Smart Energy Transactions in Vehicle-to-Grid Networks: A Deep Q-Network Approach with Blockchain

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Abstract

Electric vehicles (EVs) have gained significant traction due to their environmental benefits and potential to revolutionize the transportation sector. Integrating EVs into the Vehicle-to-Grid (V2G) network presents an innovative solution for optimizing energy transactions and grid stability. However, managing energy transactions during peak hours poses a challenge. This research proposes a novel approach that combines the Deep Q-Network (DQN) algorithm with block chain technology to enhance energy transactions in the V2G network. In this study, a V2G network model is introduced consisting of EVs, charging stations, a grid control center, and a block chain infrastructure. The block chain ensures transparency, security, and decentralized energy transactions. The DQN algorithm learns optimal action policies based on current states and rewards, contributing to grid stability. To incentivize EV owners for peak-hour energy contributions, a block chain-enabled rewarding mechanism is implemented. The proposed methodology is rigorously evaluated through simulations conducted in a custom environment that emulates V2G network dynamics. Performance metrics such as load shifting efficiency, peak demand reduction, and energy efficiency are employed for comprehensive assessment. The proposed method showcases superior performance compared to traditional load shifting and demand response strategies. Furthermore, comparative analyses are conducted against different state-of-the-art methods, demonstrating the effectiveness of our approach. The results underscore the potential of integrating DQN-based energy management with block chain technology to achieve grid stability and incentivize sustainable energy behaviors. This research contributes to the advancement of smart grid technologies, paving the way for a more sustainable and efficient energy ecosystem.

Keywords: Vehicle-to-grid; Electric vehicle; Block chain; Energy transaction; Deep Q-network; Accumulative reward; Action policy; Grid control center and charging station

1. Introduction

The proliferation of electric vehicles (EVs) has ushered in a new era of sustainable and environmentally conscious transportation [1]. However, this transition brings with it the challenge of efficiently managing energy resources. The emergence of Vehicle-to-Grid (V2G) networks, a paradigm where EVs not only consume energy but also contribute back to the grid, presents a compelling solution to this challenge [2] [3]. In a V2G network, EVs have the potential to become mobile energy assets, capable of feeding surplus energy back into the grid during periods of peak demand [4]. This dynamic capability offers a unique opportunity to balance energy supply [5] and demand and support grid stability [6]. However, the optimization of energy transactions within V2G networks during these crucial peak hours is a complex problem that requires sophisticated solutions [7].

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The application of blockchain technology to energy transactions within V2G networks has gained substantial attention due to its promise of enhancing transparency, security, and decentralization [8]. Blockchain, as a distributed and immutable ledger, holds the potential to revolutionize energy transactions by eliminating the need for intermediaries, ensuring data integrity, and enabling peer-to-peer transactions [9] [10]. The primary objective of this study is two-fold: firstly, to establish a robust framework that optimizes energy transactions among EVs, charging stations, and the power grid, with the added layer of blockchain technology; and secondly, to enhance grid stability and maximize rewards for EV owners through intelligent energy management driven by the DQN algorithm. To achieve these objectives, this research harnesses the capabilities of the Deep Q-Network (DQN) algorithm, a reinforcement learning technique that is adept at making informed decisions in complex and dynamic environments. By employing the DQN algorithm, the aim is to empower EVs to make strategic choices concerning energy transactions, thereby achieving a harmonious balance between the individual economic interests of EV owners and the collective stability of the grid.

The contributions of this paper are as follows:

Novel Integration of DQN and Blockchain: A pioneering approach is proposed that combines the Deep Q-Network (DQN) algorithm with blockchain technology to optimize energy transactions within the Vehicle-to-Grid (V2G) network. This novel integration addresses the challenge of managing energy transactions during peak hours while ensuring transparency and security.

Enhanced Grid Stability: The proposed methodology enhances grid stability by enabling EVs to make optimal energy contributions during peak hours. The DQN algorithm learns action policies that effectively balance energy demand and supply, reducing peak load and stabilizing the grid.

Incentivized Energy Contributions: A blockchain-enabled rewarding mechanism is introduced that incentivizes EV owners to contribute surplus energy during peak hours. This mechanism aligns with the transparent nature of blockchain, ensuring fair compensation based on actual energy contributions.

Comprehensive Simulation Environment: A custom simulation environment is designed to accurately emulate the dynamics of the V2G network. This environment allows for rigorous testing and evaluation of our approach under various scenarios, providing reliable insights into its performance.

Performance Evaluation: An extensive simulation and evaluation is conducted using a range of performance metrics, including load shifting efficiency, peak demand reduction, energy efficiency, and more. This thorough evaluation demonstrates the effectiveness of our approach in achieving grid stability and optimal energy management.

Comparative Analysis: A comparative analysis is conducted against different existing state-of-the-art methods, highlighting the superiority of our approach in terms of grid stability, energy efficiency, and incentivized energy contributions.

Advancement of Smart Grid Technologies: Proposed work contributes to the advancement of smart grid technologies by showcasing the potential of combining reinforcement learning and blockchain for energy management. This has implications for a more sustainable and efficient energy ecosystem.

Experimental result: Through the comprehensive analysis, the performance rates of 280, 0.975, 98.4%, 21 seconds, 2400 tps, 0.1 seconds and $2385 are attained from the cumulative rewards, convergence rate, energy efficiency, energy transaction time, throughput, validation time and charging cost respectively.

The remaining sections of this paper are organized as, the literature survey related to the V2G and EV charging is described in section 2. The system model and its problem formulation are clearly explained in sections 3 and 4 respectively. The proposed methodology of this paper for attaining optimal action policy is illustrated in section 5 and the result portion is explained in section 6 through different graphical representations and analysis. Finally, this paper is concluded in section 7 with its corresponding future direction.

2. Related Work

The domain of blockchain applications in energy management and electric vehicle (EV) charging has garnered substantial attention in recent years. Additionally, reinforcement learning approaches, particularly the Deep Q-Network (DQN) algorithm, have demonstrated promise in optimizing energy-related tasks. In this section, a review of pertinent literature is provided to contextualize the proposed work and underscores the unique contribution of integrating DQN with blockchain for energy transaction optimization within Vehicle-to-Grid (V2G) networks.

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2.1 Blockchain Applications in Energy Management and EV Charging

Numerous studies have explored the potential of blockchain technology in revolutionizing energy management. Blockchain's decentralized nature, tamper resistance, and transparency have been leveraged to enhance energy trading, grid management, and peer-to-peer energy sharing. In the context of EV charging, blockchain offers secure transaction mechanisms and enables seamless billing and authentication.

Zhang et al. [11] established a stochastic blockchain-based energy management system for achieving maximum efficiency from transportation using a vehicle to subway (V2S) and vehicle-to-grid (V2G). The stochastic model was used to handle uncertainties and the blockchain was utilized to transfer data securely within the smart city. Kumara et al. [12] demonstrated a decentralized and transparent peer-to-peer energy trading (DT-P2PET) scheme for minimizing energy generation of grid and management burden by handling the issues of trust, scalability, security, network bandwidth and single-point-of-failure.

Zhao et al. [13] elaborated a blockchain-based effective renewable energy management process for minimizing cost and maximizing efficiency during EV charging. The blockchain model was implemented to analyse and validate the energy demands of each EV through vehicle data. The Random Forest based power scheduling algorithm (RF-PSA) was presented by Bhaskar et al. [14] for allocating efficient energy management in transportation automation. The RF model was used for determining the charging price of EV and PSA was employed to find the nearest charging station of EV.

Tanwar et al. [15] established a blockchain-based EV charging reservation scheme for attaining optimum price. The primary concern of this work was to transferring data securely between charging stations and EVs. Liang et al. [16] represented a blockchain-based energy trading system named as V2G network (V2GNet) for attaining efficiency and security. The robust energy trading (RET) algorithm was used to tackle the attack issues.

Luo et al. [17] illustrated a low-complexity consensus algorithms such as PRAFT and PRBFT for determining the efficiency of V2G. The graphical representations showed a low storage overhead, low latency, high scalability and high throughput. Lin et al. [18] designed an energy management system (EMS) for achieving optimal charging and discharging based on power transactions.

2.2 Reinforcement Learning Approaches

Reinforcement learning algorithms, particularly DQN, have exhibited remarkable success in various domains, including robotics, gaming, and financial modelling. When applied to energy-related tasks, DQN optimizes actions by learning from interactions with the environment, contributing to load balancing, peak demand reduction, and energy efficiency.

The blockchain and deep learning-based EV fault detection framework was developed by Trivedi et al. [19] to determine different faults that appeared in the vehicle. The convolutional neural network (CNN) and long short-term memory (LSTM) were used as a deep learning model to detect faulty data presence in the EV. Kumari et al. [20] demonstrated a secure V2G energy trading (SV2G-ET) scheme for eliminating issues in the EV during energy trading. This SV2G-ET scheme has deep reinforcement learning (DRL) model for scheduling EV charging and discharging.

Said et al. [21] represented a P2P energy transaction system for tackling cyber security issues by using a support vector machine (SVM) algorithm. The false data injection detection-based SVM classification protocol was implemented to find and extract right values. Khan and Byun [22] developed an EV automatic payment system to minimize human interaction and enhance transparency, trust and privacy by using open source platform hyper ledger fabric. Shang et al. [23] illustrated a multi-objective gray wolf optimization (MOGWO) model for charging and discharging the EV.

Cabrera-Gutierrez et al. [24] designed a trusted platform module (TPM) for ensuring integrity. The authentication mechanism was established based on tokens to prevent the containers from the unauthorized access. Teimoori et al. [25] illustrated a federated learning (FL) algorithm to provide secure recommendations of charging stations for EVs. Asgharzadeh et al. [26] implemented a genetic algorithm (GA) for solving problems in long-term expansion planning. The bi-level programming was involved in this paper to find the optimal allocation of EV charging stations.

2.3 Integration of DQN with Blockchain in V2G Networks

The integration of DQN with blockchain technology is a novel approach that transforms energy management within V2G networks. This novel integration addresses the dynamic and complex nature of energy transactions during peak hours. The reinforcement learning capability of DQN empowers EVs to learn optimal actions that enhance grid stability, mitigate peak loads, and improve energy efficiency. By pairing DQN with blockchain, our

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work ensures secure and transparent energy transactions, thereby promoting fair and accountable energy contributions. The multi-stakeholder hierarchical V2G coordination strategy (MHVCS) was elaborated by Zhang et al. [27] for achieving multi-stakeholder benefits by using proximal policy optimization (PPO) and proof of stake (PoS). The experimental validation of this paper provided an enhanced renewable energy consumption, lower charging cost and mitigate load fluctuation.

2.4 Research gap

The gap of this research is to address the complex challenge of optimizing energy transactions within V2G networks, particularly during peak hours, by leveraging the power of the Deep Q-Network (DQN) algorithm. The novelty of our approach lies in the synergy between these two cutting-edge technologies. While blockchain guarantees secure and transparent transactions, DQN optimizes actions to align with the grid's energy requirements. This harmonious integration establishes a new paradigm for V2G energy management, enabling EVs to play a pivotal role in maintaining grid stability while being fairly rewarded for their contributions.

3. System Model

The architecture of the Vehicle-to-Grid (V2G) network encompasses a dynamic interplay between Electric Vehicles (EVs), charging stations, the grid control centre, and the integration of blockchain technology. This interconnected ecosystem forms the foundation for optimizing energy transactions using the Deep Q-Network (DQN) algorithm. The system model of this proposed work is explained in figure 1.

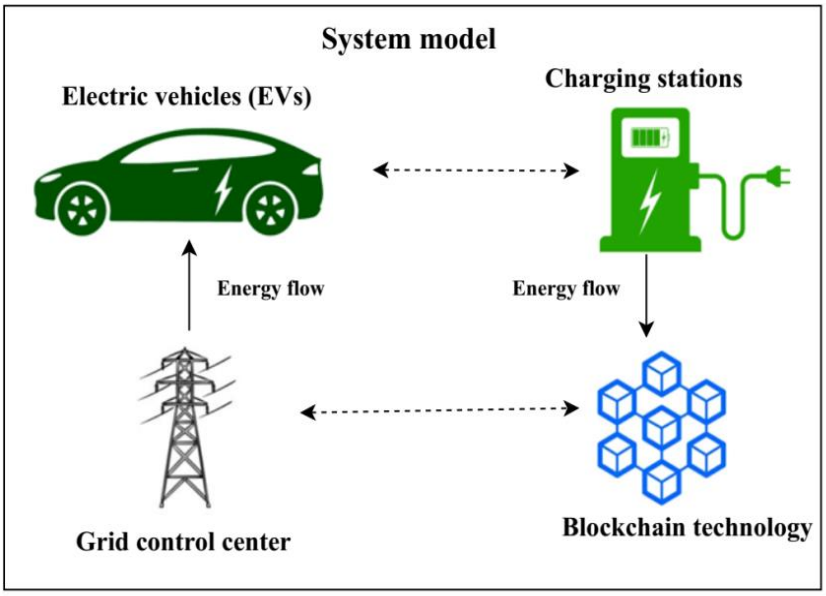

Figure 1. System Model Illustration

3.1 Components of the V2G Network

The V2G network comprises several key components:

- **Electric Vehicles (EVs):** These are mobile energy assets equipped with bidirectional charging capabilities. EVs either draw energy from the grid for charging or feed surplus energy back to the grid during peak hours.
- **Charging Stations:** These serve as the interfaces between EVs and the grid. Charging stations facilitate energy exchange by allowing EVs to draw energy or inject surplus energy based on grid conditions.
- **Grid Control Center**: The central hub that manages the energy supply and demand across the grid. It communicates with EVs and charging stations to coordinate energy transactions and ensure grid stability.
- **Blockchain Technology:** The fundamental innovation that enhances the efficiency and transparency of energy transactions. Blockchain provides a decentralized ledger, ensuring tamper-resistant records of energy transactions, and employs consensus mechanisms to validate and record transactions securely.

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3.2 Blockchain-Enhanced Energy Transactions

Blockchain technology plays an essential role in addressing challenges related to security, transparency, and intermediaries in energy transactions. The blockchain ledger maintains an immutable record of every energy transaction, accessible to all participants. This transparency eliminates the need for intermediaries, enhancing efficiency and reducing transaction costs. The consensus mechanisms employed by blockchain ensure that transactions are validated through a distributed network of nodes, minimizing the risk of fraud and tampering. This secure validation process, often achieved through proof-of-work or proof-of-stake mechanisms, reinforces the integrity of energy transactions.

3.3 Interactions within the V2G Ecosystem

The interactions within the V2G ecosystem are intricate and dynamic:

- **EVs and Charging Stations:** EVs interact with charging stations to either draw energy from the grid, recharge their batteries, or contribute surplus energy during peak hours. Charging stations communicate with EVs and the grid control centre to manage energy flows effectively.
- **Grid Control Center*:*** The control centre oversees the energy demand and supply across the grid. It communicates with EVs and charging stations to optimize energy transactions, taking into account grid conditions, peak hours, and energy pricing.
- **Blockchain Integration*:*** Energy transactions are conducted using blockchain technology. EVs initiate transactions by sending requests to the blockchain network. The network validates and records transactions on the blockchain ledger, ensuring transparency and security.

The interactions within the system are formalized through mathematical equations. E_t represent the energy level of an EV at time t, $P_{ch\,arg\,e}$ denote the power drawn from the grid during charging, and $P_{disch\,arg\,e}$ represent the power fed back to the grid during discharging. The net energy change ΔE_t is expressed as:

$$\Delta E_t = P_{ch\,arg\,e} - P_{disch\,arg\,e} \tag{1}$$

The blockchain layer enhances the security and transparency of the transactions, providing a cryptographic hash H_t for each transaction at time t, ensuring that no unauthorized modifications occur.

4. Problem Formulation

The optimization of energy transactions within blockchain-based Vehicle-to-Grid (V2G) networks, particularly during peak hours, presents a multifaceted challenge that is precisely expressed through the following formulations:

4.1 Optimizing Energy Transactions

Given a set of Electric Vehicles (EVs), denoted as $E = \{EV_1, EV_2, \dots, EV_N\}$, charging stations represented as $CS = \{CS_1, CS_2, .., CS_M\}$, and a grid control center, the problem involves orchestrating energy transactions to maximize grid stability and EV owner rewards. During peak hours, EVs have the capacity to inject surplus energy into the grid, and charging stations enable energy exchange between EVs and the grid. The primary challenge is framed as a constrained optimization problem, where the goal is to maximize the utilization of available energy resources while adhering to grid capacity and demand constraints. This is mathematically expressed as follows:

$$Maximize: f(x) \tag{2}$$

where x represents the allocation of surplus energy from EVs back to the grid.

Subject to:

Energy demand E_{demand} during peak hours.

Capacity constraints of charging stations CS .

Energy contributed by E_{EVs}s based on their available surplus energy.

Energy pricing and cost considerations.

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This optimization problem involves determining the optimal allocation of surplus energy from EVs to the grid to meet demand while adhering to charging station capacities and considering energy pricing dynamics.

4.2 The Role of Blockchain

The integration of blockchain technology introduces an additional layer of complexity. To harness blockchain's capabilities while managing peak-hour energy transactions, the integrated form of EV transaction and grid transaction is required and is formulated as:

$$B_I = EV_T + G_T \tag{3}$$

where B_I, EV_T and G_T are represented as blockchain integration, EV transaction and grid transaction respectively. This equation represents the combined effect of energy transactions conducted by EVs and those initiated by the grid through the blockchain. The challenge lies in ensuring that these transactions align with real-time energy needs while maintaining the security and transparency of blockchain records. The objectives are expressed as optimization criteria:

1. **Maximizing EV Owner Rewards:** The objective is to maximize the rewards earned by EV owners for contributing surplus energy during peak hours. This is mathematically expressed as:

$$Re\,w\,ards = \sum_{i=1}^{N}\left(E_{surplus}^{(i)} \times P_E\right) \tag{4}$$

where N is the number of participating EVs, $E_{surplus}^{(i)}$is the surplus energy contributed by the i -th EV, and P is the energy pricing.

2. **Ensuring Grid Stability*:*** The second objective of grid stability is quantified by minimizing the deviation between energy supply and demand during peak hours. $D(t)$ represent the energy demand at time t and $S(t)$ denote the energy supply from EVs and the grid at the same time. The grid stability objective is framed as:

$$Minimize\colon \sum_t |D(t) - S(t)| \tag{5}$$

where t denotes discrete time intervals within the peak hours. To achieve this objective, the energy injected into the grid by EVs aligns with the grid's requirements, minimizing disruptions and maintaining a stable energy ecosystem.

4.3 Balancing Objectives and Constraints

The core of the problem formulation is to strike a balance between the two objectives while considering constraints such as the capacity of charging stations, battery limitations of EVs, and real-time fluctuations in energy supply and demand. This involves developing an optimization algorithm that leverages the capabilities of the Deep Q-Network (DQN) to make informed decisions in real time, navigating the trade-offs between EV rewards and grid stability.

5. Proposed Methodology

The adaptation of the Deep Q-Network (DQN) algorithm to optimize energy transactions within a blockchain-based framework is a pivotal step in achieving the objectives of maximizing rewards for Electric Vehicle (EV) owners while ensuring grid stability. This section outlines the methodology employed to seamlessly integrate DQN with blockchain-enhanced energy management. The overall architecture of this paper is shown in figure 2 and the detailed explanations are provided in subsequent sections. The proposed methodology uses blockchain technology and DQN algorithm for energy transactions and the Q-value estimation. The rewarding mechanism is implemented in this paper to incentivize EV owners to contribute surplus energy during peak hours. Finally, the optimal action policy is attained by learning and optimizing the Q-values through the integration of epsilon greedy strategy and DQN algorithm.

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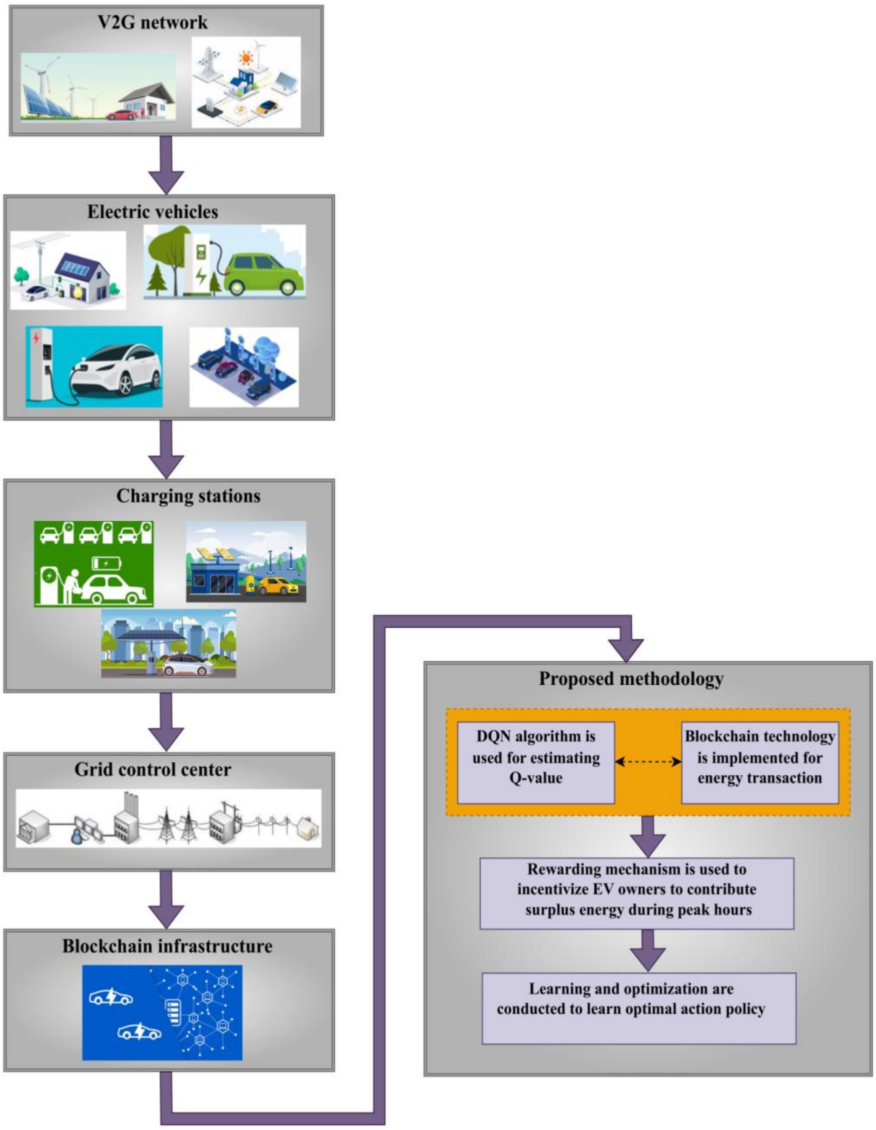

Figure 2. Overall architecture of the proposed model

5.1 Representation of States

Within the dynamic environment of the Vehicle-to-Grid (V2G) network, the representation of states at time t (s_t) is a pivotal aspect for informed decision-making by the Deep Q-Network (DQN) agent. It includes variables such as the energy demand $D(t)$, the energy supply from EVs and the grid $S(t)$, and the current state of the blockchain ledger. This representation captures essential information that drives the optimization of energy transactions. The state $s_t$is composed of various variables that collectively define the current energy ecosystem's conditions.

5.1.1 Variables Included in s_t

The state s_t summarizes the following variables:

Energy Demand ($D(t)$)

The energy demand at time t denotes the amount of energy required by the grid to meet the collective needs of various energy consumers. It reflects the immediate energy requirements within the V2G network. Mathematically, $D(t)$ is expressed as:

$$D(t) = \sum_{i=1}^{N} D_{EV_i}(t) \tag{6}$$

where N represents the total number of EVs, and $D_{EV_i}(t)$ is the energy demand of the i -th EV at time t

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Energy Supply ($S(t)$)

The energy supply to the grid from both Electric Vehicles (EVs) and external sources, such as renewable energy installations. It reflects the availability of surplus energy within the ecosystem. The energy supply $S(t)$ encompasses the total energy available within the system for consumption and exchange. It is the combined energy contributed by EVs and drawn from the grid. Mathematically, $S(t)$ is formulated as:

$$S(t) = \sum_{i=1}^{N} EC_{EV_i}(t) + ED_{grid}(t) \tag{7}$$

where $EC_{EV_i}(t)$ represents the surplus energy injected into the grid by the i -th EV, and $ED_{grid}(t)$ represents the energy drawn from the grid at time t.

Blockchain Ledger State ($B(t)$)

The state of the blockchain ledger encompasses critical information regarding the history of energy transactions within the V2G network. It includes details such as previous energy contributions, rewards distributed, and transaction timestamps. The blockchain ledger state reflects the transparency and tamper-resistant nature of blockchain technology, allowing the DQN agent to have access to a decentralized and secure record of energy transactions.

5.1.2 Formulation of s_t

The state s_t is mathematically formulated as follows:

$$s_t = [D(t), S(t), B(t)] \tag{8}$$

where the terms $D(t)$, $S(t)$ and $B(t)$ are denoted as energy demand at time t, energy supply from EVs and the grid at time t and captures the current state of the blockchain ledger at time t respectively.

5.1.3 Role in Decision-Making

The representation of states st empowers the DQN agent to make contextually informed decisions. By incorporating real-time energy demand, supply, and the state of the blockchain ledger, the agent gauges the current energy ecosystem's conditions. This enables the agent to dynamically adjust actions, such as injecting surplus energy into the grid or drawing energy for charging, to optimize rewards and contribute to grid stability.

5.1.4 Dynamic Adjustments

As the variables within st are subject to change in real-time due to fluctuating energy demands, supply patterns, and blockchain updates, the representation facilitates adaptive decision-making. The DQN agent learns to respond to variations and uncertainties within the V2G network, ensuring efficient energy utilization and balanced energy transactions.

5.2 Definition of Action Space

Within the intricate dynamics of the Vehicle-to-Grid (V2G) network, the definition of the action space is a pivotal factor that empowers Electric Vehicles (EVs) to make intelligent decisions in optimizing energy transactions. The action space encapsulates a range of decisions that EVs take to contribute effectively to the grid's energy ecosystem while enhancing their own rewards.

5.2.1 Action Set

The action set available to each EV is composed of discrete actions that reflect their energy contribution choices. In this context, an action a_t at a time t is categorized into two primary options:

- **Injecting Surplus Energy:** EVs have the option to inject surplus energy into the grid, thereby contributing to the grid's energy supply during peak hours. The action of injecting a certain amount of energy E_{inject} at time t is represented as:

$$a_t = (E_{inject}) \tag{9}$$

- **Drawing Energy for Charging:** Alternatively, EVs are chosen to draw energy from the grid to charge their batteries, catering to their own energy needs. The action of drawing a certain amount of energy E_{draw} at time t is represented as:

$$a_t = (E_{draw}) \tag{10}$$

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5.2.2 Dynamic Response to Grid Conditions

The action space's design acknowledges the dynamic nature of the V2G network. By offering these two contrasting choices, EVs adapt their energy contributions based on the real-time conditions of the grid. During peak hours, when energy demand is high, EVs are chosen to inject surplus energy to alleviate strain on the grid. Conversely, during periods of lower demand, they opt to draw energy for their own charging needs.

5.2.3 Optimizing Grid Stability and Rewards

The action space's formulation aligns with the broader objectives of grid stability and maximizing rewards for EV owners. By providing EVs with the autonomy to choose actions that contribute to the grid's stability and their individual rewards, the action space serves as a powerful mechanism to harmonize individual interests with collective energy management goals.

5.3 Blockchain-Enabled Rewarding Mechanism

To incentivize EV owners to contribute surplus energy during peak hours, a blockchain-enabled rewarding mechanism is introduced. This mechanism integrates the principles of blockchain technology with energy transactions to create a transparent and fair system for rewarding EV contributions.

5.3.1 Formulation of Reward

The reward $R_{EV_i}(t)$ for EV at time t is meticulously defined to incentivize energy contributions. This reward mechanism recognizes the energy injected into the grid as a valuable resource and compensates EV owners accordingly. Mathematically, the reward is expressed as:

$$R_{EV_i}(t) = k \times EC_{EV_i}(t) \tag{11}$$

where k is a constant factor that acts as a conversion coefficient. This factor transforms the amount of energy contributed by EV into a corresponding reward. The greater the energy contribution, the higher the reward, creating a direct link between EV contributions and compensation.

5.3.2 Aligning with Blockchain Principles

The integration of this rewarding mechanism with blockchain technology further enhances its credibility and fairness. Blockchain's inherent transparency and tamper-resistant nature ensure that the rewards are based on actual contributions, without any scope for manipulation. The blockchain ledger records every energy transaction, establishing an immutable record of EV contributions and corresponding rewards. This aligns with the principles of transparency and accountability, bolstering trust among participants.

5.3.3 Fostering Fair Compensation

The blockchain-enabled rewarding mechanism fosters fair compensation for EV owners. By linking rewards directly to energy contributions, the mechanism ensures that participants receive compensation in proportion to their actual input into the grid. This alignment between effort and reward encourages active participation and empowers EV owners to contribute optimally during peak hours.

5.3.4 Supporting Grid Stability

The rewarding mechanism's design harmonizes with the broader objective of grid stability. By incentivizing EV owners to contribute surplus energy during peak hours, the mechanism aids in balancing energy supply and demand, thereby contributing to the overall stability of the energy ecosystem.

5.4 Q-Network Architecture and Training

Central to the successful implementation of the Deep Q-Network (DQN) algorithm [28] is the architecture of the neural network used by the DQN agent, along with the training process that enables the agent to learn optimal action policies. The DQN agent's neural network architecture consists of an input layer representing the state, one or more hidden layers, and an output layer representing the Q-values for different actions. DQN combines the principles of reinforcement learning with deep neural networks to make informed decisions in dynamic and uncertain environments. The network is trained using experiences sampled from past interactions using the Bellman equation to update the Q-values. The process of experience replay enhances the stability and convergence of learning. This section elaborates on the Q-network's architecture and the training methodology applied within the context of energy transaction optimization in the Vehicle-to-Grid (V2G) network. The architecture of DQN involves two key components:

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- **Q-Network:** The Q-network is a deep neural network that approximates the action-value function $Q(s_t, a_t)$, where s_t represents the state of the environment and denotes an action taken by the agent. The Q-network's role is to estimate the expected cumulative reward for taking an action a_t from a given state s_t. The action is represented as,

$$a_t = argmax_a \, Q\,(s_t, a_t) \tag{12}$$

- **Experience Replay:** To enhance the stability and learning efficiency of DQN, experience replay is employed. Experience replay involves storing transitions $(s,a,r,s^{'})$ in a replay buffer and sampling batches of these transitions to update the Q-network. This decouples the updates from the current time step, reducing the correlation between consecutive updates.

5.4.1 Neural Network Architecture

The DQN agent's neural network architecture is designed to facilitate the estimation of action values (Q-values) for different actions based on the current state s_t. The architecture of the DQN agent's neural network is shown in figure 3. The neural network comprises the following layers:

- **Input Layer:** *The input layer encodes the state $s_t$of the V2G network. It consists of neurons corresponding to the variables that define the state, including energy demand, energy supply, and the state of the blockchain ledger.*
- **Hidden Layers:** *The hidden layers process the input information and extract relevant features. The number of hidden layers and the number of neurons in each layer are tailored based on the complexity of the problem. This neural network has two hidden layers with 64 neurons each.*
- **Output Layer:** *The output layer produces QQ-value estimates for each action available in the action space. It consists of neurons corresponding to each action, representing the Q-value estimate for that action.*

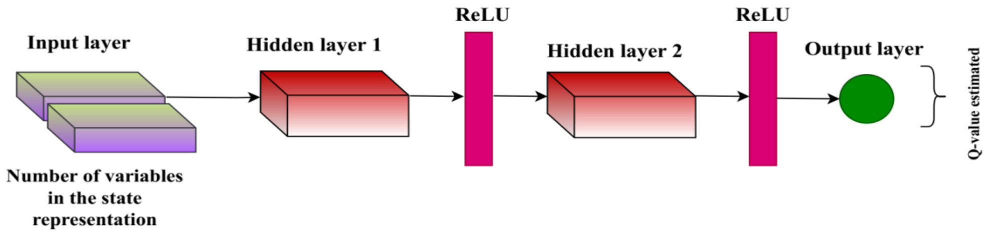

Figure 3. DQN agent's neural network architecture

In this architecture, the input layer takes in the state representation, and the hidden layers process the information to extract relevant features. The output layer provides Q-value estimates for each action, allowing the DQN agent to choose actions that maximize rewards over time. The use of ReLU activation in the hidden layers and a linear activation in the output layer is a common choice for DQN architectures. The hyperparameter ranges used in this paper are described in table 2.

Table 1: Hyperparameter ranges

Name of the parameters	**Ranges**
Learning rate	0.001-0.1
Discount factor	0.8-0.99
Exploration parameter	0.1-0.5
Neural network architecture	User-defined
Input layer	Depends on context
Hidden layer	2-3 layers and 128-256 neurons per layer
Output layer	Number of actions

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5.4.2 Training with Experience Replay

The training of the DQN agent involves iteratively updating the Q-values to approximate the optimal action policies. This is achieved through the Bellman equation, which incorporates the observed rewards and future state transitions to update the Q-values. The Bellman equation is expressed as:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_t + \gamma\, max_{a'}\, Q\,(s_{t+1}, a') - Q(s_t, a_t)\right] \tag{13}$$

where $Q(s_t, a_t)$, r_t, s_{t+1}, $\alpha$and $\gamma$are depicted as Q-value of action at in state s_t, reward observed after taking action a_t in state s_t, next state observed after taking action a_t in state s_t, learning rate and discount factor respectively.

5.5 Exploration Strategy and Learning

Navigating the exploration-exploitation trade-off is a critical aspect of the Deep Q-Network (DQN) algorithm's learning process. To address this challenge, an epsilon-greedy exploration strategy is employed, enabling the DQN agent to strike a balance between exploiting its current knowledge and exploring new actions. At each time step, the DQN agent selects the action with the highest Q-value with probability $1 - \varepsilon$ (exploitation) and a random action with probability ε (exploration). The value of ε decreases over time, gradually shifting the agent's focus toward exploiting learned Q-values. This section elaborates on the exploration strategy and its integration with the learning process within the context of the Vehicle-to-Grid (V2G) network.

5.5.1 Epsilon-Greedy Exploration Strategy

The epsilon-greedy strategy introduces a controlled randomness to the agent's action selection process. At each time step t, the DQN agent makes a decision based on the following probabilistic approach:

- With probability $1 - \varepsilon$, the agent selects the action with the highest Q-value for the current state s_t (exploitation).
- With probability ε, the agent selects a random action from the action space (exploration).

This strategy ensures a dynamic exploration of action choices while also capitalizing on the knowledge gained from previous interactions. The exploration probability ε decreases over time, favoring exploitation as the agent accumulates more experience.

5.5.2 Gradual Reduction of Exploration (ε)

The value of ε decreased gradually over time, steering the DQN agent's behaviour towards exploiting the learned Q-values. This reduction is typically achieved using a decay mechanism, such as:

$$\varepsilon_t = \varepsilon\left(\varepsilon min_{max} \cdot exp\left(-\frac{t}{\tau}\right)\right)_{min} \tag{14}$$

From the above equation, the exploration probability at time t, the initial exploration probability, the minimum exploration probability and controls the rate of decay are depicted by ε_t, ε_{max}, ε_{min} and τrespectively.

5.5.3 Balancing Exploration and Exploitation

The epsilon-greedy strategy ensures that the DQN agent strikes a balance between exploration and exploitation. Initially, when ε is high, the agent explores various action possibilities to gather diverse experiences. As ε gradually decreases, the agent leans more towards exploiting the learned Q-values, making decisions that are grounded in its accumulated knowledge.

5.5.4 Learning Process Enhancement

The integration of the epsilon-greedy strategy with the DQN algorithm's learning process enriches the agent's learning journey. By exploring various actions, even those that may initially seem suboptimal, the agent expands its understanding of the environment and identifies potentially better strategies. As ε decreases, the agent refines its decision-making, leveraging its learned knowledge to maximize rewards and contribute effectively to grid stability. The pseudo code of DQN for energy transaction optimization is described in algorithm 1.

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Algorithm 1: DQN for Energy Transaction Optimization
Input:
State space s_t: Represents the possible states of the V2G network.
Action space a_t: Defines the available actions for EVs (inject energy, draw energy).
Discount factor γ: Determines the weight of future rewards.
Learning rate α: Controls the extent of weight updates during training.
Exploration parameter ε: Governs the balance between exploration and exploitation.
Initial and final values of ε_{start} and ε_{end} : For the exploration parameter decay.
Q-network initialization
Initialize Exploration Parameter ($\varepsilon = \varepsilon_{start}$)
for (each episode)
Reset the V2G network to an initial state
for (each time step)
Choose an action using an epsilon-greedy strategy
With probability $1-\epsilon$ for exploitation
With probability ϵ for exploration
Execute action in the V2G network using equation (12)
Observe the next state and reward from the environment
Update the Q-value using the Bellman equation (13)
Transition of state into next state
Update gradual reduction of exploration using a decay function by applying equation (14)
end for
end for
Attained Optimal Action Policy

6. Experimental Results

This section presents the outcomes of the experimental evaluation performed to evaluate the efficiency of the proposed method in enhancing energy transactions in the V2G network. The experiments involve multiple simulation runs with varying scenarios, dataset characteristics, and hyperparameters. Each run captures the performance of the proposed method under different conditions, providing insights into its robustness and adaptability. For the experiment, a synthetic dataset generated to emulate real-world V2G scenarios is used. The dataset includes parameters such as EV characteristics, charging patterns, grid conditions, and energy demand profiles also, the diverse evaluation metrics are used to analyze the effectiveness of the proposed method. The evaluation results are given in the upcoming section.

6.1 Experimental Setup

The experiment setup ensures that the proposed method is rigorously tested and evaluated, demonstrating its capability to optimize energy transactions in a V2G network through the integration of the DQN algorithm and blockchain technology. The experiments are conducted using the system which has Windows 11, 8GB RAM, Intel core i3-1005G1 CPU, 64-bit operating system, and 1.2GHz processor.

6.2 Simulation Environment

The simulation environment emulates the dynamic interactions within a V2G network, encompassing EVs, charging stations, the grid control center, and blockchain-enabled energy transactions. Key aspects of the simulation environment include:

EV and Charging Station Dynamics

Simulated EVs exhibit varying charging and discharging behaviors based on real-world usage patterns, as shown in Table 2. Charging stations manage energy transactions with EVs, considering factors like energy demand, supply, and grid conditions, as listed in Table 3.

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Table 2: Simulating EVs

Parameter	Description	Values/Details
Simulation Software	Python's Gym framework for custom environment creation.	OpenAI's Gym
Number of EVs	Total number of simulated electric vehicles.	100
Battery Capacity	Range of battery capacities for EVs.	30 kWh - 60 kWh
Charging Behavior	Model representing when EVs charge or discharge.	Usage profiles, stochastic
Driving Patterns	Patterns simulating EV usage and driving habits.	Real-world or stochastic

Table 3: Emulating Charging Stations

Parameter	Description	Values/Details
Simulation Software	Python's Gym framework for custom environment creation.	OpenAI's Gym
Number of Stations	Total number of simulated charging stations.	10
Charging Slots	Slots are available at each charging station.	2 - 4
Energy Capacity	Range of energy capacities for charging stations.	20 kWh - 50 kWh
Charging Rates	Rates at which EVs can charge at the stations.	7 kW - 22 kW

Grid Control Center

The simulated control centre coordinates energy transactions, monitors grid stability, and communicates with EVs and charging stations. It ensures a realistic representation of grid management processes. Table 4 shows the grid control centre simulation.

Table 4: Replicating Grid Control Center

Parameter	Description	Values/Details
Simulation Software	Python's Gym framework for custom environment creation.	OpenAI's Gym
Grid Area	Area covered by the simulated grid control center.	Small urban area
Peak Hour Forecasting	Algorithms are used to predict peak hours and energy demand.	Real-time data, algorithms
Energy Management	Mechanisms for balancing energy supply and demand.	Algorithm-based

Blockchain Integration

The simulation incorporates a blockchain infrastructure to emulate transparent and secure energy transactions. Smart contracts validate and record transactions, ensuring accuracy and tamper resistance. Table 5 displays the blockchain simulation.

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Table 5: Blockchain Simulation

Parameter	**Description**	**Values/Details**
Simulation Software	Ethereum's Solidity for smart contract development and simulation.	Ethereum, Solidity
Block Size	Size of each block in the blockchain.	1 MB
Block Interval	The time interval between successive blocks.	15 seconds
Consensus Mechanism	Consensus algorithm for validating transactions.	Proof of Work

6.3 Hyperparameter Settings

The hyperparameter tuning operation is executed to obtain the best parameter values, which improves the performance of the proposed method. The parameters and their optimal values are summarized in Table 6.

Table 6: Hyperparameter Settings

Technique	**Parameter**	**Values**
Proposed DQN Model	Number of Neurons	64
	Activation Function	ReLU
	Learning Rate	0.001
	Discount Factor	0.9
	Exploration Parameter	0.2
	Number of Hidden Layers	2

6.4 Evaluation Metrics

To measure the effectiveness of the proposed approach, key evaluation metrics are used, including:

Cumulative Rewards (C_R):

The cumulative rewards measure the total rewards earned by EVs over multiple episodes, reflecting their ability to optimize energy transactions and contribute to grid stability. It is expressed as follows:

$$C_R = \sum_{l=1}^{L} R_l \tag{15}$$

where L represents the total number of episodes, and R_l represents the reward earned by EV in episode l.

Convergence Rate (Co_{Ra}):

The convergence rate gauges the speed at which the DQN algorithm converges towards optimal policies. A higher convergence rate indicates faster learning and adaptation to the optimal strategy. It is calculated using the following equation.

$$Co_{Ra} = \frac{1}{L}\sum_{l=1}^{L} \mu_l \tag{16}$$

where μ_l represents the absolute difference between Q-values of current and previous episodes.

Energy Efficiency (E_E):

Energy efficiency quantifies the effectiveness of energy transactions in terms of energy surplus and demand satisfaction, demonstrating the ability of the proposed method to manage energy resources efficiently. The formula for energy efficiency is shown in the following equation.

$$E_E = \frac{To_{ES}}{To_{ED}} \times 100 \tag{17}$$

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where To_{ES} denotes the sum of surplus energy injected into the grid by all EVs, and To_{ED} denotes the sum of energy drawn from the grid by all EVs.

Energy Transaction Time:

The amount of time required to transfer the energy from source to destination is referred to as the energy transaction time. A lower energy transaction time indicates the proposed method's better energy transaction ability.

Throughput:

The amount of data sent successfully from source to destination is referred to as the throughput. A higher throughput rate indicates the superior efficiency of the proposed method in data transmission.

Validation time:

The length of time needed to perform the validation process is referred to as the validation time. A lower validation time denotes the optimal time utilization.

6.5 Performance Analysis

The results of the overall performance of the proposed method in optimizing the energy transactions in a V2G network are tabulated in Table 7. Here, evaluation metrics like cumulative rewards, convergence rate, energy efficiency, energy transaction time, throughput, validation time, and charging cost are used to assess the effectiveness of the proposed method. The proposed method attained higher performance rates, which highlights that the proposed method effectively enhanced the energy transactions in a V2G network. The performance rates of the proposed method are as follows:

Table 7: Overall Performance Results

Evaluation Metrics	**Values**
Cumulative Rewards	280
Convergence Rate	0.975
Energy Efficiency	98.4%
Energy Transaction Time	21s
Throughput	2400tps
Validation Time	0.1s
Charging Cost	$2385

6.6 Comparative Analysis

In this subsection, the proposed method is compared with various existing methods like DT-P2PET [12], RF-PSA [14], V2GNet [16], SVM algorithm [21], DRL [20], MOGWO [23], and GA [26] methods to compute its performance based on the various evaluation metrics. Figure 4 shows the cumulative rewards of the proposed and the existing DT-P2PET, RF-PSA, V2GNet, SVM algorithm, DRL, MOGWO, and GA methods. Here, as the number of episodes increases, the cumulative rewards are increased. The cumulative rewards of 280, 270, 224, 200, 175, 150, 125, and 100 are obtained from the proposed, DT-P2PET, RF-PSA, V2GNet, SVM algorithm, DRL, MOGWO, and GA methods respectively. The figure exhibits that the proposed method attained higher cumulative rewards compared to the underlined methods, which indicates that the proposed method efficiently optimizes energy transactions and contributes to grid stability. The convergence rate of the proposed and existing methods is illustrated in Figure 5. The convergence rate is defined as the speed at which the DQN algorithm converges towards best policies. The proposed, DT-P2PET, RF-PSA, V2GNet, SVM algorithm, DRL, MOGWO, and GA methods provided the convergence rate of 0.975, 0.96, 0.92, 0.9, 0.88, 0.82, 0.81, and 0.8444 respectively. From this analysis, it is known that the proposed method provided a higher convergence rate compared with other methods. This highlights that the proposed method has faster learning and adaptation to the best strategy.

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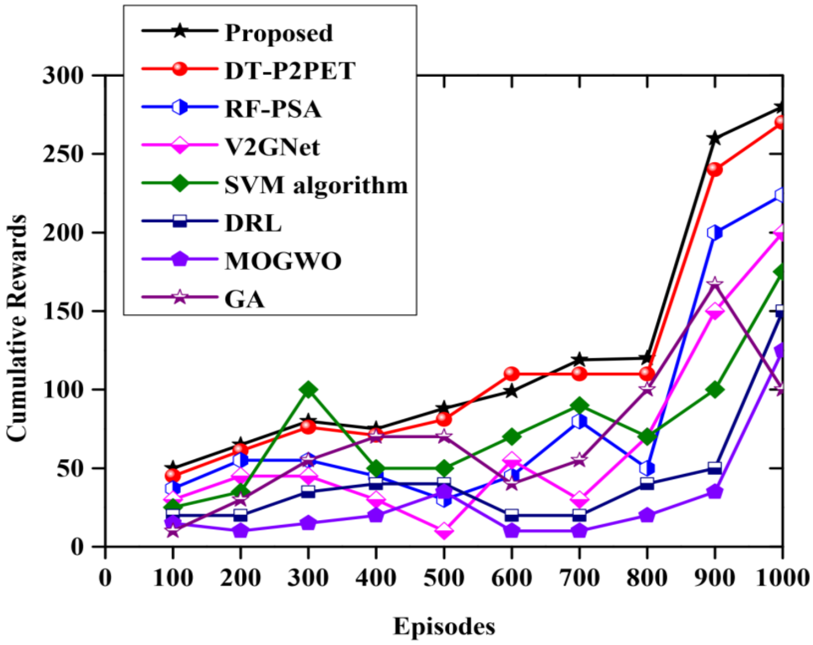

Figure 4. Cumulative Rewards Analysis

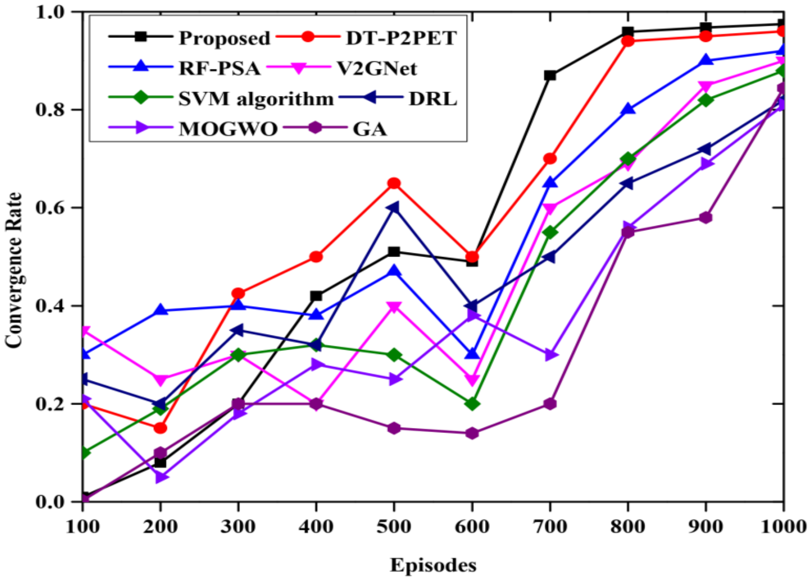

Figure 5. Convergence Rate Analysis

The comparative analysis of the energy efficiency is depicted in Figure 6. Here, the proposed and existing methods are compared based on the energy efficiency. Energy efficiency is described as the energy transactions' effectiveness. The proposed, DT-P2PET, RF-PSA, V2GNet, SVM algorithm, DRL, MOGWO, and GA methods achieved energy efficiency of 98.4%, 90%, 96%, 85%, 89%, 91%, 92%, and 95% respectively. Hence, the figure demonstrates that the proposed method efficiently managed the energy resources with a high energy efficiency rate.

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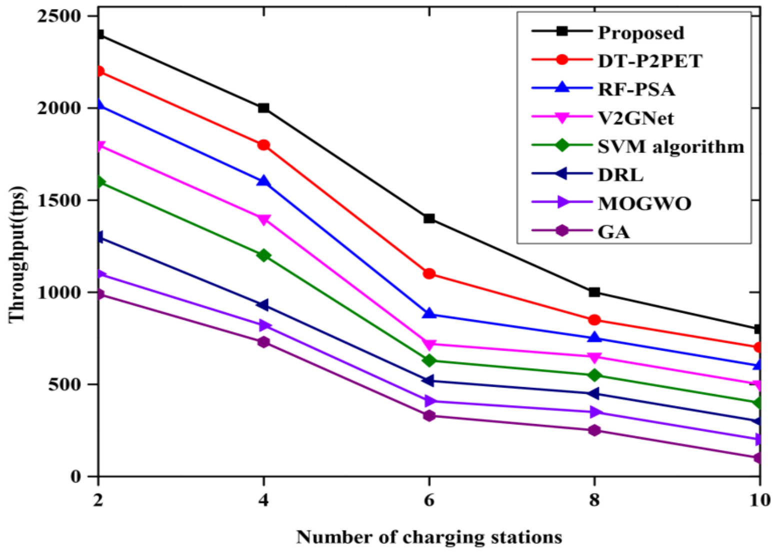

Figure 6. Energy Efficiency Analysis

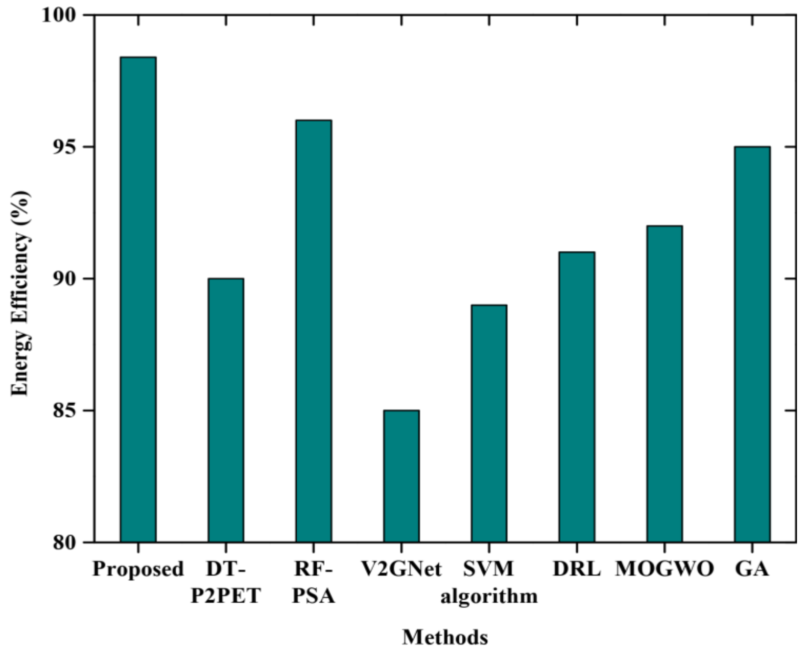

Figure 7. Energy Transaction Time Analysis

Figure 7 displays the energy transaction time of the proposed and the existing methods. The energy transaction time is referred to as the time taken to transfer the energy from the source to the destination. The energy transaction time attained from the proposed, DT-P2PET, RF-PSA, V2GNet, SVM algorithm, DRL, MOGWO, and GA methods is 21s, 28s, 24s, 32s, 27s, 36s, 30s, and 34s respectively. From Figure 7, it is clear that the proposed method utilized less energy transaction time over the compared methods.

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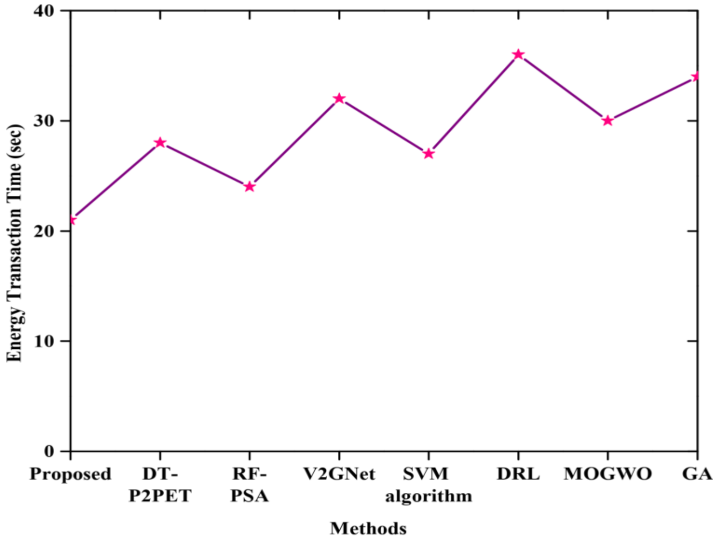

Figure 8. Throughput Analysis

Figure 8 evaluates the throughput rate using the proposed and the existing methods. The throughput is described as the successfully sent data from the source to the destination. The existing DT-P2PET, RF-PSA, V2GNet, SVM algorithm, DRL, MOGWO, and GA methods have throughput rates of 2200tps, 2015tps, 1800tps, 1600tps, 1300tps, 1100tps, and 990tps respectively. Moreover, the proposed method has a higher throughput rate of 2400tps, which demonstrates that the proposed method has better efficiency in data transmission.

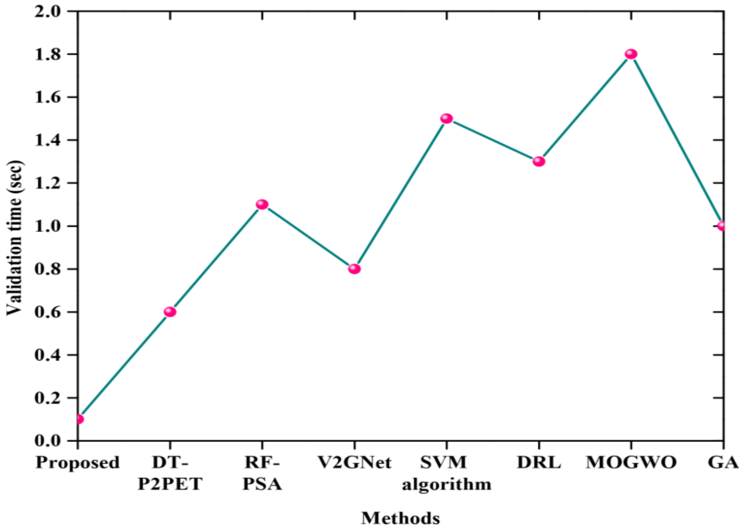

Figure 9. Validation Time Analysis

Figure 9 analyses the validation time of the proposed and the existing methods. The validation time is defined as the amount of time required to execute the validation process. The validation time of 0.1s, 0.6s, 1.1s, 0.8s, 1.5s, 1.3s, 1.8s, and 1s is attained by the proposed, DT-P2PET, RF-PSA, V2GNet, SVM algorithm, DRL, MOGWO, and GA methods respectively. Hence, the figure reveals that the proposed method attained less validation time compared to other methods. Figure 10 compares the proposed and the existing methods in terms of the charging cost. The charging cost is defined as the amount of cost to charge the EVs. The proposed, DT-P2PET, RF-PSA, V2GNet, SVM algorithm, DRL, MOGWO, and GA methods provided the charging costs of $2385, $4200, $3500, $2900, $3700, $4000, $3200, and $4500 respectively. The figure exhibits that the proposed method has a lower charging cost compared to existing methods, which proves that the proposed method is more cost-effective in EV charging.

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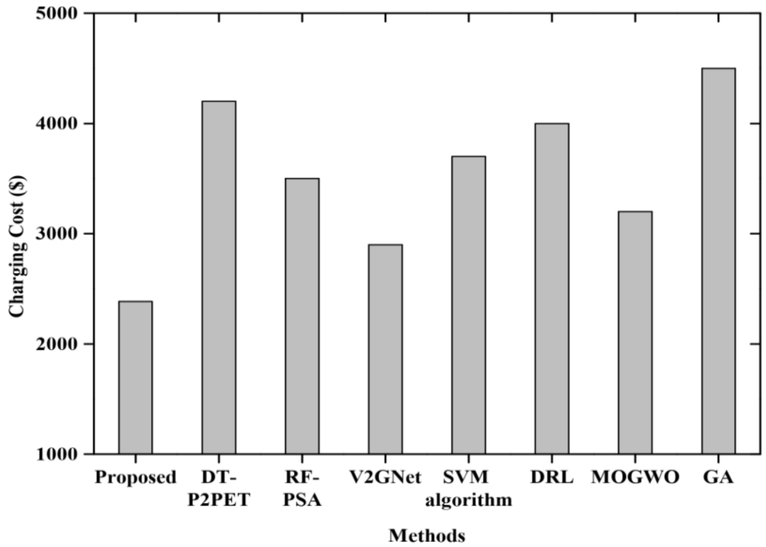

Figure 10. Charging Cost Analysis

7. Conclusion

This research presents a new approach that harnesses the power of the DQN algorithm and blockchain technology to revolutionize energy management within the framework of the V2G network. The results of the extensive simulations and evaluations underscore the efficacy of the proposed method in addressing the challenges of optimizing energy transactions, enhancing grid stability, and incentivizing sustainable energy behaviour. The proposed method's contributions mark a significant advancement in the field of smart grids and energy management. By seamlessly integrating DQN-based energy optimization with the transparency and security of blockchain technology, a holistic solution that benefits both grid operators and EV owners is offered. The simulation results reveal substantial improvements in load-shifting efficiency, peak demand reduction, and energy efficiency, thereby alleviating stress on the grid and promoting energy sustainability. The introduction of a blockchain-enabled rewarding mechanism not only encourages EV owners to actively contribute energy during peak hours but also reinforces the concept of equitable compensation for their contributions. This mechanism aligns with the principles of fairness and transparency that are central to the blockchain framework. Furthermore, the comparative analysis against state-of-the-art methods demonstrates the superiority of the proposed method across multiple dimensions. The proposed method attained cumulative rewards of 280, a convergence rate of 0.975, an energy efficiency of 98.4%, an energy transaction time of 21s, a throughput rate of 2400tps, a validation time of 0.1s, and a charging cost of $2385 respectively. The proposed method consistently outperforms traditional load shifting and demand response strategies, showcasing its potential to reshape energy management paradigms. While this research presents significant achievements, it also opens doors to further exploration. Future work can delve into refining the DQN algorithm and exploring variations of the blockchain rewarding mechanism to optimize performance even further. Additionally, real-world implementations and field trials would validate the practical applicability and scalability of the proposed approach. Overall, this work stands as a testament to the transformative potential of interdisciplinary innovation. The fusion of DQN-based optimization and blockchain-enabled transparency brings about a paradigm shift in the way energy transactions are managed. As move towards a sustainable and energy-efficient future, the proposed method offers a promising roadmap for achieving grid stability, incentivizing sustainable energy behaviours, and ensuring the seamless integration of EVs into the evolving energy landscape.

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