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Original scientific paper

An Electric Vehicle Charging Control System using LSTM Encoding-GRU Decoding

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Abstract: Electric vehicle (EV) charging is random in time and space, and a large number of electric vehicles connected in a short period of time will cause the phenomenon of "peak on peak" in the community power grid load, which has certain safety risks. The microset metering system can effectively control the charging and discharging of electric vehicles, greatly reducing the transformer load and ensuring safety. However, existing technology only regulates electricity consumption based on the current moment, and this method does not provide an estimate of what may happen in the future. We have made improvements to address this issue. The total electricity consumption of a common community consists of unchangeable public infrastructure electricity and changeable residential electricity. We divide residential electricity consumption into two categories: residential domestic electricity consumption and charging pile electricity consumption. Long Short Term Memory (LSTM) encoding- Gate Recurrent Unit (GRU) decoding is used to predict short-term residential electricity consumption, and then the transformer full load value minus the difference between the unchanged public infrastructure electricity consumption and the residential electricity consumption is used as the upper threshold for charging at the charging piles, which is finally utilized to stagger the EV charging. After constructing the complete system, we conducted relevant simulation experiments to verify our ideas, and the simulation results show that our method has some effectiveness.

Keywords: LSTM-GRU; staggered charging of electric vehicles; time series data

1 INTRODUCTION

With the construction of new power systems, a high proportion of renewable energy generation goes online, and a large number of electric vehicles and other diversified loads are connected, putting forward higher requirements for data collection, real-time control, online monitoring, and cooperative interaction. So far, on the EV charging and discharging distribution business scenario, residential EV charging has temporal and spatial uncertainty [1], and if a large number of EVs are connected to charging piles in a short period of time, it may lead to transformer overload, thus causing serious safety problems [5-6]. Therefore, in view of the above-mentioned development situation and problems, it is necessary to carry out the research and application of "microset metering system for new power system" as soon as possible, to clarify the technical route of microset metering system with the systematic thinking of "integrated micro-grid", and to improve the performance of microset metering system through digital upgrading and intelligent technology application, the system can fully mobilize its flexibility, promote the interaction between source, network, load and storage, adapt to the construction of flexible and open power market, and achieve the goal of improving system operation efficiency and global optimization of resource allocation.

By integrating software and hardware, the microset metering system establishes an automated control process known as cloud-algorithm-device. Historical data is stored in the cloud, algorithms are employed for analysis and modelling, and ultimately, microset metering switches are utilized for control, enabling automation throughout the entire process. However, existing micro-collector metering systems for EV charging and discharging planning are primarily based on current electricity consumption levels [7-10]. When the electric vehicle needs to be scheduled, a safety threshold is calculated using the power consumption at the current point in time to ensure the safe charging of all subsequent vehicles. When the charging peak is encountered, these methods will adopt conservative control strategies, such as directly restricting the entry of subsequent vehicles or reducing the power of the charging pile, which greatly affects the efficiency of charging.

Based on the above ideas, the electricity consumption in the short term is a key issue that needs to be solved urgently [2-4]. Wan et al [17] used SVMs to forecast short-term electricity load in a region with certain results. Feng [18] and Li [19] used Random Tree algorithm to forecast the electric load, but those methods will have obvious overfitting defects on larger data.

Power companies collect data based on timestamps, creating high-quality time series data. In the field of deep learning, LSTM and GRU models are commonly used to process such data. For example, Zhang et al. [11, 12] utilized time series data, implementing convolutional networks for encoding and LSTM networks for decoding, achieving accurate forecasts. Wang et al. [13] proposed a model based on LSTM and recurrent neural networks that capture short-term dependence for accurate prediction. Zhang [14] further proposed a combined prediction model incorporating time series data and cross-entropy, demonstrating its efficacy through thorough experimentation with a single model. These scholarly endeavours have inspired our research significantly.

In our research, the overall electricity consumption in a residential area comprises both fixed public infrastructure electricity consumption and variable residential electricity consumption. Residential electricity consumption can be further categorized into household electricity consumption and charging pile electricity consumption. First, we can use a LSTM encoding-GRU decoding neural network to predict the short-term household electricity consumption. Then we can calculate the safety threshold of charging pile by using the total transformer load, the short-term household electricity consumption and the electricity consumption of public facilities, so as to realize the charging control of electric vehicles. The specific process is introduced in Chapter 2.

2 STAGGERED CHARGING AND DISCHARGING OF ELECTRIC VEHICLES BASED ON MICROSET METERING SYSTEM

The schematic diagram in Fig. 1 illustrates the staggered charging and discharging of electric vehicles using a microset metering system. Cloud-based Big Data is responsible for storing historical and real-time data of electricity consumption of community utilities (denoted by S), transformer load limit threshold (denoted by L), electricity consumption of residential life (denoted by P) and electricity consumption of charging piles (denoted by C). The electricity consumption of public facilities is fixed, which implies that C is a constant. LSTM encoding-GRU decoding neural network is used to learn P (the historical data of residential electricity consumption) and predict the future short-term household electricity consumption (denoted by $\hat{P}$). Then calculate the threshold value T by equation $T = L - S - \hat{P}$. Finally use T (the threshold value) combined with the microset metering switch to reasonably schedule the charging and discharging of electric vehicles. The microset metering switch is capable of disconnecting the fully charged EVs and stopping the charging of newly connected EVs when the total load of the charging pile approaches the safety threshold. Until the total load of the charging pile drops to a reasonable interval, charging of newly connected EVs is resumed.

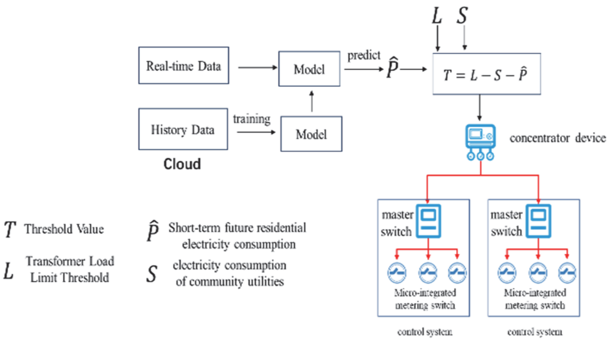

Figure 1 Staggered charging and discharging of electric vehicles based on microset metering system

3 PREDICTION MODEL BASED ON LSTM ENCODING-GRU DECODING

Deep learning has shown that LSTM and GRU networks are adept at processing time-series data. Leveraging the predictive power of LSTM and GRU networks with prior resident electricity consumption data, we have adopted this method to forecast short-term electricity usage.

3.1 LSTM Block

LSTM (Long Short-Term Memory) [15] is a type of RNN network that was proposed by Hochreiter and Schmidhuber in 1997. Compared to traditional RNN networks, LSTM networks can effectively solve the long-term dependency problem by its ability to store and access long-term memory, as well as filter unimportant information while maintaining long-term memory.

The main components of LSTM networks include three gating units: the input gate, the forgetting gate, and the output gate. The output gate controls the update of new input information, which is calculated as Eq. (1). The forgetting gate controls the forgetting of historical information, which is calculated as Eq. (2) and Eq. (3). The output gate controls the information output from LSTM network, which is calculated as Eq. (5) and Eq. (6). The structure of LSTM network is shown in Fig. 2.

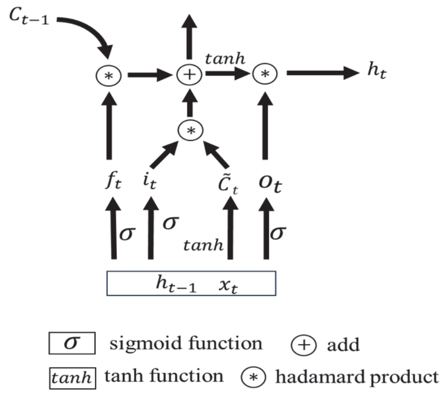

Figure 2 LSTM structure

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{2}$$

$$\tilde{C}_t = \tan h\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{3}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{4}$$

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{5}$$

$$h_t = o_t \tan h\left(C_t\right) \tag{6}$$

where x_t is the input data at the current time; σ represents sigmoid function; tan h represents tan h activation function; W_f, W_i, W_c, W_o, represent different weight matrices respectively; b_f, b_i, b_c, b_o represent different biases, which can be randomly generated by a computer; * means element-wise multiplication. Eq. (4) is used to update the output state; C_t, C_{t-1}, h_{t-1} and h_t are the memory states; f_t, i_t, o_t, $\tilde{C}_t$ are the intermediate variable.

3.2 GRU Block

GRU (Gated Recurrent Unit) [16] is a recurrent neural network (RNN) that excels in modeling sequential data. Compared with traditional recurrent neural networks, GRU has fewer parameters and more modeling power. The main feature of GRU network is the introduction of two gating units: the update gate and the reset gate. The update gate is used to control whether the network passes the state information from the previous moment to the current moment, which is calculated by Eq. (7), while the reset gate is used to control whether the network merges the state information from the previous moment with the current input, which is calculated by Eq. (8). These two gating units enable the GRU network to better handle long sequences of data and avoid the problem of gradient disappearance or explosion.The computation process of the GRU network can be simply described as follows: for a given input sequence, at each time step t, the GRU network will compute a new state based on the current input and the state of the previous moment. This new state will be passed to the next time step and used as the input for the next time step. The structure of the GRU network is shown in Fig. 3.

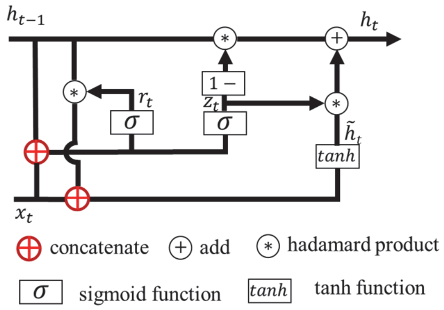

Figure 3 GRU structure

$$z_t = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right] + b_z\right) \tag{7}$$

$$r_t = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right] + b_r\right) \tag{8}$$

$$\tilde{h}_t = \tan h\left(W_h \cdot \left[r_t \cdot h_{t-1}, x_t\right] + b_h\right) \tag{9}$$

$$h_t = \left(1 - z_t\right) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{10}$$

where, h_{t-1}, x_t denote inputs, h_t denote outputs; W_z, W_r, W_h denote different weight matrices; b_z, b_r, b_h denote different biases, which can be randomly generated by computer; z_t, r_t, $\tilde{h}_t$ are intermediate variables.

4 LSTM CODING-GRU DECODING BASED NETWORK CHARGING LOAD PREDICTION PROCESS

Fig. 4 illustrates the elegant architecture of the LSTM encoding-GRU decoding model. The input time series data undergoes a sophisticated encoding process within the LSTM block, producing a highly informative encoding. The encoded result is then seamlessly transferred to the GRU block where it is skillfully decoded to generate the desired output for decoding. The number of LSTM and GRU blocks, denoted as "n", is dynamically determined based on the sampling frequency. As an example, if the sampling frequency is set at 15 minutes, a total of 96 time data points are sampled each day, leading to n being equivalent to 96.

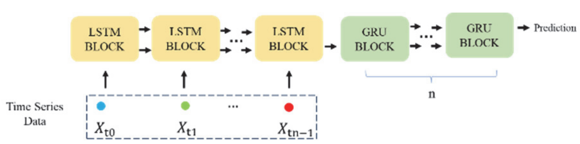

Figure 4 The structure of the LSTM encoding-GRU decoding model

The charging load prediction process using LSTM encoding-GRU decoding network is shown in Fig. 5, which can be divided into the following three main steps.

(1) Data pre-processing: Missing values are filled first, and then the training set and test set are divided.

(2) Model training: The data sampled at different moments of each day are input to the LSTM in a temporal sequence according to the time order, and the LSTM is used to encode the data in a time series, and then the encoded features are input to the GRU for decoding, and the decoded data are combined with the location and quantity information to form new input features to the two fully connected layers for predicting the data.

(3) Result evaluation: The trained model is predicted on the test set, and the fit between the predicted and true values is measured using performance evaluation metrics.

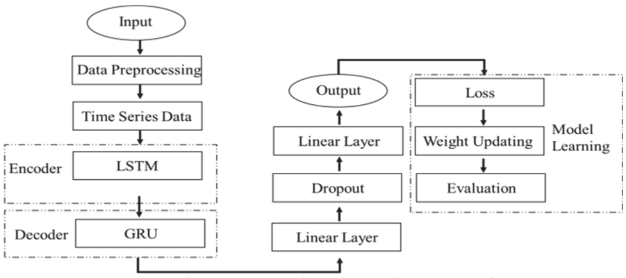

Figure 5 Prediction of charging load flow using LSTM coding-GRU decoding network

5 EXPERIMENT

5.1 Data Preprocessing

(1) Missing value processing.

In the data, missing values refer to data that is absent or unknown in some records or variables. To fill in the missing values, we use the mean substitution method to fill in the missing values data by replacing them with the mean.

(2) Feature scaling.

A depth network is more sensitive to the input data. If there is a large gap in the scale between the input features, it can impact the network convergence, so we normalize the data by dividing all the features between 0 and 1.

(3) Splitting the dataset.

In order to ensure that the data distribution of the validation set is as consistent as possible with that of the training set, we split the training and validation sets into intervals of 10, using 9 consecutive days for training data and 1 day for testing data to ensure that the data distribution of the validation set is consistent with that of the training set.

5.2 Model Parameter Design

This experiment is implemented in Python using the PyTorch deep learning toolkit to build the model framework. During the training process, the ReLU activation function is used and the loss function chosen is mean square error. The batch size is 128; the epoch is 30. The SGD optimizer with driving volume is selected. The learning rate and momentum parameters are set to 0.001 and 0.9, respectively. The hidden layer dimensions of LSTM and GRU are both 256. After the input data is processed by LSTM-GRU, we select the final output as the input of our subsequent fully connected network. Our fully connected network consists of two layers, each of which adopts relu activation function. The first layer of the network maps 256 dimensions to 256 dimensions, while the second layer of the network maps 256 dimensions to 1 dimension. To prevent overfitting, the Dropout method is used between the fully connected layers during training.

5.3 Metrics

In this paper, three most common evaluation metrics are used to measure the strength of the model regression ability, which are: mean square error (*MSE*), root mean square error (*RMSE*) and mean absolute error (*MAE*). Their formulas are given in Eq. (11) to Eq. (13).

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left(\hat{yi} - yi\right)^2 \tag{11}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(\hat{yi} - yi\right)^2} \tag{12}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}\left|\hat{yi} - yi\right| \tag{13}$$

6 EXPERIMENTAL RESULTS AND ANALYSIS

6.1 Data Analysis

Six years of residential electricity consumption data from a Chinese community were selected for analysis, and the average monthly electricity consumption is shown in Fig. 6.

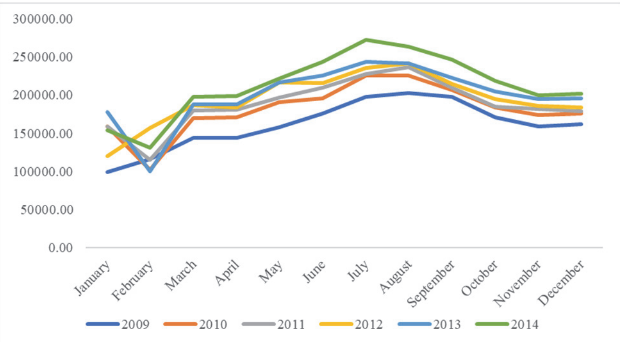

Figure 6 Average monthly electricity consumption

From the average monthly electricity consumption in the past five years, it can be seen that the overall trend of electricity consumption by customers started to rise from January, peaked in July, and then started to fall back. The peak period is mainly concentrated in June, July, August and September, probably due to the rising temperature in summer and the longer time of cooling equipment use such as air conditioners. In summer, the high demand for electricity from residents, high ambient temperature and dry weather are more likely to cause safety accidents, so the restriction on the number of charging cars accessing should be stricter and a conservative strategy for staggered charging should be adopted.

6.2 Experiment Analysis

We used three sets of sampling frequencies for sampling, namely, data collection at 15 minute intervals, for a total of 96 sets of data per day for each charging post; data sampling at 30 minute intervals, for a total of 48 sets of data per day for each charging post; and data sampling at 45 minute intervals, for a total of 32 sets of data per day for each charging post.

Through the comprehensive analysis of Tab. 1 to Tab. 3 and Fig. 7 to Fig. 9, it is evident that the proposed LSTM encoding-GRU decoding method exhibits superior performance in terms of regression error compared to other methods, irrespective of the adopted time sampling rate and performance evaluation index. For instance, when considering sampling frequencies of 15 minutes, 30 minutes, and 45 minutes, the Mean Absolute Error (MAE) values are 0.0137, 0.0199, and 0.0336, respectively, leading to improved regression accuracy.

The underlying rationale behind these commendable results lies in the ability of the network to learn from historical data, thereby introducing constraints that facilitate a smoother curve fitting process for subsequent data points. Fig. 5 further enhances our understanding, as it illustrates that electricity consumption patterns for residents across different years follow a similar trend. Beginning in January, consumption gradually increases before subsequently declining. This understanding serves as a foundational basis for the network's predictions.

Considering the forecasted data for October as an example, the network assimilates insights from past data, specifically noting the larger electricity consumption in July and August followed by a gradual decline. Consequently, when predicting the October dataset, the network is restrained by the historical data, ensuring that the predicted values do not surpass the previous observations.

Table 1 Performance of different models at a sampling frequency of 15 minutes

Model	MSE	RMSE	MAE
SVM	0.0460	0.2144	0.760
Decision tree	0.0304	0.1743	0.041
Random Forest	0.0162	0.1272	0.028
Ours	**0.0137**	**0.1170**	**0.023**

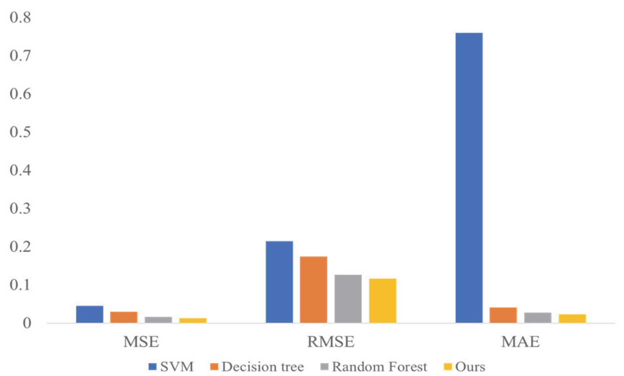

Figure 7 Performance of different models at a sampling frequency of 15 minutes

Table 2 Performance of different models at a sampling frequency of 30 minutes

Model	MSE	RMSE	MAE
SVM	0.0520	0.2280	0.817
Decision tree	0.0312	0.1766	0.044
Random Forest	0.0238	0.1542	0.031
Ours	**0.0199**	**0.1401**	**0.028**

Table 3 Performance of different models at a sampling frequency of 45 minutes

Model	MSE	RMSE	MAE
SVM	0.0830	0.2880	0.923
Decision tree	0.0425	0.2061	0.063
Random Forest	0.0414	0.2034	0.063
Ours	**0.0336**	**0.1833**	**0.047**

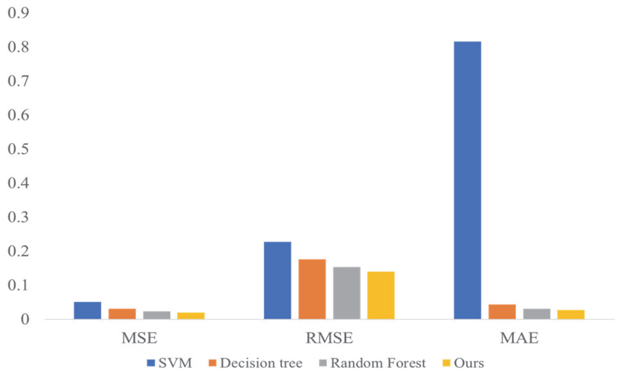

Figure 8 Performance of different models at a sampling frequency of 30 minutes

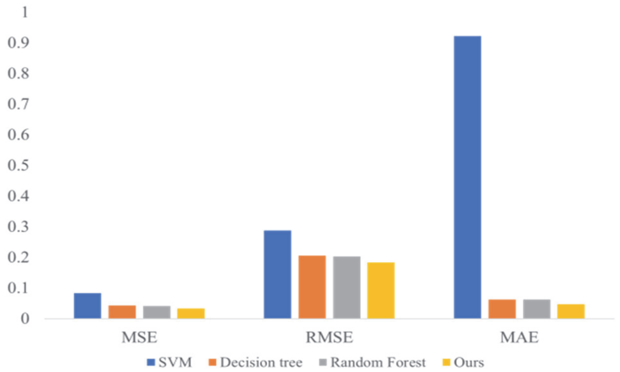

Figure 9 Performance of different models at a sampling frequency of 45 minutes

7 SCHEDULING ANALYSIS

Based on our ideas presented in the first chapter, we conducted simulation experiments with 200 electric vehicles. The specific scheduling results are shown in Fig. 10.

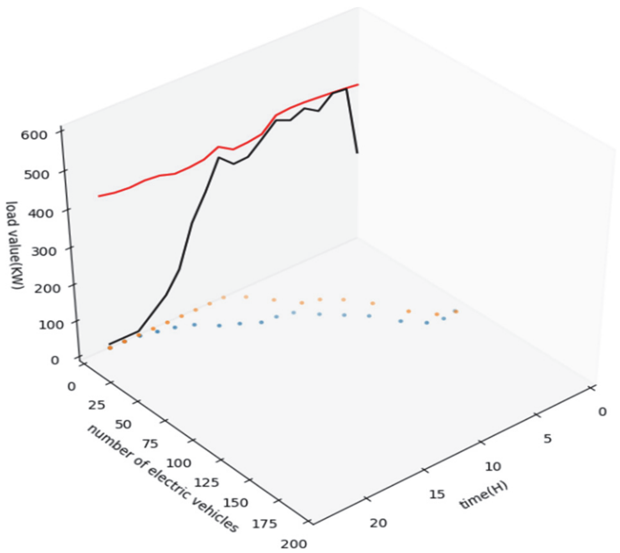

Figure 10 Results of 200 electric vehicle schedule

The figure clearly demonstrates the effectiveness of our method in managing electricity consumption during peak periods. It shows that our approach guarantees that the total load of the currently charging vehicle (represented by the black line) remains consistently below the safety threshold (represented by the red line). Moreover, it ensures that the total load remains close to the safety threshold without exceeding it. Additionally, the figure illustrates a downward trend in both the number of electric vehicles being charged (represented by blue dots) and the number of electric vehicles waiting to be charged (represented by green dots). The decrease in blue dots indicates that our method successfully meets the charging needs of vehicles, allowing them to be fully charged and leave the charging station. The decline in green dots suggests a continuous influx of cars waiting to connect to the charging station.

8 CONCLUSION

EV charging has temporal and spatial uncertainties, and if a large number of vehicles are connected to the charging station at the same time, it can lead to overloading of the transformer, causing serious safety issues. In order to optimize the EV charging and discharging peaks, we use a deep learning method based on LSTM coding- gru decoding to predict the residential domestic electricity consumption in the microcollector metering system using the difference between the total transformer load and the public infrastructure electricity consumption minus the predicted residential electricity consumption as a threshold value in the cloud. The threshold is used as a constraint to control the charging and discharging of electric vehicles in conjunction with microcollector metering switches. In order to verify the effectiveness of the prediction method, we input the daily data into the network according to the time that constitutes the time series, and encode the data by utilizing the powerful parsing ability of LSTM on the time series, and the encoded data will be inputted into the GRU network for decoding. The final output of the GRU network is then selected as the feature input of the fully connected network for regression prediction. The experimental results show the effectiveness of the method on MAE, MSE and RMSE metrics. In order to verify the security of scheduling, we combined the prediction algorithm to simulate the scheduling experiments based on the micro-set metering system. The results of the simulation experiments show that the method can effectively realize the staggered charging of electric vehicles under the premise of ensuring safety. The experiments also show that the microcollective metering system based on intelligent algorithms and microcollective metering switches has a bright application prospect in the field of electric power security by using the cloud as a carrier and forming a cloud algorithm-equipment automation control through the combination of hardware and software.

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