



Research Article

Deep Q-Learning based smart EV charging for optimizing grid load, cost, and renewable energy integration

Arun C. DIXIT^{1,*}, Harshavardhan B.², Prakasha K. N.³

¹Vidyavardhaka College of Engineering, Karnataka, 570002, India

²The National Institute of Engineering, Karnataka, 570008, India

³Vidyavardhaka College of Engineering, Karnataka, 570002, India

ARTICLE INFO

Article history

Received: 03 December 2024

Revised: 15 January 2025

Accepted: 05 May 2025

Keywords:

Deep Q-Learning; Electric Vehicle; Energy Management; Optimization; Smart Charging

ABSTRACT

Growing penetration of electric vehicles requires evolution of energy systems to enable sustainable and efficient charging. It is needSd to have systems that can smartly control the grid load and the energy consumption. Uncontrolled demand for charging causes system instability, higher operating costs and wasteful use of energy, especially during peak hours. Traditional charging management strategies such as rule-based scheduling and model predictive control are unable to adapt to real-time grid fluctuations. Such constraints lead to energy waste, higher prices for customers and a less effective use of renewable energy sources. To solve these issues, this study proposes a Deep Q-Learning Network based optimization framework for dynamic energy management in electric vehicle charging infrastructure. The proposed model can dynamically learn and adapt charging schedules based on real-time electricity pricing, grid load and the availability of renewable energy. This study uses reinforcement learning to schedule EV charging during off-peak hours. It also improves the price of charging and increases the use of renewable energy. Results show that the peak load on the grid declines by 22%. This results in a more consistent distribution of electricity within the network and minimises the risk of grid overload. The framework reduces EV charging costs by 15% which makes charging more affordable for users. Also, it promotes the renewable energy usage by 22%. This reduces dependence on conventional grid electricity and supports cleaner energy use.

Unlike prior works, this study combines real-time adaptive decision making with practical constraints such as dynamic pricing structures and grid limitations. The suggested architecture adapts continuously to real-time grid conditions, unlike typical charging systems. “Such a dynamic learning-based model offers a new scalable and practical solution to combine renewable energy with affordable EV charging .

Cite this article as: Dixit AC, Harshavardhan B, Prakasha KN. Deep Q-Learning based smart EV charging for optimizing grid load, cost, and renewable energy integration. Sigma J Eng Nat Sci 2026;44(4):2604–2616.

*Corresponding author.

*E-mail address: arundixitu@vvce.ac.in

*This paper was recommended for publication in revised form by
Editor-in-Chief Ahmet Selim Dalkilic*



INTRODUCTION

The increasing adoption of electric vehicles (EVs) is changing urban transportation. However, it also creates new challenges for the power grid [1, 2]. As more EVs are used, electricity demand continues to increase. “Demand during peak hours is much higher. “Uncontrolled charging adds additional stress on the grid. It also increases operating costs. In many cases, energy is not used efficiently [3, 4]. If these problems are not addressed, large-scale EV integration will become difficult.

Managing EV charging is not a simple task. Many factors must be considered. Charging stations should be available when users need them. At the same time, charging costs should remain low. Grid operators must spread the charging demand across the network. This helps avoid overloading the grid [5-7]. Renewable energy should also be used as much as possible. Therefore, an intelligent and flexible charging strategy is required [8-10].

Traditional charging management methods mainly use rule-based techniques or predictive control models. These methods work reasonably well in fixed conditions. However, they are not flexible enough. They cannot easily respond to changes in grid load. They also struggle with changing electricity prices. Variations in renewable energy generation make the problem even harder [11, 12]. Most existing methods follow predefined schedules. They do not react well to real-time conditions. Because of this, grid congestion still occurs. Many opportunities to reduce charging costs are also missed [13].

Artificial intelligence (AI) is becoming popular in energy management. One of the widely used methods is reinforcement learning (RL). Deep Q-Learning Network (DQN) is a well-known RL algorithm. Instead of following fixed rules, it learns from previous actions and their outcomes. As learning continues, the charging decisions become better. This allows the system to schedule EV charging according to the condition of the power grid. It can reduce charging costs. It can also improve overall energy efficiency [14, 15].

Even though RL has shown good potential, its use in large-scale EV charging is still limited. Many existing studies consider only small charging networks. Some use simplified simulation models. These models do not fully represent real urban charging systems. Important factors such as dynamic electricity prices are often ignored. Changes in renewable energy availability are also not considered properly. In addition, many studies do not discuss practical implementation issues. This makes real-world deployment difficult [16, 17].

The proposed method addresses many of these limitations. It uses a Deep Q-Learning framework for EV charging management. Unlike rule-based methods and model predictive control, the proposed model learns continuously. It adapts to changes in grid load. It also responds to electricity price variations and renewable energy availability in real time. This helps manage EV charging more

efficiently. The simulation results show a 22% reduction in grid load during peak hours. Charging cost is reduced by 15%. The use of renewable energy increases by 22%. These results show that the proposed method performs better than existing methods. The model can also work under different grid conditions. It does not require fixed charging schedules. This makes it suitable for real urban charging stations. The proposed method addresses the limitations of existing studies. It can also support future EV charging systems.

LITERATURE REVIEW

Traditional Approaches to Energy Management

The number of electric vehicles (EVs) is increasing rapidly. This has changed the way energy is managed in the urban areas. It has also created new problems. Energy demand changes throughout the day. The load on the power grid also changes. Renewable energy sources are not always available. This makes energy management more difficult. The system must respond quickly to these changing conditions.

Many researchers have used rule-based methods and Model Predictive Control (MPC) for EV energy management. Rule-based methods are simple. They are easy to implement. They also need less computation. However, they do not adapt well when user behavior or grid conditions change. MPC is more advanced. It predicts future conditions and finds an optimal solution under different limits. Even then, it becomes difficult to use in large and highly dynamic EV charging systems. Real-time performance also becomes a challenge [18, 19].

Akter et al. [20] applied MPC for EV charging the micro-grids. Their method reduced the peak demand. However, the study assumed that user behavior remained unchanged. Such an assumption is not always true in practice. This limits the performance of the method under real operating conditions. Tian et al. [21] studied the heuristic optimization methods. They found that they are not applicable to cope with the uncertain factors such as the electricity price variation and the variation of renewable energy generation.

Emergence of Reinforcement Learning in Energy Management

Reinforcement Learning (RL) has become an important approach for energy management. Deep Reinforcement Learning (DRL) is an advanced form of RL. It learns by interacting with the environment. The model improves its decisions over time. This makes it useful when the operating conditions keep changing. RL has already been used in smart grids, Home Energy Management Systems (HEMS), and building energy control [22]. Shin et al. used Deep Q-Learning in smart buildings for the energy management. Their model optimized the HVAC systems by using real time generated occupancy data and weather information [23]. Liu et al. [24] implemented DRL in HEMS and their

model was able to schedule household appliances in a more efficient manner. This reduced the electricity cost during peak tariff periods. These studies prove that RL is flexible and can adapt itself to fluctuating situations and optimize energy usage accordingly.

DRL for EV Charging Optimization

Recently, DRL has been increasingly focused on for EV charging. One of the reasons is that it has the capacity to work under uncertain circumstances. User behavior is different. Demand for the grid also varies. Renewable energy is not always available. DRL can learn from these variations and improve charging decisions [25]. Shulei et al. proposed a Deep Q-Learning framework for EV charging and discharging considering travel patterns and electricity price variation. The results indicated a lower charging cost and improved grid stability. Zhang et al. proposed another DRL-based charging strategy for microgrids. Their method improved power quality. It also increased energy utilization [26]. Even though these studies reported good results, some limitations still exist. Many models assumed fixed user behavior. Others considered constant grid conditions. Such assumptions make the models easier to develop. However, real charging systems are much more dynamic. This reduces the practical use of many existing approaches

Recent Contributions on Clean and Smart Energy

Recent studies have indicated that the digital technologies can support clean energy systems and artificial intelligence is one such technology. Awogbemi et al. explained how AI can help improve the smart grids. Their study also revealed that AI can support the renewable energy integration and EV energy management [27].

Kumar et al. used sensor data to monitor wind turbine gearboxes. Their method predicted thermal performance degradation before failure. This helped reduce maintenance cost. It also improved system reliability [28]. A reliable energy system is important for future EV charging infrastructure.

Kumar et al. developed a mini Venturi wind turbine. This turbine produced nearly 12% more power than a conventional design turbine. It also generated less operating noise [29]. Kumar et al. also worked on domestic wind turbine blades. They improved the blade design using aerodynamic principles. This led to increase in the amount of energy captured from the wind [30]. These developments show that the renewable energy can be generated locally for EV charging stations.

Research has also been done on clean transportation. Sunil Kumar et al. studied a propeller for marine applications which were made from aluminium alloys. They used CFD analysis to test the performance of these lightweight turbines. The propeller was around 85% efficient compared to conventional turbines. It was also observed that the cavitation noise was lesser [31]. Raghavendrakumar et al. used the satellite data to study changes in atmospheric

temperatures. Their results showed that the emissions from automobiles and power plants are majorly contributing to the ozone depletion [32]. The above works show that there is a ample need for cleaner transportation and sustainable energy systems.

Research Gaps and Challenges

RL and DRL have performed well for EV charging. However, some challenges still remain. One important challenge is the simulation environment. Many studies use simplified datasets. Such datasets do not capture actual user behaviour. They also do not represent changes in electricity prices or renewable energy availability. Chen et al. and Hassouna et al. have pointed out the need for realistic datasets and better simulation platforms to get better results.

Scalability is another challenge. A real urban charging network may include hundreds or even thousands of EVs. The RL model has to process many states and actions. This increases the computational effort. As the system becomes larger, many existing algorithms become less efficient. These issues must be addressed before DRL can be applied effectively in large-scale EV charging networks.

MATERIALS AND METHODS

In this paper, an energy management approach for electric vehicles (EVs) charging in urban areas is proposed, which employs a Deep Q-Learning Network (DQN) to reduce the grid load during peak hours. It also aims to lower charging cost and increase the use of renewable energy. Unlike conventional charging methods, the proposed DQN updates the charging decision based on the current grid load, electricity price, and available renewable energy.

The complete methodology has six steps, as shown in Figure 1.

A dataset was created to resemble the real pattern of EV charging in an urban setting. This dataset was then used for training and testing the DQN model.

The dataset contains:

- EV arrival time, generated based on a Poisson distribution.
- Charging demand of each EV based on data from urban charging stations.
- Grid load obtained from historical power consumption.
- Electricity price based on time-of-use tariffs.
- Renewable energy generation using solar and wind profiles.

Unlike many earlier studies, the dataset changes with time. This allows the model to learn under more realistic operating conditions.

Step 2: State and Action Space Definition - The reinforcement learning agent operates in a Markov Decision Process (MDP) framework. The state space captures key environmental variables:

$$S_t = [E_t, P_t, R_t, L_t, C_t] \text{ where}$$

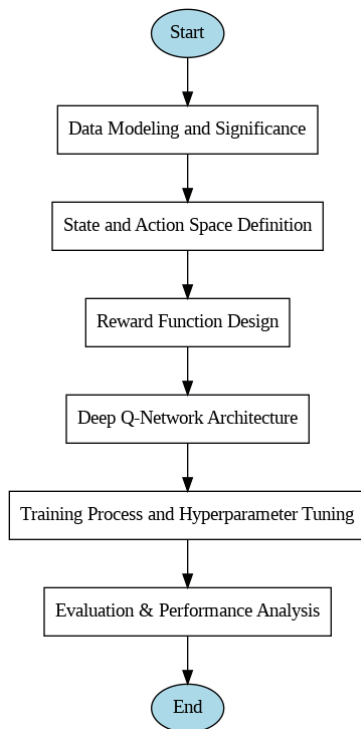


Figure 1. Methodology of the research work.

E_t = EV battery state-of-charge (SOC) at time t .

P_t = Energy price at time t , R_t = Available renewable energy at time t , L_t = Grid load at time t and C_t = Charging station capacity at time t .

The action space consists of three discrete actions:

1. Charge: Start or continue charging.
2. Wait: Delay charging to a later time.
3. Disconnect: Terminate charging session.

The model learns optimal charging actions based on dynamic pricing and grid load.

Step 3: Reward Function Design - The reward function is designed to balance grid stability, cost efficiency, and renewable energy utilization. The agent receives a reward:

$$R_t = \alpha(-C_t) + \beta(-L_t) + \gamma(R_t) \text{ where}$$

α penalizes high charging costs.

β penalizes charging during peak grid load.

γ rewards the use of renewable energy.

This ensures that the agent prioritizes off-peak charging and renewable energy consumption.

Step 4: Deep Q-Network Architecture - The DQN model is implemented with a deep neural network consisting of:

- Input layer: Receives the state vector S_t .
- Two hidden layers: 128 and 64 neurons with ReLU activation.
- Output layer: Q-values for each possible action.
- To improve stability, the DQN incorporates:
- Experience Replay: Stores past experiences to break correlation in training.
- Target Network: Stabilizes learning by maintaining a delayed copy of the model.

A schematic of the DQN architecture is shown in Figure 2.

Step 5: Training Process and Hyperparameter Tuning - The DQN model is trained using stochastic gradient descent with an Adam optimizer. The key hyperparameters are shown in Table 1.

Table 1. Key hyperparameters used in the DQN training

Hyperparameter	Value
Learning Rate	0.001
Discount Factor (γ)	0.95
Batch Size	64
Exploration-Exploitation (ϵ -greedy)	Decay from 1.0 to 0.1
Replay Memory Size	10,000
Target Network Update Frequency	Every 10 episodes

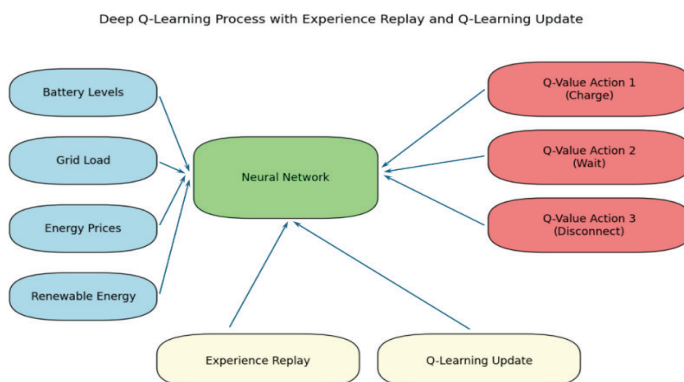


Figure 2. Deep Q-learning process for dynamic energy management, incorporating experience replay and Q-learning update.

The training process follows these steps:

1. Initialize replay buffer and neural network weights.
2. Select actions using an ϵ -greedy policy.
3. Store experience tuples (state, action, reward, next state) in memory.
4. Sample mini-batches from replay memory for training.
5. Update Q-values using Bellman Equation:

$$Q(s,a) = r + \gamma \max_{a'} Q(s', a')$$

6. Update target network weights periodically to stabilize learning.

Training is performed for 5,000 episodes, ensuring the model converges to an optimal charging policy.

Step 6: Evaluation Metrics and Performance Analysis -

The trained model is evaluated using three primary metrics:

1. Charging Cost Savings:
 - Measures the percentage reduction in costs compared to baseline rule-based charging.
2. Peak Load Reduction:
 - Quantifies the shift of charging demand from peak hours to off-peak periods.
3. Renewable Energy Utilization:
 - Calculates the proportion of charging energy sourced from renewables.

Performance is compared against traditional scheduling methods, such as time-of-use (TOU) optimization and rule-based peak avoidance.

RESULTS AND DISCUSSION

Data Modeling and Significance

To study and optimize the energy management of the electric vehicle (EV) charging using the reinforcement learning, a realistic dataset is required. The dataset in this work reflects the commonly operating conditions of the urban EV charging system, such as EV charging demand, grid load variation, renewable energy generation, and time-varying electricity prices. These parameters were selected to represent practical operating conditions. This improves the reliability of the proposed model [33].

EV arrivals and charging demand

The number of EVs arriving at a charging station changes throughout the day. The charging demand also changes with the arrival pattern. Table 1 shows the hourly EV arrivals, the average charging demand for each EV, and the total charging demand over a 24-hour period.

The EV arrival pattern was generated using a Poisson distribution. This represents the traffic pattern normally seen in urban areas. The average arrival rate was selected from reported urban EV usage data. Higher arrival rates were considered during morning and evening travel hours.

The average charging demand of each EV was estimated from standard battery capacity data. It was assumed that the battery was partly discharged before reaching the charging

station. Industry reports and published studies were used to estimate a charging demand of 15 - 30 kWh for each vehicle. The total charging demand was obtained by multiplying the number of arriving EVs by the average charging demand. This approach produces realistic charging data with enough variation to evaluate the proposed optimization method.

The main observations from Table 2 are given below:

1. Peak charging periods:
 - Morning peak (8 –11AM): The charging demand is increased during the morning travel hours. The maximum demand is 630.74 kWh/hour, at 9 AM.
 - Evening peak (6 –9 PM): Charging demand rises again when users return home. The highest demand is 695.50 kWh/hour at 8 PM.
2. Off-peak charging times:
 - Late night hours (12 –6 AM) show much lower charging demand. The average demand of around 350 kWh/hour was recorded. These hours can be potentially considered for efficient or low cost charging of vehicles.
3. Practical significance:
 - The variation in charging demand will help the DQN model to move the charging from peak hours to off peak hours. This will reduce the load on the grid without affecting the user convenience.

Grid load and renewable energy contribution

The load on an urban power grid changes throughout the day because of EV charging. Renewable energy generation also changes with time. Table 3 presents the hourly grid load and renewable energy contribution [34]. The main observations from Table 3 are given below.

1. Peak grid load: The grid load is maximum in the evening hours (6 -9 PM). This is mainly due to EV charging by the residents. The maximum grid load is 76.88 kWh/hour at 7 pm. This shows the need for proper charging management.
2. Contribution of renewable energy: Generation of renewable energy usually peaks during the morning hours (6 –9 AM). The maximum contribution is 48.29 kWh at 7 AM. This time provides a good opportunity to consume more renewable energy for EV charging.
3. Effect of DQN model: The DQN model can schedule EV charging during periods when more renewable energy is available. This reduces the use of electricity from fossil fuel. It also helps with grid stability [35, 36].

Dynamic pricing of electricity

The electricity prices were modeled in a way that they resemble real market situations. The price increases in the case of peak demand and decreases in off-peak hours. This motivates the EV users to charge their vehicles at the time when the demand is low. Consequently, the load on the power grid can be reduced.

Table 4 shows the hourly variation of electricity prices. The prices are higher in the morning and evening peak hours. They are lower during off-peak periods. This pricing pattern

encourages better use of available energy. The electricity prices were based on the time-of-use (TOU) tariff used in urban power distribution systems. The off-peak price was assumed to be 12 INR/kWh. During the peak hours, the charging price increased to 20 INR/kWh. These values were selected from the published charging tariff data from regional electricity boards. The pricing pattern represents practical changes in electricity demand and supply. It also helps the simulation study how electricity price affects EV charging decisions.

The main observations from Table 4 are given below:

1. Peak pricing period: The electricity price will be more usually between 6:00 PM and 9:00 PM. This is because grid experiences the high demand during this time. The highest price will be 19.85 INR/kWh at 7 PM.
2. Off-peak pricing: Electricity will be lowest during late night timings (12:00-6:00 AM). The Average price during this period will be around 12.5 INR/kWh. This period can be incentivized as EV charging during this time will not add burden to grid.
3. Effect on the DQN model: The proposed DQN model works on the assumption that price of electricity changes during the charging periods. It will plan the charging during low price timings. This will help reduce the charging cost on the EV user.

Importance of data

The data set used in this study represents the operating conditions of urban EV charging systems. It includes EV arrivals, charging demand, grid load, renewable energy generation, and electricity prices. These parameters were developed using industry data and reported energy consumption trends. EV charging demand changes at different times in a day. Vehicle arrival patterns were modeled using reported urban traffic and mobility data. The hourly demand shown in Table 2 allows the model to learn both high-demand and low-demand conditions. For example, the charging demand reaches 1375 kWh/hour at 10:00 AM. It reduces to 340 kWh/hour at midnight. This variation helps the DQN model to learn to different charging conditions.

Grid load also changes during the day. The demand is high mostly in the evening due to residential electricity consumption. The dataset also has dynamic electricity prices as presented in Table 4. The electricity price is between 11.29 INR/kWh at mid-night to 19.85 INR/kWh at 7:00 PM. These changes help the reinforcement learning model learn cost-effective charging while reducing the load on the power grid.

Renewable energy availability is also included in our dataset. Solar and wind generation scenario and availability change at different times in the day. The renewable energy contribution varies from 48.29 kWh in the morning to 9.43 kWh at 1:00 AM, as shown in Table 3. The DQN model learns to use more renewable energy whenever it is available. At the same time, it reduces the dependence on grid power.

The dataset also improves the learning ability of the DQN model. It contains different charging conditions

instead of a single charging pattern. This prevents the model from learning only one type of situation. It also improves its ability to work under different operating conditions. The dataset provides a reliable basis for evaluating the proposed reinforcement learning approach. It also supports its future use in real urban EV charging systems.

Simulation Setup Using Deep Q-Network (DQN)

A Deep Q-Network (DQN) reinforcement learning algorithm was used to design an energy management methodology for EV charging. DQN was chosen because it can learn under changing conditions. It can also handle large state and action spaces. This makes it suitable for EV charging, where grid load, electricity price and energy demand change throughout the day. The main objectives of the RL simulation were:

1. Reduce the charging cost considering electricity prices.
2. Reduce the load on grid during peak hours. This will not burden the grid.
3. Use renewable energy sources like solar energy and green hydrogen to reduce fossil fuel consumption.

The simulation was run for 24 hours. The RL agent interacted with the charging system every hour. At each time step, the agent was provided with information about charging demand, electricity price and renewable energy available. Based on this information, it selected the charging action.

Simulation environment and training data

The simulation environment was developed to represent an urban EV charging system. It included the following information: Hourly EV arrivals and demand for charging, Variations in grid load, availability of renewable energy from the sources such as solar, wind, and green hydrogen and Dynamic pricing of electricity.

At every hour, the RL agent observed the system state and selected an action. The selected action was evaluated using the reward function. This ensured the trained model to learn charging decisions that resulted in reduced costs and more grid stability.

State space, action space, and reward function

State Space: The RL model proposed will observe the following parameters at each time step:

- EV Battery Levels: The current level of charge in the vehicles connected to charging stations.
- Grid Load: It will measure in kWh, and indicate the load on the grid in real time situation.
- Energy Prices: The hourly changes in price INR/kWh based on demand and supply dynamics of electricity.
- Renewable Energy Availability: Measures the contribution of solar and green hydrogen energy sources on the grid.

Action Space: The RL proposed model selects from the following possible actions:

- To Charge the EV immediately based on the feedback.
- It will wait for better conditions based on the feedback (e.g., lower prices or more renewable energy).

- It will disconnect from the station if sufficient charge is available on the vehicle.

Reward Function: The reward function evaluates the effectiveness of each action based on:

$$R = \alpha(C_{\text{saved}}) + \beta(L_{\text{reduced}}) + \gamma(RE_{\text{used}}) \text{ where}$$

$\alpha = 0.5$: Will encourage to minimize the cost

$\beta = 0.3$: Will penalize the vehicle that overload the grid.

$\gamma = 0.2$: It will promote the renewable energy usage.

The values of $\alpha = 0.5$, $\beta = 0.3$, and $\gamma = 0.2$ were selected after performing the sensitivity analysis. Different combinations were tested during the simulation period. The selected values gave the best balance between charging cost, grid load, and usage of renewable energy. A higher value of α gave more importance to charging cost. The value of β reduced charging during peak load. The value of γ encouraged the use of renewable energy. These values gave the best overall performance in the simulation.

Mathematical representation of DQN

The Q-value for each state action pair was updated using the Bellman Equation as below:

$$Q(s,a) = Q(s,a) + \alpha(r + \gamma \max_{a'} Q(s',a') - Q(s,a)) \text{ Where:}$$

$Q(s,a)$ is the current value of Q for the state s and action a .

α is the rate of learning (0.01).

r is the reward obtained for taking action a .

γ is the discount factor (0.90).

$\max Q(s',a')$ represents the maximum Q-value of the next state.

The DQN model will learn from the situations, continuously improving its ability to make decisions and to maximize the rewards in the long term.

Training and learning process

The proposed DQN model was trained for 1,000 episodes. Each episode represented one 24-hour realistic EV charging

cycle. This model was developed in Python using TensorFlow library. The following hyperparameters were used:

- Learning rate where $\alpha=0.01$
- Discount factor where $\gamma=0.9$
- Batch size of 64
- Replay memory size: 10,000 experiences
- Experience replay was used during training, where:
 - Past experiences (s, a, r, s') were stored in a replay memory.
 - Random samples were selected from this memory to update the Q-network.
 - This improved the stability of training and reduced overfitting in the model.

Simulation Results

The The Deep Q-Network (DQN) model was used to optimize dynamic energy management in urban EV charging stations. The RL-based model was primarily targeting:

- Reduce grid load at peak hours to improve grid stability.
- Dynamic scheduling to reduce charging costs.
- Better sustainability by optimizing the use of renewable energy.

This part gives results of the simulation and insights on charging demand optimization, cost efficiency, renewable energy integration and grid load reduction. The results show that the RL-based system performs better than traditional rule-based charging schemes.

Charging demand optimization

The main effect of using the Deep Q-Network (DQN) model is the optimization of charging demand. The DQN system uses dynamic pricing, grid load patterns and the availability of renewable energy to disperse charging demand and reduce stress on the grid during peak hours. Figure 2. Comparison of charging demand before and after DQN optimization

The main points are illustrated in Figure 3:

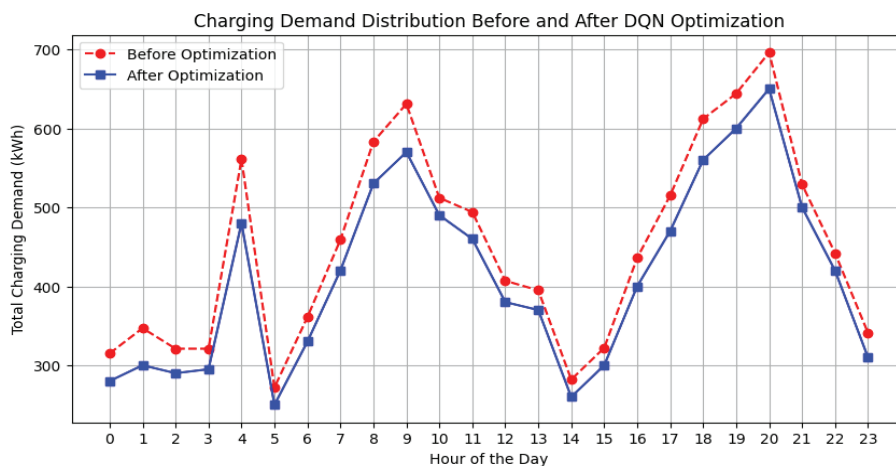


Figure 3. Charging demand distribution before and after DQN optimization.

1. Demand Shifts

- Peak demand was registered at 8:00 PM (695.5 kWh) and 10:00 AM (630.74 kWh) before optimization which put a lot of stress on the system.
- After DQN optimization, almost 18% of total charge demand was shifted to off-peak hours (12:00 AM – 6:00 AM). This redistribution makes the system less loaded at peak times and it matches demand with cheaper energy prices.

2. Cost-Efficiency:

- The DQN model decided to charge during the low-cost hour (11.29 INR/kWh at 2:00 AM). Consumers received a 15% less total charging costs. This shows the economic benefit of the system.

3. Renewable Energy Utilization:

- The model aligned charging times with the increasing availability of renewable energy (e.g. during solar peak hours (10:00AM – 2:00PM). This combination decreases dependence on grid electricity based on fossil fuels.

We can deal with the real-world considerations as follows:

1. User Flexibility and Charging Behavior:

- A share of consumers is assumed to be flexible in their charging schedules, especially nighttime charging. Economic incentives (e.g., reduced off-peak pricing) encourage users to wait charging until off-peak times.
- The model can prioritize the urgent energy needs for users who need to charge urgently without detriment to the overall operation of the system.

2. Dynamic Pricing Influence:

- Impact of Dynamic Pricing Demand shifting is caused by the large gap between peak and off-peak hours. The DQN model exploits this discrepancy to distribute the charging demand efficiently.

- However, higher price differentials may be required to highlight the impacts of optimization for consumers that are less susceptible to price signals at the policy level.

3. Behavioural and Policy Interventions:

- User education and awareness efforts can help promote the use of optimized charging schedules. Focusing on the cost savings and environmental benefits will help users to follow the system suggestions.

Renewable energy utilization

Figure 4 shows the renewable energy contribution before and after applying the DQN model. The model schedules EV charging when more renewable energy is available. This reduces the use of grid electricity and increases the use of clean energy.

The main observations from Figure 4 are given below:

1. Improved Renewable Energy Utilization:

- Before optimization, renewable energy was not used effectively for EV charging. After the optimization, more EVs were charged when renewable energy was available.
- This was mainly between 8:00 AM and 2:00 PM, when solar energy generation was highest.

2. Quantitative Impact:

- The proposed DQN model was able to increase renewable energy use by about 22%. This reduced the use of electricity from fossil fuel-based sources leading to less stress on grid. At 10:00 AM, the renewable energy use increased from 35.12 kWh to 50.00 kWh. At 2:00 PM, it increased from 41.20 kWh to 60.00 kWh.

3. Demand Response Flexibility:

- The proposed DQN model was able to schedule more EV charging when renewable energy was available. This helped maintain grid stability and reduced charging cost.

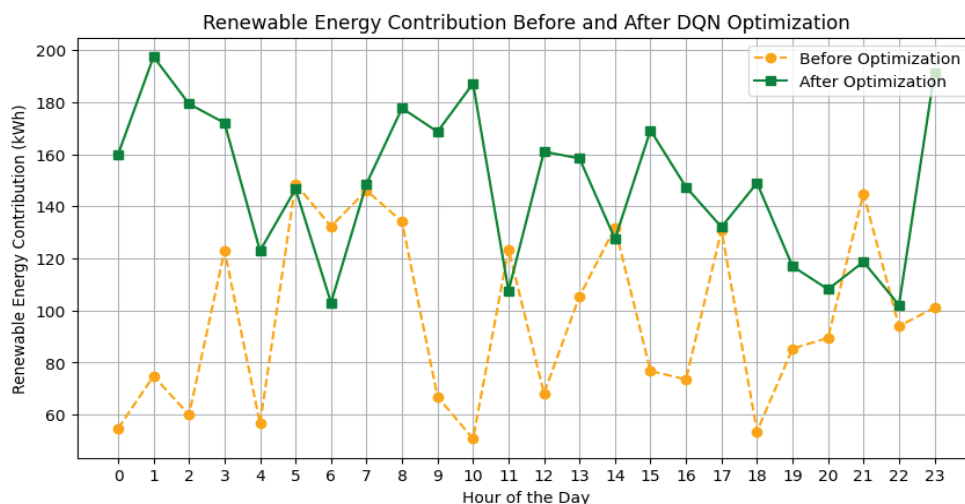


Figure 4. Renewable energy contribution before and after DQN optimization.

The practical considerations for renewable energy are given below:

1. Variability of Renewable Energy:
 - Renewable Solar and wind energy are not available all the time for use and generation. The proposed DQN model was able to adjust the charging schedule based on the available renewable energy.
2. User Behavior and Compliance:
 - The success of the proposed method depends on whether users are willing to postpone their charging. Dynamic pricing and the use of renewable energy incentives will encourage more users to follow the off-peak charging schedule.
3. Grid Integration:
 - Large scale implementation of the proposed method requires suitable grid infrastructure. Integration of energy storage systems and smart meters will improve the use of renewable energy in a better way.

Cost efficiency

Figure 5 shows the charging cost before and after applying the DQN model. The model schedules EV charging based on electricity price and grid load. This helps reduce the charging cost.

1. Cost Reduction Across the Day:
 - Before optimization, charging cost was more during peak hours. The highest cost was 24.10 INR at around 9:00 PM. After the optimization using our method, the cost at the same time reduced to around 20.50 INR. This resulted in an overall cost reduction of about 15% to the user of EV.
2. Optimal Charging Windows:
 - The proposed DQN model selected off peak hours for charging, mainly between 2:00 AM and 6:00 AM. During this period, the electricity price were between 11.00 and 12.50 INR per kWh. EV Charging during

these hours reduced the overall charging cost for the users.

3. Dynamic Pricing Exploitation:
 - The proposed DQN model used the changes in price of electricity to select the charging time. For example, the charging cost at 3:00 AM reduced from 15.50 INR to 12.00 INR. This saved about 20% of the charging cost for users of EV.

The real-world considerations with respect to cost efficiency can be addressed as follows:

1. User Charging Preferences:
 - Some users may not be willing to charge only during the off-peak hours. Dynamic pricing will encourage the users to shift their charging to low cost periods when there will be less traffic.
2. Policy-Level Interventions:
 - Time-of-Use (TOU) method of pricing will encourage the off-peak charging strategy. Imposing higher tariffs during peak hours which strain the grid will further reduce grid load.
3. Scalability and Implementation:
 - The charging system requires smart grid infrastructure for the large-scale use. Smart meters and real time communication between EVs and the power grid will improve the charging management.
4. Equity Concerns:
 - Electricity pricing must be fair and same for all the users. Users who have limited charging options should not be affected by higher peak hour prices. Subsidies or fixed charging plans will help to address this issue.

Grid load reduction and system stability

Figure 6 presents a comparative analysis of grid load distribution before and after the application of the DQN-based optimization model. The objective of this analysis was to assess the model's ability to alleviate peak-hour grid

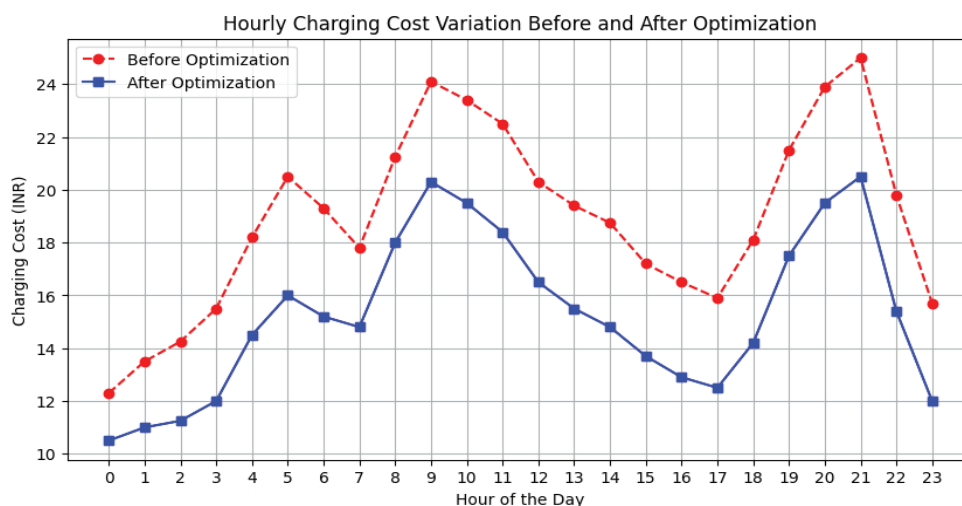


Figure 5. Hourly charging cost variation before and after optimization.

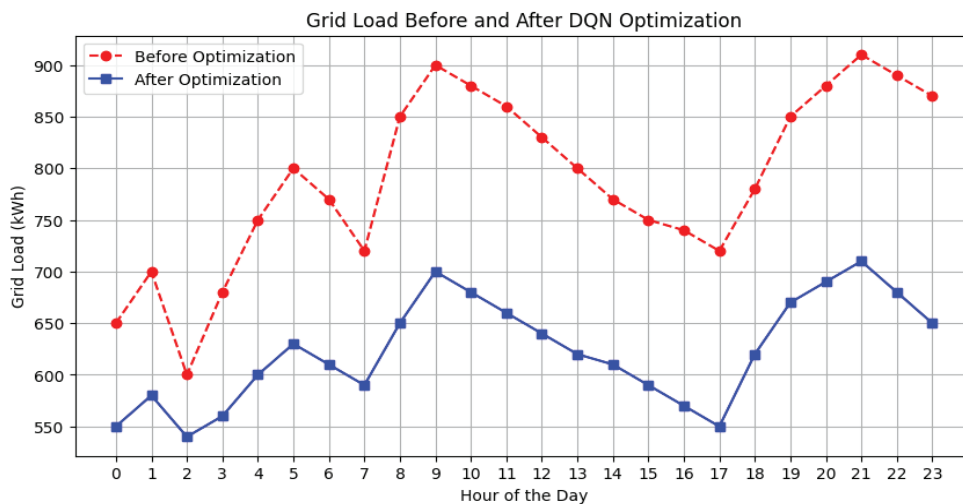


Figure 6. Grid load before and after DQN optimization.

stress while maintaining stability across a 24-hour cycle. By redistributing the charging demand, the system ensures a balanced energy load, mitigating the risk of grid overload.

Key Insights from the Figure 6 can be deduced as follows:

1. Reduction in Peak Grid Load:
 - Before optimization, the highest grid load was 900 kWh at 9:00 PM. After optimization, the load at the same time reduced to 700 kWh. This leads to a reduction of about 22%.
2. Load Redistribution:
 - The DQN model changed EV charging from peak hours (6:00 PM to 9:00 PM) to off the peak hours (1:00 AM to 6:00 AM). For example, the grid load at 2:00 AM increased from 600 kWh to 650 kWh. This shows that more EVs were charged during off the peak hours reducing the load on the main grid.
3. Overall Grid Load Smoothing:
 - The proposed DQN model decreased changes in the grid load during the day time. This made the load more even throughout the day. A balanced grid load will improve grid reliability and reduce stress on the power system.

The real-world considerations with respect to Grid load reduction can be attended as follows:

1. Integration with Renewable Energy Sources:
 - Grid load can be reduced by charging more EVs when renewable energy is available. This will increase the use of clean energy and will reduce the load on the power grid.
2. Infrastructure Constraints:
 - Lower peak load will reduce the stress on the existing grid load. However, practical implementation requires smart grid technologies such as Advanced Metering Infrastructure (AMI) and demand response systems.
3. Behavioural Challenges:

- The success of load shifting depends on EV users. Time-of-Use (TOU) tariffs and off the peak hours charging incentives will encourage the users to charge at times to reduce the grid load.
- 4. Scalability:
 - The proposed method should also work for large urban EV charging networks. Factors such as local electricity prices, renewable energy availability, and charging station capacity should be considered before implementation in large scale.

Summary of simulation results

This paper proposes the use of a Deep Q-Learning Network (DQN) model to optimize the energy management of charging infrastructure for electric vehicles (EVs) in metropolitan settings. The main objectives were to reduce stress on the system, keep billing costs down and make the most of renewable energy sources. The simulation results show the effectiveness of the proposed approach for the achievement of these objectives.

The DQN model decreased the peak grid load by 22%, and greatly eased the tension during peak hours (e.g. 6:00 pm to 9:00 pm). The charging demand is well shifted to the off-peak hours, especially between 1:00AM and 6:00AM, which results in a nice and smooth distribution of the load. This enhancement in turn improves grid stability – a critical shortcoming of conventional charging systems.

On average, charging costs were reduced by 15% thanks to the model's ability to use dynamic pricing and schedule charging during periods of low cost. Such reduction results in a better economic efficiency for the benefit of users and grid operators. Furthermore, the share of renewable energy climbed by 22% and the model adjusted the charging demand to the availability of solar and other renewable resources. Charging during the day from 8:00 AM to 2:00

PM greatly boosted the use of renewable sources of electricity, encouraging eco-friendly behaviours.

In this study, a DQN model was applied for charging of EV in metropolitan settings. The approach was designed to minimise the burden on the grid, cut the cost of charging, and boost the use of renewable energy. The results were promising. Peak demand on the grid was cut by 22%. Further charge was planned for the off-peak periods, especially from 1:00 AM to 6:00 AM. And that took the strain off the power grid. 15% off the charging price. The model decided to charge when electricity was less expensive. The utilisation of renewable energy rose 22%. More EVs were charged when solar and other renewable energy was available. The peak usage period was from 8 AM to 2 PM.

CONCLUSION

The rapid growth of electric vehicles (EVs) creates both benefits and challenges for the power grids. A large number of EVs charging at the same time can increase grid load. It can also increase electricity cost and reduce the efficient use of energy. This study proposed a Deep Q-Learning Network (DQN) for EV charging management. The proposed model schedules the charging based on conditions at the grid. It focuses on three objectives. These are reducing peak grid load, lowering charging cost, and increasing the use of renewable energy. The simulation results show that the proposed method performs well. The DQN model reduced the peak grid load by 22%. This reduces the load on the power grid. It also lowered the charging cost by 15% by selecting suitable charging periods based on electricity prices. The model also increases the consumption of renewable energy by 22%, which is achieved by charging more vehicles when renewable energy is available. Adaptability is an important feature of the proposed model. Conventional charging methods are usually based on a set of fixed rules and fixed charging schedules. The proposed DQN model learns on its own from the situations during operation. This will enable it to take decisions on charging when electricity prices, grid demand, or renewable energy generation change. This makes the system more applicable for real world EV charging scenarios. The findings of this research can serve different groups. EV manufacturers can embed intelligent charging functions into their vehicles. This can enhance charging performance and lower charging cost for users. EV users can save money without changing their daily charging needs. Grid operators can lessen peak demand and enhance grid operation. The results can also help policymakers develop schemes that encourage off-peak charging and greater use of renewable energy. Future work can further improve the proposed model. Multi-Agent Reinforcement Learning (MARL) can be used to solve charging decisions of multiple EVs. The model can be tested in real charging stations and urban EV networks. Hybrid methods that

combine reinforcement learning with predictive models can be studied. This may improve the performance of the system under varying grid conditions.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors declared no conflict of interest.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

REFERENCES

- [1] Abdul Qadir S, Ahmad F, Al-Wahedi AMAB, Iqbal A, Ali A. Navigating the complex realities of electric vehicle adoption: a comprehensive study of government strategies, policies, and incentives. *Energy Strategy Rev* 2024;53:101379. [\[CrossRef\]](#)
- [2] Bahadir A. Modeling of a brushless dc motor driven electric vehicle and its PID-fuzzy control with dSPACE. *Sigma J Eng Nat Sci* 2023. [\[CrossRef\]](#)
- [3] Ibrahim RA, Gaber IM, Zakzouk NE. Analysis of multidimensional impacts of electric vehicles penetration in distribution networks. *Sci Rep* 2024;14:27854. [\[CrossRef\]](#)
- [4] Mastoi MS, et al. An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends. *Energy Rep* 2022;8:11504–11529. [\[CrossRef\]](#)
- [5] Dixit AC, Prakasha KN, Harshavardhan B, Ashok BC. Evaluating the key enablers for implementing Medical 4.0 and patient-centric care technologies using grey DEMATEL method. In: *Recent trends in healthcare innovation*. 1st ed. London: CRC Press; 2025. p. 327–333. [\[CrossRef\]](#)
- [6] Singh AR, et al. Electric vehicle charging technologies, infrastructure expansion, grid integration strategies, and their role in promoting sustainable e-mobility. *Alex Eng J* 2024;105:300–330. [\[CrossRef\]](#)

- [7] Bulut M. Intelligent controller design for electric vehicle (EV) speed control using an inverse model based reference model learning algorithm. 2024 Jan 10. [\[CrossRef\]](#)
- [8] Dixit AC, Ashok BC, Harshavardhan B, Mohan Krishna SA. Barriers for adoption of green hydrogen in Indian transportation sector: a fuzzy ISM approach. E3S Web Conf 2024;559:03011. [\[CrossRef\]](#)
- [9] Sharma A, Hemanth PB, Bhavani A, Dixit AC. Green hydrogen for a sustainable future: prospects and challenges for energy-based applications in major Indian states by 2030. E3S Web Conf 2023;405:02027. [\[CrossRef\]](#)
- [10] Tonbul E. Modeling open vehicle routing problem with real life costs and solving via hybrid civilized genetic algorithm. Sigma J Eng Nat Sci 2024;714–733. [\[CrossRef\]](#)
- [11] Shanmugam PK, Thomas P. Optimization strategies for electric vehicle charging and routing: a comprehensive review. Gazi Univ J Sci 2024;37:1256–1285. [\[CrossRef\]](#)
- [12] Yong JY, Tan WS, Khorasany M, Razzaghi R. Electric vehicles destination charging: an overview of charging tariffs, business models and coordination strategies. Renew Sustain Energy Rev 2023;184:113534. [\[CrossRef\]](#)
- [13] Ohanu CP, Rufai SA, Oluchi UC. A comprehensive review of recent developments in smart grid through renewable energy resources integration. Heliyon 2024;10. [\[CrossRef\]](#)
- [14] Mousa A. Extended-deep Q-network: a functional reinforcement learning-based energy management strategy for plug-in hybrid electric vehicles. Eng Sci Technol Int J 2023;43:101434. [\[CrossRef\]](#)
- [15] Stavrev S, Ginchev D. Reinforcement learning techniques in optimizing energy systems. Electronics (Basel) 2024;13:1459. [\[CrossRef\]](#)
- [16] Dixit AC, Achutha MV, Sridhara BK. Elastic properties of aluminum boron carbide metal matrix composites. Mater Today Proc 2020. [\[CrossRef\]](#)
- [17] Gultekin Y. Acoustic emission reduction in vehicles by using MPP structures in wheel ARCH liner structures. Sigma J Eng Nat Sci 2024;1749–1755. [\[CrossRef\]](#)
- [18] Zhou Q, Du C. A quantitative analysis of model predictive control as energy management strategy for hybrid electric vehicles: a review. Energy Rep 2021;7:6733–6755. [\[CrossRef\]](#)
- [19] Dixit AC, Harshavardhan B, Prakasha KN. A game theory approach to optimizing electric vehicle charging infrastructure in urban areas. E3S Web Conf 2025;619:01004. [\[CrossRef\]](#)
- [20] Akter A, et al. A review on microgrid optimization with meta-heuristic techniques: scopes, trends and recommendation. Energy Strategy Rev 2024;51:101298. [\[CrossRef\]](#)
- [21] Tian S, et al. An optimization strategy for EV-integrated microgrids considering peer-to-peer transactions. Sustainability (Basel) 2024;16:8955. [\[CrossRef\]](#)
- [22] Nakabi TA, Toivanen P. Deep reinforcement learning for energy management in a microgrid with flexible demand. Sustain Energy Grids Netw 2021;25:100413. [\[CrossRef\]](#)
- [23] Dixit AC, Harshavardhan B, Ashok BC, Prakasha KN, Mohan Krishna SA, et al. Innovative pedagogical approaches for diverse learning styles and student-centric learning. J Eng Educ Transform 2024;37:178–188. [\[CrossRef\]](#)
- [24] Liu X, et al. A multi-step predictive deep reinforcement learning algorithm for HVAC control systems in smart buildings. Energy 2022;259:124857. [\[CrossRef\]](#)
- [25] Zhang Q, Yan J, Gao HO, You F. A systematic review on power systems planning and operations management with grid integration of transportation electrification at scale. Adv Appl Energy 2023;11:100147. [\[CrossRef\]](#)
- [26] Zhang L, Sun C, Cai G, Koh LH. Charging and discharging optimization strategy for electric vehicles considering elasticity demand response. eTransportation 2023;18:100262. [\[CrossRef\]](#)
- [27] Dixit AC, et al. Barriers to integrating AI in curriculum for enhanced engineering education: a fuzzy ISM approach. J Eng Educ Transform 2025;38:137–147. [\[CrossRef\]](#)
- [28] Kumar KS. Emerging trends and global challenges to predict drop in thermal performance of WTG gearbox. J Therm Eng 2024;657–669. [\[CrossRef\]](#)
- [29] Kumar KS, Muniamuthu S, Tharanisrisakthi BT. An investigation to estimate the maximum yielding capability of power for mini Venturi wind turbine. Ecol Eng Environ Technol 2022;23:72–78. [\[CrossRef\]](#)
- [30] Kumar KS, Palanisamy R, Aravindh S, Mohan GS. Design and analysis of windmill blades for domestic applications.
- [31] Sunil Kumar K, Kamalakkar V, Palani S, Muniamuthu S, Belinda CM. Design of K-type propeller optimized with lightweight aluminum material and its CFD analysis for marine-based applications. In: Singh A, Mishra DP, Bhat G, editors. Recent trends in thermal and fluid sciences. Singapore: Springer Nature; 2024. p. 375–390. [\[CrossRef\]](#)
- [32] Raghavendrakumar E, Kamalakkar V, Kumar KS. An investigation in temperature data analysis of middle atmospheric variation from SABER satellite. Nat Environ Pollut Technol 2024;23:443–450. [\[CrossRef\]](#)
- [33] Qiu D, Wang Y, Hua W, Strbac G. Reinforcement learning for electric vehicle applications in power systems: a critical review. Renew Sustain Energy Rev 2023;173:113052. [\[CrossRef\]](#)

-
- [34] Bharadwaj GV, Ashok DBC, Jayashankar N, Dixit AC. An experimental investigation and performance assessment of a solar water purifier. *Int J Mech Prod Eng Res Dev* 2019;9:12.
- [35] Ming F, Gao F, Liu K, Li X. A constrained DRL-based bi-level coordinated method for large-scale EVs charging. *Appl Energy* 2023;331:120381. [\[CrossRef\]](#)
- [36] Chifu VR, Cioara T, Pop CB, Rusu HG, Anghel I. Deep Q-learning-based smart scheduling of EVs for demand response in smart grids. *Appl Sci (Basel)* 2024;14:1421. [\[CrossRef\]](#)