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A Novel Dual Attention Network Approach for Ultra-Short-Term Charging Load Prediction of Electric Vehicle

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Abstract. *In recent years, with the support of national policies and the maturity of electric vehicle related technologies, the number of electric vehicles has exploded, which means that a large number of charging loads will be connected to the power grid, causing enormous pressure on the safe and stable operation of the power grid. The research on the integration of electric vehicles into modern power grids plays an important supporting role in the future development of electric vehicles. Therefore, this article starts with actual operating data of electric vehicle charging stations and conducts research on charging load forecasting. Considering the time requirements of ultra short term load forecasting, this paper combines attention mechanism and the dual characteristics of charging load data in terms of time. Based on long short-term memory neurons, a charging load forecasting model based on time dual feature attention network (TDFAN-CLF) is proposed to achieve accurate prediction of ultra short term charging load. Through comparative experiments, it was found that the MSE and MAE values of the TDFAN-CLF model were the smallest among the four models, at 0.09 and 0.082, respectively. Therefore, the TDFAN-CLF model has higher prediction accuracy. Moreover, by observing the images, it was found that the model not only performs well on sunny days, but also accurately predicts the peak of daily load on rainy days, proving that the model meets the demand for ultra short term load forecasting.*
Keywords: LSTM, Charging load forecasting, Ultra-short-term

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1. **Introduction.** As a new generation of transportation, electric vehicles have good sustainability and alleviate the greenhouse effect problem, which is conducive to maintaining the health of the ecological environment. Therefore, the rise of electric vehicles is foreseeable. In recent years, governments around the world have introduced various policies

to stimulate the development of electric vehicles, and the electric vehicle industry has received strong policy support from countries around the world [1].

Electric vehicles are developing rapidly in major cities, and the charging load is also constantly increasing. Electric vehicles are a movable load, and their charging process has a certain degree of randomness. This charging behavior will increase the burden on the power grid and pose potential threats to it. If not guided and controlled, it will lead to a series of problems such as voltage quality degradation, excessive network loss, harmonics, etc. [2]. Especially when charging electric vehicles in clusters or in a disorderly manner, it poses a huge challenge to the safety and economic operation of the power system, which can easily lead to voltage instability in the power grid, and in severe cases, may cause regional power grid collapse [3–6]. So accurate prediction of charging load is particularly important.

Since the 1980s, scholars have been studying the problem of power load forecasting. Load forecasting is an important component of the power energy management system, which predicts the future load demand under specific time conditions based on the system's operating characteristics, energy enhancement decisions, natural conditions, etc., providing reference for power system scheduling. Accurate prediction of electric vehicle charging load can help the power grid better allocate resources, while pursuing economic efficiency and minimizing operational risks, improving the stability and reliability of the power grid.

Due to the high charging power and randomness of electric vehicles, the load is more complex and variable. As a necessary supporting infrastructure, electric vehicle charging stations are being planned and constructed on a large scale. At present, there has been a lack of accurate load forecasting models to represent the load of charging stations in the research on the impact of electric vehicle charging on grid voltage stability and the formulation of charging strategies. Therefore, it is urgent to establish a scientific and reasonable load forecasting model for electric vehicle charging stations to meet the research needs of all aspects and provide a solid foundation for the sustained and high-speed development of electric vehicles. According to the duration of the forecast, load forecasting can be roughly divided into four categories: long-term load forecasting (3-5 years), medium-term load forecasting (14 days-3 years), short-term load forecasting (1h-7 days), and ultra short term load forecasting (1min-1h) [7].Among them, research on long-term and medium-term load forecasting has been relatively mature [8], while short-term and ultra short term load changes have high randomness and difficulty in forecasting, and are still in the early stages of research, which has always been a focus of researchers' attention [9].

To address these issues, this study compared different research methods and considered the dual characteristics of charging load data over time. The model input simultaneously used historical load values at different times and historical load values at the same time as the model input data. Based on this, attention mechanism was combined and LSTM (Long Short Term Memory) was used for feature extraction and regression, selectively extracting key features. A TDFAN-CLF model was proposed based on the above method, and comparative experiments were conducted to demonstrate the accuracy of the model's predictions.

2. **Related work.** Accurate prediction of electric vehicle charging load is a prerequisite for future research on the impact of electric vehicles on the distribution network, the development of optimal charging strategies, as well as grid safety monitoring and preventive control. Overall, the existing methods for predicting the charging load of electric vehicles can be divided into two types: statistical methods and artificial intelligence algorithms.

Statistical prediction models are based on the theories of probability theory and statistics, such as Monte Carlo method, which is one of the mainstream prediction methods. This method calculates the probability density distribution of the starting charging amount and starting charging time of different types of electric vehicles through data such as daily travel time and daily mileage. In experiments, variables such as electric vehicle penetration rate, charging power, and daily average charging times are used to accumulate the charging load of each electric vehicle using Monte Carlo simulation, and finally obtain the total load curve. This type of method simply superimposes the charging behavior of each electric vehicle [10]. Although this method is simple, considering the randomly selected distribution parameters, it is not suitable for estimating accurate load forecasting [11]. Some other scholars have also used statistical analysis methods to study load forecasting problems [12–14]. However, these statistical methods lack generality due to the difficulty in determining parameters, and as the number of influencing factors increases, these methods often fail to achieve satisfactory forecasting accuracy.

With the gradual popularization of electric vehicles, a large amount of charging data has been generated and accumulated. This massive amount of data undoubtedly lays the foundation for machine learning, giving it a huge advantage in predicting the charging load of electric vehicles. With the rapid development of artificial intelligence technology, intelligent algorithms mainly based on artificial neural networks are gradually being applied by scholars to load forecasting of electric vehicle charging stations [15]. Hippert et al. analyzed the application of neural networks in load forecasting and demonstrated that neural networks are effective in both accuracy and efficiency of load forecasting [7].

Zhu et al. used artificial neural networks and deep learning methods based on long short-term memory models to predict short-term charging loads of electric vehicles from the perspective of charging stations. They proved that compared with traditional artificial neural networks, the LSTM model has better performance and higher accuracy in short-term load prediction of electric vehicles [16]. Tan et al. used LSTM neural networks to predict the charging load of future hourly level charging stations, and demonstrated the effectiveness of the LSTM model in charging load prediction through comparison [17]. The attention mechanism is achieved by constructing neural networks based on tasks and has been successful in a wide range of tasks. Some scholars have proposed LSTM models based on attention mechanisms for research in multiple fields, and the results show that this method has better accuracy [18–20]. Therefore, this study will build a long short-term memory model based on attention mechanism for predicting the charging load of electric vehicles.

3. **Data set description and preprocessing.** Charging stations have stored a large amount of historical charging message data during long-term operation, and in terms of data scale, they have already possessed the basic characteristics of power big data. The charging load data has obvious time series characteristics, and how to deeply and effectively mine and analyze it and apply it has become an urgent problem to be solved.

3.1. **Data set introduction.** The charging data used in this article are all from an electric vehicle charging station in Minhou County, Fuzhou City, Fujian Province, China. We have obtained the original message data of the charging station from December 2020 to November 2021 for approximately one year. The charging station has 5 fast charging stations, each with 2 charging ports. In the charging data, except for some missing and abrupt data that need to be processed, as the charging stations selected for each vehicle are random and the start and end times of charging are not fixed, it is necessary to integrate and divide the data in the time dimension. For example, when calculating the load at the end, the power of each charging port at the same time must be added up to obtain the total load of the charging station at each time.

The original message data of electric vehicle charging stations is encrypted by the information terminal in the charging station collection system at a fixed time period T to form text information with a small memory footprint, such as the charging user card number, charging start time, charging start time SOC, etc. Then, using mobile cellular communication technology, the data is transmitted to the data center. The manager can download the original charging data from the data center and decrypt the data through the corresponding protocol. The charging data used in this article is collected by charging stations with a cycle of 7 seconds, mainly including charging start time, charging station number, charging station number, charging station voltage and current during charging, SOC at charging start time, etc. After downloading the original message data, the original charging data is parsed according to the specified protocol. The parsed data format and related examples are shown in Table 1.

Table 1. Data format and related examples

Field name	Data type	Describe	Examples
cardNo	Int	Charging card number	013859330553001
beginTime	DATETIME	Charging start time	2021-04-01 03:45:18
endTime	DATETIME	Charging end time	2021-04-01 04:30:10
pileNum	Int	Charging pile serial number	1
plugNum	Int	Charging port serial number	1
pileVoltage	Float	Charging voltage(V)	344.5
pileCurrent	Float	Charging current(A)	32.2
beginSoc	Float	SOC at the beginning of charging	69.0
endSoc	Float	SOC at the end of charging	100.0

3.2. **Data set preprocessing.** During the communication between the charging station and the big data platform, some abnormal situations may occur in the transmission of data due to network delays, equipment failures, maintenance, and upgrades. So after parsing the data, it is necessary to preprocess the abnormal data. For charging load data, the main abnormal situations that occur are data loss and data mutation. Data loss refers to the loss of data at certain times, and the data during the loss period is usually represented as a "0" value or "nan". In this case, data missing points need to be filled in. The filling method is as follows

$$Y(t) = \frac{Y(t-1) + Y(t+1)}{2} \big(Y(t) > \sigma\big) \tag{1}$$

Where $Y(t)$ represents the current or voltage value at time t; $Y(t-1)$ represents the current or voltage value at time $(t-1)$; $T(t+1)$ shows the current or voltage value at time $(t+1)$; σ is the set threshold.

Data mutation is usually caused by abnormal reactions of some components, resulting in values exceeding the normal range. When the voltage or current value at a certain moment exceeds the set threshold, it is necessary to correct the abnormal point data, and the correction method is as shown in (1).

When organizing data, it was found that some rows had empty values for the entire row. The main cause of this issue is the loss, flipping, and shifting of communication protocol data bytes due to network or other reasons. During the parsing process, the server fails to decrypt or verify the data. This type is extremely rare, and after comparative analysis, it was found that most of the problems with this type are missing at a certain moment in time, and there will not be a situation of missing for a long period of time. Therefore, interpolation method is used to use the data from the previous moment as the data for the current moment. Additionally, it has been found that there may be inconsistencies in the time intervals between adjacent data. For example, if data with a normal interval of 7s changes to a 6s interval in a certain segment, it is necessary to resample all data with a 7s interval, and fill in the closest data segment if it is not in that period.

In order to better describe the changes in load within a day, the time interval for cumulative load is usually set to 15 minutes to observe the changes in load. Adding the power of 10 charging ports at the same time can obtain the charging load of the charging station at a certain time. The calculation formula is:

$$P_i = \sum_{n=1}^{10} U_{ni} \times I_{ni} \tag{2}$$

In the above equation, P_i is the power of charging station i at time i, that is, the load; $N = (1, 2, ..., 10)$ is the charging slogan of the charging station; U_{ni} is the voltage at time i of the nth charging port; I_{ni} is the current at time i of the nth charging port. Considering that the power consumption of each charging station to maintain its own operation accounts for one-tenth of the total power consumption, and the efficiency η of the charging station is 0.9, the total load of the charging station at a certain moment is:

$$P_i' = \frac{P_i}{\eta} \tag{3}$$

3.3. **Charging data characteristics.** The changes in power load have both temporal continuity and periodicity. By analyzing the time series of load data, we can identify its changing characteristics. The load of power stations has randomness and volatility, as the charging start time and charging power of each electric vehicle are uncertain, and the charging load value will fluctuate up and down within a certain period of time; Taking the charging station studied in this article as an example, the daily load curve is used to analyze the load variation characteristics of the charging station.

The daily variation characteristics of charging station load refer to the trend of charging load changing over time within 24 hours. In general, electric vehicles are mostly in use during the day, and there is no idle time or need to charge the car. People's outdoor activities will significantly decrease at night, when electric vehicles are idle. Most people choose to charge their electric vehicles during this time. So, according to normal calculations, the peak charging period will occur at night, while the daytime load is in a low state. However, guided by policies such as time of use electricity pricing, there may also be several peak load periods during the day to avoid situations where electric vehicles are charging at night and the peak load is too high. Although users may be guided by policies such as time of use electricity prices to change their traditional charging habits, a new charging pattern will still emerge in the end, with fixed peak and valley periods.

Figure 1 shows the daily load curve of the charging station on October 16, 17, and 18, 2021. From the red dashed box in the figure 1. It can be observed that the charging station will have varying degrees of load peaks at 0-1, 6, 8-9, 12, 17-18, and 21-22. The black dashed box indicates the low load periods of the charging station at 2-4, 9-10, and 14-16. From the time when the peaks and valleys appear on the three curves, it can be seen that the charging load curves show very similar peak valley patterns on adjacent dates. In addition, the load curve will show a continuous upward or downward trend in a short period of time, so the load of the charging station has continuity for a certain period of time. These characteristics indicate that the peak and off peak periods of electricity consumption at charging stations are traceable, and historical load data can serve as important reference conditions for charging load forecasting.

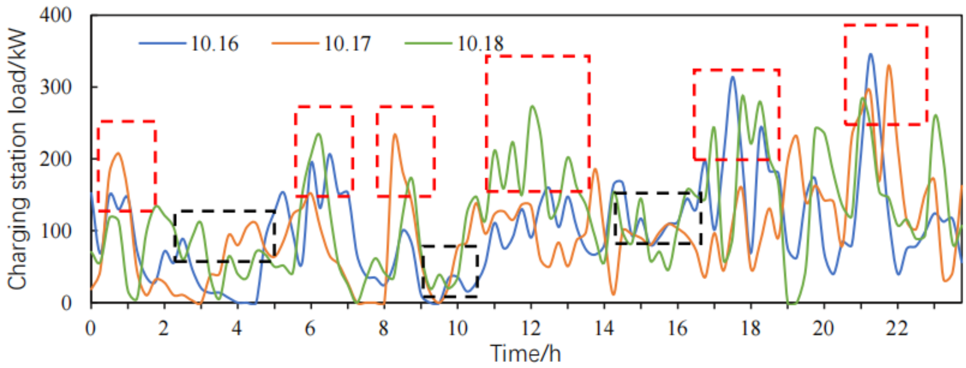


Figure 1. Daily load curve of charging station on October 16, 17 and 18, 2021

4. **Modelling.** Considering the time requirements of ultra short term load forecasting, this study combines attention mechanism and the dual characteristics of charging load data in terms of time. LSTM neurons, a charging load forecasting model based on TDFAN-CLF model is proposed to achieve accurate prediction of ultra short term charging load.

4.1. **Model framework.** The TDFAN-CLF model framework proposed in this article is shown in Figure 2. As can be seen from the figure, the model consists of an input layer, a feature extraction layer, an attention layer, and a feature regression layer, and ultimately outputs load forecasting values. The model takes into account the dual characteristics of charging load data in terms of time which increases the potential features of the input data and enables the model to have high prediction accuracy. By selectively extracting key features through attention layers, hidden information with temporal features can be obtained. Decoding hidden information with temporal features through feature regression layer to obtain output, and finally comparing the output value with the true value to calculate the loss value.

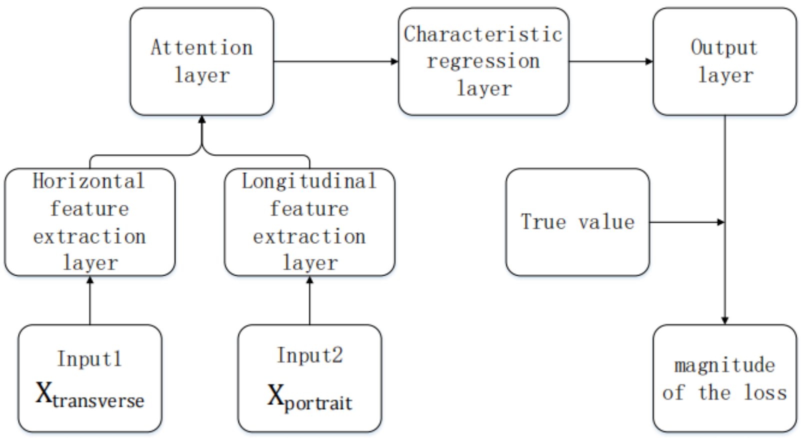


Figure 2. TDFAN-CLF Model framework

4.2. **Feature extraction unit.** The feature extraction unit is responsible for extracting features from load data with different correlations to obtain complete feature information. We need to extract dual features from the load data here, using LSTM neurons. The data flow within LSTM goes through multiple sub modules, which use weight links internally. The structure contains multiple gates for selectively remembering or forgetting historical information, which meets the needs of users and is a neural network algorithm structure that can save a lot of memory, as shown in Figure 3. After extracting weight linked features from historical information at different time points, the data flows to multiple activation unit functions, and then the required output feature information is calculated through multiple matrices. The memory of historical information contains two different contents, one is that longer-term information is stored in C_t, and the other is that short-term information is stored in h_t.

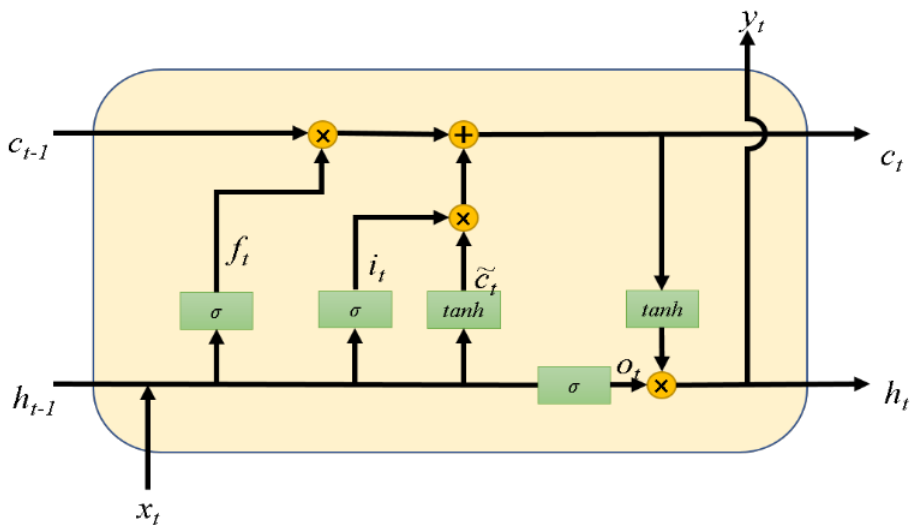


Figure 3. Memory module structure

The internal data flow of this memory module can be expressed as the following equations:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{4}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{5}$$

$$\widetilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{6}$$

$$C_t = C_{t-1}f_t + \widetilde{C}_t i_t \tag{7}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{8}$$

$$h_t = o_t \tanh c_t \tag{9}$$

Among them, h and b respectively represent the weight and bias values of the neural connections within the module; $\sigma()$ and $\tanh()$ are activation functions.

4.3. **Attention mechanism.** The attention mechanism can allocate input weights, just like how the human eye can give greater attention to scenes of interest to the brain, making the model pay more attention to important features in the input. The input-output relationship of the attention layer can be described as an equation; $Q_w^{'}$ is the result obtained by activating Q_w through the Softmax function, and Q_w is calculated by the next equation;

$$Att = (Q_w^{'})^{TR} X_{info} \tag{10}$$

$$(Q_{wi,j}^{'}) = \frac{\exp(Q_{wi,j})}{\sum_{j=1}^{M} \exp(Q_{wi,j})} \tag{11}$$

$$Q_w = W_q X_{info}^{TR} \tag{12}$$

Among them, X_{info} represents the input of the temporal attention layer; Att represents the output of the temporal attention layer, which is the attention weight; TR represents matrix transpose.

4.4. **Model parameter setting.** The values of charging load at adjacent times are continuous and there will be no significant jumps. At the vertical level, there is a periodic pattern, which means that the load curve trends have a high degree of similarity between adjacent dates. Li et al. used a fuzzy clustering analysis method based on transition closure to select historical loads similar to the predicted load as training samples, which improved the prediction accuracy 21. Therefore, in the charging load prediction model, the selection of historical load has a significant impact on the accuracy of the model prediction. Existing research only considers the horizontal level of time, using the first n historical time points as inputs to predict the current time point; Some only consider the longitudinal aspect of time and use the same historical time of the previous n days as input to predict the current time, but the prediction results are not ideal. So this chapter starts from the perspective of historical load, comprehensively considering the horizontal and vertical aspects of load data in time. At the same time, historical load values at different times and historical load values at the same time are used as input data for the model, and the predicted charging load at the next time is used as output.

Input vectors of charging load history at different times:

$$X_{transverse}^{t} = (p^{t-1}, p^{t-2}, \cdots, p^{t-i}) \tag{13}$$

In the above equation, $X_{transverse}^{t}$ is the charging load value of the previous i times before the current time t; p^{t-1} is the charging load value at time $(t-i)$; i depends on the historical depth traced back to the current time t. When $i = 4$, it means that the historical time can be traced back to the first four time points of the current time.

Input vector at the same time of charging load hist

$$X_{portrait}^{t} = (p_{m-1}^{t}, p_{m-2}^{t}, \cdots, p_{m-k}^{t}) \tag{14}$$

In the above equation, $X_{portrait}^{t}$ represents the charging load at the same historical time k days before the current time t; p_{m-k}^{t} is the charging load value on the $(m-k)$th day at the current time t; k depends on the historical depth traced back to the current time t. When $k = 5$, the historical time is traced back to the same time value in the previous 5 days.

$$Y = p^{t} \tag{15}$$

In the above equation, p^t is the charging load value output at time t.

Loss function The loss function, also known as the objective function, serves as the basis for updating and iterating the model, and is used here to calculate the error between the actual value and the predicted value. This article uses the mean square error of charging load as the loss value to optimize the model. Formula (16) is the calculation method for the loss value

$$loss = \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y}_i)^2 \tag{16}$$

In the above equation, $\tilde{y}_i$ is the predicted load value, y_i is the actual load value, and n is the number of samples.

The optimization algorithm of the model adopts the adaptive optimization algorithm Adam, where the parameters of the algorithm are defined as follows:$lr = 0.001$,$\beta1 = 0.9$, $\beta2 = 0.999$,$\epsilon = 1e - 08$,$decay = 0.0$.

Experimental parameter setting The network structure of the TDFAN-CLF model is shown in Table 2.

Table 2. TDFAN-CLF model parameter setting

Layer name	Number of neurons
Input layer	10×1(Input 1),7×1(input 2)
Feature extraction layer	128
Merge layer	17×128
Attention layer	128×128
Regression layer	1×1

5. **Experiments.** o verify the effectiveness of the model proposed in this study, we conducted comparative experiments. This study compared the LSTM-1 model (considering historical same time points), LSTM-2 model (considering historical different time points), LSTM-3 model (considering both historical same time points and historical different time points, but without adding attention mechanism) with the TDFAN-CLF model proposed in this chapter. The parameters of the LSTM-1, LSTM-2, and LSTM-3 models will also be given below. Finally, based on the evaluation index values of the four models and the plotted curves of real and predicted values, the predictive performance of the four models will be compared and analyzed.

5.1. **Evaluating indicator.** The quality of the prediction results needs to be measured by relevant indicators. The prediction of charging load belongs to regression problems, so Mean Square Error (MSE) and Mean Absolute Error (MAE) are selected as evaluation indicators. MSE and MAE can reflect the degree of change between predicted and actual values. The smaller the values of the two, the higher the prediction accuracy of the model. The calculation formula is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y}_i)^2 \tag{17}$$

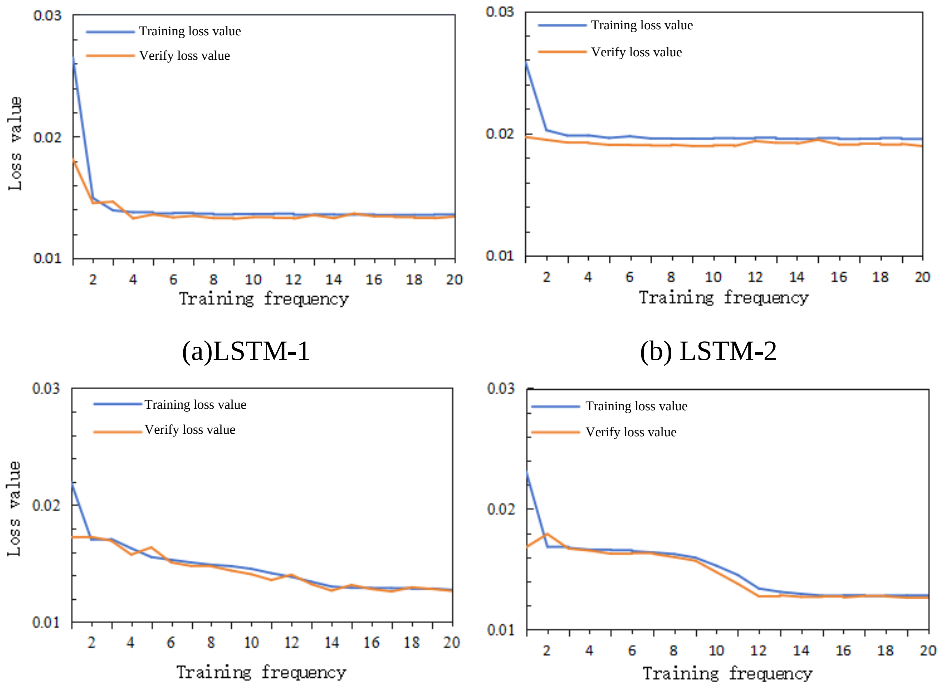
$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \overline{y}_i| \tag{18}$$

In the above equation, $\overline{y}_i$ is the predicted charging load value, y_i is the actual load value, and n is the number of samples.

5.2. **Experiment and comparative analysis.** The evaluation results of the model are shown in Table 3. It can be seen from the table that the MSE and MAE of the LSTM-1 model are 0.013 and 0.090, and the MSE and MAE of the LSTM-2 model are 0.020 and 0.1113, respectively. The MSE and MAE of the LSTM-3 model considering the dual characteristics of load data time are reduced to 0.012 and 0.086, respectively. The MSE and MAE values of the TDFAN-CLF model with attention mechanism are the smallest, reduced to 0.09 and 0.082, respectively. Figure 4 shows the loss function curve, from which it can be seen that the TDFAN-CLF model converges the fastest and tends to stabilize in the second training.

Table 3. Evaluation results of each model

Model	LSTM-1	LSTM-2	LSTM-3	TDFAN-CLF
MSE	0.013	0.020	0.012	0.009
MAE	0.090	0.113	0.086	0.082



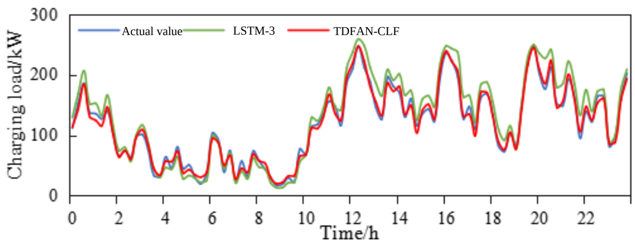
(a)LSTM-1 (b) LSTM-2

(c)LSTM-3 (d) TDFAN-CLF

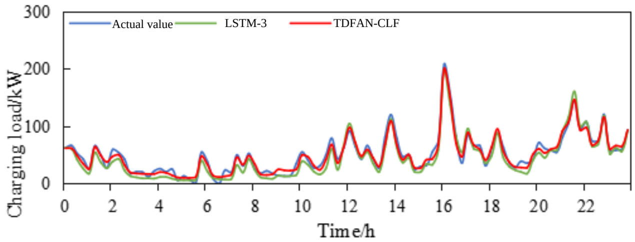
Figure 4. Loss function curve

From the perspective of evaluation indicators, the LSTM-3 model, which considers both the same time and different time point correlations of load data, has higher prediction accuracy than the LSTM-1 and LSTM-2 models. The TDFAN-CLF model with attention mechanism added on the basis of LSTM-3 model has further improved its prediction accuracy.

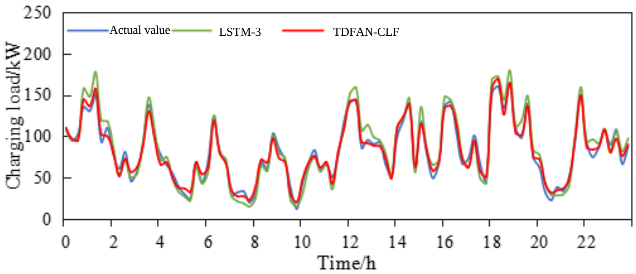
In order to compare the prediction accuracy of TDFAN-CLF model and LSTM-3 model more intuitively, the prediction results of one day each in spring, summer, autumn, and winter were randomly selected and plotted. Observing Figures 5 (a), (b), (c), and (d), it can be seen that both model prediction curves can fit the actual charging load curve well. In comparison, the TDFAN-CLF model prediction curve is closer to the actual value. It is worth mentioning that after checking the historical weather conditions, January 13th, August 9th, and November 17th were all sunny days. From Figures 5 (a), (c), and (d), it can be seen that the TDFAN-CLF model's predicted values were highly consistent with the actual values for these three days, while May 20th was rainy. From Figure 5 (b), it can be seen that although the TDFAN-CLF model's predictions were slightly biased during the low load periods of 3-5 and 19-21, it was able to accurately predict the highest load value for that day at 16:00. The peak of daily load poses a threat to the voltage stability of the distribution network, and the TDFAN-CLF model can accurately predict the peak of daily load even on rainy days. Therefore, this model is suitable for the study of voltage stability in distribution networks and meets the needs of safety monitoring and emergency handling for ultra short term load forecasting.



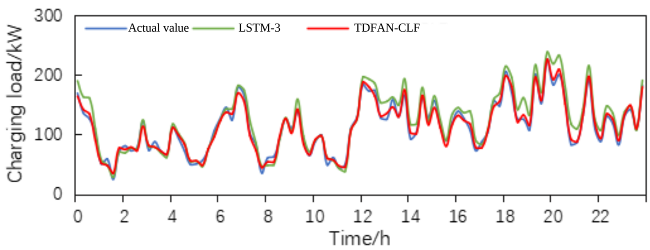
(a) January 13, 2021



(b) May 20, 2021



(c) August 9, 2021



(d) November 17, 2021

Figure 5. Actual load curve of each season of charging station and prediction curve of each prediction model

6. **Conclusion.** This article mainly focuses on the research of electric vehicle charging load prediction. Starting from the charging load data of electric vehicles at charging stations, missing and abnormal data are preprocessed, and the characteristics of the data are analyzed. Compared with other prediction methods, considering the dual characteristics of charging load data in time, historical load values at different times and historical load values at the same time are used as input data for the model, which increases the potential features of the model input data. On the basis of the LSTM prediction model, attention mechanism is combined, and a single-layer LSTM neuron is used as the feature extraction and feature regression layer to selectively extract key features, thereby obtaining hidden information with temporal features.

Through comparative experiments, it was found that the TDFAN-CLF model proposed in this study has the smallest MSE and MAE values among the four models mentioned in this paper, which are 0.09 and 0.082, respectively. Therefore, the TDFAN-CLF model has better performance in predicting electric vehicle charging load. By observing the images, it was found that the model has good prediction accuracy regardless of whether it is sunny or rainy, which can alleviate the pressure of electric vehicle charging load on the power grid, especially during peak electricity consumption periods. The prediction curve and load curve are very close, proving that the model is suitable for the research of ultra short term prediction of electric vehicle charging load and can also meet the demand for voltage stability in distribution networks.

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