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REVIEW

New technologies for optimal scheduling of electric vehicles in renewable energy-oriented power systems: A review of deep learning, deep reinforcement learning and blockchain technology

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Abstract

With global concerns about carbon emissions, the proportion of renewable energy generation worldwide is increasing, and the demand for flexible resources in power systems is growing. In recent years, as a clean means of transportation, the number of electric vehicles has increased, and the optimal scheduling of electric vehicles has become a research hotspot. The rise of artificial intelligence, blockchain, and other innovative technologies has enriched research on optimal scheduling of electric vehicles. To reveal the latest developments in electric vehicle optimal scheduling studies, this paper summarises the application of state-of-the-art technologies, including deep learning, deep reinforcement learning, and blockchain technology in the optimal scheduling of electric vehicles. Moreover, the advantages and disadvantages of various technical applications are highlighted. Finally, considering the shortcomings and developmental status of applications of the above three technologies, some suggestions for future research directions are proposed.

KEYWORDS

electric vehicles, optimal scheduling, artificial intelligence applications, blockchain applications

1 | INTRODUCTION

In November 2021, the 26th United Nations climate change conference [1] was held in Glasgow, Scotland. The conference adopted the Glasgow climate convention, which calls for the goal of limiting global temperature rise to 1.5°C and the gradual reduction of coal use. Several countries, including China, the United States, and Russia, have pledged to halt deforestation, phase out coal, reduce methane emissions, and aim for net zero emissions.

The power system is an integral component of the energy structure of all countries globally, and promoting the upgrade and transformation of power systems has become a key measure for countries in fulfilling their pledge to reduce carbon emissions. As a primary means of reducing greenhouse gas emissions [2, 3], there has been a surge in the proportion of photovoltaic (PV) power generation, wind power, and other renewable energy generation. According to the International Renewable Energy Agency (IRENA), the total share of global renewable energy generation capacity in electricity generation has risen from 36.6% in 2020 to 38.3% in 2021. By the end of 2021, the installed capacity of renewable energy generation increased by 257 GW, up to 9.1% annually [4]. However, the influx of renewable energy generation equipment presents new challenges to the safe operation and optimal scheduling of power systems. Many problems, such as voltage deviation [5, 6] and power balance [7], are becoming increasingly prominent. To cope with these new challenges, there is an urgent need to find innovative ways to address the uncertainty of renewable energy generation [8, 9]. The rapid development of electric vehicles (EVs) [10, 11] provides a solution to the new problems faced by power grids. EVs are not only a new type of load, but also a crucial flexible resource because of their long parking time and large energy storage capacity [12–14]. However, if a large number of electric vehicle (EV) loads are not optimally scheduled in an orderly manner, the peak and off-peak differences in the power system loads will be further aggravated, resulting in congestion of the distribution network and a waste of resources [15, 16]. Therefore, formulating the charging and discharging strategy of EVs is key to the interaction between EVs and the smart grid.

Several studies have harnessed the flexibility of EVs to address the challenges of power systems. According to the types of problems solved, the optimal scheduling of interactions between EVs and the power grid can be categorized into five categories:(1) Load shifting [17], (2) frequency modulation [18], (3) voltage regulation [19], (4) promotion of renewable energy accommodation [20], and (5) congestion management of the distribution network [21]. According to the time scale of problem solving, they can be classified as (1) day-ahead problems [22, 23] and (2) real-time problems [24]. According to the procedures of optimal scheduling, it can be divided into: (1) The market mechanism [25, 26]; (2) scenario generation [27]; (3) load prediction [28]; (4) flexibility prediction [29]; (5) optimization dispatch and control [30, 31]. Optimization solutions can be divided into traditional optimization methods and new technologies. Traditional optimization methods include linear programming, mixed-integer linear programming, and quadratic programming. New technologies primarily refer to deep learning (DL), deep reinforcement learning (DRL), and blockchain technology. The literature [32, 33] has comprehensively summarised the application of traditional optimization algorithms in EV strategy optimization. However, few studies have summarised the application of novel technologies in EV optimization.

This paper reviews new technologies for the optimal scheduling of electric vehicles in renewable energy-oriented power systems. The research contributions of this paper primarily include the following: (1) From the perspective of application scenarios and algorithm categories, the detailed application of three new technologies in optimal scheduling of EVs is introduced, including DL, DRL, and blockchain technology. (2) The advantages and disadvantages of the three new technologies in the application of EVs optimization scheduling are summarised, and improvement measures for further application of the new technologies are proposed. (3) Based on the studies on the optimal scheduling of EVs, suggestions for future research directions are provided.

The remainder of this paper is organised as follows. The deep learning technology in EVs is discussed in Section 2. In Section 3, three types of deep reinforcement learning frameworks are introduced for scheduling EVs: value base, policy base, and actor-critic. The optimization of blockchain technology in EVs is described in Section 4. Recommendations and conclusions for future research are presented in Sections 5 and 6, respectively.

2 | DEEP LEARNING TECHNOLOGY FOR OPTIMAL SCHEDULING OF EVS

This section introduces the application of DL to the optimal scheduling of EVs. With the advancement of big data technology and the improvement of computer computing power, DL, which originated from artificial neural networks, has evolved into a new branch of machine learning. The core idea of DL is to use a series of nonlinear transformations to achieve a hierarchical representation of the input information. DL can fit data relationships, feature extraction, classification, and prediction. With improvements in algorithm performance and substantial increases in hardware computing power, DL has been applied to solve the optimal scheduling problem of EVs, exhibiting irreplaceable advantages. In short, DL can help achieve the following objectives in the optimal scheduling of EVs: (1) Scenario generation, (2) load prediction, (3) flexibility prediction, and (4) strategy optimization.

2.1 | Scenario generation

In EV optimization scheduling, it is often difficult to obtain a large amount of real data. Scenario generation can simulate the real operating state of an EV, guide researchers in their studies on EV traffic flow, charging demand, and scheduling strategy, which can provide support for scheduling optimization. Most existing research on EV operation scenario generation has used generative adversarial networks (GANs) [34] of DL. The generative adversarial network (GAN) was first proposed in 2014. Inspired by game theory, the algorithm generates and trains two adversarial neural network models: Generator and discriminator. As illustrated in Figure 1, the role of the generator is to approximate the potential distribution of the real data as closely as possible and to generate new data samples. The discriminator is a binary classifier aimed at accurately distinguishing real data from generated data and maximising discriminative accuracy.

During the training process, the generator and discriminator continuously improve their respective data generation and discriminant abilities through the game, and the optimization goal is to find the Nash equilibrium between them. Recently, GAN have attracted increasing attention and research fervours. The GAN and its derivative models are prominent in scenario generation and data restoration of electric vehicle operations. To enhance data quality, Zhao et al. [35] proposed a data

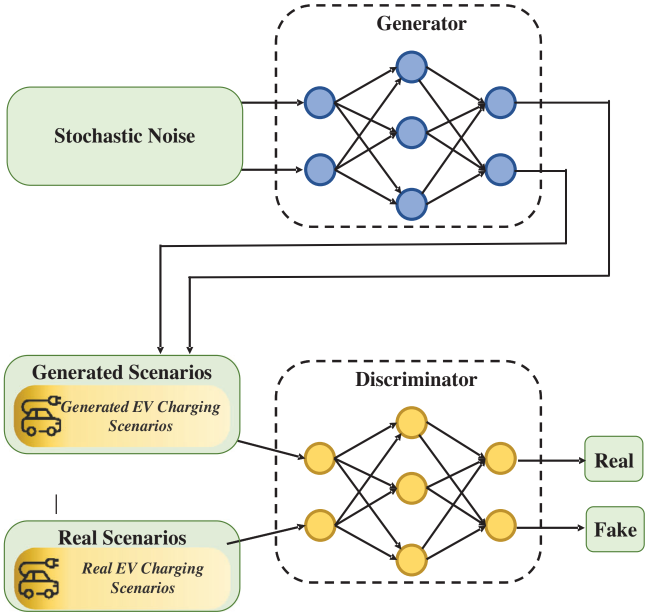

FIGURE 1 Framework of GAN in EV scenario generation

interpolation model based on gated recurrent unit neural network cells for imputation and a GAN for the accurate interpolation of missing and outlier values in the load data of EVs. In [36], a data-driven convolutional self-encoder and conditional adversarial generative network-based EVs charging load scenario generation method was proposed to implicitly learn the conditional probabilities of EVs charging loads corresponding to different traffic network travel patterns, which supports grid and charging station operations. The evaluation indexes of the load generated by the GAN method were improved to different degrees compared with those generated by the non-convolutional encoder method.

2.2 | Load prediction of EVs

Load prediction is a vital step in the optimal scheduling of EVs [28, 37, 38]. It can evaluate the charging requirements of charging facilities in advance, formulate guidance measures to guide the optimized scheduling of EVs, and balance the load of different charging facilities. Owing to the time-series nature of EVs loads, it is suitable to predict EV loads using a recurrent neural network (RNN) [39]. An RNN is a class of neural networks that processes sequence data.

To simplify the network structure, an RNN uses a parameter sharing network structure. RNN can be regarded as several hidden layer chain connections, whose network structure in series maintains the long-term dependence relationship in the data. Lv et al. [40, 41] adopted RNN techniques to predict the load of EVs on multiple timescales, and achieved good predictions. However, RNN has a gradient dispersion effect in the training process, resulting in information not being transmitted over long distances. Therefore, to address the problem of long sequence data, Hochreiter et al. [42] proposed long short-term memory (LSTM) networks. Linear intervention and an internal sector control mechanism were added to the network structure of LSTM, which effectively solved the problem of long-distance dependence. LSTM has been widely used to recognize speech, describe the image, and process natural language. Zhu et al. [43, 44] used the charging price and blocking factor as input features to predict the load of EVs charging stations with LSTM networks. Compared with traditional artificial neural networks, the prediction accuracy of LSTM is significantly improved.

Ref. [35] introduced a gating mechanism in LSTM networks to form a Mogrifier LSTM that fully interacts with the hidden state h with the current input x. Mogrifier LSTM networks obtained more accurate short-term prediction results for the load of EVs via training. Wang et al. [45] proposed an EVs load forecasting method based on fuzzy entropy and integrated learning. Accordingly, the sub-sequences with different frequencies are predicted using LSTM networks and support vector machines. The method based on fuzzy entropy and integrated learning achieved outstanding results in both single-step and multi-step short-term predictions. The prediction error reduced more than 30% compared with the LSTM.

It is worth mentioning that some studies also used deep belief networks (DBN) [46] to predict the EVs load. In [47], Li et al. learned and analysed the historical data of operating charging stations based on the DBN, extracted the feature information of the generalised influence factors, and established the feature mapping neural network accordingly. The final DBN capacity prediction model was obtained by iteratively learning historical data.

2.3 | Prediction of electric vehicle flexibility

Flexibility of EVs is defined as the adjustable power of EVs. Similar to a traditional generator that can provide a two-direction reserve to the power system, the adjustable power of EVs is divided into up reserve and down reserve. The up reserve is the amount of power that can be reduced, and the down reserve is the amount of power that can be increased. This flexibility provides a power-adjustable range for the optimal scheduling of EVs. Although the definitions of EV flexibility and the EV load mentioned in Section 2.2 are different, the same forecasting method applies to the prediction of both powers because of their similarity.

Ren et al. [48] used convolutional neural networks (CNNs) to predict flexibility. A convolutional neural network (CNN) [49] is a neural network that processes grid structural data, such as image data, with a 2D pixel grid. A CNN structure comprises multiple convolution layers and pooling layers, which perform convolutional operations and pooling on the input data layer by layer to obtain a feature representation with constant data translation, rotation, and scaling. The convolution layer maintains the spatial continuity of the image and extracts its local features. The pooling layer reduces the dimensions of the hidden layers and computation. CNNs are the most successful DL models for processing 2D image data and have become a research hotspot in image processing. The prediction of EV flexibility

TABLE 1 General comparison between the DL algorithms

Algorithms	Performance	Drawback	Applicability	References
CNN	CNN performs well in dealing with 2D EV data.	The problem of gradient dissipation occurs easily.	(1) EV load prediction (2) Flexibility prediction	[48]
TCN	TCN is less prone to vanishing /exploding gradient	Poor transfer learning ability	(1) Flexibility prediction	[50]
RNN	RNN is a model in time dimension, which can model the sequence	A set of training parameters, vanishing /exploding gradient	(1) EV load prediction (2) Flexibility prediction	[40, 41]
LSTM	LSTM exhibits the function of long-term memory	Difficulty in parallel processing	(1) EV load prediction (2) Flexibility prediction (3) Strategy optimization	[52, 53]
GAN	GAN is a generative model	Nash equilibrium difficulty	(1) Scenario generation	[35, 36]
DBN	DBN learns joint probability distribution and reflects data similarity	Higher complexity	(1) EV load prediction	[47]

requires considering the time dimension and the spatial distribution characteristics. Another study [48] proposed a temporal and spatial prediction method for the flexibility of shared EVs. In that study, the training sample set included three dimensions: Time, space, and the value of flexibility. Compared with similar prediction algorithms, the mean square error of the prediction method proposed in this study decreased by 2.41% and 2.36% in the weekday and non-weekday scenarios, respectively. In addition, [50] proposed a flexibility prediction method based on the temporal convolution network (TCN) transformer. The EV resource and demand response signals, as well as historical data, are used to train the network model, improving its long-term dependence ability through its multi-attentional and self-generating mechanisms. Compared with other neural networks, this makes the prediction of flexibility more accurate.

2.4 | Optimization strategy

The DL algorithm is not only applied in scene generation, load prediction, and flexibility prediction but also the optimization strategy of EVs. First, a traditional optimization model is established to solve the scheduling strategy of EVs, and the deep neural network is trained based on the results of the optimized scheduling strategy. The optimization strategy results can be obtained by providing input information to the trained network in real time. Shi et al. [51] established an EV strategy optimization structure that includes day-ahead optimization and model training. First, a mixed-integer linear model is established to solve the EV scheduling strategy. Second, the long short-term memory networks are trained based on the solution results. In the intra-day scheduling stage, the input information is turned over to the trained network to obtain the intra-day scheduling plan for the EVs. A real-time automatic optimal scheduling strategy for EVs based on a k-means clustering algorithm and LSTM has been proposed [52, 53]. The computation time of the proposed strategy can reach the millisecond level, and the average value is lower than 0.005 s, which is 0.016% of the solution time using the mixed-integer linear programming method.

Table 1 lists a summary of the performance, insufficiency, and applicability of DL algorithms. The GAN has unique advantages for solving the problem of scenario generation. However, it is difficult to achieve a balanced state. Generating EV operation scenarios often requires considerable computing resources, resulting in high time costs. For the prediction problem, if it is the prediction of the load power or adjustable power, the performance of the LSTM is the best. The LSTM exhibits an improvement over the RNN. It inherits the characteristics of RNN time-series data processing and simultaneously realizes the mining of time-series data associations. Although LSTM can accurately predict power time series, it cannot handle the spatial relationship between data. The advantage of CNN is that it can achieve the feature extraction of 2D data, but its prediction accuracy is somewhat reduced compared to LSTM. The DBN can predict the probability distribution of power data, which has critical guiding significance for the uncertainty analysis of the optimal scheduling of EVs. However, its complexity is higher, and convergence is more difficult. The advantage of the DL method for the optimal scheduling problem of EVs is that it can realize a rapid solution to the scheduling plan. However, the DL-trained decision-making model exhibits poor transferability and can only be applied to training data scenarios. If the EV operating scenario changes, a significant amount of time is required to retrain the applicable model.

3 | DEEP REINFORCEMENT LEARNING TECHNOLOGY FOR OPTIMAL SCHEDULING OF EVS

This section introduces the application of DRL in EV scheduling. In recent years, reinforcement learning (RL) has been widely studied as a sequential decision-making problem. In contrast, DRL integrates DL with robust perceptual capabilities based on RL, which significantly improves the quality of model decisions. DRL is mainly applied to the optimization of EV charging and discharging. Unlike the structure in Section 2, this section presents a review of the application of DRL to the optimal scheduling of EVs according to the algorithm class. The DRL algorithms can be divided into three categories: (1) Value-based, (2) policy-based, and (3) actor-critic (AC). Value-based algorithms require sample actions, they can only deal with discrete actions. The policy-gradient algorithm, a policy-based representative algorithm, directly uses the policy network to search for actions and can be used to handle the case of continuous actions. AC algorithms combine value-based algorithms with policy-based algorithms. In the structure of AC algorithms, the actor uses the strategy gradient method to select actions, and the critic evaluates the actions. In addition, the parameters of the actor and critic are updated alternately during training.

3.1 | Reinforcement learning

The RL has been used to optimize the scheduling strategies of EVs. Chis et al. [54] proposed an RL algorithm to reduce EV charging costs. The algorithm uses the EV charging quantity daily as a decision variable to construct an Markov Decision Process (MDP). However, the training dataset was produced using a linear model. The simulation demonstrated that the proposed algorithm could save EV users 10%–50% of the cost. Liu et al. [55] developed an energy management strategy for parallel hybrid EVs based on speed prediction and RL. A new energy management strategy based on RL was introduced to determine the optimal control behaviour and distribution between multiple power storage systems. The test results show that the optimization can significantly reduce cost and time for EV users.

3.2 | Value-based algorithms

Value-based algorithms use a deep neural network to fit the value or action value functions, defined as a critic network. During the network training process, a value or action-value function is updated through Q-learning. Value-based DRL algorithms primarily include a deep Q-network series of algorithms. In 2015, the deep Q-network (DQN) [56] developed by the DeepMind team reached the level of human players in Atari 2600 games. The framework of the DQN is shown in Figure 2.

Considering the randomness of EV charging and the uncertainty of renewable energy and load, Li and Wang et al. [57] established a real-time scheduling model based on the DQN to minimize power fluctuation and charging cost. However, because the optimization objective of the DQN is to maximize the valuation function, a maximum operation is performed on the target network at each update, which leads to overestimation. A double deep Q-network (DDQN) [58] adopts the structure of a double network in the objective function to address this problem. The DDQN selects the optimal action based on the Q-network and evaluates the optimal action using the target Q-network. The two sets of parameters of the Q-networks consider action selection separately from strategy evaluation, thereby preventing the risk of overestimation. The literature [59] focuses on applying DDQN to the EV charging control problem to increase the EV state of charge at departure.

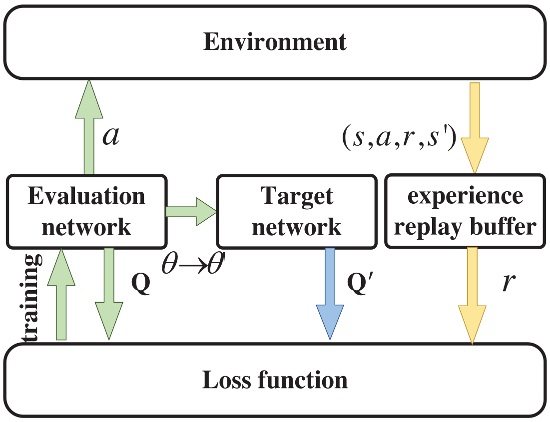

FIGURE 2 Framework of DQN

The duelling deep Q-network (duelling-DQN) [60] algorithm was developed to improve the accurate estimation of the Q-function. Unlike the DQN and DDQN algorithms, the duelling-DQN algorithm splits the Q-function into two parts: The state value function without the action and the advantage function with the action. The dominant function is often decentralised to improve the stability of the algorithm. Du and Li et al. [61, 62] optimized an EV charging control strategy to maintain the node voltage stability. Based on the duelling-DQN algorithm, the state evaluation function and action advantage evaluation function networks are trained. Compared with the DQN training process, the duelling-DQN structure has a higher loss function decline rate; however, the loss function fluctuation rate is lower during the iterative training process, indicating that the duelling-DQN structure algorithm is more stable.

The DQN, DDQN, and duelling-DQN use evenly distributed sampling in experience replay, which is inefficient. These data are often of different importance to an agent; therefore, the prioritised replay deep Q-network was proposed by Schaul et al. in 2016 [63]. The prioritised replay DQN adds priority replay technology based on the DQN. The prioritised replay DQN first builds a sum tree. Next, the weights are added based on the time difference errors of samples during network training such that the importance of different data is introduced into the network training process. Tuchnitz et al. [64] investigated a smart charging strategy for an EV fleet based on a prioritised replay DQN, which offers a flexible, easily adaptable, scalable approach for an EV fleet under realistic operating conditions.

DDQN, duelling-DQN and prioritised replay DQN all improve the performance of DQNs in different manners. Because the algorithms mentioned above are all built on the same framework, these technologies can be integrated into a rainbow-deep Q-network. Wang and Chen et al. [65] analysed the random characteristics of EV charging on a time scale and optimized the EV charging strategy based on the rainbow deep Q-network algorithm; however, convergence still restricts the development of this algorithm.

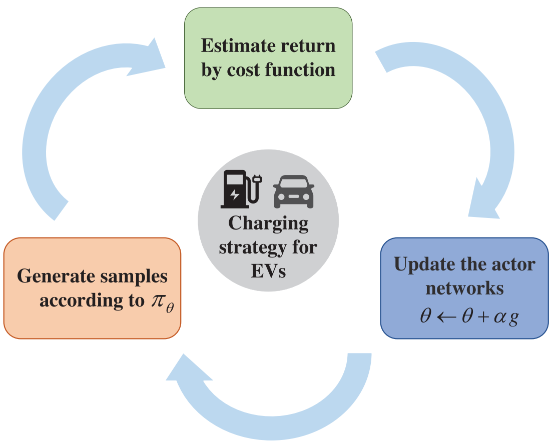

FIGURE 3 Flow chart of PG application to electric vehicle strategy optimization

3.3 | Policy-based algorithm

In contrast to value-based deep reinforcement learning algorithms, policy-based deep reinforcement learning algorithms create actor networks, instead of critic networks. It is observed that the process of finding the optimal decision is accomplished through an actor-network update.

The policy gradient (PG) algorithm was used in [66] to establish a real-time optimization scheduling model for EV charging and battery swap station. The flow chart of PG application to EV strategy optimization is shown in Figure 3. The optimal actor network is learned from the battery status data, time of use, and number of queuing EVs.

Since each set of training data acquired by the PG algorithm can only update the model parameters once, training data must be collected again after updating the model parameters, which results in inefficient training. If the training data can update the model parameters several times, the training efficiency can be improved significantly. The proximal policy optimization (PPO) [67] algorithm proposes the use of two policy networks, one for collecting training datasets and the other for training. As the first network does not participate in the training, its parameters do not change, and the corresponding data group could be used for repeated training. In [68], a queue-charging control method was proposed for EVs in intelligent buildings based on the PPO algorithm. It has been proven that the PPO algorithm can significantly improve training efficiency and shorten the training time.

3.4 | Actor-critic

The structure of actor-critic algorithms combines value-based and policy-based algorithm structures, as shown in Figure 4. AC constructs two networks: Actor and critic. The actor is used to predict the probability of the behaviour, and critic is used to evaluate the value of the state.

The advantage of AC is that it can realize an one-step update in the training process, which does not need to wait for the end

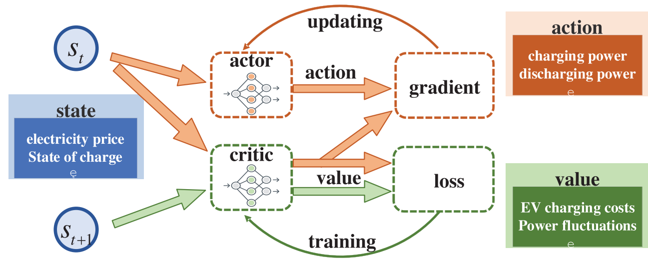

FIGURE 4 Structure of AC algorithms

of the sequence to update, making data collection easier and improving training efficiency. Relatively few studies have been conducted on EV optimization control using the AC algorithm. Nevertheless, most studies have used an improved AC algorithm. The advantage actor-critic (A2C) algorithm was adopted to optimize the EV charging strategy in [69]. The value function is replaced by an advantage function in the algorithm to improve the probability of the occurrence of actions with a high state value by reducing the variance of the algorithm. Pan and Wang et al. [70] proposed a cooperative mode between a wind farm and an EV aggregator, developed a cooperation and benefit distribution model, and adopted the asynchronous advantage actor-critic (A3C) [71] algorithm to solve the model. A3C introduces the idea of asynchronous reinforcement learning, which significantly reduces the training time and improves the average performance of the algorithm.

To improve the convergence of the algorithm, the deep deterministic policy gradient (DDPG) [72] algorithm combines the ideas of DPG and DQN to generate four neural networks: actor, target actor, critic, and target critic networks. The actor network is equivalent to the actor in the AC structure; the critic network is used to evaluate the action, and the target networks are used to estimate the target value. Indeed, DDPG is more stable in continuous action-space tasks. Following an analysis of the uncertainty of electric vehicles, [73] proposed an optimal EVs charging strategy that satisfies the voltage safety constraints of the distribution network. Compared with the traditional stochastic optimization method, the DDPG algorithm strictly guarantees voltage safety primarily because the DDPG method considers the temporal correlation more comprehensively. Additionally, the payoff of the DDPG-based agent is higher than that of Q-Learning in all cases, which proves that the DDPG algorithm performs better.

The twin delay deep deterministic policy gradient (TD3) [74] algorithm further optimizes DDPG. In TD3, two sets of networks were used to represent different Q values, and the smallest set was selected as the value used to suppress persistent overestimation. However, the update frequency of critic networks is adjusted slightly higher than that of actor networks in TD3 to reduce some incorrect updates. Finally, in the expected return of the target value network estimation, random noise was introduced into the actor network to ensure better exploration. Hu and Zhao et al. [75] optimized the EVs charging behaviour from the perspective of an aggregator based on real-time feedback data and the time-of-use signal of charging. The charging process of a single EV was modelled using TD3. The model has strong generalisation ability, good stability, and fast convergence speed, realising high-speed distributed optimization of the charging behaviour of large EVs.

Furthermore, the deep reinforcement learning of AC structures has a soft actor-critic (SAC), which introduces the idea of adding entropy into the objective function. SAC maximises the reward as well as entropy. In other words, the agent can complete the task while using random actions as soon as possible. The SAC algorithm solves the convergence problem in the AC algorithm and avoids fine adjustments of the learning rate, exploration factor, and other hyperparameters. On one hand, SAC can avoid agent convergence to a suboptimal strategy; on the other hand, it can improve the robustness of the algorithm. Considering the multiple spatial and temporal characteristics of optimal operation in EV charging and battery change stations, Liu et al. [76] developed an optimization scheduling model under different scenarios. SAC has achieved excellent economy and high efficiency when applied to the real-time optimization scheduling of large-scale EVs. Moreover, the simulation proves that the SAC algorithm has an excellent performance, similar to that of the TD3 algorithm. A novel continuous SAC control framework was adopted to design a DRL-based approach for optimal EVs charging to realize fine-grained control in [77].

In addition, in transportation and power systems, deep reinforcement learning can effectively solve the complex coupling problem and provide support for optimal scheduling of EVs. Ref. [78] considered the randomness of traffic conditions, charging price, and charging waiting time and proposed an optimal charging strategy based on deep reinforcement learning to reduce the total driving time and charging cost to the maximum degree. A traffic network flow modelling method based on DRL was proposed in [79]. The driving area of EVs is divided into regular hexagons, and the optimal scheduling strategy of the EV fleet is formulated via the optimization of the traffic and charging actions of EVs. The simulation results verify that the proposed method can effectively improve the revenue of EV fleets and satisfy the travel demands of users.

A general comparison between the DRL algorithms is presented in Table 2. DRL algorithms have been applied to the optimal scheduling problems of EVs. However, different algorithms have distinct advantages, disadvantages, and applicable scenarios. Early algorithms, such as RL, DQN, and PG, provide a new solution for the optimal scheduling of EVs; however, their performance is relatively poor and can only solve simple optimization problems. As the problem of the optimal scheduling of EVs becomes more complex, these basic algorithms are no longer sufficient. The prioritized replay DQN, duelling-DQN, DDQN, and rainbow DQN algorithms improve the performance of the DQN algorithm from different aspects and better handle the optimal scheduling problems of EVs. DDPG, TD3, and SAC, which are deep reinforcement learning algorithms for continuous action space problems, exhibit excellent performance in dealing with uncertainty and network coupling constraints in the enhanced scheduling of EVs; however, these algorithms consume higher computing resources, which makes them infeasible. In the future, with the development of computer technology, this problem is likely to be solved.

TABLE 2 General comparison between the DRL algorithms

Algorithms	Categories	Problems solved	References
RL	/	Suitable for simple optimization	[54, 55]
DQN	Value-based	Basic optimization problems	[57]
Prioritized replay DQN	Value-based	Higher training efficiency	[63]
Duelling-DQN	Value-based	Value function without action	[61]
DDQN	Value-based	Application scenarios with overestimation problems	[59]
Rainbow DQN	Value-based	Optimizing scheduling requires algorithms with the best overall performance	[64]
PG	Policy-based	Just need to get the policy network	[66]
PPO	Policy-based	Get the policy network while taking into account the training efficiency	[67]
A2C	Actor-critic	It integrates the features of deep reinforcement learning based on value and strategy	[69]
A3C	Actor-critic	Short training time required	[71]
DDPG	Actor-critic	Complex problems requiring strong convergence performance	[73]
TD3	Actor-critic	Continuous action interval	[75]
SAC	Actor-critic	Problems with suboptimal strategy	[76, 77]

4 | BLOCKCHAIN TECHNOLOGY FOR OPTIMAL SCHEDULING OF EVS

The EVs centralised energy management model has some problems such as poor expansibility, lack of anonymity, and privacy. With the increase in participants and transaction volume, the centralised network severely restricts the operational efficiency of the system, which cannot satisfy the requirements of massive distributed power transaction scales and data processing, and the security of data cannot be guaranteed. Therefore, it is crucial to design a transparent, secure, and efficient trading model and method. Blockchain technology is essentially a decentralised, open, transparent, and distributed database with two core features: Data are decentralised and difficult to tamper [80]. Therefore, it is not only feasible but also necessary to integrate blockchain into electric vehicle energy management. Blockchain technology can effectively solve the problems of privacy and safety in the centralised energy management of EVs, and can provide a safe and efficient guarantee for the optimal scheduling of EVs.

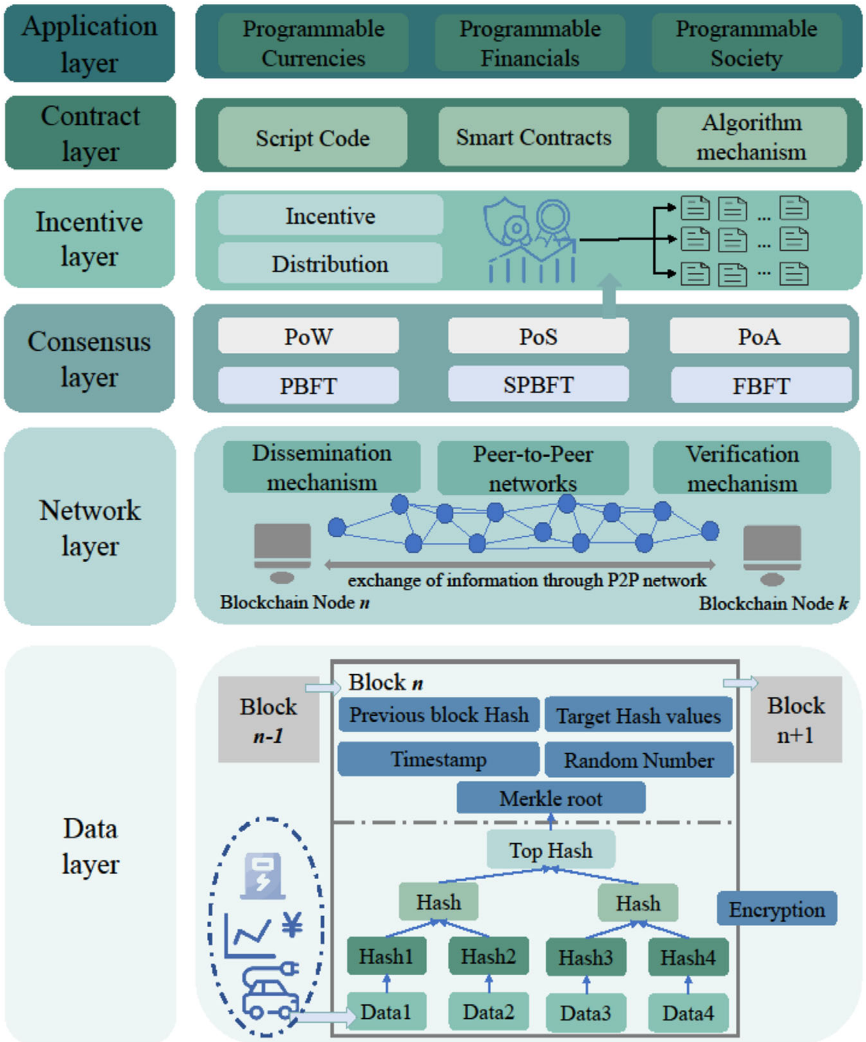

FIGURE 5 Basic architecture of blockchain

4.1 | Blockchain technology

In general, a blockchain consists of a data layer, network layer, consensus layer, incentive layer, contract layer, and application layer (see Figure 5).

The data layer encapsulates the underlying data blocks, and its main role is to define the data structure inside the blockchain. The network layer includes a distributed networking mechanism, data propagation mechanism etc., which stipulates the network communication protocol, and peer-to-peer transmission technology ensures the status of each node in the network. The consensus layer stipulates the consensus algorithm of the blockchain technology, which is used to ensure the symmetry and consistency of the block data. The incentive layer stipulates the issuance, encryption, and distribution mechanism of virtual currency, which adopts an asymmetric encryption algorithm to encrypt virtual currency. Each block is also interconnected via this encryption technology. The contract layer stipulates the smart contract written by the developer, and the user can not only renew the contract operation but also send other messages or even create a contract, and the user can create a new contract on the blockchain using the code. The application layer encapsulates various application and blockchain scenarios.

4.2 | Protect Privacy and secure information in EV charging management

The optimal scheduling of EVs is normally centrally performed by the aggregator platform. If the control platform has problems, there are risks of disclosure or loss of all data, leading to the failure of EVs optimization scheduling. Blockchain technology effectively solves this problem.

To solve the security problem of EV charging pile information interactive transmission, Gao et al. [81] introduced blockchain technology and used an elliptic curve encryption algorithm to generate keys, which reduced the key storage space and improved the communication security of charging piles. Considering the poor interoperability between charging piles and user identities, the difficulty of cross-carrier settlement, and the high risk of identity data leakage, Wang et al. [82] proposed a blockchain-based alliance trust distributed digital identity authentication system applicable to the power industry that can achieve cross-domain secure sharing and autonomous control of identity data and cross-domain identity authentication of users.

Blockchain has obvious advantages in the security protection of data collected in the pre-transaction stage. In [83], a novel decentralised security model based on lightning networks and smart contracts was utilized to protect transactions between EVs and charging stations. Li et al. [84] proposed a new blockchain-based energy transaction scheme that uses anonymous authentication to protect user privacy and a time-commitment-based mechanism to verify the fairness of energy transactions. Mohamed et al. [85] proposed blockchain-based energy trading schemes for vehicle-to-charge stations (V2CS) and vehicle-to-vehicle (V2V), which preserve the privacy of EVs' drivers. To thwart Sybil attacks, a common prefix linkable anonymous authentication method is adopted. Simultaneously, an anonymous blockchain-based payment system was developed and integrated into schemes, enabling EV drivers to pay for charging with untraceable digital coins.

The above studies primarily used the traditional blockchain architecture of Bitcoin or Ethereum. However, as transaction throughput is limited and transaction data are transparent to all nodes in a public blockchain project, a blockchain architecture that is more suitable for the performance requirements of EV energy trading needs to be selected. Some scholars have used a consortium blockchain, which is weakly centralised to improve the efficiency and security of energy trading. Hu et al. [86] used a partially decentralised consortium blockchain approach to address privacy protection and transaction security of EVs.

4.3 | Decentralized energy trading

Recently, the ubiquitous power Internet of Things (IoT) has developed rapidly. The EVs and charging piles are located in the perception and access layers of the ubiquitous power IoT, respectively, which correspond to its basic levels of the perception and identification, respectively. Reacting quickly during the transaction decision to meet the real-time needs of multi-party transaction participants, including the power grid, is the key problem of electric vehicle energy trading. As a distributed database and decentralised peer-to-peer network, blockchain structure can provide technical support for the EV electric energy trading market in terms of the operation mode and other aspects.

The distributed optimization management of electric vehicle energy trading through blockchain can not only meet the privacy requirements of users but also the requirements related to the autonomous operation of subjects. The blockchain-based energy trading process can be divided into phases, such as information distribution, matching, settlement, and storage [87–89]. The framework of electric vehicle energy trading is presented in Figure 6.

Based on the peer-to-peer electricity trading mechanism, the literature [25, 90–94] addressed the electricity price and amount of traded electricity among EVs by deploying smart contracts in the blockchain to implement auction mechanisms for maximising the social welfare of electricity trading. Alvaro et al. [95] presented a novel peer-to-peer (P2P) energy trading mechanism for two EV groups that greatly reduces the impact of the charging process on the power system during working hours and optimizes the energy cost per EV in the time-space dimension. Xia et al. [96] proposed a Bayesian game-based vehicle-to-vehicle electricity-trading scheme for blockchain-enabled Internet of Vehicles and obtained the optimal price under linear strategic equilibrium. Luo et al. [88] further constructed a blockchain-based vehicle-to-vehicle (V2V) and vehicle-to-grid (V2G) electricity-trading architecture and proposed a two-way auction mechanism based on Bayesian games, which reflects the superiority of BABG compared with algorithms such as the iterative double auction (IDA) algorithm proposed in [90] and algorithm proposed in [96]. Blockchain technology can effectively reduce transaction costs and increase the transaction forms. In [97–99], blockchain technology was used to optimize the electric vehicle charging management scheme. To optimize the economic dispatch of the grid, Liu et al. [100] proposed a bidding mechanism for electric vehicle participation in a grid using blockchain smart contract technology. Their proposed framework achieves peak and valley reduction of the grid load while protecting the interests of customers, agents, and power dispatch centres.

In addition to auction mechanisms, blockchain-based trading platforms have also introduced dynamic pricing mechanisms [101–104]. Meanwhile, the abovementioned blockchain-based EV charging studies have mainly focused on V2V, V2CS, or V2G, whereas the coordination of CSs has rarely been considered. To improve the EV charging capability, Wu et al. [101] effectively guided EVs to charge in areas with low charging flow considering the benefits of the platform and dynamic tariff, which relieves the charging pressure in the region to a certain extent. In [98], a two-stage EV charging coordination mechanism based on the alternating direction method of multipliers was proposed to protect individual privacy. The mechanism is implemented on a blockchain to enable the fully autonomous charging coordination of EV charging stations without third-party coordination.

Owing to the randomness, dispersion, and individual interest nature of EV charging, the transaction default phenomenon of distributed energy trading may be more serious compared to the traditional centralised energy trading mode. If the transaction default situation increases, it will increase the difficulty in power grid dispatching; therefore, it is necessary to conduct research on the credit management for transaction subjects. To meet the charging demands of EV users with distinct energy consumption preferences, Su et al. [105] proposed a contract-based energy blockchain system. To motivate electric vehicles to participate in energy trading, a reputation-based delegated Byzantine fault tolerance consensus algorithm is proposed to efficiently reach consensus in an energy blockchain. Ping et al. [106] analyzed the causes and hazards of credit risks in a distributed energy trading market and proposed a distributed energy credit control mechanism based on a proof-of-credit

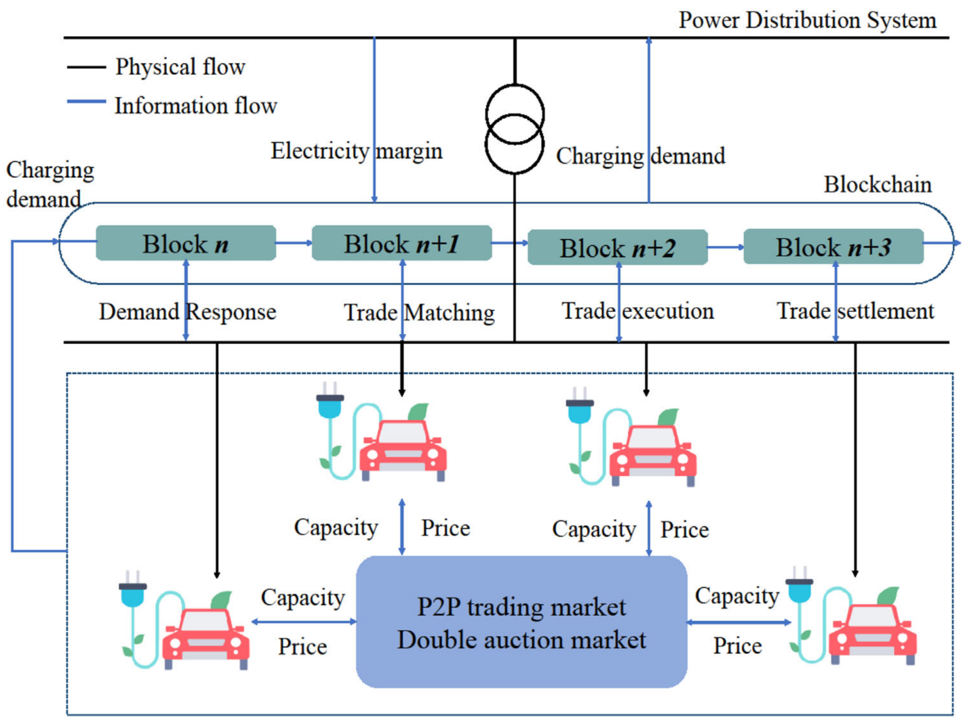

FIGURE 6 The framework of electric vehicle energy trading

(PoC) consensus algorithm. The PoC consensus algorithm sets the mining difficulty of each subject as the exponential function of credit score. The nodes with higher credit scores attain lower mining difficulty and higher bookkeeping rights probability. Accordingly, the market subjects are guided to consciously fulfil the contract transaction and realize the credit risk control of distributed energy trading. Table 3 presents a comparative analysis of related works.

In summary, the application of blockchain technology to EV energy trading has several advantages. First, blockchain technology can ensure and respect users' privacy to a significant extent. Second, the blockchain has the characteristic of invalid tampering of individual nodes to ensure the security of transaction information. Finally, the distributed structure decentralizes EV energy trading, prevents monopolies, removes the benefits of middlemen, and improves the system operation efficiency. However, the application of blockchain technology has some disadvantages as well [107]. Because blockchain technology needs to master all transaction information, it will require significant storage space, and generating numerous blocks will result in huge energy consumption and a waste of resources.

5 | RECOMMENDATIONS FOR FUTURE RESEARCH

Recent developments in EVs have reached a new peak with the development of fast charging technologies for electric transportation and breakthroughs in charging equipment for conventional and heavy-duty EVs, which will further expand the regulatory potential of EVs. Based on the discussion in this study, future research directions are suggested as follows:

First, regarding the application of DL in the optimal scheduling of EVs, obtaining massive amounts of real data is key to realizing a wider range of DL applications. In the future, combining deep learning and big data will be a research direction regarding the application of this technology to the optimal scheduling of EVs. In addition, DL can be applied to represent user willingness. Electric vehicle users' behaviour has uncertainty, which cannot be fully represented by traditional methods. Owing to their ability of powerful knowledge extraction, neural networks present a novel way to extract and characterise the behaviour of users in the future.

Second, regarding DRL, the convergence of complex problems is an important factor that restricts its application to the optimal scheduling of EVs. Improving the convergence of the DRL algorithm and realizing a hyperparameter search is an effective means of improving the application prospects of DRL. With the inception of the carbon market, the optimal scheduling problem of EVs should not only consider the relationship between electric energy and traffic but also the impact of carbon emissions. Consequently, the optimal scheduling problem for EVs will become more complicated. DRL is an effective method to address this problem.

Finally, in the application of blockchain technology, it is necessary to continuously improve the communication network for electric vehicle user transactions to efficiently allocate communication resources in the future.

TABLE 3 Blockchain technology applied in EV energy trading

Reference	Main technologies used	Pricing mechanism	Contribution
[91]	Public blockchain Peer-to-peer Smart contract	Double auction mechanism	Proposed a blockchain-based charging right trading mechanism and model.
[92]	Peer-to-peer Smart contract Sub gradient method Vickery–Clark-groves	Bidding trading mechanism	Proposed a peer-to-peer market trading mechanism and model for the virtual power plant energy management.
[93]	Peer-to-peer Smart contract	Auction mechanism	Considered an energy trading system involving multiple MCSs and EVs and formulated the incentive mechanism between MCSs and EVs as an auction game, designed a distributed action-based energy trading mechanism.
[94]	Consortium blockchain RPCA consensus algorithm Bipartite graph	Auction mechanism	A V2V power trading architecture based on federated blockchain technology is proposed to address the mileage anxiety of electric vehicle users.
[96]	Public blockchain Smart contract Bayesian game	Auction mechanism	Proposed a Bayesian game-based vehicle-to-vehicle electricity trading scheme for blockchain enabled Internet of Vehicles, and obtained the optimal price under linear strategic equilibrium.
[97]	Consortium blockchain Kafka consensus algorithm Improved krill herd (KH) algorithm	Smart contracts for charging transactions	The KH algorithm is used to solve the large-scale MIP problem to improve the convergence rate and accuracy of the optimal model solution.
[98]	Public blockchain SDBFT consensus algorithm Alternating direction method of multipliers	Nash-bargaining trading	Proposed a two-stage EV charging coordination mechanism that frees the distribution system operator from extra burdens of EV charging coordination.
[99]	Consortium blockchain PBFT consensus algorithm Smart contract	Smart contracts for charging transactions	PBFT consensus algorithm is used to verify EV charging transactions, and smart contracts are used to complete process.
[100]	Public blockchain Smart contract Particle swarm and genetic algorithm	Bidding trading mechanism	Proposed a bidding mechanism for EVs participating in the grid under blockchain smart contract technology.
[101]	Public blockchain DPOS consensus algorithm	Dynamic pricing mechanism	A blockchain-based transaction strategy for a private charging pile sharing platform is proposed, considering the demands of electric vehicle users. Moreover, a charging tariff formulation method that considers the benefits of the platform and regional charging pressure is proposed.
[102]	Public blockchain Smart contract	Dynamic pricing Contrary auction mechanism	The novelty in this framework is using a dynamic pricing algorithm that can benefit all participating discharging EVs for winning the auction.
[103]	Public blockchain PoC consensus algorithm	Auction mechanism	Proposed a blockchain-based two-stage electric vehicle charging stake phase transaction optimization method.
[104]	Consortium blockchain PBFT consensus algorithm Smart contract	Dynamic pricing mechanism	Proposed a feed-in tariff model for electric vehicle electricity and a decentralized market trading model.
[105]	Permissioned blockchain PBFT consensus algorithm Contract theory	Contract mechanism	A contract-based energy blockchain is proposed to optimize the charging of electric vehicles with different energy consumption preferences.
[106]	Public blockchain PoC consensus algorithm Smart contract	Credit score pricing mechanism	Proposed a distributed energy credit assessment index, established blockchain-based credit assessment technology for distributed energy transactions, and proposed a distributed energy credit control mechanism based on credit proof consensus mechanism.

6 | CONCLUSION

In summary, the advantages and disadvantages of deep learning, deep reinforcement learning, and applying blockchain technology in EV strategy optimization are the learning outcomes of this study.

DL technologies exhibit excellent performance in electric vehicle scenario generation and data prediction. The neural networks trained by optimized data achieve the same effect as the traditional model in strategy optimization but greatly shorten the computing time. Although DL technologies have been widely used in academic research regarding the optimal scheduling of EVs, they still face several difficulties in practical applications. DL requires a large amount of historical data to train neural networks to ensure their convergence and generalisation ability. Therefore, the source and accuracy of historical data directly affect its application. Improving the authenticity and scale of training data are crucial to the greater success of DL.

DRL technologies are mainly oriented toward the strategy optimization for EVs. The main advantage of DRL is that there is no need for historical data to train the model. DRL models the charging process of EVs through a Markov process, sets a reasonable reward function, and realizes an optimal decision through the interaction between the agent and environment. However, DRL struggles with convergence, especially during hyperparameter tuning of the value function network. Although DDPG, TD3, and other algorithms have improved the model convergence significantly, the convergence problem remains a restricting factor for the promotion of DRL.

With its decentralisation and protection against data tampering, blockchain technology ensures data transparency in the optimal scheduling of EVs and reduces the uncertainty in energy trading. In addition, an asymmetric encryption algorithm is used to encrypt transaction data to protect personal information security and avoid private data leakage. However, as the scale of EV trading data increases, the limited computing capacity and response speed of blockchain technology limits trading throughput. Accordingly, there is a risk that the real-time settlement of trading cannot be completed. Moreover, the consensus algorithm determines the efficiency and fault-tolerance rate of blockchain; the determination of a consensus algorithm adapted to the needs of the scene is crucial for the study of blockchain technology applications. Nevertheless, currently, there are few blockchain consensus algorithms and incentive mechanism optimization frameworks for specific trading scenarios of EVs entering networks.

Finally, the technologies mentioned in this study do not conflict with each other in practical applications. Different technologies can be applied in different applications of EVs optimization scheduling, and greater benefits can be obtained through integrating these technologies.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All data used have been described in the text.

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