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Optimization Strategies for Real-time Energy Management of Electric Vehicles Based on LSTM Network Learning

Abstract: - The orderly control of electric vehicle load can improve the load characteristics of regional power grid and reduce the charging cost. Since it is impossible to predict the accurate access time and charging demand of electric vehicles in the future, it is impossible to make a global optimal arrangement for accessing the grid when electric vehicles are charging. Aiming at this problem, a real-time energy management system and optimization strategy of electric vehicle based on deep long-term and short-term memory neural network are proposed. Firstly, a three-tier electric vehicle management architecture including power grid layer, regional energy management system and charging station energy management system is constructed to manage large-scale electric vehicles in layers and regions; Then, a region station interaction strategy based on deep long-term and short-term memory neural network is proposed. The historical optimal solution solved by historical load information is used to train the learning network to guide the new real-time optimization; The proposed strategy can further reduce the charging cost and improve the peak valley characteristics of regional load on the premise of ensuring the charging demand of users. Finally, a simulation example is given to verify the effectiveness and superiority of the proposed layered architecture and management strategy.

Keywords: Electric vehicle, Layered architecture, Short and long term memory neural network, Deep learning, Ordered scheduling strategy.

I. INTRODUCTION

A. Background

The massive load growth brought by the large number of electric vehicles (EVs) coming online further exacerbates the peak-to-valley load difference in the distribution network, which negatively affects the safe operation of the distribution network. The literature [1]-literature [2] provides a detailed review of the impact of EV access on the grid, and how to effectively regulate EVs is a current research hotspot.

A series of studies have been carried out by scholars at home and abroad to solve the problem of orderly charging of EVs. The current more feasible idea is to manage EVs in a hierarchical partition. Literature [3] introduced the concept of EV hierarchical partitioned scheduling and constructed an EV charging and discharging scheduling model based on a two-layer optimization model; literature [4] established a two-stage optimization model with the objectives of minimizing the squared difference of the total system load and maximizing the transferable charging and discharging, and used yalmip to solve it. Literature [5]-Literature [6] constructed a two-tier coordinated optimization model containing EV and renewable energy and solved the whole model using genetic algorithm. The hierarchical partitioned management approach effectively reduces the size of the EVs dispatched by each agent and greatly reduces the computational effort and computational time for model solving. The algorithms proposed in the above literature are all a deterministic local optimization algorithm, which can only consider the currently connected EVs and the grid state, and the solution results are only the local optimal solutions for that time period, and there is still some optimization space for the results from the consideration of the global load level of the day.

B. Our Motivation

Considering that the grid load and EV charging load are time-series data and show periodic patterns under certain time scales. And the deep long short term memory (LSTM) is a deep learning algorithm based on recurrent neural network (RNN) improvement, which has good effect on processing time series data [7].The regular information in the historical serial data can be learned effectively.

Therefore, an EV 3-tier energy management system based on deep learning of LSTM networks is proposed. Based on the 3-tier energy management architecture consisting of the dispatch center (grid layer), which is responsible for the grid, the regional energy management system and the charging station energy management system, which is responsible for the agents, the historical base load of the grid and the EV historical load data are used to solve the optimal solution of the historical dispatch optimization task, which is used to train the learning

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network, and the network is used to quickly and efficiently guide the optimization of the current real-time EV dispatch task. Finally, the effectiveness, flexibility and superiority of the proposed method are verified by simulation calculations

II. EV 3-TIER ENERGY MANAGEMENT SYSTEM

A. *Three-layer Architecture Model*

Based on the 3-layer architecture model of EV charging energy management including grid layer, regional energy management system and charging station energy management system proposed in literature [8], the architecture model is further improved by combining LSTM learning network as shown in Figure 1.

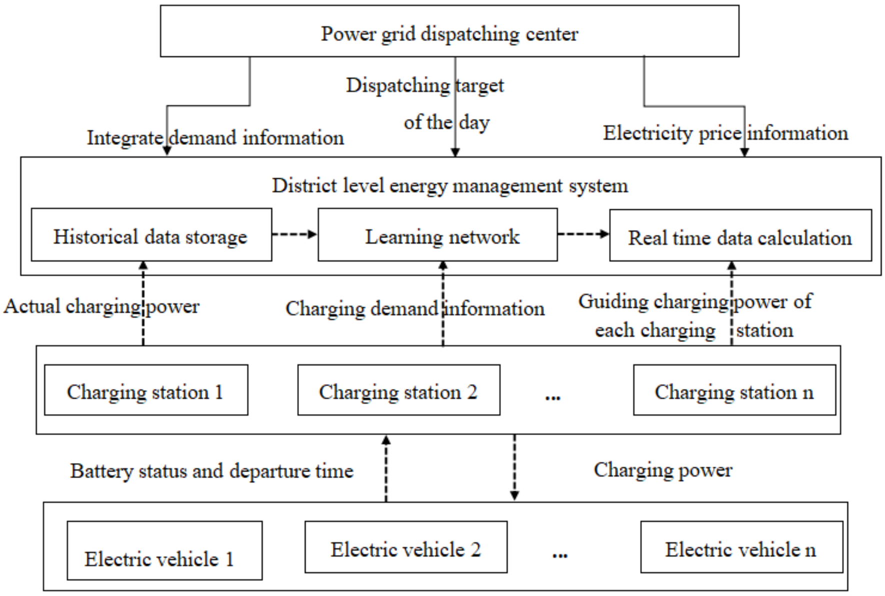

Figure 1: Three tier management structure of electric vehicle

Since the main functions of each layer of the EV 3-tier architecture management system are similar to existing research, among which the key of the grid layer strategy is to set the guiding tariff or to set the charging power threshold, and there are more research results [9-12], the research in this paper focuses on how the energy management system constructs the optimal guiding charging power deep learning network, the method to develop the guiding charging power based on this learning network, and the charging station energy In this paper, we focus on how the energy management system constructs the optimal guiding charging power deep learning network, the method to develop the guiding charging power based on the learning network and the allocation strategy of the charging station energy management system to the guiding charging power.

B. *Three-tier Architecture Energy Management Process*

The 3-tier energy management flow chart is shown in Figure 2.

Prior to the start of daily moderation, the RMS is required to perform 3 steps.

(1) Receive information from the dispatch layer on the guide tariff $c(t)$ (yuan/kWh) for that day based on the historical load; the regional charging load power limit $M(t)$ (kW); and the dispatch target for that day [13-15].

(2) Based on the historical EV load simulation optimization process, calculate the optimal solution for each station-level management system-guided charging power under the condition that the exact EV access time and charging demand for the whole day are known (the objective function is consistent with the scheduling objective issued by the scheduling layer).

(3) Using the calculated historical daily optimal solution of the guiding power as the learning objective, a deep learning network of guiding power is constructed based on historical load data and historical electricity price information, ready to start the regulation for that day.

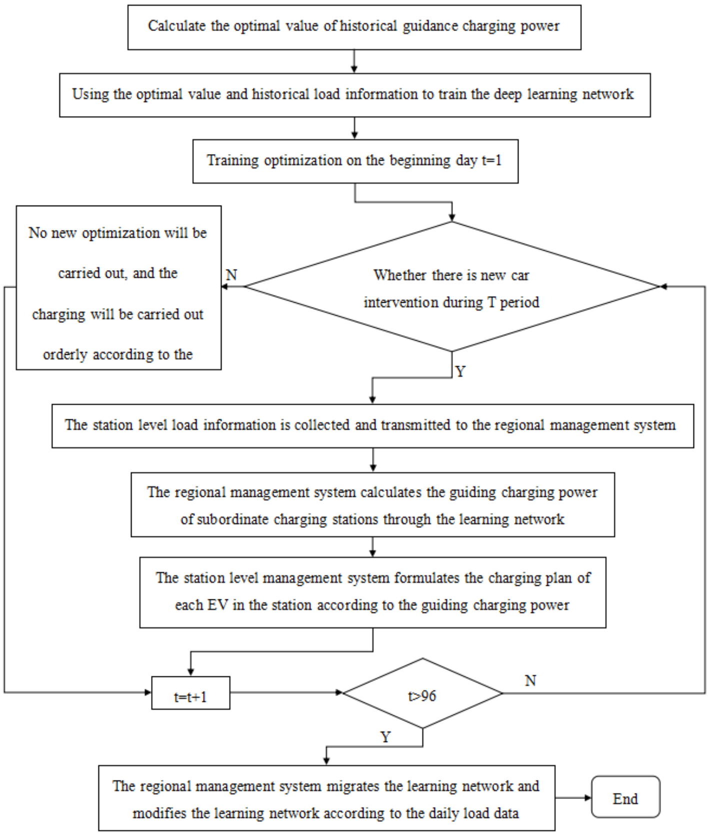

Figure 2: Three-tier architecture energy management process

After receiving the tariff information and power limit from the dispatching layer, the EV charging is controlled in real time by the regional management system in cooperation with the station level management system. A day is divided into 96 control periods (each period is 15 min long), and the end of each control period is used as an optimization calculation point for that period to optimize the charging behavior of EVs waiting to be charged.

Assuming that a total of n EVs are connected to all charging stations in the region during a control period (none of them are fully charged) [16-19], the process of optimizing these n EVs at the end of that control period and calculating their charging power for the next control period requires a 3-step process.

(1) Each station-level management system counts the battery type and status information (current battery status $SOC_{i,j,t}$ and battery capacity $B_{i,j}$) of m vehicles among n EVs that still have optimization margin, the time period T at the arrival time $T_{i,j,0}$, the time period $T_{i,j}$ at the departure time, the number of time periods required to be filled, the type of charging post (DC charging post or AC charging post) to which the vehicle belongs and its corresponding charging power rating P^{DC} and P^{AC}, and calculates the average urgency factor $R_{i,j(t)}$ of vehicles in each charging station. The average urgency factor $R_{i,j(t)}$ of the vehicles in each charging station is calculated as in equation (1), and this information is uploaded to the regional management system.

$$R_{i,j}(t)=\frac{(T_{i,j}-T_{i,j}^{lastest})}{(T_{i,j}-t)},t=T_{i,j,0},T_{i,j,0}+1,...T_{i,j}^{lastest} \tag{1}$$

In which: $T_{i,j}^{lastest}$ is the time period in which the jth EV at the ith charging station has its latest charging moment, which is calculated as follows

$$T_{i,j}^{lastest}=T_{i,j}-\frac{(1-SOC_{i,j}(t))\times B_{i,j}}{P_{i,j}^{N}} \tag{2}$$

In which: $P_{i,j}^{N}$ is the rated charging power of the jth EV at the ith charging station.

(2) After receiving the information submitted by each station-level management system in its jurisdiction, the regional base load data, tariff, EV quantity and urgency information for that control period and the previous periods

are input into a deep learning neural network, which calculates the guiding charging power $P_i^{ref}(t+1)$ for each charging station in the next control period and issues it to the corresponding station-level management system.

(3) The station-level management system receives the instruction charging power command and uses it as a reference to allocate charging power to EVs in m vehicles in the station, calculates the charging power of each EV in the next control period, and sends it to the corresponding charging post.

III. Regional EV Management System Based on LSTM Network Learning

A. *LSTM Cell Structure*

Since the guided charging power of each charging station is actually a set of time series, and the LSTM model in the deep learning model happens to have the memory capability to learn the information in the historical series data effectively, the long short-term memory deep neural network model is used.The cell structure of the LSTM is shown in Figure 3 .

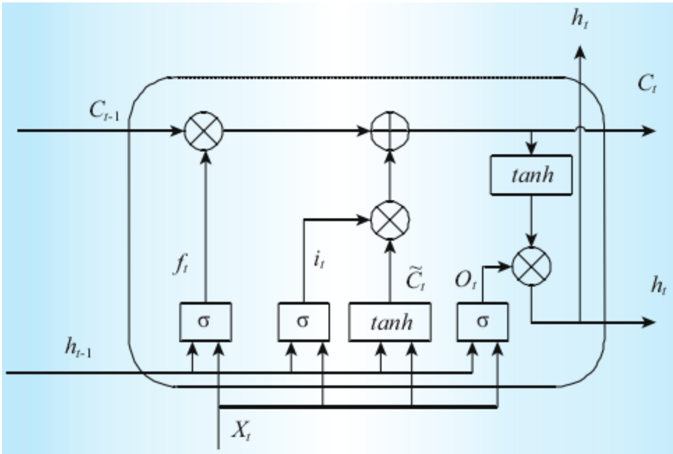

Figure 3: LSTM unit structure

In Figure 3 C_{t-1} is the memory of the previous cell; h_{t-1} is the output of the previous cell; X_t is the input of the current cell; C_t is the memory of the current unit; h_t is the output of the current unit;the function f_t is the forgetting gate, used to select forgetting the parameter information in h_{t-1}; i_t and C_t form the input gate, used to read and correct the parameters and create the candidate vector C_t to add to the unit memory; O_t is the output gate, used to select the output part of the unit memory information. The calculation formula is:

$$f_i = \sigma(W_{xf} \cdot x_t + W_{xf} \cdot h_{t-1} + b_f) \tag{3}$$

$$i_t = \sigma(W_{xi} \cdot x_t + W_{hi} \cdot h_{t-1} + b_i) \tag{4}$$

$$\tilde{C}_t = \tanh(W_{xc} \cdot x_t + W_{hc} \cdot h_{t-1} + b_c) \tag{5}$$

$$C_t = f_t \cdot C_{t-1} + i \cdot \tilde{C}_t \tag{6}$$

$$O_t = \sigma(W_{xo} \cdot x_t + W_{ho} \cdot h_{t-1} + b_o) \tag{7}$$

$$h_t = O_t \cdot \tanh(C_t) \tag{8}$$

In which, W and b are the weight coefficient matrix and bias term of the corresponding gate, respectively; σ is the sigmoid activation function for mapping the real numbers to within [0, 1]; $\tanh$ is the hyperbolic tangent function for mapping the real numbers to within [-1, 1].

When processing sequential data, each time step corresponds to one LSTM cell. Each cell makes a decision by considering the current input, the output of the previous cell and the memory, while it produces a new output and changes its memory. When there are multiple LSTM layers, the output of the cell of each time step in the first layer will be used as the input of the cell of the corresponding time step in the second layer, and the memory of the last time step in the first layer will be used as the initial memory of the second layer [20-24].

B. LSTM Long Short Term Memory Recurrent Neural Network Model

The LSTM model constructed in this paper includes an input layer, two LSTM hidden layers, two fully connected layers, a Dropout layer and an output layer. After the input matrix enters the input layer, it passes through the LSTM hidden layer and the Dropout layer, and then the final prediction value is obtained through the fully connected output layer, and the LSTM model is shown in Figure 4.

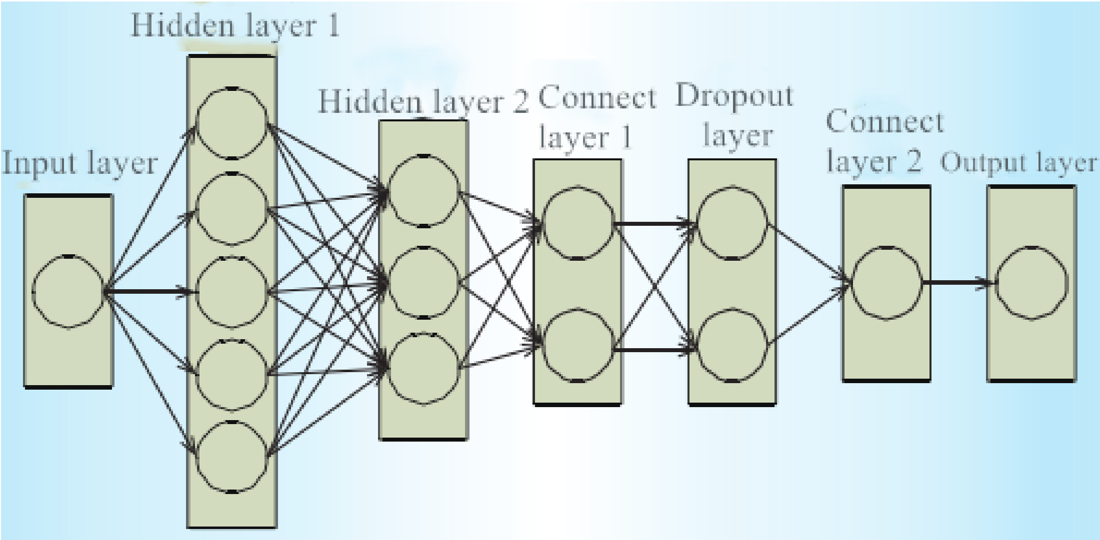

Figure 4: LSTM network model

The role of the LSTM layer is to filter out the important information and forget the unimportant information.The Dropout layer problematically deactivates the inputs and recursive connections of the LSTM neurons during the forward pass and weight update, which prevents a network from being over-fitted to the training set and "over-learning". In this paper, the deactivation probability is set to 0.5. The role of the fully connected layer is to transform the high-dimensional inputs into low-dimensional outputs while retaining the information from the previous layer. The output dimension of the fully connected layer 2 in Figure 4 needs to be the same as the predicted outcome dimension.

1) Network Training Set Input Data: The following factors are selected as input features: base load, tariff, number of stay EVs, average EV urgency factor for each time period, number of EVs and average urgency factor for time periods t-1 and t-2. Each training data set contains 96 time periods of data. The specific input data for the training set are shown in Table 1.

Table 1: Input data of training set

	Input data of training set
1	Base load for periods t-1
2	Period t-1Tariff
3	Number of EVs staying at charging stations at time period of (t-1)
4	Number of EVs staying at charging stations at time period of (t-2)
5	Average urgency factor of EVs in charging stations in time period (t-1)
6	Average urgency factor of EVs in charging stations in time period (t-2)

In Table 1, the optimal solution for the guided charging power of each charging station within the jurisdiction of the regional management system at time period t is found according to the optimization-seeking algorithm under the condition that the full-day load situation is known, and its objective function is chosen to be consistent with the instructions of the scheduling layer, with the objective of minimizing the overall charging cost of M charging stations in the region over 96 control periods.

$$\min\sum_{i=1}^{M}(\sum_{t=1}^{96}P_i^{ref}(t)\times c(t)\times\Delta t) \tag{9}$$

Where, $P_i^{ref}(t)$ is the guideline charging power at charging station i for the tth control period within the zone optimization interval; $c(t)$ is the tariff for that control period; and $\Delta t = 1/4$ is the conversion factor of 15min to 1h.

2) Real-time Input and Output Data: The input data and the corresponding output data required by the network during the real-time optimal scheduling are shown in Table 2.

Table 2: Real time input and output data

	Input data
1	Base load for periods 2-t-1
2	Period 2-t-1Tariff
3	Number of EVs staying at charging stations in time period 2-(t-1)
4	Number of EVs staying at charging stations in time period 1-(t-2)
5	Average urgency factor of EVs in charging stations in time period 2-(t-1)
6	Average urgency factor of EVs in charging stations in time period 1 - (t-2)
	output data
1	Guideline charging power at charging stations in time period T

3) Training Process: In order to improve the training speed, while taking into account the training accuracy, the minibatch technique is used, and the batchsize = 20 is selected, that is, 20 groups of training data as a whole training, the specific training process is as follows.

(1) Normalizing the data, it can be seen from Table 1 that each set of data contains six input quantities, one target value, and the number of periods is 96, so that the size of each input data matrix is 7 × 96.

(2) Inputs from the training set are fed into the LSTM network model to obtain preliminary predicted values and to calculate the error from the target value.

(3) Supervised learning of LSTM networks by updating the network weights using the Adam back-propagation algorithm.

(4) After the training is completed, the data from the test set is fed to the LSTM network in real time to derive the real-time guided charging power for that charging station.

IV. Station-level Energy Management Strategies

The charging station energy management system in this paper allocates the guiding charging power issued by the regional energy management system according to the urgency factor of each vehicle, the higher the factor, the higher the allocated charging power. AC slow charging EVs are assigned a charging power of 0 or the rated power P^{AC}, and the charging power of DC fast charging EVs can be continuously adjusted between 0 and P^{DC}.

Assuming that the set of AC charging EVs connected at the ith charging station in the tth control period is AC_t, and the set of DC charging EVs is DC_t, then the charging power allocated to the AC charging EVs is

$$P_{i,j}^{AC} = \left[\left[\frac{R_{i,j}(t) \times P_i^{ref}(t)}{\sum_{\tau \in AC_t \cup DC_t} R_{i,\tau}(t)} \geq P^{AC} \right]\right] \times P^{AC} \tag{10}$$

In which, $P_{i,j}^{AC}$ is the charging power allocated to the jth AC electric vehicle in the ith charging station; if X is true, [[X]] = 1, and if X is false, [[X]] = 0.

The charging power allocated to the DC charging EV is

$$P_{i,j}^{DC} = \frac{R_{i,j}(t) \times P_i^{ref}(t)}{\sum_{\tau \in AC_t \cup DC_t} R_{i,\tau}(t)}, \; j \in DC_t \tag{11}$$

In which, $P_{i,j}^{DC}$ is the charging power allocated to the jth DC EV in the ith charging station.

The sufficient number xxxxxxxxxxx.

V. Algorithms Analysis

A. Simulation Model Setup.

Suppose there are three charging stations (M=3) under a regional energy management system, which are installed in office, commercial and residential areas. The DC rated charging power is 45 kW, the AC rated charging power is 7 kW, and the EVs have two types of battery capacity, 24 kWh and 32 kWh. 101 sets of measured base load data and electricity price information are collected for a region, while the EV travel chain is simulated according to the Monte Carlo-based method proposed in the literature [14], and 101 sets of EV travel data are obtained for a total of 101 sets of initial data. One set is selected as test data for validating the final results, and the rest of the data are used as training data to train the LSTM learning network. Figure 5 shows the base load curve for that day, Table 3 shows the information of EVs connected to each charging station on that day, and Table 4 shows the guide tariff issued by the dispatch layer on that day.

The number of hidden units in the 2 LSTM layers is set to 200 and 100, respectively, and the number of iterations is 300.

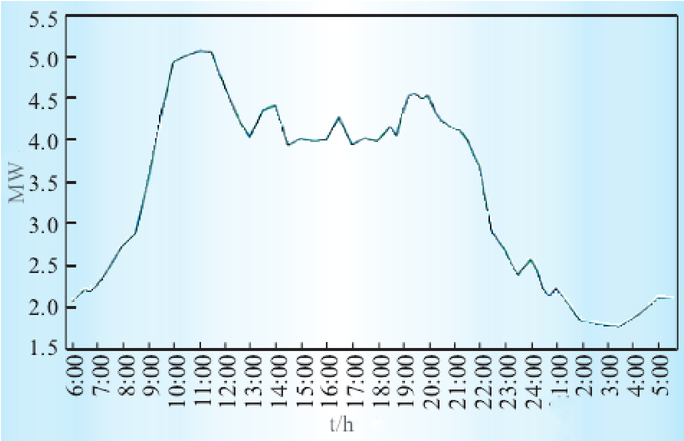

Figure 5: Load data of the day

Table 3: EV information of each charging station of this day

Charging station locations	AC charging	DC charging	Type1（24Wh）	Type2（32Wh）
Office area	360	90	276	174
Commercial area	0	150	60	90
Residential areas	800	0	344	456

B. Analysis of Arithmetic Results

The method in this paper is compared with other local optimization algorithms (rolling optimization strategies) proposed in the literature. Figure 6 shows the actual charging power of the three charging stations under the jurisdiction of the regional management system, Figure 7 shows the base load curve of the region with the full load curve under different control methods, the corresponding charging cost and peak-valley difference are shown in Table 5, and Figure 8 shows the average charging power for different time periods under different strategies.

Table 4: Electricity price of each period

Time	Price
2:00-7:00	0.300
7:00-9:00	0.712
9:00-10:00	1.070
10:00-14:00	1.210
14:00-18:00	1.070
18:00-23:00	1.120
23:00-02:00	0.712

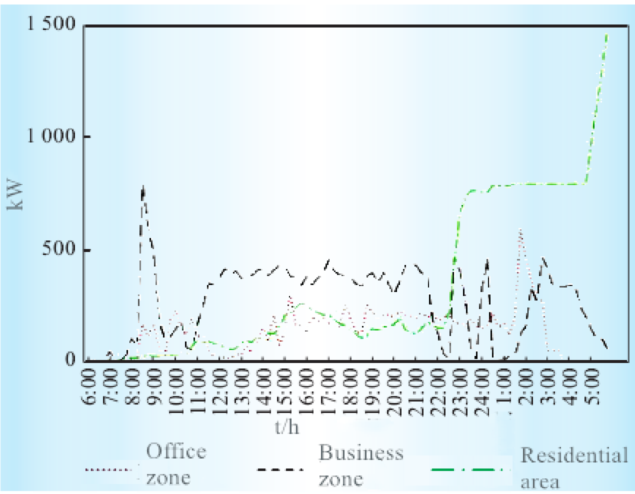

Figure 6: Actual charging power of each charging station

Combined with Fig. 6, Fig. 7, Fig. 8 and Table 5, it can be seen that if electric vehicles are charged in a disorderly manner, not only the charging cost is high, but also the daily load peak-to-valley difference of the grid is substantially increased, which is not conducive to the safety and stability of the grid. In contrast, both the strategy in this paper and the rolling optimization strategy can reasonably coordinate the guiding charging power of each charging station[25-29], reduce the charging power during the high electricity price hours (10:00-14:00, 18:00-23:00) as much as possible, shift the charging load to the hours with relatively low electricity price, and compare the instant charging method, which greatly reduces the Charging cost.

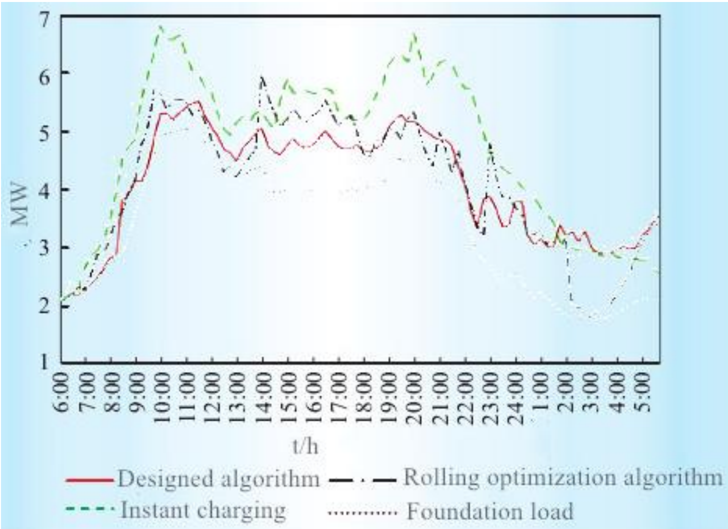

Figure 7: Comparison of load curves under different strategies

Meanwhile, it can be seen from Fig. 8 that the method proposed in this paper has lower charging power during peak load hours and significantly higher charging power during low load hours, and the load shifting effect is more significant. Comparing the full-day peak-to-valley difference under different algorithms in Table 5, the peak-to-valley difference of the strategy in this paper is smaller, and the effect of peak shaving and valley filling is better. On the other hand, in the real-time simulation of 96 periods of test data, the rolling optimization strategy takes 2 min, while the method proposed in this paper takes only 30 s, which is more computationally efficient.

In summary, the strategy proposed in this paper does achieve better results than the general algorithm from the final optimization results, and the real-time computational efficiency is higher, and when the number of managed EVs is more massive, the computational speed of the ordinary optimization-seeking algorithm will further decrease, and even the dimensional disaster may occur, but the strategy proposed in this paper can still maintain a high solution efficiency, which fully reflects the effectiveness and superiority of the strategy.

Table 5: Comparison of peak-valley\charing cost and optimization duration

	Strategy of this article	Rolling optimisation strategy	Instant charging	Base load
Charging cost/yuan	18027	20022	30313	
Peak-to-valley differential/MW	3.473	4.138	4.766	3.290
Optimisation time/s	30	121		

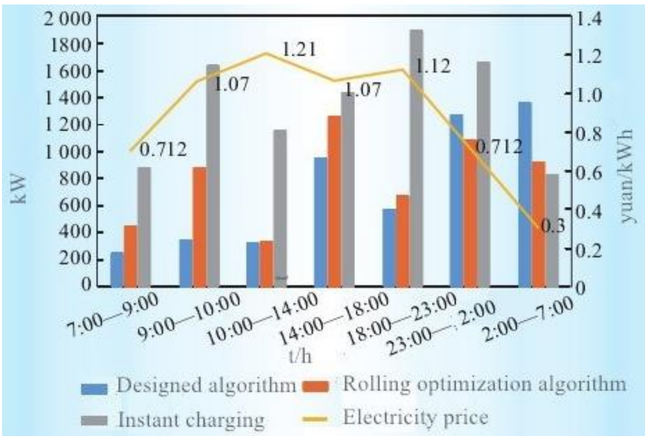

Figure 8: Average charging power of each period under different control strategies

VI. CONCLUSIONS

In this paper, a 3-tier EV charging load real-time optimization management model including dispatching layer, district management layer, and station management layer is established, based on which a deep learning-based district-level energy management strategy is focused on and proposed, and validated by simulation arithmetic examples. The main findings are as follows.

(1) The deep learning network-based RMS management strategy proposed in this paper can make full use of historical load data and deeply mine the information of historical optimization tasks for guiding online real-time optimization, and the optimization effect is better compared with the general local optimization strategy.

(2) The strategy in this paper optimizes a smaller number of variables, does not have the problem of dimensional disaster, is less difficult to solve, is more efficient in real-time computation, and is suitable for the case of large-scale electric vehicle access.

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