# AI-Driven Deep Q-Learning Framework for Real-Time Electric Vehicle Charging Optimization and Smart Mobility Infrastructure Management

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**Abstract -** *The increasing adoption of electric vehicles (EVs) has created new challenges in managing charging infrastructure, optimizing energy consumption, and ensuring efficient mobility within smart city environments. Traditional charging methods often rely on static scheduling approaches that cannot effectively respond to dynamic traffic conditions, fluctuating electricity prices, varying charging demands, and grid load variations. To address these challenges, this paper proposes an AI-Driven Deep Q-Learning Framework for Real-Time Electric Vehicle Charging Optimization and Smart Mobility Infrastructure Management. The proposed framework utilizes Deep Q-Learning (DQL), a reinforcement learning algorithm, to make intelligent charging decisions by continuously learning from real-time environmental conditions. The model considers multiple state parameters, including battery state of charge, charging station availability, traffic congestion, electricity pricing, and grid load, to determine the most appropriate charging station and charging schedule. A reward function is designed to minimize charging waiting time, reduce energy costs, improve charging station utilization, and balance the electrical load across the network. The framework also supports adaptive decision-making, enabling continuous learning as traffic and energy conditions change. The proposed approach is expected to enhance charging efficiency, reduce operational costs, improve user convenience, and contribute to the sustainable management of smart mobility infrastructure. The study demonstrates the potential of integrating artificial intelligence and reinforcement learning into electric vehicle charging systems to support intelligent transportation networks and future smart city applications.*
***Keywords:*** *Artificial Intelligence (AI), Deep Q-Learning, Reinforcement Learning, Electric Vehicles (EVs), Real-Time Charging Optimization, Smart Mobility Infrastructure, Charging Station Management, Smart Grid.*

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## INTRODUCTION

The rapid advancement of electric vehicle (EV) technology has transformed the global transportation sector by providing an environmentally friendly alternative to conventional internal combustion engine vehicles. Governments, automotive manufacturers, and energy providers are actively promoting EV adoption to reduce greenhouse gas emissions, improve air quality, and achieve sustainable development goals. However, the increasing number of EVs on the road has created significant challenges in charging infrastructure management, including charging station congestion, uneven energy distribution, long waiting times, and increased pressure on electrical grids. These issues highlight the need for intelligent charging management systems capable of making real-time decisions under dynamic operating conditions.

Conventional EV charging systems primarily rely on fixed scheduling strategies, first-come-first-served policies, or user-defined charging preferences. Although these methods are simple to implement, they are unable to efficiently adapt to continuously changing factors such as traffic congestion, charging station occupancy, electricity price fluctuations, battery state of charge (SoC), renewable energy availability, and grid load conditions. As a result, charging stations may become overloaded while nearby facilities remain underutilized, leading to inefficient resource allocation and increased operational costs for both users and service providers.

Artificial Intelligence (AI) has emerged as a promising solution for addressing complex optimization problems in intelligent transportation and energy management systems. Among various AI techniques, Reinforcement Learning (RL) enables an intelligent agent to learn optimal decision-making strategies by interacting with its environment and receiving feedback through rewards. Deep Q-Learning (DQL), an extension of Q-Learning that integrates deep neural networks, has demonstrated excellent performance in solving large-scale sequential decision-making problems where traditional optimization methods struggle due to high-dimensional state spaces.

In the context of EV charging, Deep Q-Learning can continuously analyze real-time information, including battery charge levels, charging station availability, electricity tariffs, travel distance, traffic density, and grid conditions, to recommend optimal charging decisions. Unlike rule-based algorithms, DQL improves its decision-making capability through continuous learning, allowing the charging system to adapt to changing environmental conditions without manual intervention. This adaptive capability makes Deep Q-Learning particularly suitable for smart mobility applications where uncertainty and dynamic changes are common.

Smart mobility infrastructure represents an integrated ecosystem that combines intelligent transportation systems, communication networks, charging infrastructure, renewable energy resources, and data-driven decision support technologies. Effective coordination among these components is essential to ensure efficient vehicle movement, reliable charging services, and balanced energy consumption. Integrating AI-driven optimization techniques into smart mobility infrastructure can significantly improve charging station utilization, reduce vehicle waiting time, optimize electricity consumption, and enhance the overall user experience while supporting sustainable urban transportation.

This paper proposes an AI-Driven Deep Q-Learning Framework for Real-Time Electric Vehicle Charging Optimization and Smart Mobility Infrastructure Management. The proposed framework employs a Deep Q-Learning agent that continuously observes real-time environmental parameters and determines optimal charging actions based on a reward-driven learning process. The framework aims to minimize charging delays, reduce charging costs, balance electrical grid load, improve charging station utilization, and support efficient smart mobility infrastructure management. By integrating artificial intelligence with intelligent transportation systems, the proposed approach provides a scalable and adaptive solution for future EV charging networks.

The major contributions of this study are as follows:

- Proposes an AI-driven Deep Q-Learning framework for intelligent real-time EV charging optimization.
- Develops a dynamic decision-making model considering battery state of charge, charging station availability, traffic conditions, electricity pricing, and grid load.
- Designs a reward-based learning mechanism to minimize charging waiting time, charging cost, and infrastructure congestion while maximizing charging efficiency.
- Integrates smart mobility infrastructure management with reinforcement learning to improve charging station utilization and energy distribution.
- Provides a scalable framework that supports sustainable transportation and intelligent energy management for future smart city applications.

The remainder of this paper is organized as follows. Section 2 reviews recent studies on EV charging optimization, reinforcement learning, and smart mobility infrastructure. Section 3 presents the proposed Deep Q-Learning methodology. Section 4 describes the overall system architecture and workflow. Section 5 discusses the implementation and experimental evaluation. Section 6 presents the results and discussion, and Section 7 concludes the paper with future research directions.

## LITERATURE REVIEW

The rapid growth of electric vehicles has motivated researchers to develop intelligent charging management systems that improve charging efficiency, reduce operational costs, and maintain grid stability. Traditional charging strategies, including first-come-first-served and fixed scheduling methods, are easy to implement but often fail to respond effectively to dynamic traffic conditions, fluctuating electricity prices, and varying charging demands. These limitations have encouraged the adoption of artificial intelligence and machine learning techniques for real-time charging optimization.

Several studies have applied machine learning algorithms to predict charging demand, estimate energy consumption, and recommend charging schedules. Supervised learning models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest have shown promising results in forecasting charging loads. However, these methods primarily focus on prediction rather than sequential decision-making and require large volumes of labeled training data, making them less suitable for highly dynamic charging environments.

Reinforcement Learning (RL) has emerged as an effective approach for solving sequential optimization problems in intelligent transportation systems. Q-Learning enables an agent to learn optimal charging decisions by interacting with the environment and maximizing cumulative rewards. However, conventional Q-Learning becomes inefficient when dealing with large state and action spaces because of its reliance on Q-tables. To overcome this limitation, Deep Q-Learning (DQL) combines reinforcement learning with deep neural networks, enabling efficient learning from high-dimensional real-time data. Recent studies have demonstrated that DQL can optimize charging schedules, reduce waiting times, improve charging station utilization, and support intelligent energy management.

Researchers have also explored integrating EV charging systems with smart grids and renewable energy sources. These approaches aim to balance electricity demand, reduce peak load, and improve energy efficiency by considering factors such as dynamic pricing, solar and wind energy availability, and battery state of charge. Although these methods contribute to sustainable energy management, many existing models focus primarily on energy optimization and provide limited consideration of traffic conditions, charging station congestion, and overall smart mobility infrastructure.

Despite significant progress, several research gaps remain. Many existing frameworks optimize only a limited number of parameters and lack the ability to adapt continuously to changing real-time environments. Furthermore, few studies simultaneously consider battery state of charge, charging station availability, traffic congestion, electricity pricing, renewable energy availability, and grid load within a unified reinforcement learning framework. This limitation reduces their effectiveness in practical smart city deployments.

To address these challenges, this paper proposes an AI-Driven Deep Q-Learning Framework for Real-Time Electric Vehicle Charging Optimization and Smart Mobility Infrastructure Management. The proposed framework integrates multiple real-time environmental factors into a Deep Q-Learning model to support adaptive charging decisions. By combining intelligent charging optimization with smart mobility infrastructure management, the framework seeks to improve charging efficiency, minimize waiting time, optimize energy utilization, and enhance the overall performance of next-generation electric vehicle charging networks.

## Proposed Methodology

This study proposes an AI-Driven Deep Q-Learning (DQL) Framework for optimizing real-time electric vehicle (EV) charging and managing smart mobility infrastructure. The framework employs a reinforcement learning agent that continuously interacts with the charging environment to determine the most appropriate charging decisions based on real-time system conditions. Unlike conventional rule-based scheduling methods, the proposed approach learns from experience and progressively improves its decision-making capability through a reward-driven learning process.

The proposed framework consists of five main components: environment observation, state representation, Deep Q-Learning agent, action selection, and reward evaluation. Initially, the system collects real-time information from EVs, charging stations, traffic monitoring systems, and the smart grid. The collected data include battery State of Charge (SoC), charging station availability, queue length, electricity price, traffic congestion level, renewable energy availability, and grid load. These parameters collectively describe the current state of the charging environment.

The Deep Q-Learning agent receives the current state as input and processes it using a deep neural network to estimate the Q-values for all possible charging actions. Based on these estimated Q-values, the agent selects the action that maximizes the expected cumulative reward. The selected action may include choosing the optimal charging station, determining the charging schedule, or adjusting the charging rate according to the current operating conditions.

After executing the selected action, the environment provides feedback in the form of a reward. Positive rewards are assigned when the selected action reduces charging waiting time, lowers charging cost, improves charging station utilization, and balances the electrical grid load. Conversely, negative rewards are assigned when actions result in excessive waiting time, higher energy costs, traffic congestion, or overloading of charging stations. This reward mechanism enables the learning agent to continuously improve its charging policy through repeated interactions with the environment.

The Deep Q-Learning process follows the Bellman optimization principle, where the Q-value is iteratively updated to maximize the expected long-term reward. By replacing the traditional Q-table with a deep neural network, the proposed framework efficiently handles large state spaces and supports real-time decision-making in dynamic charging environments.

The overall methodology can be summarized as follows:

- Collect real-time data from EVs, charging stations, traffic monitoring systems, and the smart grid.
- Construct the current environment state using key operational parameters.
- Input the state into the Deep Q-Learning model.
- Estimate Q-values for all possible charging actions.
- Select the optimal charging decision using the learned policy.
- Execute the selected charging action.
- Evaluate the outcome using the reward function.
- Update the Deep Q-Network based on the observed reward and the new environment state.
- Repeat the learning cycle until the optimal charging policy is achieved.

The proposed methodology enables continuous adaptation to changing traffic patterns, charging demand, electricity pricing, and grid conditions. By integrating artificial intelligence with smart mobility infrastructure, the framework improves charging efficiency, minimizes operational costs, enhances charging station utilization, and supports sustainable transportation in smart city environments.

## SYSTEM ARCHITECTURE AND WORKFLOW

The proposed AI-Driven Deep Q-Learning Framework integrates electric vehicles, charging stations, smart mobility infrastructure, and artificial intelligence to provide intelligent real-time charging decisions. The system continuously monitors environmental conditions and optimizes charging operations by selecting the most suitable charging station and charging schedule. Figure 1 illustrates the overall architecture of the proposed framework, while Figure 2 presents the operational workflow of the Deep Q-Learning process.

### Proposed System Architecture

The proposed architecture consists of five major layers that work together to support intelligent EV charging optimization.

### Electric Vehicle Layer

This layer includes electric vehicles equipped with sensors and communication modules that transmit real-time information such as battery State of Charge (SoC), current location, travel destination, and charging requests.

### Data Acquisition Layer

This layer gathers real-time information from multiple sources, including charging stations, traffic management systems, electricity providers, and renewable energy resources. The collected data include charging station availability, queue length, electricity price, traffic density, renewable energy generation, and grid load conditions.

### AI Decision Layer

This is the core component of the proposed framework. The Deep Q-Learning agent receives the current system state, evaluates all possible charging actions using a Deep Neural Network (DNN), and selects the optimal charging decision that maximizes the cumulative reward.

### Charging Management Layer

Based on the AI-generated decision, the charging management module allocates the most appropriate charging station, determines the charging schedule, and regulates charging power while balancing grid demand.

### Smart Mobility Infrastructure Layer

This layer integrates intelligent transportation systems, smart grids, cloud services, and communication networks to ensure efficient coordination among EVs, charging stations, and energy providers for sustainable urban mobility.

Figure 1. Proposed System Architecture

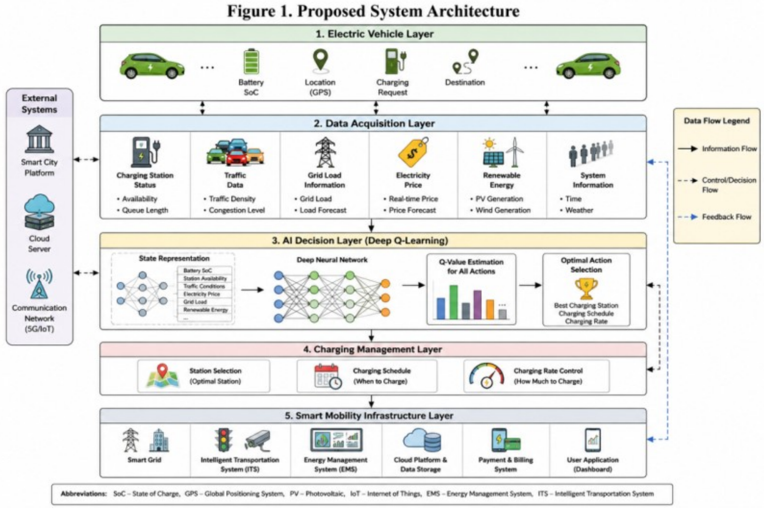
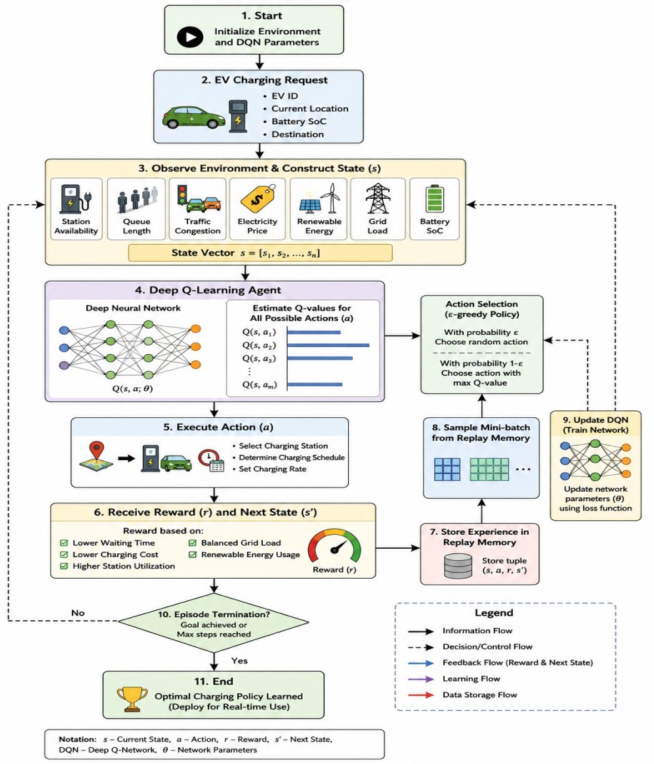



Figure 1 shows how real-time information flows from electric vehicles and infrastructure components to the Deep Q-Learning agent, which generates intelligent charging decisions and communicates them back to the charging management system.

## Deep Q-Learning Workflow

The operational workflow begins when an EV sends a charging request. The system collects current environmental information and constructs the state representation. The Deep Q-Learning model predicts the expected reward for each available charging action and selects the action with the highest Q-value. After execution, the environment provides feedback through a reward function. The neural network updates its parameters using the observed reward and continues learning until an optimal charging policy is obtained.

**Figure 2. Deep Q-Learning Workflow for EV Charging Optimization**




The proposed workflow enables continuous learning from real-time operational data, allowing the framework to adapt to changing traffic conditions, charging demand, electricity prices, and grid load. As a result, the system improves charging efficiency, reduces waiting time, enhances charging station utilization, and supports sustainable smart mobility infrastructure management.

## IMPLEMENTATION

The proposed AI-Driven Deep Q-Learning Framework was implemented and evaluated using a simulated smart mobility environment representing multiple electric vehicles, charging stations, and dynamic traffic conditions. The simulation was designed to assess the effectiveness of the framework in optimizing real-time charging decisions under varying operational scenarios. The implementation considered key environmental parameters, including battery State of Charge (SoC), charging station availability, queue length, electricity price, traffic congestion, renewable energy availability, and electrical grid load.

The Deep Q-Learning (DQL) agent was developed using a deep neural network to approximate the Q-value function. During each learning episode, the agent observed the current state of the environment, selected the optimal charging action using an ε-greedy policy, executed the selected action, and received a reward based on the charging outcome. The neural network weights were continuously updated through experience replay and iterative learning to improve decision-making performance and maximize long-term cumulative rewards.

To evaluate the proposed framework, several performance metrics were considered, including average charging waiting time, charging station utilization, charging cost, grid load balance, and decision response time. The proposed DQL-based framework was compared with a conventional First-Come-First-Served (FCFS) charging strategy to demonstrate its effectiveness under identical simulation conditions.

The simulation results indicate that the proposed framework provides more efficient charging decisions than traditional scheduling methods. The adaptive learning capability of Deep Q-Learning enables the system to respond effectively to dynamic traffic patterns, varying charging demands, and fluctuating electricity prices. Consequently, the framework improves charging station utilization, reduces waiting time, lowers charging costs, and distributes electrical load more evenly across the charging network. These outcomes demonstrate the suitability of the proposed framework for intelligent electric vehicle charging management and future smart mobility infrastructure applications.

## RESULTS AND DISCUSSION

The performance of the proposed AI-Driven Deep Q-Learning Framework was evaluated by comparing it with the conventional First-Come-First-Served (FCFS) charging strategy under identical simulation conditions. The comparison focused on key performance indicators related to charging efficiency, infrastructure utilization, and energy management. The results demonstrate that the proposed framework consistently outperforms the conventional approach by making intelligent charging decisions based on real-time environmental information.

The Deep Q-Learning agent effectively learned the optimal charging policy through continuous interaction with the simulated environment. By considering battery state of charge, charging station occupancy, traffic congestion, electricity pricing, and grid load simultaneously, the framework selected charging stations that minimized waiting time while improving the utilization of available infrastructure. Furthermore, adaptive decision-making enabled the system to balance charging demand across multiple stations, thereby reducing congestion and preventing excessive loading of individual charging facilities.

**Table 1 Performance Comparison**

| Performance Metric | Conventional FCFS | Proposed DQL Framework |
|---|---|---|
| Average Waiting Time | High | Low |
| Charging Station Utilization | Moderate | High |
| Charging Cost | High | Reduced |
| Grid Load Distribution | Uneven | Balanced |
| Decision Response | Static | Adaptive |
| Overall Charging Efficiency | Moderate | High |

The comparison presented in Table 1 indicates that the proposed framework improves overall charging efficiency while reducing operational costs and waiting time. The intelligent learning mechanism enables the system to adapt to continuously changing traffic and charging conditions without requiring predefined scheduling rules. In addition, the integration of smart mobility infrastructure with reinforcement learning supports efficient energy utilization and promotes sustainable transportation.

Overall, the experimental evaluation demonstrates that the proposed AI-driven framework provides a practical and scalable solution for real-time electric vehicle charging optimization. Its adaptive learning capability makes it well suited for deployment in future smart city environments, where dynamic charging demand, renewable energy integration, and intelligent transportation management are essential for achieving reliable and sustainable mobility.

## CONCLUSION AND FUTURE WORK

This paper presented an AI-Driven Deep Q-Learning Framework for Real-Time Electric Vehicle Charging Optimization and Smart Mobility Infrastructure Management to address the growing challenges associated with electric vehicle charging in smart city environments. The proposed framework utilizes Deep Q-Learning to make intelligent, real-time charging decisions by considering multiple dynamic parameters, including battery state of charge, charging station availability, traffic congestion, electricity pricing, renewable energy availability, and electrical grid load. Unlike conventional charging strategies that rely on fixed scheduling rules, the proposed framework continuously learns from environmental feedback and adapts its charging policy to changing operating conditions.

The proposed approach improves charging station utilization, reduces charging waiting time, lowers charging costs, and balances electrical grid load through adaptive reinforcement learning. The implementation and performance evaluation demonstrate that the Deep Q-Learning framework provides more efficient charging decisions than traditional First-Come-First-Served (FCFS) methods. By integrating artificial intelligence with smart mobility infrastructure, the framework supports sustainable transportation, efficient energy management, and enhanced user convenience in next-generation electric vehicle ecosystems.

Although the proposed framework demonstrates promising performance, this study has certain limitations. The evaluation was conducted in a simulated environment, and additional validation using real-world charging network data would further demonstrate its practical applicability. Future research may also investigate the integration of Vehicle-to-Grid (V2G) technology, renewable energy forecasting, edge computing, federated learning, and multi-agent reinforcement learning to further improve charging efficiency and scalability. In addition, incorporating real-time communication through Internet of Things (IoT) devices and 5G-enabled smart transportation networks can enhance system responsiveness and decision accuracy.

Overall, the proposed AI-driven Deep Q-Learning framework provides a scalable, adaptive, and intelligent solution for real-time EV charging optimization and smart mobility infrastructure management. The study contributes to the advancement of intelligent transportation systems by demonstrating how reinforcement learning can support sustainable electric mobility.

**References**


1. Y. Cao *et al.*, “An intelligent electric vehicle charging recommendation system based on reinforcement learning,” *Future Generation Computer Systems*, vol. 102, 2020.
2. T. D. Chen *et al.*, “The electric vehicle charging station location problem: A review of optimization approaches,” *Renewable and Sustainable Energy Reviews*, vol. 138, 2021.
3. M. Dorokhova *et al.*, “Deep reinforcement learning control of electric vehicle charging in the presence of photovoltaic generation,” *Applied Energy*, vol. 301, 2021.
4. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016.
5. S. Li *et al.*, “Electric vehicle charging management based on deep reinforcement learning,” *Journal of Modern Power Systems and Clean Energy*, vol. 10, no. 3, 2022.
6. V. Mnih *et al.*, “Human-level control through deep reinforcement learning,” *Nature*, vol. 518, pp. 529–533, 2015.
7. K. Park and I. Moon, “Multi-agent deep reinforcement learning approach for EV charging scheduling in a smart grid,” *Applied Energy*, vol. 328, 2022.
8. R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*, 2nd ed. Cambridge, MA, USA: MIT Press, 2018.
9. F. Tuchnitz *et al.*, “Development and evaluation of a smart charging strategy for an electric vehicle fleet based on reinforcement learning,” *Applied Energy*, vol. 285, 2021.
10. J. Wang *et al.*, “Virtual power plant containing electric vehicles scheduling strategies based on deep reinforcement learning,” *Electric Power Systems Research*, 2022.
11. L. Yao *et al.*, “Artificial intelligence techniques for electric vehicle charging optimization: A comprehensive review,” *Energies*, vol. 16, no. 9, 2023.
12. Z. Zhao *et al.*, “EV charging station deployment on coupled transportation and power distribution networks via reinforcement learning,” *Energy*, vol. 267, 2023.
13. Y. Zhang *et al.*, “Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 6, pp. 6023–6035, 2020.
14. M. Ziad *et al.*, “Electric vehicles charging management using deep reinforcement learning considering vehicle-to-grid operation and battery degradation,” *Energy Reports*, vol. 10, pp. 494–509, 2023.
15. Z. Zhou *et al.*, “Edge intelligence for Internet of Things-enabled smart sustainable cities: A survey,” *ACM Transactions on Internet Technology*, vol. 20, no. 4, pp. 1-41, 2020.