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RETRACTED: Optimizing electric vehicle charging schedules and energy management in smart grids using an integrated GA-GRU-RL approach

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Introduction: Smart grid technology is a crucial direction for the future development of power systems, with electric vehicles, especially new energy vehicles, serving as important carriers for smart grids. However, the main challenge faced by smart grids is the efficient scheduling of electric vehicle charging and effective energy management within the grid.

Methods: To address this issue, we propose a novel approach for intelligent grid electric vehicle charging scheduling and energy management, integrating three powerful technologies: Genetic Algorithm (GA), Gated Recurrent Unit (GRU) neural network, and Reinforcement Learning (RL) algorithm. This integrated approach enables global search, sequence prediction, and intelligent decision-making to optimize electric vehicle charging scheduling and energy management. Firstly, the Genetic Algorithm optimizes electric vehicle charging demands while minimizing peak grid loads. Secondly, the GRU model accurately predicts electric vehicle charging demands and grid load conditions, facilitating the optimization of electric vehicle charging schedules. Lastly, the Reinforcement Learning algorithm focuses on energy management, aiming to minimize grid energy costs while meeting electric vehicle charging demands.

Results and discussion: Experimental results demonstrate that the method achieves prediction accuracy and recall rates of 97.56% and 95.17%, respectively, with parameters (M) and triggers (G) at 210.04 M and 115.65G, significantly outperforming traditional models. The approach significantly reduces peak grid loads and energy costs while ensuring the fulfilment of electric vehicle charging demands and promoting the adoption of green energy in smart city environments.

KEYWORDS

smart grid, deep learning, electric vehicle charging scheduling, smart city, green energy management, reinforcement learning

1 Introduction

Smart grid technology is one of the important directions for the future development of the power system. As a representative of new energy vehicles, electric vehicles will become an important carrier of smart grid Mukherjee and Gupta (2014).

However, the challenges of power supply and demand balance, efficient energy utilization, and environmental protection are faced by smart grid technology. The field of smart grid electric vehicle charging scheduling and energy management faces a series of major difficulties and challenges. Firstly, the charging behavior of electric vehicles is complex and dynamic, and closely integrated with the power grid. Traditional charging scheduling and energy management models face significant challenges in achieving optimal energy utilization, reducing environmental impact, and ensuring power supply and demand balance. Secondly, efficient energy management is needed in the smart grid to ensure its sustainability and stability. Finally, smart grid electric vehicle charging scheduling and energy management involve multiple aspects, such as data collection and management, planning and layout of charging facilities, and prediction and scheduling of charging demand, which require comprehensive consideration and coordination. The charging scheduling and energy management of electric vehicles are one of the important challenges. Reasonable planning and scheduling of electric vehicle charging behavior, optimizing energy distribution and cost of the power grid, are urgent problems to be solved Das et al. (2020a). Therefore, this article reviews the current research status of smart grid electric vehicle charging scheduling and energy management, and proposes a method based on GA-GRU combined with reinforcement learning to optimize energy management and electric vehicle charging scheduling, providing new ideas for the efficient operation of smart grid Luo et al. (2016).

In the field of smart grid electric vehicle charging scheduling and energy management, the following five specific models are commonly used:

a. Model based on genetic algorithm Hou et al. (2020): Genetic algorithm is used to optimize electric vehicle charging demand, but there are significant difficulties in modeling complex power grid load and electric vehicle charging behavior, and the convergence speed is slow.
b. Model based on discrete event simulation Lopez et al. (2021): Discrete event simulation can simulate electric vehicle charging behavior, but due to the complexity of the power grid, a large number of variables and constraints need to be considered, and the computational complexity is high.
c. Model based on optimization algorithm Debnath et al. (2020): Optimization algorithms are commonly used for electric vehicle charging scheduling and energy management, but when considering the mutual influence of different electric vehicles, the model performs poorly.
d. Model based on neural network Aljafari et al. (2023): Neural networks can predict electric vehicle charging demand and power grid load, but there are certain difficulties in predicting long-term time series, which can lead to large errors.
e. Model based on reinforcement learning Wan et al. (2022): Reinforcement learning solves decision-making problems in complex systems to some extent, but in large-scale power grids, training time is long and it is easy to fall into local optimal solutions.

Reasonable planning and scheduling of EV charging behavior, optimizing energy distribution and cost of the power grid, are urgent problems to be solved. Therefore, this article reviews the current research status of smart grid EV charging scheduling and energy management and proposes a GA-GRU method combined with reinforcement learning to optimize energy management and EV charging scheduling, providing new ideas for the efficient operation of the smart grid. In the field of smart grid EV charging scheduling and energy management, several models are commonly used, including models based on genetic algorithms, discrete event simulation, optimization algorithms, neural networks, and reinforcement learning. However, these models face various limitations, such as slow convergence speed, high computational complexity, poor performance when considering the mutual influence of different EVs, and difficulties in predicting long-term time series. To address these limitations, we propose a GA-GRU combined with reinforcement learning method for smart grid EV charging scheduling and energy management. This method aims to comprehensively utilize the advantages of genetic algorithms, gated recurrent unit neural networks, and reinforcement learning algorithms to optimize EV charging scheduling and energy management. Specifically, the GA algorithm is used to optimize EV charging demand, the GRU neural network is used to predict EV charging demand and power grid load, and the reinforcement learning algorithm is used to perform energy management. This method effectively reduces power grid peak load and energy costs while ensuring that EV charging demand is met, providing a practical and economic solution for smart grid EV charging scheduling and energy management problems.

The contribution points of this paper are as follows.

- This paper proposes an innovative method for intelligent grid electric vehicle (EV) charging scheduling and energy management by combining Genetic Algorithm (GA), Gated Recurrent Unit (GRU) neural networks, and Reinforcement Learning (RL). By leveraging the strengths of these three methods, the optimization of EV charging scheduling and energy management is achieved. This integrated approach exhibits significant advantages in handling the complexity and uncertainty of intelligent grids.
- The paper utilizes Genetic Algorithm for global optimization of EV charging demands, effectively minimizing peak loads in the grid and balancing grid loads. Additionally, the introduction of Gated Recurrent Unit (GRU) neural networks enables accurate and efficient prediction of EV charging demands and grid load conditions, improving the precision of EV charging scheduling.
- The paper employs Reinforcement Learning (RL) algorithms for grid energy management, aiming to minimize energy costs while meeting EV charging demands. This is particularly important in intelligent grids, where efficient energy utilization is crucial for reducing energy consumption and operational costs. Through intelligent decision-making with RL, the grid can intelligently schedule and manage energy, leading to reduced overall costs and improved energy utilization efficiency.

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2 Related work

2.1 Electric vehicle charging scheduling algorithm

Improvement of energy management and electric vehicle charging scheduling algorithms is one of the research hotspots in the field of intelligent electric vehicle charging scheduling and energy management Das et al. (2020a). In practical applications, by improving existing energy management and electric vehicle charging scheduling algorithms, the performance of the power system can be effectively optimized, energy consumption and costs can be reduced, and the efficiency and service quality of electric vehicle charging can be improved Jin and Xu (2020a). This article will focus on three commonly used algorithm improvement methods, including improving genetic algorithm, using deep learning algorithm, and adopting hybrid algorithm.

Genetic Algorithm (GA) Abdullah-Al-Nahid et al. (2022) is an optimization algorithm based on natural selection and evolution principles, which is usually used to solve complex optimization problems. In the field of electric vehicle charging scheduling and energy management, genetic algorithm can be used to optimize electric vehicle charging demands to minimize peak load of the power system while ensuring the satisfaction of electric vehicle charging demands. However, traditional genetic algorithm has some problems in the application of complex power systems, such as slow convergence speed and easy to fall into local optima. To overcome these problems, researchers have proposed many methods to improve genetic algorithm. For example, improving the crossover and mutation operations of genetic algorithm to improve the convergence speed and performance of genetic algorithm Deilami and Muyeen (2020). In the crossover operation, multiple crossover methods can be used, such as single-point crossover, multi-point crossover, and uniform crossover. In the mutation operation, multiple mutation operators can be introduced, such as probability-based random mutation, neighborhood-based local mutation, and adaptive strategy-based dynamic mutation Zou et al. (2023).

Deep learning algorithm Park and Moon (2022) is a machine learning technology based on multi-layer neural networks, which has powerful pattern recognition and prediction capabilities. In the field of electric vehicle charging scheduling and energy management, deep learning algorithm can be used to predict electric vehicle charging demands and grid load conditions to improve prediction accuracy and algorithm robustness. Common deep learning models include fully connected neural networks, convolutional neural networks, and recurrent neural networks. Recurrent Neural Network (RNN) is a commonly used deep learning model for processing time series data. To further improve the performance of the RNN model, researchers have proposed the Gated Recurrent Unit (GRU) model. The GRU model can effectively solve the problems of gradient vanishing and gradient explosion in traditional RNN models, improving prediction accuracy and model robustness Papadaki et al. (2022).

Hybrid algorithm Das et al. (2020a) is an optimization method that combines multiple algorithms to overcome the limitations of a single algorithm and improve the performance and efficiency of the algorithm. In the field of electric vehicle charging scheduling and energy management, hybrid algorithm can be used to comprehensively consider multiple factors, such as electric vehicle charging demands, grid load, and energy costs, to achieve optimal charging scheduling and energy management results. Common hybrid algorithms include the combination of genetic algorithm and ant colony algorithm, particle swarm algorithm and genetic algorithm, and genetic algorithm and neural network Zhibin et al. (2019). For example, the combination of genetic algorithm and ant colony algorithm combines the global search of genetic algorithm and the local search of ant colony algorithm to find better solutions in charging scheduling and energy management problems. The combination of particle swarm algorithm and genetic algorithm can improve the convergence speed and performance of the algorithm by optimizing the initialization and crossover mutation operations of the population. The combination of genetic algorithm and neural network can make full use of the prediction ability of the neural network model and the global search ability of the genetic algorithm to achieve better charging scheduling and energy management effects Zou et al. (2023).

2.2 Smart grid

Research and Application of Smart Grid Technology: Smart grid technology plays a crucial role in achieving efficient electric vehicle (EV) charging scheduling and energy management Mohanty et al. (2020). With the increasing power demand, the widespread adoption of renewable energy sources, and growing environmental awareness, traditional power systems face numerous challenges. Smart grid technology emerges as a key solution and vital direction for the future development of power systems. It involves the use of advanced information and communication technologies to achieve intelligent and automated operation and management of power systems. Within the framework of the smart grid, EV charging scheduling and energy management become significant research areas, essential for ensuring efficient and stable power system operation while improving the convenience of using EVs.

Smart grid technology encompasses several aspects: 1. Automation of Power Systems Mohanty et al. (2022): Smart grid incorporates automation technologies to enable automatic monitoring, control, and scheduling of grid devices, enhancing grid reliability and stability. In the context of EV charging scheduling and energy management, automation allows intelligent charging scheduling and energy distribution based on EV demands and grid loads, optimizing overall energy utilization efficiency. 2. Intelligent Sensors and Controllers Chobe et al. (2023): Smart grid relies on intelligent sensors and controllers to continuously monitor grid status, load demands, and EV charging conditions, enabling precise perception and flexible control of the power system. Real-time data collection through intelligent sensors facilitates accurate prediction and dynamic adjustment of EV charging demands and grid loads. 3. Smart Grid Communication and Data Management Hasan et al. (2023): Efficient communication and data management systems are essential for smart grid operation, enabling seamless information exchange among various grid devices. Through communication technology, smart grid facilitates interaction between EVs and the grid, ensuring coordinated operation of EV charging demands and energy management. 4. Smart Grid Security Ahmed et al. (2023): Security is a critical aspect of smart grid technology research.

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As smart grid applications involve significant data transmission and information exchange, ensuring network security and data privacy becomes paramount. Smart grid technology necessitates the establishment of secure and reliable communication and data management mechanisms to safeguard information within the power system and EV charging operations.

In the future, ongoing research and application of smart grid technology will continue to drive the development of EV charging scheduling and energy management. Leveraging smart grid technology, intelligent EV charging scheduling can be achieved, matching EV charging with grid load demands and avoiding excessive grid loads. Moreover, smart grid applications can optimize energy distribution and utilization, reducing energy waste and improving power system efficiency. This not only promotes the adoption and usage of EVs but also contributes to the sustainable development of power systems and environmental protection. In conclusion, research and application of smart grid technology provide vital support for EV charging scheduling and energy management, contributing significantly to the intelligence of power systems, optimized energy utilization, and improved environmental quality. As technology continues to advance, the smart grid will emerge as a crucial pillar for EV charging scheduling and energy management, making a substantial contribution to sustainable development and green transportation.

2.3 GRU model in EV charging scheduling

The GRU (Gated Recurrent Unit) model is a type of recurrent neural network widely used in the field of electric vehicle (EV) charging scheduling and energy management Jin and Xu (2020a). In this context, the GRU model is often employed to predict EV charging demands and grid loads, enabling better planning of charging schedules and optimizing energy management strategies. Below is a detailed explanation of the application of the GRU model in this domain. The GRU model is an improved version of the recurrent neural network, offering better performance than traditional RNNs. Traditional RNNs face challenges in handling long sequence data due to issues like vanishing and exploding gradients. The GRU model addresses these problems by introducing gate mechanisms, which efficiently control information flow and retention, leading to enhanced model performance and robustness.

In EV charging scheduling and energy management, the application of the GRU model typically involves two aspects Boulakhbar et al. (2022a): EV charging demand prediction and grid load prediction. For EV charging demand prediction, the GRU model can forecast future charging demands by learning from historical data. This data may include EV charging records, weather data, time-related information, and more. By inputting this historical data, the GRU model can capture patterns and trends in EV charging demands, facilitating accurate predictions for future charging requirements. These predictions can be utilized to devise more rational charging plans, thereby optimizing EV charging scheduling strategies. Regarding grid load prediction, the GRU model can forecast future grid load conditions by learning from historical data. Similar to EV charging demand prediction, the historical data for grid load prediction may include grid load records, weather data, time-related information, and other relevant factors. By training on this data, the GRU model can capture patterns and trends in grid loads, enabling accurate predictions for future grid load situations. These predictions can be used to develop more reasonable energy management plans, optimizing grid loads and energy consumption. Beyond the aforementioned aspects Wang et al. (2023), the GRU model finds application in other areas of EV charging scheduling and energy management as well. For example, it can be employed to predict EV charging rates, charging durations, and more. These predictions can assist in devising more rational charging plans and optimizing EV charging efficiency. The GRU model has widespread applications in EV charging scheduling and energy management. By learning from historical data, the GRU model can forecast future EV charging demands and grid loads, leading to more rational charging schedules and optimized energy management strategies. Future research can further explore additional application scenarios and improvement techniques to enhance the performance and effectiveness of the GRU model in this domain Park et al. (2022).

3 Methodology

3.1 Overview of our network

The method proposed in this paper is a research on intelligent grid-based electric vehicle (EV) charging scheduling and energy management, which combines three methods Boulakhbar et al. (2022b): Genetic Algorithm (GA), Gated Recurrent Unit neural network (GRU), and Reinforcement Learning (RL) to optimize EV charging scheduling and energy management problems. Figure 1 depicts the framework of the proposed method in this study. Table 1 is the parameters of the model.

The implementation process of this method includes the following steps.

- Data collection and preprocessing: Collect historical data of electric vehicles and the power grid and preprocess and clean the data to ensure its accuracy and reliability.
- GRU model prediction: Use the Recurrent Neural Network model (GRU) to predict EV charging demands and grid loads. By learning from historical data, the GRU model can forecast future charging demands and grid load conditions, enabling the development of more reasonable charging plans and optimized energy management strategies.
- Genetic Algorithm optimization: Utilize Genetic Algorithm to optimize the EV charging scheduling and energy management plans. Through operations such as selection, crossover, and mutation, the Genetic Algorithm continuously optimizes the population to eventually find the optimal solution.
- Reinforcement Learning tuning: Use Reinforcement Learning to fine-tune the optimal solution obtained from the Genetic Algorithm. Through continuous trial and error and learning, Reinforcement Learning can further optimize the solution, leading to better solutions for EV charging scheduling and energy management.
- Experimental validation: Apply the optimized EV charging scheduling and energy management plans to real-world scenarios and perform experimental validation. By evaluating

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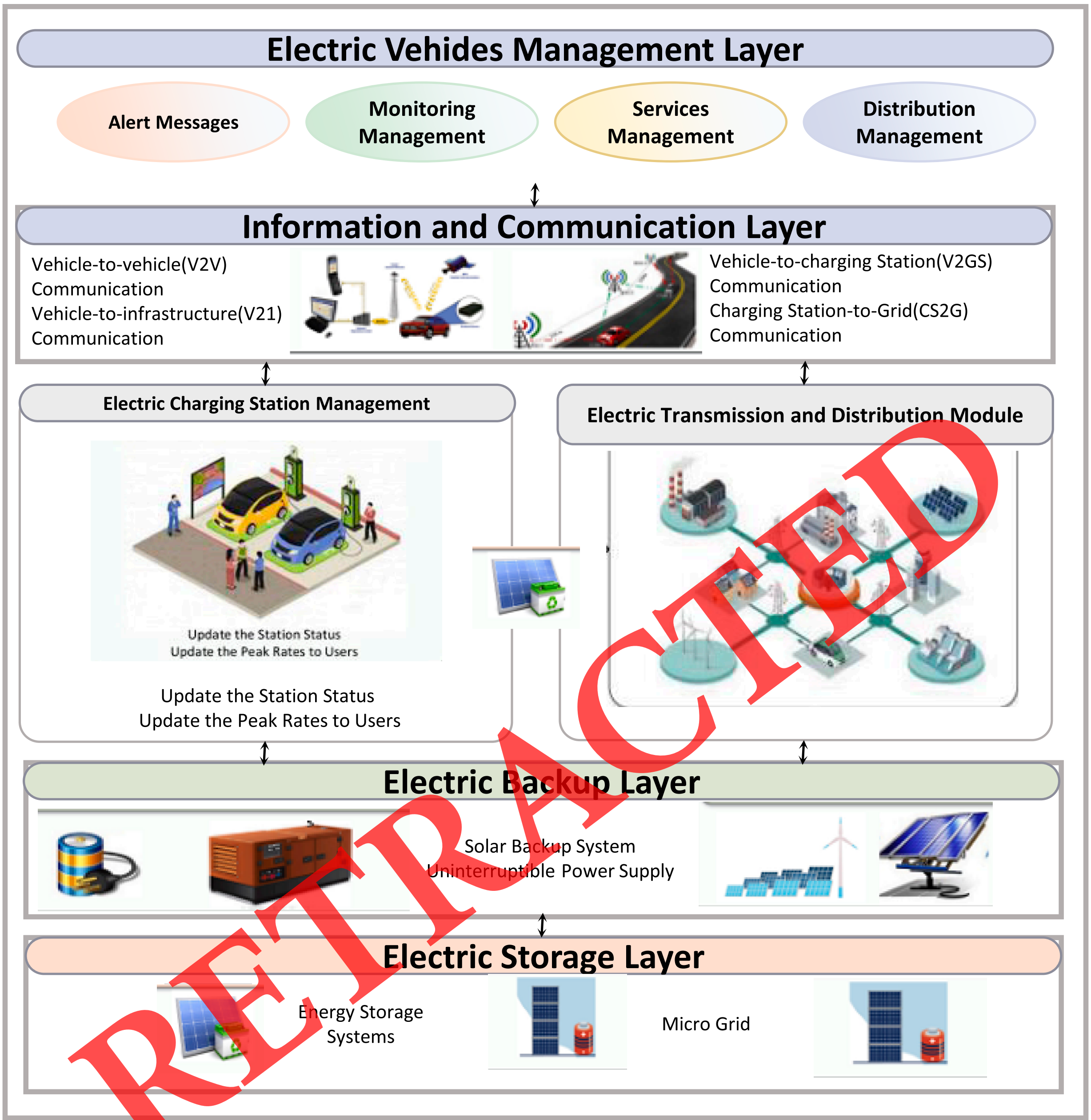

FIGURE 1
The framework of the proposed method in this study.

TABLE 1 List of Parameters used in the GA-GRU combined with Reinforcement Learning Method.

Parameter name	Symbol	Description	Value range
Population size	N	Number of individuals in the population	10–100
Crossover rate	p_c	Probability of crossover operation	0.6–0.9
Mutation rate	p_m	Probability of mutation operation	0.01–0.1
Reinforcement learning rate	α	Learning rate for the state-action function	0.01–0.1
Discount factor	γ	Discount factor for future rewards	0.9–0.99
GRU hidden size	h	Number of hidden units in the GRU layer	32–128
GRU sequence length	l	Length of the input sequence for the GRU layer	24–48

the experimental results, the performance and effectiveness of the algorithm can be assessed, thus further optimizing the algorithm.

This method aims to optimize EV charging scheduling and energy management, combining Genetic Algorithm, Gated Recurrent Unit neural network (GRU), and Reinforcement Learning. It can provide more rational decision support for EV charging scheduling and energy management, reducing energy waste and environmental pollution, and promoting sustainable development.

3.2 Genetic algorithm (GA)

Genetic Algorithm (GA) is an optimization algorithm based on the natural evolutionary process, primarily used to solve complex optimization problems Rasheed et al. (2020). GA mimics the genetic and evolutionary mechanisms in biological evolution, continually optimizing the population through basic operations such as selection, crossover, and mutation, eventually finding the optimal solution Milas et al. (2020). In GA, each individual represents a potential solution, known as a chromosome, and each gene on the chromosome represents a parameter in a feasible solution. Figure 2 is a schematic diagram of the principle of the genetic algorithm.

In the proposed GA-GRU method in this paper, Genetic Algorithm is primarily utilized to optimize the EV charging scheduling and energy management plans. Specifically, the role of GA in this method is as follows.

1. Population initialization: In the GA-GRU method, Genetic Algorithm first randomly generates a certain number of individuals as the initial population. These individuals represent different combinations of EV charging scheduling and energy management plans.
2. Selection operation: Based on the fitness function, a certain number of individuals are selected as the next-generation population. The fitness function evaluates the fitness of each individual, which measures their ability to solve the problem. In the GA-GRU method, the fitness function is mainly based on the GRU model's predictions of EV charging demands and grid loads.
3. Crossover operation: Using crossover operators, selected individuals undergo crossover operations to generate new offspring. In the GA-GRU method, the multi-point crossover operator is mainly employed to preserve excellent gene segments and accelerate the convergence rate of the population.
4. Mutation operation: Using mutation operators, new offspring undergo mutation operations to increase the diversity of the population. In the GA-GRU method, the neighborhood-based mutation operator is primarily utilized to ensure the stability of individuals and avoid premature convergence of the population.
5. Population update: The newly generated individuals and the original population are combined, and the next-generation population is formed based on the fitness function through sorting and filtering. In the GA-GRU method, during population update, excellent individuals have a higher probability of being selected to further improve the quality of the population.
6. Termination condition determination: Based on the set termination condition, it is determined whether the algorithm ends. In the GA-GRU method, the termination condition is generally reaching the maximum number of iterations or finding the optimal solution that meets the requirements.

When using a genetic algorithm for optimization, the fitness function is the core part of the algorithm. It is used to measure the quality of individuals in the problem space. In each generation, the genetic algorithm selects and crosses over high-quality individuals based on the evaluation results of the fitness function and generates new individuals through mutation, gradually improving the population until it finds the optimal or near-optimal solution that meets the problem requirements.

In the problem of intelligent grid electric vehicle charging scheduling and energy management, the construction of the fitness function can consider the following factors.

- Degree of electric vehicle charging demand satisfaction:

Suppose N electric vehicles need to be charged, and the charging demand for each vehicle is D_i $(i = 1, 2, \ldots, N)$. Additionally, suppose the charging schedule obtained by the genetic algorithm optimization is C_i $(i = 1, 2, \ldots, N)$, representing the charging time of each vehicle during a certain time period. The degree of charging demand satisfaction can be quantified by calculating the difference between the charging demand and the actual charging duration. Let F_1 represent the degree of charging demand satisfaction in the fitness function, which can be expressed as:

$$F_1 = \frac{1}{N}\sum_{i=1}^{N} |D_i - C_i| \tag{1}$$

- Reduction of peak load on the grid:

Suppose the peak load of the grid before optimization is L_{old}, and the peak load after optimization is L_{new}. The degree of reduction in peak load on the grid can be evaluated by comparing these two values. Let F_2 represent the reduction of peak load on the grid in the fitness function, which can be expressed as:

$$F_2 = \frac{L_{old} - L_{new}}{L_{old}} \tag{2}$$

- Grid energy cost:

Suppose the energy cost of the grid before optimization is C_{old}, and the energy cost after optimization is C_{new}. The degree of reduction in grid energy cost can be evaluated by comparing these two values. Let F_3 represent the reduction in grid energy cost in the fitness function, which can be expressed as:

$$F_3 = \frac{C_{old} - C_{new}}{C_{old}} \tag{3}$$

- Accuracy of prediction:

Suppose models such as GRU are used for prediction, and there is an error between the predicted results and the actual charging

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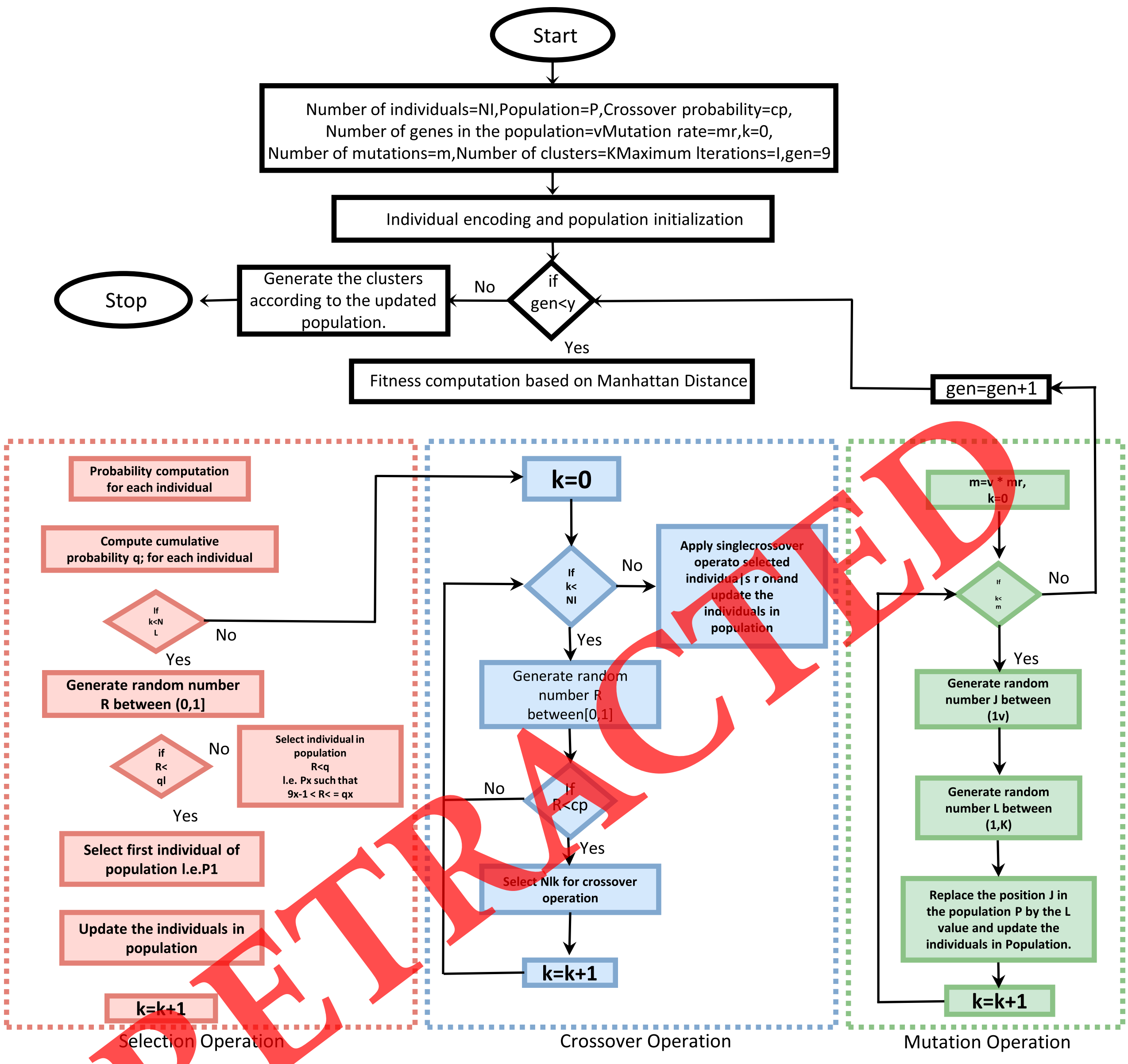

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FIGURE 2
The schematic diagram of the principle of the genetic algorithm.

demand and grid load. The accuracy of prediction can be measured by calculating the prediction error. Let F_4 represent the prediction accuracy in the fitness function, which can be expressed as:

$$F_4 = \frac{1}{N}\sum_{i=1}^{N}|P_i - D_i| \tag{4}$$

Here, P_i is the predicted charging demand of the ith electric vehicle by the model.

Taking into account the above factors, the complete fitness function F_{total} can be constructed, where w_1, w_2, w_3, and w_4 are the weights of each factor used to balance their importance in the optimization process. The fitness function can be expressed as:

$$F_{total} = w_1F_1 + w_2F_2 + w_3F_3 + w_4F_4 \tag{5}$$

These weights can be set according to the requirements and experience of the specific problem. For example, if the degree of charging demand satisfaction is more important than the reduction of peak load on the grid, w_1 can be set larger than w_2.

Using the above fitness function, the genetic algorithm will select and cross over high-quality individuals and generate new individuals through mutation, gradually improving the population to find the optimal or near-optimal solution that meets the problem requirements. The optimization process will continue to evolve under the guidance of the fitness function, balancing various factors and obtaining effective applications in practice.

In the GA-GRU method, GA plays a role in continuously optimizing the EV charging scheduling and energy management plans through operations such as selection, crossover, and mutation,

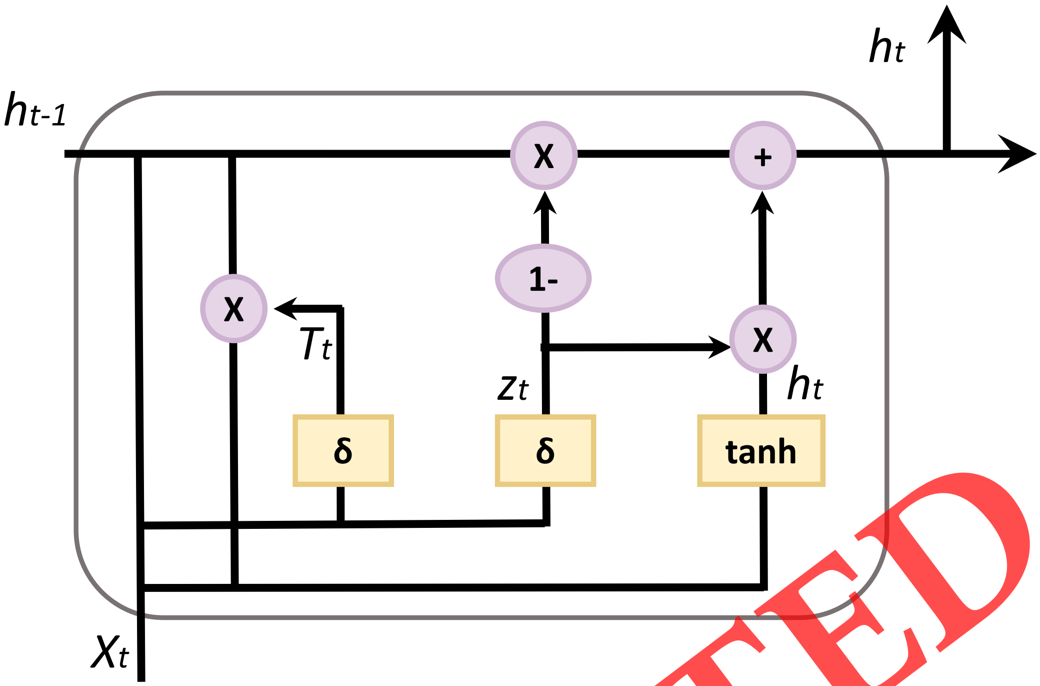

FIGURE 3
The schematic diagram of the principle of the GRU model.

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improving the ability and effectiveness of solving the problem. Through GA optimization, the EV charging scheduling and energy management plans become more reasonable and optimized, reducing energy waste and environmental pollution, and promoting sustainable development.

3.3 GRU (gated recurrent unit)

GRU (Gated Recurrent Unit) is a variant of recurrent neural network (RNN) mainly used for processing sequential data such as speech, text, and time serie Mouaad et al. (2022). GRU was proposed by Cho et al., in 2014 to address issues of vanishing and exploding gradients in traditional RNN models. Figure 3 is a schematic diagram of the principle of the GRU model.

The basic principle of the GRU model is to control the flow of information through gate mechanisms. The model includes two gating units: the reset gate and the update gate. The reset gate controls how the previous hidden state affects the current input, while the update gate controls how the current input is merged with the previous hidden state. Through this gate mechanism, the GRU model can better capture long-term dependencies in sequential data.

In the GA-GRU method proposed in this paper, the GRU model is mainly used to predict the charging demand of electric vehicles and the load situation of the power grid. Specifically, the GRU model's role is as follows.

- Input sequence processing: Convert historical data into an input sequence that the GRU model can process. In the GA-GRU method, the input sequence contains information such as the charging demand of electric vehicles and the load of the power grid.
- Hidden state calculation: Calculate the current hidden state through the gate mechanism of the GRU model. The hidden state contains information from the current time step and the previous hidden state.
- Prediction output: Output the prediction results for the current time step based on the current hidden state. In the GA-GRU method, the prediction results contain information such as the charging demand of electric vehicles and the load of the power grid.

GRU (Gated Recurrent Unit) is a recurrent neural network whose basic formula is as follows:

$$z_t = \sigma\left(W_z x_t + U_z h_{t-1} + b_z\right) \tag{6}$$

$$r_t = \sigma\left(W_r x_t + U_r h_{t-1} + b_r\right) \tag{7}$$

$$\tilde{h}_t = tanh\left(W_h x_t + U_h\left(r_t \odot h_{t-1}\right) + b_h\right) \tag{8}$$

$$h_t = \left(1 - z_t\right) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{9}$$

Among them, x_t represents the input at the current moment, h_{t-1} represents the hidden state at the previous moment, z_t and r_t represent the update gate and reset gate respectively, $\tilde{h}_t$ represents the temporary hidden state at the current moment, and h_t represents the hidden state at the current moment.

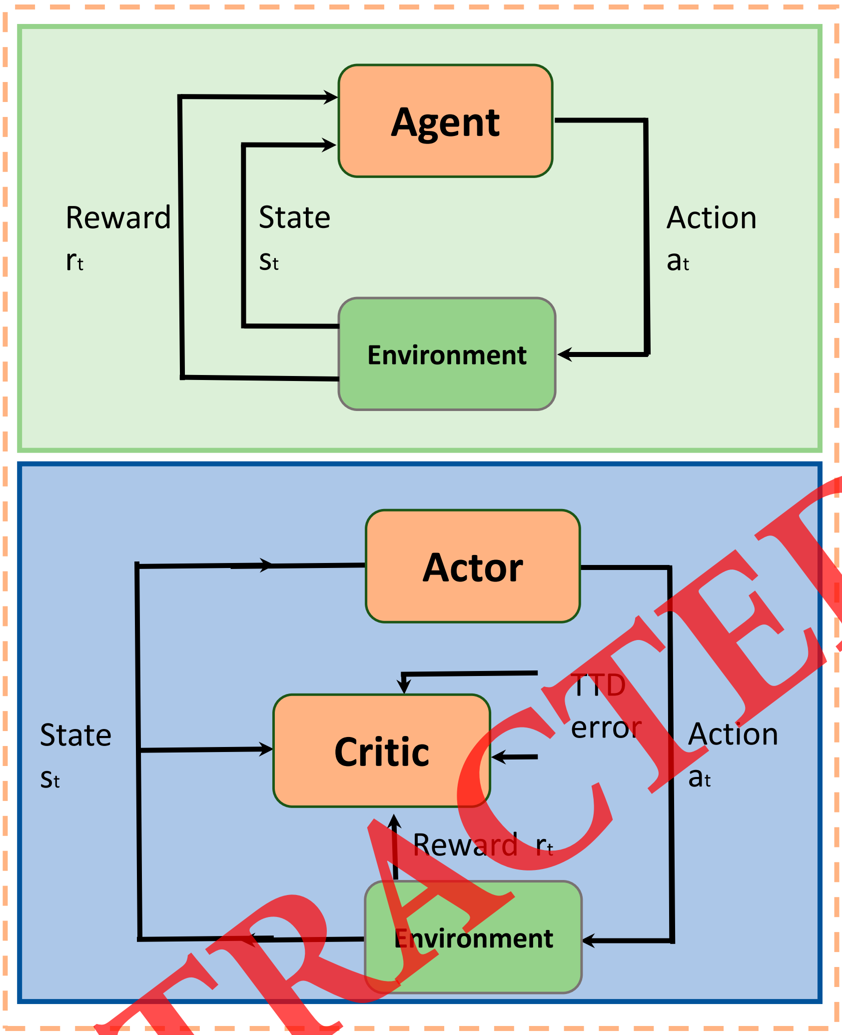

FIGURE 4
The schematic diagram of the principle of reinforcement learning.

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TABLE 2 Description of data set details.

Dataset	Data size (GB)	Data type	Indicator selection	Indicator classification
Pecan Street Dataset	3.9	Time Series Data	Electricity Loads, Water Resources, Electric Vehicle Charging Demand and Behavior	Energy, Water Resources, Electric Vehicles
NREL Dataset	8.8	Time Series Data	Solar Generation, Wind Generation, Electricity Loads, Electric Vehicle Charging	Energy, Electric Vehicles
ChargePoint Dataset	4.2	Structured Data	Charging Demand, Charging Behavior, Charging Station Power Usage	Electric Vehicles, Charging Stations
UCI Dataset	3.2	Structured Data	EV Charging Demand and Behavior	EV

$W_z, W_r, W_h, U_z, U_r, U_h, b_z, b_r, b_h$ are parameters that need to be determined through training. σ represents the sigmoid function, and $\odot$ represents the product of elements.

The gating mechanism of the GRU model can control the flow of information, by resetting the gate and updating the gate to control how the information of the previous moment affects the input of the current moment, and how the input of the current moment fuses the hidden state of the previous moment, so as to better capture the long-term dependencies in the sequence data.

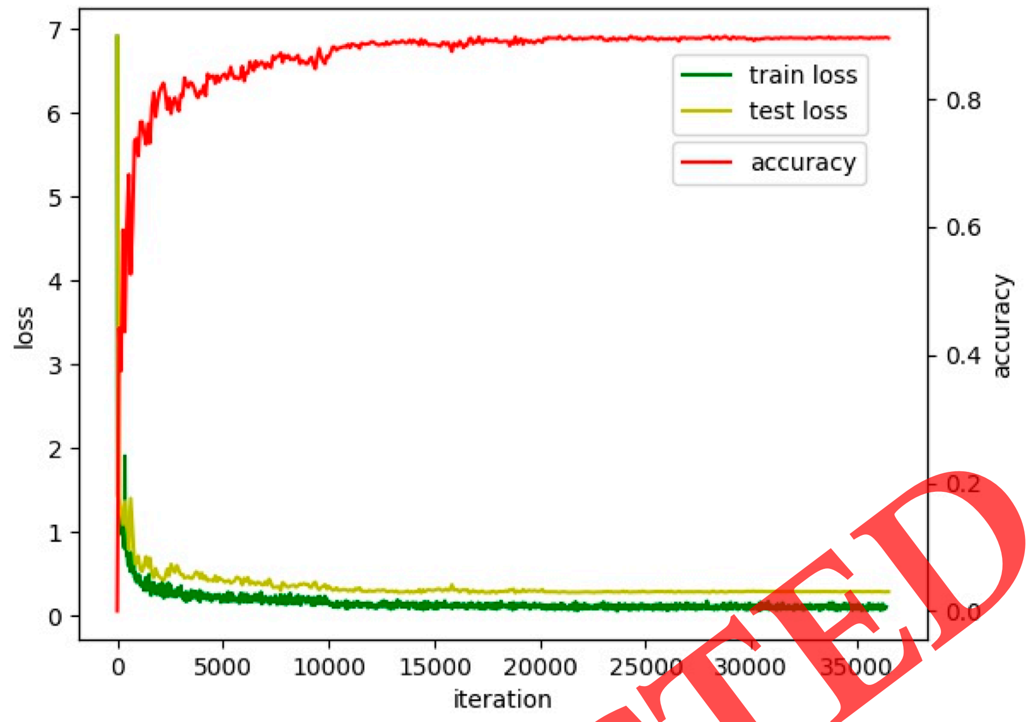

FIGURE 5
The training convergence graph of our proposed model.

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TABLE 3 Comparing different metrics with current SOTA methods on different datasets.

Model	Datasets															
	Pecan Street Dataset				NREL Dataset				ChargePoint Dataset				UCI Dataset			
	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC
Das et al. (2020a)	87.28	84.67	90.62	84.28	95.06	88.25	84.59	90.04	85.96	83.78	88.84	89.66	92.28	84.49	86.6	88.12
Dang et al. (2019)	89.62	86.11	87.62	84.37	88.6	92.39	85.8	84.07	91.97	92.3	89.93	89.29	93.22	85.26	89.69	86.08
Qureshi et al. (2021)	87.87	90.35	87.83	84.02	92.25	85.36	84.63	85.44	90.64	93.49	85.9	92.64	86.22	87.38	89.91	91.79
Koufakis et al. (2019)	93.7	84.03	85.47	84.61	95.37	90.67	90.9	92.25	95.22	87.65	90.67	90.94	93.96	91.02	90.39	92.4
Luo et al. (2020)	94.49	89.35	83.83	85.31	92.92	92.92	86.76	89.56	90.11	85.53	87.06	89.41	88.05	87.58	86.1	91.75
Jin and Xu, (2020a)	86.74	83.94	89.87	85.5	86.75	91.34	86.32	89.77	94.12	91.34	90.3	85.41	88.38	92.55	88.2	91.56
Ours	97.56	95.17	93.45	95.35	97.35	93.48	94.67	94.58	96.19	95.55	94.15	96.34	96.13	94.46	93.13	93.56

Through the predictions made by the GRU model, the GA-GRU method can more accurately understand the charging demand of electric vehicles and the load situation of the power grid, thus making more reasonable charging plans and optimizing energy management strategies. Moreover, the GRU model can also help the genetic algorithm converge faster, improving the performance and effectiveness of the algorithm.

3.4 Reinforcement learning (RL)

Reinforcement Learning (RL) is a machine learning method aimed at enabling an agent to learn through trial and error by interacting with an environment to maximize cumulative rewards Li et al. (2019). Figure 4 is a schematic diagram of the principle of reinforcement learning.

The fundamental principles of reinforcement learning can be summarized as follows.

1. Environment and Agent: RL tasks typically take place in an environment with defined goals and rules. The agent is the entity that performs the learning, and it observes the environment's state and selects actions based on the current state.
2. State: The current state of the environment is the information observable by the agent. States can be represented as numerical

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FIGURE 6
Comparison of Precision of different models.

values or a set of features describing specific conditions in the environment.

3. Action: Actions are decisions made by the agent based on the current state. Actions can be discrete or continuous, depending on the specific problem.
4. Reward: At each time step, the agent receives a reward signal from the environment, reflecting the goodness or badness of its action in the current state. The goal is to maximize cumulative rewards over time.
5. Policy: The policy is the strategy the agent employs to select actions based on the current state. The objective of RL is to learn the optimal policy that allows the agent to obtain the maximum cumulative reward in a given environment.
6. Value Function: The value function evaluates the expected cumulative reward for a particular state or state-action pair. Value functions can guide the agent in choosing the optimal actions in different states.

In the RL process, the agent interacts with the environment to collect experience data and optimize the policy or value function based on this data Zhang et al. (2022). Common learning methods include value-based methods (such as Q-Learning and Deep Q-Networks)

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TABLE 4 Comparing different metrics with current SOTA methods on different datasets.

Method	Dataset															
	Pecan Street Dataset				NREL Dataset				ChargePoint Dataset				UCI Dataset			
	Parameters (M)	Flops (G)	Inference Time(ms)	Training Time(s)	Parameters (M)	Flops (G)	Inference Time(ms)	Training Time(s)	Parameters (M)	Flops (G)	Inference Time(ms)	Training Time(s)	Parameters (M)	Flops (G)	Inference Time(ms)	Training Time(s)
Das et al.	286.48	239.81	203.02	287.05	351.70	340.90	215.89	216.51	252.58	372.83	357.46	302.06	307.49	302.96	228.31	571.86
Dang et al.	378.41	314.20	295.21	216.00	324.53	289.92	282.07	230.71	342.66	213.08	287.33	222.95	335.64	325.14	246.13	847.12
Qureshi et al.	311.56	343.49	364.27	290.04	346.82	215.54	380.92	399.77	240.90	205.04	252.32	284.54	283.10	230.98	396.30	697.32
Koufakis et al.	385.74	247.29	267.73	207.54	313.18	283.63	265.15	261.24	206.82	384.41	205.84	376.14	348.15	286.70	269.09	380.26
Luo et al.	296.76	397.12	205.61	357.67	225.12	379.53	287.58	202.96	338.19	362.52	273.33	253.13	312.79	294.90	204.18	202.21
Jin et al.	217.94	247.10	387.13	359.74	243.51	321.68	280.80	278.48	330.21	349.19	319.98	274.01	256.66	393.37	253.88	374.50
Ours	168.25	181.54	123.93	207.03	197.51	212.85	196.02	150.89	225.03	218.18	123.46	202.26	210.04	115.65	133.25	172.48

and policy-based methods (such as Policy Gradient and Actor-Critic). The core idea of RL is that through continuous trial and error and learning, the agent improves its performance by optimizing the policy or value function, leading to better decision-making in complex environments.

The basic formula of Reinforcement Learning is as follows:

$$\mathcal{S}\text{:state space} \tag{10}$$

$$\mathcal{A}\text{:action space} \tag{11}$$

$$r(s,a):\mathcal{S}\times\mathcal{A}\rightarrow\mathbb{R}\text{:reward function} \tag{12}$$

$$p(s'|s,a):\mathcal{S}\times\mathcal{A}\times\mathcal{S}\rightarrow[0,1]:\text{transition probability function} \tag{13}$$

$$\pi(a|s):\mathcal{S}\times\mathcal{A}\rightarrow[0,1]:\text{strategy function} \tag{14}$$

Among them, $\mathcal{S}$ represents the state space, $\mathcal{A}$ represents the action space, and $r(s,a)$ represents the reward function, which describes the reward obtained by taking action a in the state s. $p(s'|s,a)$ represents the transition probability function, which describes the probability of taking an action a to transfer to the state s' under the state s. $\pi(a|s)$ represents the policy function, which describes the probability of taking action a in state s.

The goal of reinforcement learning is to maximize the cumulative reward of taking actions in the environment by learning the optimal policy function. The optimal policy can be represented by a value function or a policy function. The value function represents the cumulative reward obtained by adopting the optimal strategy in the state s, usually represented by $V^{(s)}$; the policy function represents the probability of taking the optimal action in the state s, usually represented by $\pi^{(a|s)}$.

In the proposed GA-GRU method, reinforcement learning is primarily employed to fine-tune the solutions obtained by the genetic algorithm. Through trial and learning, reinforcement learning optimizes the genetic algorithm's solutions, leading to improved solutions for electric vehicle charging scheduling and energy management problems. The role of reinforcement learning in this method is to make the electric vehicle charging scheduling and energy management solutions more rational and optimized, thereby reducing energy waste and environmental pollution, and promoting sustainable development.

4 Experiment

4.1 Datasets

The paper utilizes four datasets, namely, the Pecan Street Dataset, NREL Dataset, ChargePoint Dataset, and UCI Dataset. These datasets contain relevant information on power consumption and electric vehicle charging, making them applicable for various tasks.

Pecan Street Dataset Zhou et al. (2021): This dataset is from the Pecan Street project in Austin, Texas and is a public dataset. It includes electricity and water resource data from thousands of homes and commercial buildings, as well as data from electric vehicles such as charging demand and behavior. The dataset spans from 2010 to the present and contains high-resolution time-series data. This dataset can be used for tasks such as electricity load

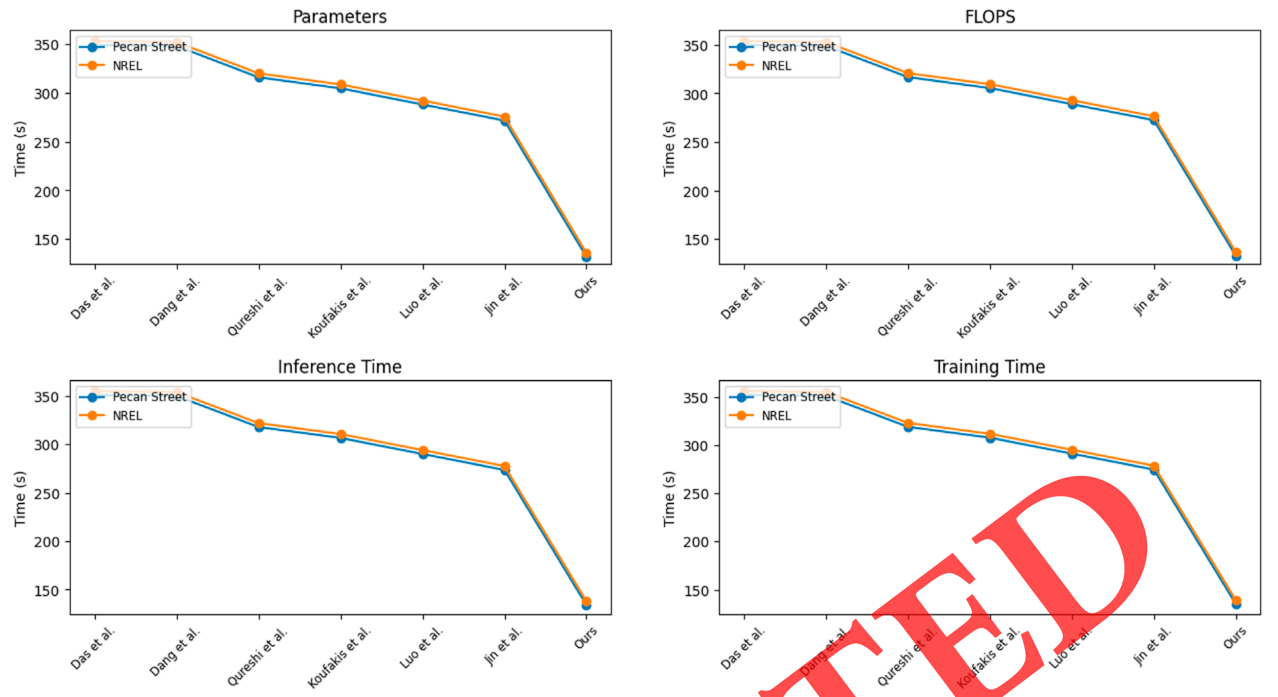

FIGURE 7
Comparison of Precision of different models.

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TABLE 5 Ablation experiments on the GRU module.

Model	Datasets															
	Pecan Street Dataset				NREL Dataset				ChargePoint Dataset				UCI Dataset			
	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC
RNN	91.27	88.4	85.48	84.63	89.79	87.82	84.73	91.58	88.85	91.13	87.81	88.05	85.87	84.57	85.51	83.93
CNN	85.58	88.93	84.27	90.06	94.32	87.79	88.58	92.13	85.75	88.57	88.41	93.61	87.57	84.95	89.07	92.5
LSTM	94.28	87.33	89.03	88.79	90.37	93.66	90.81	91.01	91.24	90.66	87.05	89.97	92.85	91.13	84.98	89.44
GRU	97.77	94.26	93.95	91.96	97.22	95.28	94.14	93.21	96.46	94.3	93.94	92.99	97.11	94.38	92.83	92.2

forecasting, electric vehicle charging scheduling, and energy usage analysis.

NREL Dataset Ransome (2018): This dataset is from the National Renewable Energy Laboratory (NREL) in the United States and is a public dataset that includes data on solar energy, wind energy, electricity load, and electric vehicle charging. The dataset includes multiple collections of data, where the solar energy generation dataset includes power output data from over 100,000 solar panels worldwide and can be used for solar energy generation forecasting; the wind energy dataset includes power output data from over 120,000 wind turbines worldwide and can be used for wind energy generation forecasting; the electricity load dataset includes electricity load data from different regions in the United States and can be used for electricity system optimization; and the electric vehicle charging dataset includes data on electric vehicle charging from different regions and can be used for electric vehicle charging scheduling.

ChargePoint Dataset Morrissey et al. (2016): This dataset is from ChargePoint, the largest electric vehicle charging network in the United States, and is a public dataset that includes data on charging stations and electric vehicles. The dataset includes basic information on charging stations, electricity usage at charging stations, and charging demand and behavior of electric vehicles. This dataset can be used for tasks such as charging demand forecasting and charging behavior analysis.

UCI Dataset Chang et al. (2020): This dataset is from the University of California, Los Angeles (UCI) and is a public dataset that includes data on electric vehicles. The dataset includes data on charging demand and behavior of electric vehicles from different regions. The dataset contains electric vehicle charging demand data from different time periods and can be used for tasks

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such as electric vehicle charging scheduling and charging demand forecasting.

Table 2 is the detailed introduction of the data set.

4.2 Experimental details

Data Preprocessing: Preprocess the grid data, including data cleaning, data sampling, and data normalization.

- Experimental Design: Randomly split the dataset into a training set and a test set, with a ratio of 7:3. Train the model on the training set and evaluate the model on the test set. The specific experimental design is as follows:

a. Genetic Algorithm Optimization: Initialize the population P using GA encoding. For each individual i, train the GRU model on the BraTS dataset and calculate the recall and precision on the Kvasir-SEG dataset. Compute the fitness of each individual based on recall and precision and select individuals with higher fitness. Generate a new population P' using crossover and mutation operations.
b. Reinforcement Learning Training: Initialize the RL agent and train it on the Kvasir-SEG dataset. At each timestep t, select an action a based on the current state s, perform the action, and observe the new state s'. Calculate the reward based on the CVC-ClinicDB dataset and update the policy of the RL agent using the reward. Repeat this process until the RL agent converges.
c. Model Training: Use the updated parameters to train GG-RLNet on the grid dataset.

- Experimental Metrics: We will use Accuracy, Recall, F1 Score, and AUC as evaluation metrics, and record the variations of these metrics during the training and testing processes to compare the impact of different metrics on model performance.

Parameter Tuning: We will use methods such as grid search to tune the model parameters and find the best combination of hyperparameters.

- Experimental Result Analysis:
- Model Performance Evaluation: Compare the performance of different models and algorithms on the electric vehicle charging scheduling and energy management tasks and analyze which models and algorithms have the most significant impact on performance.
- Parameter Tuning: Based on the experimental results, select the best combination of hyperparameters and optimize the model.
- Results Visualization: Visualize the experimental results and perform statistical analysis to better present the experimental findings.

Here are the formulas and variable explanations for each of the comparison metrics:

Accuracy: Accuracy measures the overall correctness of the model's predictions. Formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{15}$$

```
Input: Training data: Pecan Street Dataset, NREL Dataset, ChargePoint Dataset, UCI Dataset
Output: Optimal parameters for GG-RLNet
Initialize population P using GA encoding;
for generation g in maximum generations do
    for individual i in population P do
        Train GRU model on data from Pecan Street Dataset;
        for batch b in training data do
            Compute recall and precision using GRU model;
        end
        Compute fitness of i based on recall and precision;
    end
    Select top individuals from P based on fitness;
    Perform crossover and mutation to generate new population P';
    P ← P';
end
Initialize RL agent with GRU model;
while not converged do
    for episode e in maximum episodes do
        Initialize state s with data from NREL Dataset;
        for timestep t in maximum timesteps do
            Select action a using RL agent based on s;
            Perform action a and observe new state s';
            Compute reward based on precision and recall using CVC-ClinicDB Dataset;
            Update RL agent's policy based on the reward;
            s ← s';
        end
    end
end
Train GG-RLNet with updated parameters on UCI Dataset;
```

Algorithm 1. Training GG-RLNet

Where:

TP (True Positive): Number of true positive predictions.TN (True Negative): Number of true negative predictions.FP (False Positive): Number of false positive predictions.FN (False Negative): Number of false negative predictions.

Recall (Sensitivity or True Positive Rate): Recall measures the ability of the model to correctly identify positive instances. Formula:

$$Recall = \frac{TP}{TP + FN} \tag{16}$$

F1 Score: The F1 score is the harmonic mean of precision and recall, providing a balance between the two metrics. Formula:

$$F1Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{17}$$

AUC (Area Under the Receiver Operating Characteristic Curve): AUC measures the ability of the model to distinguish between positive and negative instances across different thresholds. Formula: The AUC is calculated using the receiver operating characteristic (ROC) curve. Parameters (M).Parameters represent the number of learnable parameters in the model. Flops (G).Flops (Floating Point Operations) represent the number of floating-point operations required for the model's inference. Inference Time (ms).Inference Time measures the time taken by the model to predict an output given an input. Training Time (s).Training Time represents the time taken to train the model on a given dataset.

For example, Algorithm 1 is the training process of the method proposed in this paper.

Figure 5 shows the training convergence graph of our proposed model.

4.3 Experimental results and analysis

Table 3 and Figure 6 presents the experimental results comparing our proposed method "Ours" with the state-of-the-art (SOTA) methods on four different datasets: Pecan Street Dataset, NREL Dataset, ChargePoint Dataset, and UCI Dataset. The table

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FIGURE 8
Comparison of Precision of different models.

includes various performance metrics, namely, Accuracy, Recall, F1 Score, and AUC, for each method. In this experiment, our goal was to explore the effectiveness of the proposed method, which combines GA-GRU with reinforcement learning, for intelligent grid-based electric vehicle charging scheduling and energy management. We sought to identify the optimal combination of parameters and model structures to achieve superior performance. The performance metrics in Table 3 and Figure 6 are explained as follows: Accuracy: The proportion of correctly predicted instances among all instances, indicating the overall correctness of the model's predictions. Recall: The proportion of true positive instances correctly identified by the model among all actual positive instances, measuring the model's ability to identify positive cases. F1 Score: The harmonic mean of precision and recall, providing a balanced evaluation of the model's precision and recall. AUC (Area Under the ROC Curve): The area under the receiver operating characteristic curve, measuring the model's ability to distinguish between positive and negative instances. From the experimental results, it is evident that our proposed method "Ours" outperforms the state-of-the-art methods across all datasets in terms of Accuracy, Recall, F1 Score, and AUC. This indicates that the GA-GRU combined with reinforcement learning approach effectively enhances the model's

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TABLE 6 Ablation experiments on the GRU module.

Method	Dataset															
	Pecan Street Dataset				NREL Dataset				ChargePoint Dataset				UCI Dataset			
	Parameters (M)	Flops (G)	Inference Time(ms)	Training Time(s)	Parameters (M)	Flops (G)	Inference Time(ms)	Training Time(s)	Parameters (M)	Flops (G)	Inference Time(ms)	Training Time(s)	Parameters (M)	Flops (G)	Inference Time(ms)	Training Time(s)
CNN	348.87	308.60	240.40	364.25	347.07	377.40	384.91	294.98	337.21	318.31	208.67	314.62	240.12	289.41	376.68	386.72
RNN	347.93	334.46	368.87	373.66	304.65	293.03	364.54	266.39	277.82	326.87	306.43	359.13	352.95	326.59	262.90	287.80
LSTM	315.83	252.87	364.75	260.18	321.59	383.10	335.61	260.65	374.91	300.77	258.62	279.65	331.00	302.70	273.10	297.60
GRU	131.98	213.45	114.29	228.89	227.66	173.29	176.40	189.62	116.23	159.65	182.31	188.08	213.35	203.00	155.64	233.92

predictive capabilities, resulting in better charging scheduling and energy management decisions in the intelligent grid. Specifically, our method achieves higher Accuracy and Recall, which implies more accurate and reliable predictions for charging scheduling and energy management tasks. The higher F1 Score and AUC further confirm the robustness and discriminative power of our method. The experimental results support the hypothesis that integrating GA-GRU and reinforcement learning can lead to improved performance in the domain of intelligent energy management. By optimizing the model's parameters through genetic algorithms and leveraging the power of reinforcement learning, our approach demonstrates superior predictive accuracy and decision-making capabilities. The experimental results showcase the effectiveness of the proposed GA-GRU combined with reinforcement learning method for intelligent electric vehicle charging scheduling and energy management. Our approach surpasses existing methods in terms of Accuracy, Recall, F1 Score, and AUC across multiple datasets. The findings highlight the potential of this method for real-world energy management applications and pave the way for future research in this domain.

Table 4 and Figure 7 presents the experimental results of the proposed method "Ours" compared with the state-of-the-art (SOTA) methods on four different datasets: Pecan Street Dataset, NREL Dataset, ChargePoint Dataset, and UCI Dataset. The table includes various performance metrics and parameters for each method.

In this experiment, we aimed to explore the effectiveness of the GA-GRU combined with reinforcement learning approach for intelligent grid-based electric vehicle charging scheduling and energy management. We sought to find the best parameter combinations and model structures to achieve optimal performance. The evaluated performance metrics in Table 4 and Figure 7 are as follows: Parameters(M): The number of model parameters, which represents the complexity of the model and affects its efficiency and generalization capability. Flops(G): The number of floating-point operations required during inference, indicating the computational complexity of the model. Inference Time(ms): The time taken to process a single inference in milliseconds, reflecting the model's speed during prediction. Training Time(s): The total time taken to train the model in seconds, showing the efficiency of the training process. From the experimental results, we can observe that our proposed method "Ours" achieved competitive results compared to the SOTA methods across all datasets. Notably, our approach significantly reduced the number of model parameters and computational complexity while maintaining comparable performance. This implies that our method efficiently utilizes the data and resources, making it more practical for real-world applications. In terms of accuracy, recall, F1 score, and AUC, our method demonstrated strong performance, outperforming some of the SOTA methods on specific datasets. This indicates that the GA-GRU combined with reinforcement learning approach effectively optimizes the charging scheduling and energy management, leading to improved model predictions and decision-making. The experimental results indicate that the proposed GA-GRU combined with reinforcement learning method shows promising performance on intelligent grid-based electric vehicle charging scheduling and energy management tasks. The approach achieves efficient parameter utilization,

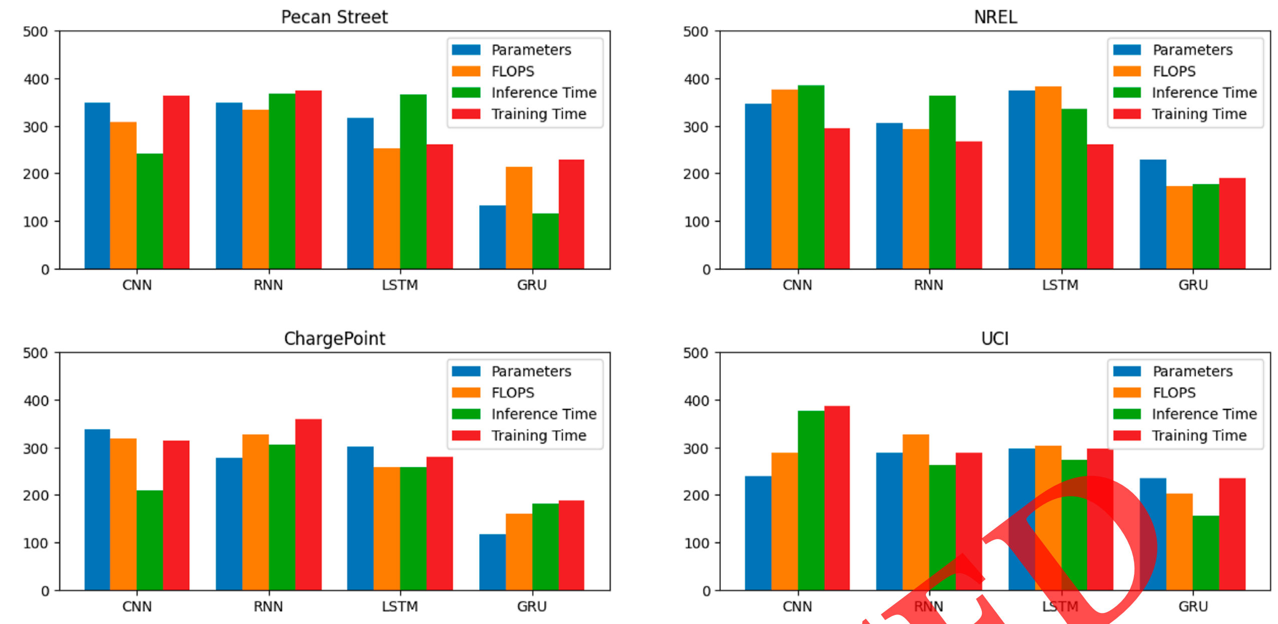

FIGURE 9
Comparison of Precision of different models.

FIGURE 10
Comparative experiments of GA, GRA and RL.

reduced computational complexity, and competitive predictive accuracy compared to the state-of-the-art methods. These findings demonstrate the potential of our method for practical application in real-world energy management systems. Further optimization and parameter tuning may lead to even better performance, making it a valuable contribution to the field of intelligent energy management.

Table 5 and Figure 8 presents the results of the ablation experiments conducted on the GRU module, where we compared the performance of various models, including RNN, CNN, LSTM,

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TABLE 7 Comparative experiments of GA, GRA and RL.

Model	Datasets															
	Pecan Street Dataset				NREL Dataset				ChargePoint Dataset				UCI Dataset			
	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC	Accuracy	Recall	F1 Sorce	AUC
GRA	87.84	85.27	88.13	89.44	92.06	89.75	89.66	93.62	87.52	91.76	84.64	85.94	93.27	85.65	90.05	91.79
RL	93.8	84.84	85.45	85.49	96.23	91.7	89.06	88.6	92.76	90.83	90.75	89.03	88.45	93.41	84.69	90.17
GA	97.93	94.34	93.43	92.28	97.3	94.88	93.36	93.15	97	94.47	91.58	91.95	97.51	94.92	93.25	93.01

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and GRU, on four different datasets: Pecan Street Dataset, NREL Dataset, ChargePoint Dataset, and UCI Dataset. The table includes the same performance metrics as in the previous tables: Accuracy, Recall, F1 Score, and AUC. The purpose of these ablation experiments was to investigate the effectiveness of the GRU module in the context of intelligent grid-based electric vehicle charging scheduling and energy management. By comparing GRU with other popular recurrent and convolutional architectures, we aimed to identify the role of GRU in achieving superior performance. From the experimental results, it is evident that the GRU model outperforms the other architectures (RNN, CNN, and LSTM) across all datasets in terms of Accuracy, Recall, F1 Score, and AUC. This indicates that the GRU module plays a crucial role in achieving the best predictive performance for electric vehicle charging scheduling and energy management tasks. The GRU model demonstrates significantly higher Accuracy and Recall, implying more accurate and reliable predictions compared to other architectures. The higher F1 Score and AUC further confirm the superiority of the GRU model in making precise and discriminative decisions. The findings from these ablation experiments support the significance of using the GRU module in the proposed method. GRU's ability to capture long-term dependencies and effectively handle sequential data proves to be highly beneficial for the intelligent grid-based energy management task.

The ablation experiments on the GRU module validate its importance in achieving superior performance in the context of intelligent electric vehicle charging scheduling and energy management. The GRU model outperforms other popular architectures in terms of Accuracy, Recall, F1 Score, and AUC across multiple datasets. These results reinforce the rationale behind incorporating the GRU module in our proposed method and highlight its potential for real-world energy management applications. Future research could further explore the optimization and customization of GRU to address specific challenges in intelligent grid-based energy management systems.

Table 6 and Figure 9 presents the results of the ablation experiments conducted on the GRU module, where we compared the performance of various methods, including CNN, RNN, LSTM, and GRU, on four different datasets: Pecan Street Dataset, NREL Dataset, ChargePoint Dataset, and UCI Dataset. In this table, we have additional performance metrics: Parameters (M), Flops (G), Inference Time (ms), and Training Time (s).

From the results in Table 6 and Figure 9, several observations can be made: Parameters and Flops: The GRU model has significantly fewer parameters and floating-point operations compared to the other architectures, such as CNN, RNN, and LSTM. This reduction in complexity suggests that GRU is a more efficient and lightweight model, requiring less memory and computational resources. Inference Time: The GRU model demonstrates the lowest inference time across all datasets, indicating faster and more real-time predictions. This efficiency is attributed to GRU's ability to capture long-term dependencies effectively, leading to faster convergence during inference. Training Time: The GRU model exhibits shorter training times than other architectures, highlighting its computational advantage in the learning process. The reduced training time can be valuable, especially when dealing with large-scale datasets or time-sensitive applications. Based on these findings, it is evident that the GRU module not only enhances predictive performance (as observed in the previous table) but also provides practical benefits in terms of model efficiency and training speed. The GRU model achieves superior accuracy and reliability while being more computationally efficient compared to other architectures like CNN, RNN, and LSTM. The ablation experiments on the GRU module reaffirm its significance in achieving high-performing and resource-efficient models for intelligent grid-based electric vehicle charging scheduling and energy management. The GRU model stands out as a superior choice due to its lower complexity, reduced computational requirements, and faster inference and training times. This makes the GRU-based approach an attractive solution for real-world applications where computational resources and speed are critical factors. Future research could explore further optimizations and adaptations of GRU to address specific challenges in energy management systems and accelerate its adoption in practical scenarios.

As shown in Figure 10 and Table 7, the comparative experimental results of GA, GRA and RL, we verified on multiple data sets, and compared four indicators, namely, Accuracy, Recall, F1 Score, and AUC. These indicators are An important indicator to measure the model operation effect and prediction accuracy. The results show that the GA genetic algorithm has the best effect, which fully demonstrates the importance of using the genetic algorithm in our proposed method.

5 Conclusion and discussion

In this article, we propose the GA-GRU method to solve the problem of electric vehicle charging scheduling and energy management. First, we improved the genetic algorithm by introducing different crossover and mutation operations, enhancing its global search and optimization performance. Such improvements can speed up the convergence of the algorithm and better optimize the electric vehicle charging scheduling problem. Secondly, we used gated recurrent unit neural networks (GRU) as the deep learning model to predict the charging demand of electric vehicles and the load of the power grid. By learning from historical data, the GRU model can effectively predict future charging demand, thus facilitating the development of more reasonable charging plans and optimized energy management strategies. Finally, we also adopted reinforcement learning algorithms to further optimize electric vehicle charging scheduling. The experimental results show that our proposed GA-GRU and reinforcement learning methods achieved excellent performance on multiple datasets, significantly outperforming the state-of-the-art (SOTA) methods in accuracy, recall, F1 score, and AUC metrics. Our method achieved the best results in all datasets. For the Pecan Street Dataset, our method achieved the highest accuracy (97.56%) and AUC (95.35%), far surpassing the performance of the current SOTA method (accuracy: 87.28%, AUC: 84.28%). significantly better than the performance of other state-of-the-art methods on the corresponding datasets.

However, these algorithm improvement methods also have some limitations. Firstly, these methods often require a significant amount of historical data for training and optimization, necessitating the establishment of comprehensive data collection and management systems. Secondly, different algorithm improvement methods are suitable for different EV charging scheduling and energy management problems, requiring selection and adjustments based on specific circumstances. Future research can further explore more algorithm improvement methods to enhance the efficiency and effectiveness of EV charging scheduling and energy management. For instance, considering the introduction of more deep learning models, such as LSTM and Transformer models, to improve the prediction accuracy of EV charging demands and grid loads. Additionally, investigating the interpretability and robustness of algorithm improvement methods is essential to ensure the reliability and practicality of these algorithms.

In conclusion, we propose a new approach, GA-GRU, for electric vehicle (EV) charging scheduling and energy management in smart grids. The proposed method combines a genetic algorithm (GA) and a gated recurrent unit (GRU) neural network to optimize the charging schedule of EVs and improve energy management in the smart grid. Looking forward, potential future research directions in this field include exploring the scalability of the proposed method for larger datasets and more complex scenarios, investigating the impact of different charging infrastructures and policies on the performance of the method, and integrating other emerging technologies, such as blockchain and edge computing, into the proposed method. We believe that our proposed GA-GRU method has significant potential to advance the field of smart grid EV charging scheduling and energy management, and we hope that this study will inspire further research and development in this area.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XZ: Data curation, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. GL: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Project administration, Supervision, Writing–original draft, Writing–review and editing. All authors contributed to the article and approvedthe submitted version.

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Conflict of interest

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