Research on Multi Scenario User Charging Behavior Habit Model Based on LSTM Driven by Historical Data

Rui Yang[1, a], Tuo Wang[1, b], Ruiqi Wang[2, c], Peng Yan[1, d], Lin Huang[2, e], Yong Zheng[2, *]

[1]State Grid Jiangsu Electric Vehicle Service Co., Ltd. Nanjing, China

[2]School of Eletric Power Engineering, Nanjing Institute of Technology Nanjing, China

* Corresponding Author Email: zy1063195938@163.com, [a]13952198090@163.com, [b]85476794@qq.com, [c]1061119545@qq.com, [d]524601688@qq.com, [e]1667530513@qq.com

Abstract. Under the advocacy of low-carbon and environmental protection, electric vehicles have ushered in rapid development, and the following user charging problems also need to be considered. The consistency of charging stations makes the charging power the same, resulting in different charging efficiencies of different electric vehicles. Based on this, this paper proposes a multi-scenario user charging behavior habit model based on LSTM driven by historical data, which predicts the charging habits of different electric vehicle users, and provides better support for the subsequent multi-charging power allocation strategy. Finally, the data simulation results show that the model and method can more accurately predict the user's charging behavior.

Keywords: electric vehicle, LSTM, charging behavior habit model, charging power.

1. Introduction

With the increasingly serious resource pressure and environmental pollution in my country, the implementation of electric vehicles is imperative. Electric vehicles have become the first choice of customers due to their high efficiency and low emissions. According to statistics, electric vehicles reduce greenhouse gas emissions by an average of 1,000 liters per year, greatly reducing environmental pollution and reducing resource pressure. According to the report, the number of electric vehicles in my country will reach 60 million in 2030 [1]. With the rapid increase in the number of electric vehicles, charging challenges have arisen. The increasing charging load of electric vehicles, insufficient charging efficiency, and insufficient utilization of charging piles have become increasingly prominent. Therefore, how to use a series of methods to study key issues such as the reasonable distribution of charging power for different vehicles has become the focus of everyone's attention.

At present, there are few researches on electric vehicle charging power distribution at home and abroad. Reference [2] studies multi-objective optimization aiming at uniform distribution of charging load and minimum charging time and distance; Reference [3] proposes a data-driven charging demand prediction model for electric vehicles; Reference [4] proposes a The overall layout structure of the charging station with the complementary structure of fast and slow charging double parking spaces; the literature [5] simulation modeling obtains the probability distribution of electric vehicle charging variables; literature [6] proposes an electric vehicle load modeling method based on the charging power scenario model ; Reference [7] proposes a charging power calculation model for electric vehicles that takes into account travel temperature; Reference [8] proposes a model of electric vehicle charging demand in distribution systems based on traffic attributes, which avoids the need for network geographic information. The above literature mentions the charging requirements of electric vehicles and the construction of charging models, but seldom mentions the charging requirements based on users' charging behavior habits.

Taking the conventional electric vehicle charging station as the background, this paper studies the user's charging behavior habit model: first, determine the characteristics of charging behavior; secondly, use the characteristics of charging behavior to establish charging scenarios for different users; finally, based on historical data, establish a user's charging habit model, and predict the possible behavior of users. charging behavior.

2. Feature extraction

Electric vehicle charging data directly affects the charging characteristics of the vehicle. Therefore, using the existing historical data to reasonably mine the user's charging behavior is the key to building a model.

2.1. Data description

The data used in this paper are from Jiangsu State Grid Electric Vehicle Company. Contains some charging pile charging data sets in Jiangsu Province, the main data format is shown in Table 1.

Important data includes the following:

Table 1. Important data

Field Name	Field Type	Field Description
Charging start time	TimeStamp	T_s
Charging end time	TimeStamp	T_e
consumption time	TimeStamp	T_d
Charging time	TimeStamp	T_c
Degree of charge	float	Energy
address	char	Address
User ID	Int	User_id

From Table 1, the starting and ending time of each charge, as well as the time spent and charging, the degree of charging, the type of charging pile and the charging address can be directly obtained through the historical data. Screening requires data analysis of historical data and extraction of relevant factors to describe user charging power characteristics.

2.2. Analysis of user charging characteristics based on data

2.2.1 Data processing

In order to eliminate the uncertainty and error of the original data, it is necessary to preprocess the original data:

a) Data cleaning: Clean the dead pixel data in the dataset.

b) Data screening: Sort the remaining data in chronological order, and discard some factors that are obviously irrelevant to the charging characteristics.

2.2.2 Feature selection

The most distinctive feature of electric vehicle charging is the time period of charging. Each electric vehicle has its own unique charging time, and the charging time is also significantly different between working days, weekends and holidays, and the charging time is also different between residential areas and residential areas.

Another distinguishing feature of EV charging is the charging location. For different types of electric vehicles, the charging location is often determined according to the actual situation. For example, private cars are often charged at charging piles that are close to the company or residence, taxis are often charged at charging piles that are close to the travel track, and electric vehicles Buses are charged at designated locations. The latitude and longitude of each charging station is obtained through web information [Google Maps].

The charging model of an electric vehicle is roughly as formula(1):

$$\begin{cases} M = (T_s, T_e, Address, Energy, Car\_ID) \\ \mathrm{T}_c = T_e - T_s \\ Distance = \sqrt{(Lat_c - Lat_n)^2 + (Lon_c - Lon_n)^2} \\ Power = Energy / T_c \end{cases} \tag{1}$$

Among them, M is the model, Distance is the straight-line distance between the location of the charging pile and the location of the user, Latc and Lonc are the longitude and latitude of the location of the charging pile, Latn and Lonn are the longitude and latitude of the location of the user, and Power is the charging power.

3. Multidimensional scene analysis

This paper mainly considers the charging behavior of the city under normal circumstances. Electric vehicle charging is a complex behavioral activity, and users make decisions based on different situations. The charging scene consists of multiple elements, so it is described as a composite structure.

3.1. Scene elements

The objects of a charging activity are mainly users and charging piles. The interaction between the two constitutes a charging activity. One of the user elements of charging activities can be roughly divided into the following aspects:

a) Time: charging start time, charging end time, charging time
b) Location: the location of user
c) Date: working day or rest day, a day of the week
d) Energy: charging energy
e) User's information: the ID of user

The charging pile elements in a charging activity are divided into the following aspects:

a) Charging pile power: fast charge or slow charge
b) Charging pile occupancy rate: whether the charging pile is congested
c) Location: The location of the charging pile

3.2. Scene Construction

The scene type is composed of the user side and the charging pile side, so it is a comprehensive structure, which is expressed as $C = \{C_U, C_P\}$, C_U is the user-side element, C_P is the charging pile side element. User-side elements can be expressed as $C_U = [T_s, T_e, Date, Energy, Address_U, ID_U]$, where Ts is the charging start time, Te is the charging end time, Date is the charging date, Energy is the transaction power, the unit is kwh, $Address_U$ is the location of the user, the format is latitude and longitude, ID_U is the user ID, which is reflected in the known data as the user account number; $Power_{max}$ is the maximum charging pile Charging power, Occupancy is the occupancy rate of the charging pile, the format is percentage, AddressP is the location of the charging pile, and the format is latitude and longitude. The formula(2) is the description form of each parameter.

$$\begin{cases} T_s, T_e : (hh:mm:ss) \\ Date : (yyyy - MM - dd) \\ Energy : (Float) \\ Address_U : (Latitude_U, Longitude_U) \\ ID_U : (Int) \end{cases} \qquad \begin{cases} Power_{\max} : (Int) \\ Occupancy : (xx\%) \\ Address_P : (Latitude_P, Longitude_P) \end{cases} \tag{2}$$

According to the different scenes, this paper classifies the elements according to the scenes obtained after data mining. After data cleaning, an accurate database is obtained, and the charging records of the same user are analyzed. According to the user-side elements, the time area, date, geographic area, and geographic area on the charging pile side are divided.

4. User charging habits model

The above scene construction provides a large number of scenario descriptions for the model, so this section will build a user charging habit model based on the charging behavior of a single user. The following assumptions are made: the user's charging behavior is valid each time, the time and transaction power are in line with normal conditions, and there are n groups of historical data.

4.1. element determination

4.1.1 time element

First, extract the charging start time and charging end time of the user each time, establish a time period set , and use the covariance formula to determine whether the charging time is concentrated. The covariance formula is shown in formula (3).

$$\begin{cases} \overline{T_s} = \frac{1}{n}\sum_{i=1}^{n} T_{si} \\ \overline{T_e} = \frac{1}{n}\sum_{i=1}^{n} T_{ei} \\ \Sigma_T = E\{(T - (\overline{T_s}, \overline{T_e}))^T (T - (\overline{T_s}, \overline{T_e}))\} \\ \quad = \frac{1}{n}(T - (\overline{T_s}, \overline{T_e}))^T (T - (\overline{T_s}, \overline{T_e})) \end{cases} \tag{3}$$

4.1.2 date element

The dates considered in this paper are the charging characteristics of the car during the week, so the charging dates should be converted into the corresponding days of the week. Convert the user's charging record from the beginning to the current period into a weekly table, and record a week's record as, where is the number of charging times on that day, use statistics to calculate the number of weekly charging times, observe the weekly charging habits, and mark holidays as special dates. Features that distinguish working days from holidays.

4.1.3 location element

This paper assumes that the user’s location is within 1km of the charging pile. The location is the best charging location. The data requirements of latitude and longitude are also used to facilitate the calculation of the distance from the user to the charging pile, instead of calculating the route distance, which reduces the difficulty of calculation.The charging pile locations in the user's charging record are expressed in the form of latitude and longitude, and the covariance formula is used to determine whether the charging locations are concentrated.

4.1.4 Charging pile elements

In addition to the user history, the charging pile elements are also related to the user's charging. If the occupancy rate of the charging pile in the charging station is large, the user will choose another charging station for charging activities, or the charging power of the charging pile may not be large enough. The satisfaction level is not enough, and repeat customers are lost. Therefore, it is necessary to record the occupancy rate of the charging pile within an hour and observe the usage of the charging pile. The hourly occupancy rate can be expressed as $Occ_h = C_h / A \times 100\%$, where Occ_h is the occupancy rate, C_h is the number of charging piles used per hour, and A is the total number of charging piles in the charging station. Record it in a tabular form and discover the charging pile usage characteristics.

4.2. User charging habits model

This paper builds a user charging habit model based on the above elements, which is mainly divided into short-term habits and long-term habits.

4.2.1 LSTM

Long Short-Term Memory Network (LSTM) is a special recurrent neural network (RNN). This paper uses LSTM for model training. The schematic diagram of the LSTM cell is shown in Figure 1.

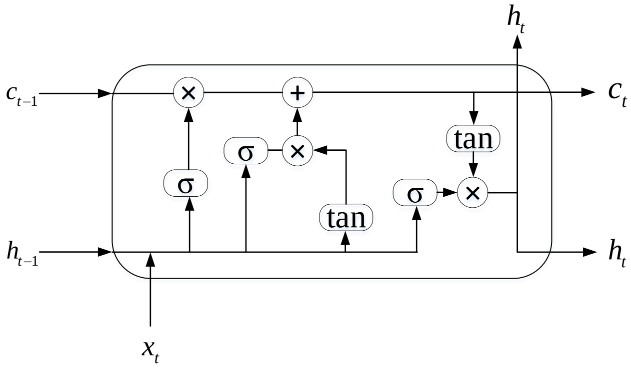

Figure 1. LSTM cell diagram

Where xt is the input, ht-1 is the last output, ct-1 is the last cell state, ht is the current output, and ct is the current cell state.

4.2.2 Short-term habit model

The short-term habit model describes the user's daily charging characteristics, including the user's charging time, charging location, and transaction power. Since it is a short-term model, the impact of dates on charging activities is not considered, and the following analysis is made:

a) When does the user usually charge the battery?
b) Where do users usually charge?
c) How much does the user usually charge?

a short-term user charging prediction table is obtained, which gives the possible charging activities of the user in the near future, and the output is shown in the case analysis.

4.2.3 Long-term Habit Model

The long-term habit model describes the user's periodic charging characteristics, including the user's charging date, charging time, charging location, and transaction power. The following analysis is made:

a) At what times of the week do users typically charge on this day of the week?
b) Where do users typically charge on this day of the week?
c) How often users charge within a week and the exact time period.

A one-week user charging prediction table is obtained, which gives the possible charging activities of the user in one week, and the output is shown in the calculation example.

5. Case analysis

In this paper, an example is used to analyze the reliability of the model mentioned above. Taking the historical charging data of two different users as an example, the charging behavior within 20 days is calculated as shown in the figure below. The time span is from 2022-4-23 to 2022-5-12, including charging time period and charging energy.Because of the full dataset, long- and short-term habit model analysis is possible.

From the charging behavior of user 1, it can be clearly analyzed that the user comes to charge every day, and the charging location is the same, so there is no need to judge the charging location; and the charging time is relatively concentrated, all within 11:00-12:30, The transaction power is also relatively stable, within 25-30kwh, so the user's charging behavior habit model is easy to determine, and the short-term and long-term predictions are more accurate.

The charging behavior of user 2 is more complex, but it also changes periodically. It is easy to obtain that the user charges on working days, but does not charge on rest days. According to this characteristic, the charging behavior prediction of user 2 can be obtained. The short-term model shows that the user Usually, the charging start time is around 07:10-07:20, and the charging end time is around 08:20-08:30. The charging location is the same, which is relatively stable, and the charging power is around 26kwh; the long-term model shows that the user has regularity The charging habit of the model, charging on working days and not charging on rest days, the charging frequency is 5 times a week, and the charging time period is the same as that of the short-term model.

The results of the short-term habit model analysis are shown in Figures 2 and 3. The long-term habit model analysis results are shown in Figure 4 and Figure 5.

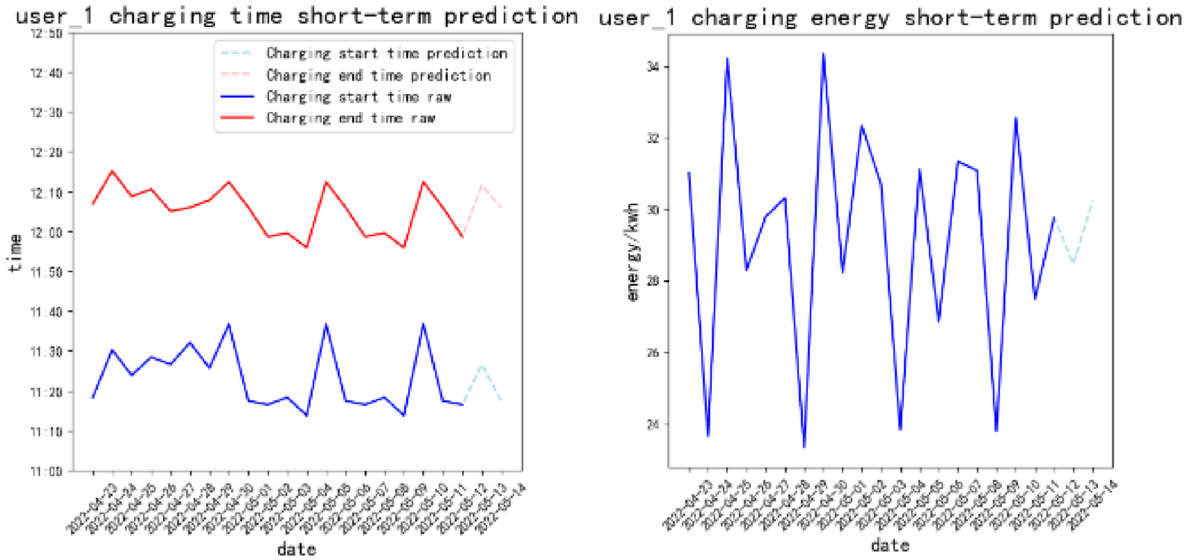

Figure 2. User 1 charging behavior short-term prediction

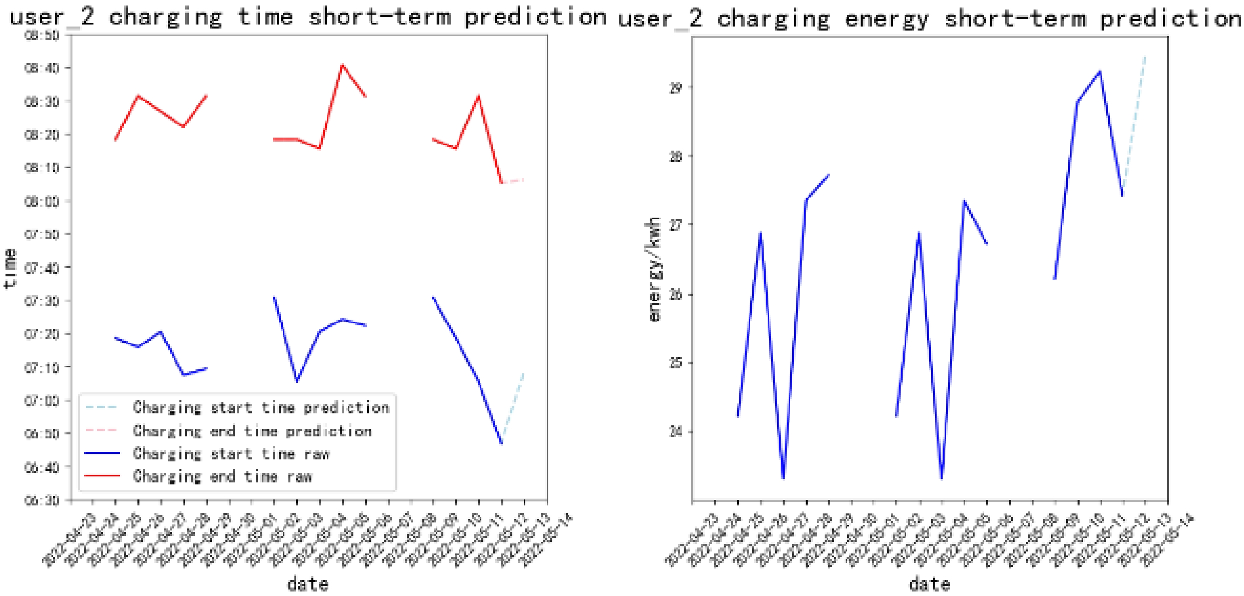

Figure 3. User 2 charging behavior short-term prediction

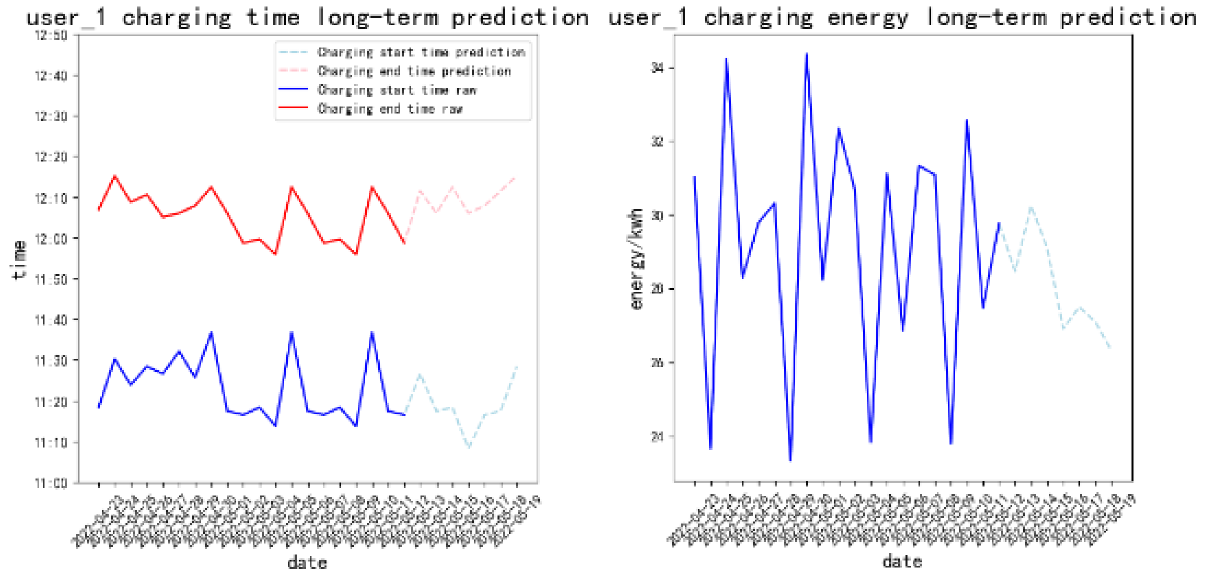

Figure 4. User 1 charging behavior long-term prediction

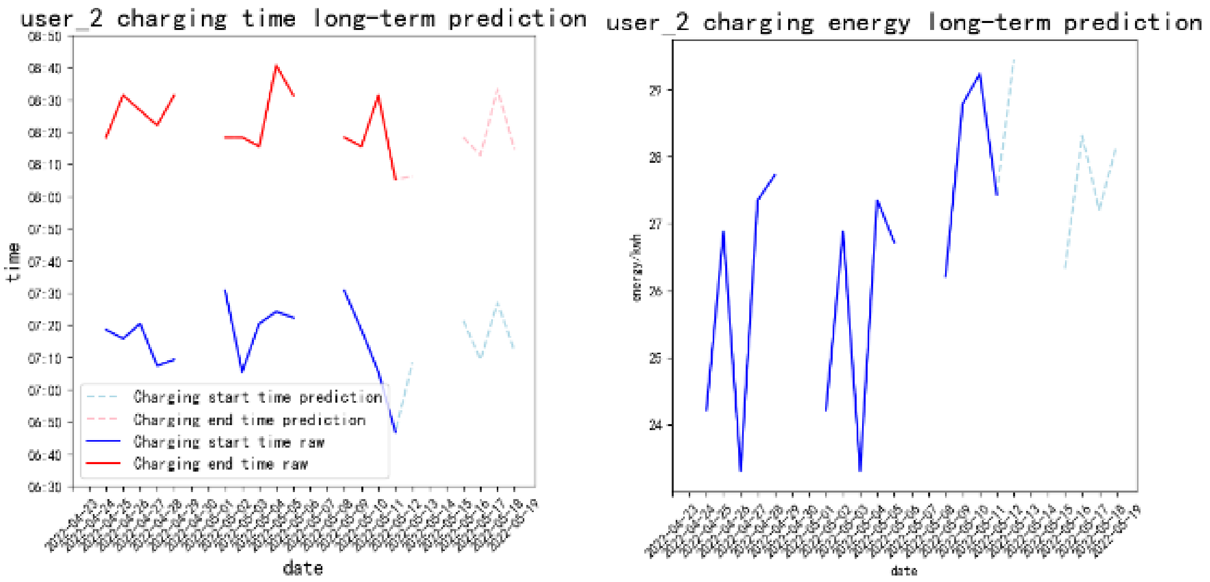

Figure 5. User 2 charging behavior long-term prediction

6. Conclusion

The user charging behavior habit model studied in this paper is applied in the prediction of user charging behavior. Two of the models can effectively analyze the charging needs of users in different situations, provide timely forecasts for charging stations, and provide forecast data for reducing charging loads. The calculation example results show that the user charging behavior habit model in this paper is relatively accurate, which is conducive to the subsequent research on the dynamic power allocation strategy of multiple charging.

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