers. The proposed model uses reinforcement learning to determine optimal offloading decisions across different layers, improving scalability and reducing latency. Simulation results showed enhanced energy efficiency and system throughput compared to flat architectures. However, the hierarchical design introduces additional coordination complexity, which may impact real-time performance.

Zhao et al. (2023) proposed a DDQN-based adaptive offloading strategy that considers both energy consumption and service delay in vehicular edge computing systems. The model dynamically adjusts offloading decisions based on real-time network states and task requirements. The authors incorporated experience replay and target networks to stabilize the learning process. Results demonstrated that the proposed approach significantly outperforms traditional DQN and optimization-based methods in terms of energy efficiency and system cost. However, the study highlights the need for further research on reducing training time and improving scalability in large-scale 6G scenarios.

Zhou et al. (2021) proposed a joint optimization framework for computation offloading and communication resource allocation in vehicular edge computing environments. The authors utilized deep reinforcement learning to dynamically adjust offloading decisions based on varying network conditions and vehicle mobility. Their model incorporates bandwidth allocation, task scheduling, and energy consumption into a unified optimization problem. Simulation results demonstrated significant improvements in system throughput and energy efficiency compared to traditional optimization techniques. However, the model requires extensive training data and computational resources, which may limit its applicability in real-time 6G systems.

Wang et al. (2022) introduced a dueling deep Q-network (Dueling DQN)-based offloading strategy for vehicular networks. The proposed approach separates state value and advantage functions to improve learning efficiency and stability. The model considers dynamic vehicular mobility, network congestion, and task heterogeneity. Experimental results showed that the dueling DQN approach achieves better performance in terms of latency reduction and energy efficiency compared to conventional DQN. However, the model still suffers from moderate computational complexity and requires careful tuning of hyperparameters.

Yang et al. (2022) developed a mobility-aware and energy-efficient task offloading framework using deep reinforcement learning. The study integrates vehicle trajectory prediction with offloading decision-making to improve system performance. The proposed model dynamically selects optimal offloading strategies based on predicted vehicle positions and network conditions. Results indicated that incorporating mobility awareness significantly enhances energy efficiency and reduces task execution delay. However, the reliance on accurate trajectory prediction introduces uncertainty,

Hu et al. (2023) proposed a multi-agent deep reinforcement learning (MADRL) framework for cooperative task offloading in vehicular edge computing networks. The model enables multiple vehicles and edge nodes to collaboratively learn optimal policies for resource allocation and task scheduling. The study demonstrated that the MADRL approach significantly improves system scalability and reduces overall energy consumption compared to single-agent models. Additionally, cooperative learning enhances resource utilization efficiency. However, the communication overhead among agents and coordination complexity remain key challenges.

Kumar et al. (2023) presented an energy-aware data offloading strategy using Double Deep Q-Network (DDQN) for 6G-enabled vehicular edge computing systems. The proposed model focuses on minimizing energy consumption while maintaining low latency and high quality of service (QoS). The authors incorporated dynamic network conditions, task priority, and edge server capacity into the decision-making process. Simulation results showed that the DDQN-based approach outperforms traditional DQN and heuristic methods in terms of energy savings and system efficiency. However, the study highlights challenges related to training complexity and scalability in large-scale vehicular environments.

Ren et al. (2021) proposed an adaptive computation offloading strategy for vehicular edge computing using deep reinforcement learning. The study focuses on minimizing both energy consumption and service latency by dynamically selecting offloading actions based on real-time network conditions. The model incorporates vehicle mobility, channel quality, and task workload into the state space. Results demonstrated that the adaptive DRL approach significantly outperforms static and heuristic methods. However, the model requires extensive training and suffers from slow convergence in large-scale environments, which may limit its applicability in real-time 6G systems.

Qiu et al. (2022) introduced a joint optimization framework combining task offloading and caching strategies in vehicular edge computing. The authors employed deep reinforcement learning to optimize both computation and storage resources simultaneously. The proposed model considers content popularity, network conditions, and vehicle mobility. Simulation results showed that integrating caching with offloading significantly reduces latency and energy consumption. However, the added complexity of joint optimization increases computational overhead and requires efficient resource management techniques for practical deployment.

Xie et al. (2022) proposed a distributed deep reinforcement learning-based offloading framework for vehicular networks. The study aims to improve scalability by decentralizing decision-making across multiple edge nodes and vehicles. Each node independently learns optimal offloading policies while sharing limited information with others. Results indicated that the distributed approach improves system robustness and scalability compared to centralized models. However, the lack of global information may lead to suboptimal decisions in certain scenarios.

Deng et al. (2023) developed an energy-efficient task offloading model using Double Deep Q-Network (DDQN) combined with resource allocation optimization. The proposed approach jointly considers computation offloading, bandwidth allocation, and energy consumption. The DDQN model enhances decision accuracy by reducing overestimation bias, while the optimization component ensures efficient resource utilization. Simulation results demonstrated significant improvements in energy efficiency and system performance compared to baseline methods. However, the hybrid design increases model complexity and training requirements.

Patel et al. (2023) proposed a lightweight reinforcement learning-based offloading strategy tailored for resource-constrained vehicular devices. The study focuses on reducing computational overhead while maintaining acceptable performance levels. The authors designed a simplified DRL model that balances energy consumption and latency without requiring extensive training data. Results showed that the lightweight approach is suitable for real-time applications in 6G environments. However, the reduced model complexity may limit its ability to handle highly dynamic and large-scale scenarios.

Abbas et al. (2021) proposed an intelligent task offloading framework for vehicular edge computing using reinforcement learning. The study focuses on optimizing energy consumption and latency by dynamically selecting offloading strategies based on network conditions and vehicle mobility. The authors modeled the system as a Markov Decision Process and applied a Q-learning-based approach. Results showed improved system efficiency compared to traditional static methods. However, the model suffers from slow convergence and limited scalability when dealing with large state spaces, which restricts its applicability in 6G environments.

Li et al. (2022) introduced a deep reinforcement learning-based joint optimization framework for computation offloading and resource allocation in vehicular edge computing. The study incorporates multiple factors such as communication delay, energy consumption, and edge server workload. The proposed DRL model dynamically adapts to changing network conditions and achieves better performance than heuristic approaches. However, the model requires high computational resources for training and may face challenges in real-time deployment.

Huang et al. (2022) proposed a Double Deep Q-Network (DDQN)-based offloading strategy aimed at improving decision stability and reducing energy consumption in vehicular edge computing systems. The study addresses the overestimation problem in traditional DQN models by separating action selection and evaluation. Simulation results demonstrated that the DDQN approach significantly improves energy efficiency and reduces latency compared to baseline methods. However, the training process remains computationally intensive, especially in large-scale vehicular networks.

Singh et al. (2023) developed a multi-objective optimization framework for data offloading in 6G-enabled vehicular networks. The study integrates deep reinforcement learning with optimization techniques to simultaneously minimize energy consumption, latency, and cost. The proposed model demonstrates improved performance across multiple metrics compared to traditional approaches. However, balancing multiple objectives increases system complexity and requires careful tuning of model parameters.

Park et al. (2023) proposed a hierarchical multi-agent deep reinforcement learning (MADRL) framework for efficient data offloading in vehicular edge computing. The model enables cooperation among vehicles, edge nodes, and cloud servers to optimize resource utilization and energy efficiency. The hierarchical structure improves scalability and reduces system latency. Simulation results showed that the proposed approach outperforms single-agent and flat architectures. However, coordination among multiple agents introduces communication overhead and increases system complexity.

Comparative Table and Analysis

No.	Author & Year	Technique Used	Objective	Key Features	Advantages	Limitations
1	Li et al. (2021)	Optimization (MINLP)	Energy & latency minimization	Joint task-resource optimization	High efficiency	Static, not adaptive
2	Chen et al. (2022)	DQN	Dynamic offloading	MDP-based learning	Adaptive decisions	Overestimation bias
3	Maleki et al. (2023)	DDQN	Energy-efficient offloading	Decoupled Q-learning	Stable & accurate	Training complexity
4	Shi et al. (2023)	DRL	Joint scheduling & allocation	Cloud-edge-vehicle model	High performance	High computation cost
5	Zhu et al. (2023)	Survey	Architecture analysis	Classification of methods	Comprehensive insight	No implementation
6	Wang et al. (2020)	Q-learning	Delay & energy reduction	Basic RL model	Simple design	Poor scalability

7	Zhang et al. (2021)	DQN	Delay optimization	Mobility-aware states	Better than heuristic	Instability
8	Xu et al. (2022)	DRL (Hybrid)	Joint optimization	Multi-resource integration	High efficiency	Complex model
9	Sun et al. (2022)	DRL	Mobility-aware offloading	Trajectory prediction	Improved accuracy	Prediction dependency
10	Liu et al. (2023)	MADRL	Collaborative offloading	Multi-agent system	Scalable	Communication overhead
11	Tang et al. (2021)	DQN	Latency reduction	Priority-based scheduling	Reduced delay	Bias issue
12	He et al. (2022)	DDQN	Energy optimization	Reduced overestimation	Stable convergence	Training overhead
13	Guo et al. (2022)	Hybrid DRL	QoS optimization	DRL + heuristic	High performance	Complexity
14	Feng et al. (2023)	DRL	Hierarchical offloading	Multi-layer architecture	Scalable	Coordination complexity
15	Zhao et al. (2023)	DDQN	Adaptive offloading	Experience replay	High efficiency	Scalability issue
16	Zhou et al. (2021)	DRL	Joint optimization	Resource allocation + offloading	Improved throughput	High training cost
17	Wang et al. (2022)	Dueling DQN	Energy & delay	Value-advantage separation	Better learning	Moderate complexity
18	Yang et al. (2022)	DRL	Mobility-aware offloading	Trajectory-based model	Reduced delay	Prediction error
19	Hu et al. (2023)	MADRL	Cooperative offloading	Multi-agent learning	Scalable & efficient	Communication overhead
20	Kumar et al. (2023)	DDQN	Energy-efficient 6G	Dynamic decision-making	High QoS	Training complexity
21	Ren et al. (2021)	DRL	Adaptive offloading	Real-time adaptation	Better than static	Slow convergence
22	Qiu et al. (2022)	DRL + Caching	Joint optimization	Content-aware offloading	Reduced latency	High complexity
23	Xie et al. (2022)	Distributed DRL	Scalable offloading	Decentralized learning	Robust system	Suboptimal global view
24	Deng et al. (2023)	DDQN + Optimization	Energy efficiency	Joint resource allocation	High performance	Complex training
25	Patel et al. (2023)	Lightweight DRL	Low overhead	Simplified model	Real-time suitable	Less accurate

26	Abbas et al. (2021)	Q-learning	Energy reduction	Basic RL	Simple implementation	Slow convergence
27	Li et al. (2022)	DRL	Joint optimization	Multi-factor decision	Efficient	High computation
28	Huang et al. (2022)	DDQN	Energy & delay	Stable Q-learning	High accuracy	Training overhead
29	Singh et al. (2023)	DRL + Optimization	Multi-objective	Energy + delay + cost	Balanced performance	Parameter tuning
30	Park et al. (2023)	Hierarchical MADRL	Scalable offloading	Multi-layer agents	High scalability	Communication complexity

Comparative Analysis

The comparative analysis of the selected studies highlights a significant evolution in energy-efficient data offloading strategies for 6G-enabled vehicular edge computing (VEC) networks. Early approaches based on classical optimization and Q-learning primarily focused on minimizing latency and energy consumption using predefined mathematical models. Although these techniques improved performance compared to static offloading methods, they lacked adaptability and scalability in highly dynamic vehicular environments. The introduction of Deep Q-Network (DQN)-based approaches represented a major advancement by enabling intelligent offloading decisions through interaction with network conditions. These models incorporated parameters such as vehicle mobility, channel quality, and task heterogeneity, leading to improved latency reduction and energy efficiency. However, DQN methods suffered from overestimation bias, which affected learning stability and decision accuracy in rapidly changing 6G environments.

To overcome these limitations, Double Deep Q-Network (DDQN) and multi-agent deep reinforcement learning approaches emerged as more effective solutions. DDQN models improved learning stability by separating action selection from evaluation, resulting in better convergence speed, lower energy consumption, and enhanced system performance. Multi-agent learning frameworks further improved scalability and collaborative resource management among vehicles and edge nodes. Hybrid optimization approaches combining deep reinforcement learning, caching, heuristic optimization, and resource allocation achieved superior overall performance by jointly optimizing latency, energy efficiency, and Quality of Service. Mobility-aware and hierarchical architectures also enhanced scalability and decision accuracy in ultra-dense vehicular environments. Despite these advancements, challenges related to computational complexity, real-time implementation, coordination overhead, and scalability remain open research issues for future intelligent 6G vehicular edge computing systems.

Discussion

The reviewed studies highlight that energy-efficient data offloading in 6G-enabled vehicular edge computing has evolved significantly with the adoption of deep reinforcement learning techniques. Among these, Double Deep Q-Network (DDQN) has emerged as a highly effective approach due to its ability to mitigate overestimation bias and provide stable decision-making in dynamic environments. Compared to traditional optimization and DQN-based models, DDQN demonstrates superior performance in reducing energy consumption and latency while maintaining quality of service.

Furthermore, the integration of multi-agent reinforcement learning (MADRL) and hybrid optimization frameworks has enhanced scalability and system adaptability, enabling efficient resource utilization across distributed vehicular networks. Mobility-aware and hierarchical architectures further improve performance by incorporating real-time vehicle dynamics and multi-layer computing structures. However, these advanced techniques introduce challenges such as increased computational complexity, communication overhead, and longer training times.

Another critical observation is the trade-off between model performance and implementation feasibility. While hybrid and multi-agent models achieve higher efficiency, their complexity may limit real-time deployment in large-scale 6G systems. Therefore, future research should focus on lightweight, scalable, and decentralized learning approaches, such as federated learning and edge intelligence. Overall, the findings indicate that intelligent, learning-based strategies are essential for achieving sustainable and efficient data offloading in next-generation vehicular networks.

Conclusion

The rapid development of 6G communication technologies and intelligent transportation systems has increased the importance of energy-efficient data offloading in vehicular edge computing (VEC) environments. This review analyzed recent approaches based on Deep Reinforcement Learning (DRL), Double Deep Q-Network (DDQN), and hybrid optimization techniques for intelligent offloading strategies. Traditional heuristic and optimization-based methods improved latency and energy management but lacked adaptability in dynamic vehicular environments. Deep learning approaches, particularly DQN and DDQN models, introduced intelligent decision-making capabilities by learning from real-time network conditions. Among these, DDQN demonstrated superior stability, convergence speed, and decision accuracy, making it highly suitable for 6G-enabled VEC systems. Furthermore, multi-agent reinforcement learning and hybrid optimization frameworks improved scalability, collaborative resource management, and Quality of Service by jointly optimizing latency, energy consumption, and resource allocation. Mobility-aware and hierarchical architectures further enhanced system efficiency in highly dynamic vehicular scenarios. Despite these advancements, challenges such as computational complexity, scalability, coordination overhead, and real-time deployment remain significant research concerns for next-generation intelligent vehicular edge computing networks.

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