Optimal Scheduling Strategy for Real-time Charging of Electric Vehicles Based on Deep Learning

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Abstract: In recent years, the automotive industry has informed the development situation. Under the problems related to automobile exhaust emissions and serious air pollution and energy shortages, new electric vehicles have sufficient advantages due to their low emissions, high energy efficiency, and low noise. It has been recognized by the people and governments of all countries. The research purpose of this paper is to meet the electricity demand of users, adopt the boundary model of charging and discharging energy and fully adopt deep learning to optimize the real-time charging optimization scheduling strategy of electric vehicles. In order to meet the electricity demand of users, the charge-discharge energy boundary model is used to characterize the charge-discharge behavior of electric vehicles. After the day-ahead training and parameter saving of the proposed model, according to the real-time state of system operation at each moment of the day, the charge-discharge scheduling strategy at that moment is generated. It is verified that the proposed charging scheduling method based on deep reinforcement learning can effectively reduce the power fluctuations in the microgrid and reduce the daily charge and discharge costs on the premise of meeting the charging needs of users; during the development of electric vehicles, different electronic components, especially the power consumption of electric motors, must be faced. A deep learning algorithm based on an improved recurrent neural network (MRNN) is proposed. The system is modeled according to different data and parameters inside the vehicle, and the network is modeled by the MRNN deep learning algorithm. Carry on training, predict the power demand and provide the best power, so as to expand the mileage, better optimize the power distribution of the motor, and compare the improved models. Experimental research results show that the efficiency of the related scheduling strategy model is increased by about 37.2% compared with the traditional model. The proposed method is fast in calculation and does not require iterative calculation, which fully meets the needs of real-time scheduling.

Keywords: Deep Learning, Electric Vehicle, Charging and Discharging Optimization, Real-time Scheduling Strategy, Neural Network
1. Introduction

In recent years, significant progress has been made in the research and development of electric vehicle motor control systems and power batteries [1]. Our country has formulated a key national strategic plan for the development of the electric vehicle industry to promote the progress of our country's automobile technology, promote the conversion of our country's automobile consumption to electric vehicles, and establish an electric vehicle technology research and development system to develop plug-in hybrid vehicles and modern electric vehicles [2]. After many efforts, epoch-making results have finally been achieved, and as the main part of the auto parts company, the research and development system has achieved results and finally established a joint research and development system with application demonstration, standard test platform and research and development [3].

There are certain technical difficulties in the power supply and cruising range of electric vehicles. Therefore, the construction of supporting facilities for electric vehicles needs to be further improved. The optimized scheduling of charging can further reduce the travel cost of electric vehicles and improve the travel efficiency of electric vehicles; fully meet the charging characteristics of electric vehicles and improve the matching degree of charging station resources [4]. The resource utilization rate of charging stations is related to the overall grid load. By optimizing the scheduling of intelligent charging services for electric vehicles, the allocation of high-quality resources of charging stations can be completed for specific electric vehicle conditions. Minimize the resource waste of charging stations, improve the matching degree of electric vehicle charging stations and charging resources, and improve the utilization rate of charging stations, so as to avoid the waste of electric energy [5].

With the rapid development of electric vehicles, the Chinese government and enterprises pay more and more attention to the construction and improvement of charging facilities. In the charging station, photovoltaic power generation system, energy storage system and various adjustable loads are integrated as a whole. A joint hierarchical multi-time scale optimal scheduling method for charging stations is proposed [6]. The time scale is subdivided into one day in advance, quasi-real-time stage and real-time stage, and a multi-stage opportunity-constrained electric vehicle charging station coordination optimization and control method is proposed [7]. The above research shows that multi-scale scheduling can reduce the impact of net load forecast fluctuations, which is conducive to achieving higher economic goals. However, in fact, most of the above-mentioned long-term studies belong to open-loop optimal scheduling, and ignore the impact of actual operations on optimal decision-making control. It is easy to cause the scheduling plan to be not strictly optimal. Therefore, the optimal scheduling model for electric vehicle charging stations needs to be further improve [8].

This paper mainly studies the application of distributed energy storage charging and discharging optimization strategy in the optimal dispatch of large-scale electric vehicles. The centralized optimization strategy has higher computational efficiency than this strategy, and has a good impact on real-time scheduling, and is basically not affected by the size of the EV plan [9]. Through the analysis of the model in this paper, considering the orderly charging of electric vehicles in the planning stage can effectively reduce the cost of the distribution network at the investment and operation levels, and the resulting grid scheme has greater economic advantages. The deterministic model is very important. After the introduction of load, DG and load timing models, the scene modeling will be more accurate. The peak staggering phenomenon between different types of loads and the interaction between different DGs will be beneficial to the safety and stability of the distribution network [10].

2. Algorithm Establishment

2.1 Analysis of Charging Error Based on the Improved Average Integral Error Function of Deep Learning

Usually in cluster analysis, the mean square integral error function (MISE) is generally selected to optimize the bandwidth. The specific definition is as follows:

$$MISE(h) = E\int(\hat{f}(x) - f(x))^2\,dx$$  \hspace{1cm} (1)
\[
MISE(h) = AMISE(h) + o\left(\frac{1}{(nh)} + h^4\right)
\]  
\[
AMISE(h) = \frac{R(K)}{nh} + \frac{1}{4}m_2(K)^2h^4R(f^{\prime\prime\prime})
\]

Among them:
\[
R(K) = \int K(x)^2 \, dx
\]
\[
m_2(K) = \int x^2K(x) \, dx
\]

Minimizing MISE(h) is equivalent to minimizing AMISE(h). Find the partial derivative and make the derivative equal to 0. There are:
\[
\frac{\partial}{\partial h} AMISE(h) = -\frac{R(K)}{nh} + m_2(K)^2h^3R(f^{\prime\prime\prime}) = 0
\]

\[
h_{AMISE} = \frac{R(K)\frac{3}{2}}{m_2(K)^2R(f^{\prime\prime\prime})\frac{1}{5}n^\frac{1}{2}}
\]

Among them, m and R are determined according to the kernel function.

Represents the total number of data points falling in the hypercube C; O_C represents the set of candidate outliers in the grid. grid statistics \(S_k^1=[s_1^1, ..., S_k^1]\), where the calculation formula of element \(s_k^1\) is as follows:
\[
s_k^1 = \sum c \theta^{t_a-t_c} r_i
\]

In the formula, \(r_i\) represents the data point. The calculation formula of the element \(s_k^2\) is as follows:
\[
s_k^2 = \sum c \theta^{t_a-t_c} r_i^2
\]

The grid statistics \(S_k^1, S_k^2\) satisfy the following formula at time t:
\[
\tilde{s}_k^2 = t^{t_a-t_c} \times \tilde{s}_k^1
\]

3. Modeling Method

3.1 Experimental Data Analysis

The main key purpose of this experiment in this paper is to study the research and analysis of electric vehicle real-time charging optimization scheduling strategy under the strong support of current deep learning technology and computer technology. From the perspective of the current development form and future development prospects of electric vehicles in our country, Beijing, Shanghai, Guangzhou, Shenzhen, Wuhan, Hangzhou and other five regions have a wide distribution of electric vehicles, and the related infrastructure is indeed relatively complete compared to other provinces and cities. Therefore, this article mainly selects these five regions as the main source of current data, and we use the relevant algorithm proposed above to conduct experimental analysis and simulation.

Table 1. Evaluation and analysis of the comprehensive results of user data in the five provinces surveyed

| Sales/Ten Thousand Yuan | 2016S | 2017S | 2018S | 2019S | 2020S |
|-------------------------|-------|-------|-------|-------|-------|
| Beijing                 | 15    | 16    | 22    | 28    | 26    |
| Shanghai                | 22    | 18    | 19    | 24    | 27    |
| Guangzhou               | 17    | 16    | 25    | 26    | 23    |
| Shenzhen                | 19    | 13    | 21    | 19    | 25    |
| Hangzhou                | 23    | 15    | 19    | 21    | 21    |
3.2 Distributed Energy Storage Aggregation Model

Mathematical model of energy storage:

Charging and discharging model of energy storage. When the energy storage is charged, it absorbs active power and the SOC increases; when it discharges, it emits active power and the SOC decreases. The formula for calculating the value of \( \text{SOC}_t \) at time \( t \) is:

\[
\begin{align*}
\text{SOC}_t & = \text{SOC}_{t-1} + \left( \frac{P_{\text{ch}}}{P_{\text{rate}_{\text{ch}}}} \right) \eta_{\text{dis}_{\text{rate}}} - \frac{P_{\text{dis}}}{\eta_{\text{dis}_{\text{rate}}}} \Delta t, \quad t > 1 \\
\text{SOC}_1 & = \text{SOC}_0 + \left( \frac{P_{\text{ch}}}{P_{\text{rate}_{\text{ch}}}} \right) \eta_{\text{dis}_{\text{rate}}}, \quad t = 1
\end{align*}
\]

(9)

Energy storage is generally connected to the grid through a PCS (power conversion system). While absorbing or emitting active power, it can also absorb or emit reactive power, which can provide a certain amount of reactive power support and voltage management to the grid. In the actual operation process, its reactive power can be controlled according to the situation.

The constraints of energy storage include SOC constraints and charge-discharge constraints. SOC constraints are:

\[
\text{SOC}_{\text{min}} \leq \text{SOC}_i \leq \text{SOC}_{\text{max}}
\]

(10)

In the formula, \([\text{SOC}]_{\text{min}}\) and \([\text{SOC}]_{\text{max}}\) are the minimum and maximum allowed energy storage SOC, respectively.

The charge and discharge constraints are:

\[
\begin{align*}
0 & \leq P_{\text{ch}} \leq P_{\text{ch max}} \\
0 & \leq P_{\text{dis}} \leq P_{\text{dis max}}
\end{align*}
\]

(11)

The maximum charging power and maximum discharging power of energy storage, respectively.

Multi-form distributed charging and discharging power distribution

In order to make the power distribution of each energy storage reasonable and maintain the relative balance of SOC during the scheduling process, the rated power and SOC value of each energy storage are used to jointly determine its charging and discharging power. The specific determination method is as follows:

Charging:

\[
\begin{align*}
P_{\text{ch}} & = \frac{P_{\text{ch}}}{P_{\text{rate}_{\text{ch}}(\text{SOC}_i)}}, \quad \forall i, j \in N \\
\sum_{i=1}^{N} P_{\text{ch}} & = P_{\text{all}_{\text{ch}}}
\end{align*}
\]

(12)

Discharge:

\[
\begin{align*}
P_{\text{dis}} & = \frac{P_{\text{dis}}}{P_{\text{rate}_{\text{dis}}(\text{SOC}_i)}}, \quad \forall i, j \in N \\
\sum_{i=1}^{N} P_{\text{dis}} & = P_{\text{all}_{\text{dis}}}
\end{align*}
\]

(13)

In this article, in order to make the principle of more charge and less discharge of the stored energy, in order to improve the required efficiency, it is necessary to ensure the full use efficiency of the electric vehicle after the charging is completed. In this paper, a function is used to stretch and translate it as a function of charging and discharging. The specific function is as follows:

\[
\begin{align*}
f_{\text{ch}}(x) & = 1 - \frac{1}{1 + \exp^{-20(x-0.5)}} \\
f_{\text{dis}}(x) & = \frac{1}{1 + \exp^{-20(x-0.5)}}
\end{align*}
\]

(14)
4. Evaluation Results and Research

4.1 Experimental Investigation and Analysis Results

![Figure 1](image1.png)

**Figure 1.** The system predicts that the system has user data in real time

**Table 2.** Experimental simulation parameters

| Parameter         | S       | M       | Z       |
|-------------------|---------|---------|---------|
| Deployment area   | Beijing | Shanghai| Guangzhou |
| C                 | 2       | 2       | 2       |
| L                 | 700     | 300     | 400     |
| T                 | 0-700   | 300     | 0-400   |
| Number of nodes   | 700     | 300-700 | 400-700 |
| Node characteristics | The node is static, the power is constant, and the communication range is stable |
| Simulation times  | Run 100 times in each case |

The experimental analysis data shown in Figure 1 and Table 2 show that after relevant departments have optimized the real-time scheduling strategy of electric vehicles, the surveyed regions will have a sharp increase in real-time users of electric vehicles in the next five years. In order to respond to the government's call for low-carbon travel, civilized travel has laid a good foundation for the development of modern electric vehicles. The distributed charging and discharging energy storage model established in this paper optimizes its charging stations in the three regions of Beijing, Shanghai, and Guangzhou. The comparison results of network connectivity in case S are also increasing as the proportion of Z nodes increases. But the connectivity presented by different charging and discharging performance ranges is obviously different. Due to the limitation of communication range and network depth, it is impossible to add all nodes to the Z-tree, and the number of S increases to a certain
network connectivity tends to a fixed value. In the whole process of network connectivity changes, the connectivity of this algorithm is significantly higher than other algorithms.

Figure 2. Comparison of the difference in data processing results of different regions by deep learning algorithms in fusion of charging and discharging energy storage models

Through the processing of large-scale data by the charging and discharging model of distributed energy storage, we can know their calculation accuracy and statistical rate. Figure 1 shows it in a more intuitive form. Because the accuracy of the deep learning algorithm is relatively high, we conducted a second experiment on the deep learning algorithm. We use deep learning algorithms to process 100 million times, one billion times, tens of billions, and hundreds of billions of data, and then watch their calculation error rates. According to experiments, as the amount of data increases, the error rate is slowly increasing, while the correct rate is slowly decreasing. This shows that the data processing of the distributed energy storage charging and discharging model based on the deep learning algorithm will still change as the amount of data grows.

5. Conclusion
Based on the above research, there are still big problems in the promotion and development of electric vehicles in my country. In particular, the construction of charging facilities related to electric vehicles is not complete. In terms of charging types and construction density, it cannot meet the charging service needs of electric vehicles. In view of the difficulty of charging electric vehicles, we will further explore the optimization of intelligent charging services from both the user and the charging station, which can improve the service quality of the charging station, improve the charging scheduling system and rationally allocate the charging load, reduce the user's queuing time, and improve user satisfaction. By applying the MISE deep learning algorithm to electric vehicles for power prediction, the power demand of electric vehicles can be optimized and their driving distance can be expanded. With the help of the MISE deep learning algorithm, the prediction behavior becomes smooth and the jitter in the training phase is avoided. By allowing the system to accept more training data sets, the prediction accuracy can be improved, and with the increase of real scenes, the power prediction can converge to more accurate results over time. This paper combines the SAE model and Elm model in deep learning by selecting the factors that affect the load forecast of the charging station to carry out short-term load forecasting of the charging station. Compared with the traditional load forecasting methods Sae-bp and elm, this method is more accurate and stable for short-term load forecasting of charging stations.

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