Research on Forecast of Daily Electricity Consumption of Household Air Conditioning Based on Improved Long-short Memory Network

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Abstract: Daily electricity consumption forecasting of home appliances can improve the accuracy and efficiency of the operation of home energy management systems. In this paper, an improved bidirectional long short memory network (BILSTM) model for predicting daily electricity consumption of household air conditioning is proposed. Firstly, the "mutual information" is used to analyze the correlation between the daily electricity consumption of air conditioning and some environmental factors. Second, the environmental factors with strong correlation with the daily electricity consumption of air conditioning are selected as the influence factors, and these influence factors and the electricity data are taken as the characteristic input of the network. Finally, the improved bidirectional LSTM load prediction model which has been trained is used to forecast the daily electricity consumption of air conditioning. The experimental results show that the improved bidirectional LSTM network proposed in this paper can predict the daily electricity consumption of air conditioning in short term, and the maximum relative error of the predicted result is less than 5%.

1. Introduction
With the economic growth and the development of smart grids, the proportion of household electricity consumption is increasing rapidly [1], household power management has received more and more attention [2], the key to the household power management system is the system Modeling, where the typical load (air-conditioning, electric heating, etc.) daily electricity consumption forecast is the bottleneck of the modeling. In the past, only data on the total load of electrical appliances could be obtained, and it was difficult for residents to obtain the energy consumption of individual household appliances. With the development of non-intrusive load monitoring, users can obtain estimates of the energy consumption of individual household appliances from smart meters [3], as Electricity consumption forecasts for household appliances provide the possibility.

However, there are certain difficulties in short-term forecasting of electricity consumption of electrical appliances. As we all know, the electricity consumption of electrical appliances is directly affected by the user's electricity consumption habits, showing a certain periodicity and strong randomness [4]. Factors such as temperature, humidity, rainfall or date type (whether it is a holiday) may also affect users. The consumption of electric energy [5], therefore, the electric energy time
series have non-linear characteristics, and the forecasting problem has become a random and multi-factor influence time series forecasting problem.

In the short-term time series forecasting problem, researchers have proposed some traditional statistical methods, such as linear regression [6], multiple regression [7]. The author of literature [8] considered the relationship between weather and other influencing factors and electric energy consumption patterns, and developed a multiple linear regression model of energy consumption in different seasons for electric energy prediction. The author of literature [9] considered the influence of economic and demographic variables on electricity consumption, and proposed a multiple linear regression electricity forecasting model to obtain a relatively good forecasting effect. Then, a model based on ARIMA (Autoregressive Integrated Moving Average) [10] was proposed for future electric energy estimation and prediction, which improved the prediction accuracy. However, these methods are often more complicated in system modeling, the computational burden is too high, and the effect of processing the nonlinear characteristics of time series is poor, and the prediction accuracy is difficult to meet the higher requirements.

With the rapid development of machine learning, new possibilities are provided for improving the accuracy of HEMS demand forecasting. Compared with traditional statistical methods, machine learning requires less effort in system modeling, and is very effective in dealing with time series with strong randomness, multi-factor influence, and nonlinearity. In recent years, machine learning algorithms such as artificial neural networks [11], support vector regression [12], and long short-term memory networks (LSTM) [13] have been widely used in time series prediction problems. Literature [14] proposed a machine learning model for short-term load forecasting in the electricity market. Compared with the back-propagation neural network method, the model is established faster and the prediction effect is good. Literature [15] uses the combination of PSOA-CNN to predict the electrical load. However, power load data is a time series that is highly correlated with time. CNN has no cyclic characteristics. Traditional RNN has cyclic characteristics but has a longer effect on processing longer time series. The network is prone to the problem of gradient disappearance. With the development of deep learning, the LSTM network is widely used in load forecasting due to its "time memory", the characteristics and advantages of complex data fitting and data time correlation analysis. In 2016, [16] first tried the residential load forecasting problem with LSTM. It designed a sequential LSTM (S2S-LSTM) model to predict the electricity consumption of a residential building. After this work, [17]–[20] tried to reproduce the method and compared LSTM with other machine learning methods. The results showed that LSTM has better accuracy in resident load forecasting. Literature [18] also predicts power load based on deep learning LSTM network, but a single LSTM network has many gated units and complex algorithms, so the training speed is slow and the prediction model stability is poor.

In this paper, an improved bidirectional neural network is proposed to predict the daily electricity consumption of air conditioning of household appliances by using mutual information method to select input features. The rest of this paper is arranged as follows: Section 2 describes the correlation between the daily electricity consumption of air conditioning and environmental factors by mutual information analysis; Section 3 introduces the proposed method for predicting the daily electricity consumption of bidirectional LSTM air conditioning; Section 4 presents the experimental results and analysis; and finally, Section 5 summarizes the work of this paper.

2. Analysis of the correlation between the daily electricity consumption of air conditioning and environmental factors.
Since the daily electricity consumption value of household appliances is often affected by many environmental factors, such as temperature, humidity, rainfall, and holiday types, etc. [5] Before short-term forecasting, a comprehensive analysis should be made to grasp the law of daily electricity consumption, and analyze the correlation between daily electricity consumption and influencing factors, so as to improve the accuracy of load forecasting. This paper uses "mutual information" to analyze the correlation between the daily electricity consumption of air conditioning and some
environmental factors, and chooses the influential environmental factors as the influencing factors and uses them as the input value of the network to predict the daily electricity consumption of air conditioning.

2.1. Mutual information principle
The traditional correlation analysis methods mostly use the Pearson method, and the Pearson method only needs to be used to analyze the linear correlation between variables. However, the daily electricity consumption of electrical appliances and temperature and other factors are not linear, so this article uses "Mutual information" to analyze the correlation between the non-linear relationship between the daily electricity consumption of electrical appliances (air conditioner) and environmental factors such as temperature. The principle of mutual information is simple and the amount of calculation is small.

Mutual Information is a measure of the mutual dependence between two sets of events. The mutual information of two random variables is a measure of the interdependence between variables. The mutual information measure shares the information contained in two variables. Knowing the value of one variable will reduce the unpredictability of the other variable.

The mutual information value between two discrete variables can be calculated using the following formula:

\[ I(X; Y) = \sum_{y \in Y} \sum_{x \in X} p(x, y) \log \left( \frac{p(x, y)}{p(x)p(y)} \right) \]  

(1)

Where \( p(x, y) \) is the joint probability distribution function of \( X \) and \( Y \), and \( p(x) \) and \( p(y) \) are the marginal probability distribution functions of \( X \) and \( Y \) respectively. The greater the value of mutual information, the stronger the correlation between the two variables.

2.2. Correlation analysis based on mutual information principle
In this paper, the data of electrical daily electricity consumption of household 7951 in Austin area from DataPort database in the summer of 2018 for 49 days (July 11 solstice August 28) and data of some environmental factors were selected as the data set, selected typical household air conditioning. We consider the environmental factors that affect the electricity consumption of air conditioning: average temperature, average humidity, rainfall, date type (whether it is a holiday), and use mutual information principles and formulas to calculate the mutual information value of daily electricity consumption and these factors, The statistics are as follows:

| Mutual information value | average temperature | Average humidity | Rainfall | Date type |
|--------------------------|--------------------|-----------------|---------|-----------|
| Daily electricity consumption | 0.87               | 0.69            | 0.28    | 0.42      |

From the correlation analysis in Table 1, it can be seen that the daily electricity consumption of air conditioning in summer has a strong correlation with the average temperature and average humidity, and the correlation with date type is moderate, the correlation with rainfall is weak. So the average temperature, average humidity, date type (holiday or not) are used as the influencing factors and the electricity data are used as features as the input values of the prediction network model.
Figure 1 Daily electricity consumption and influencing factors of air conditioning

3. The improved bidirectional LSTM forecasting method

3.1. LSTM neural network

Long Short Term Memory cell (Fig.2) is an improved variant of Recurrent Neural Networks (RNN) cell. LSTM retains the ability of the RNN network to efficiently process time series data. LSTM effectively solves the gradient vanishing and gradient explosion problems in RNN network, and has the ability of processing nonlinear data by neural network. Unlike recurrent neural networks, long-term short-term memory networks have three special structures: input gates, output gates, and forgetting gates, which enable it to remember long-term information.

3.2. The Improved Bidirectional LSTM neural network prediction model

Figure 3 The proposed improved Bidirectional LSTM load forecasting model
The overall structure of the Bidirectional improved LSTM neural network prediction model is shown in Figure 3. The Bidirectional LSTM (BiLSTM) layer is composed of two LSTM layers superimposed on top of each other. Its advantage is that the relationship between the forward and backward time directions of the time series can be used to learn information that has a long-term dependence on time. Compared with the LSTM, BiLSTM has one more reverse calculation. For each time \( t \), the input will be provided to two LSTM layers with opposite directions at the same time, and the output is jointly determined by the two LSTMs with opposite directions. In the regression prediction of time series, it can achieve better prediction effect than LSTM, avoiding the problem of gradient disappearance and gradient explosion of LSTM on long-term series.

### 3.3. Sample data sets and network parameter Settings

This paper establishes an improved LSTM network model for load forecasting research, selects typical electric appliance (air conditioning), selects the data set based on the database in the field of non-intrusive load monitoring research, the selected database is the dataport database. The air daily electricity consumption data, average temperature, average humidity, and date type of 7951 household in Austin area for 49 days in summer (7.11- 8.28) are used as data sets. The data sets are divided into training set, validation set, and test set. The datas for training and verifying are the air conditioning daily electricity consumption datas and influencing factor datas (9:1 division) from July 11 to August 16, and the datas for the test set use the data of the air conditioning daily electricity consumption and influencing factors from August 17 to 28, the algorithm is used to predict the air daily electricity consumption of the last 4 days (8.25-8.28) of test set.

The input of the network is the daily electricity consumption of the 7 days before the air conditioning, the average temperature of the 7th day, the average humidity, the average temperature of the 8th day, the average humidity of the 8th day and the date type, a total of 12 Features (normalization) are used as input, so the input layer of the network has 12 nodes, the output is the 8th day load daily electricity consumption, and the output layer of the network is 1 node.

The network structure is detailed in section 3.2. The other parameters of the network are set as follows: the loss function is the mean square error (mse) function, the maximum number of iteration steps is set to 200, batch training, the number of training samples each time is 6, and the initial trial learning rate is set to 0.1, the Adam optimization algorithm is used for network training instead of the traditional stochastic gradient descent method.

### 4. Experimental results and analysis

#### 4.1. Evaluation indicators of network prediction effect

Compare the prediction results of the proposed improved bidirectional LSTM neural network model with the actual value to verify whether the performance of the proposed improved LSTM model is good, and select the average absolute Error (MAE), maximum relative error (S) evaluation indicators to evaluate the prediction effect, the formula is as follows:

1) Mean absolute error:

\[
\text{MSE} = \frac{1}{T} \sum_{t=1}^{T} |\hat{y}_t - y_t| \tag{2}
\]

2) Maximum relative error:

\[
s = \max \left( \frac{|\hat{y}_t - y_t|}{y_t} \right) \tag{3}
\]

Where \( y \) is the estimated daily electricity consumption value of the appliance, \( y_t \) is the true value of the electricity consumption of the appliance that day, \( T \) is the total number of days, and \( t \) is the time (days).

#### 4.2. The experimental results and comparison

The value of the loss function in the process of network training and verification varies with the number of iteration steps as shown in the figure below:
As can be seen from Figure 4, the proposed model has a fast convergence rate for training. When the number of iteration steps reaches about 100, the loss values of the training set and the validation set have already reached an acceptable range.

In order to reflect the accuracy of the improved Bidirectional neural network model proposed in this paper to predict short-term power load, a new model with the same learning samples and some parameters is established with LSTM network and BP neural network for prediction, and added the traditional statistical algorithm Multiple linear regression (Multiple linear regression) also performs prediction, and the comparison of the obtained prediction results of each algorithm is shown in the figure below.

The prediction performance of the proposed improved Bidirectional LSTM network, LSTM network, BP neural network, and multiple linear regression are analyzed with evaluation indicators, and the statistics are as follows:
As can be seen from the figure 5 and table 2, the proposed improved bidirectional LSTM network with the greatest relative error of the predicted results is 4.37%, within the acceptable range of 5%, the proposed improved Bidirectional LSTM network can perform short-term electricity prediction for home appliance air conditioning. while the other contrast algorithm of the maximum relative error of 10% or more, the proposed improved bidirectional LSTM network to predict the average absolute error value is smaller than other contrast algorithm, the proposed network prediction accuracy is higher.

5. Conclusion
In this paper, the influence of environmental factors on the forecast of daily electricity consumption of air conditioning is considered comprehensively. Firstly, the "mutual information" is used to analyze the correlation between the daily electricity consumption of air conditioning and the nonlinear relations of some environmental factors. Second, the significant features (average temperature, humidity, date type) that affect the daily electricity consumption of air conditioning are selected as the input values of the network. Finally, an improved bidirectional LSTM load prediction model is established to predict the short-term daily electricity consumption of household air conditioning. The experimental results show that the improved bidirectional LSTM load prediction model can predict the short-term daily electricity consumption of air conditioning. Compared with the LSTM network, BP neural network and multiple linear regression prediction algorithm, the prediction accuracy of the proposed network is higher. The model proposed in this paper is also applicable to the short-term prediction of the daily electricity consumption of other typical household appliances (such as electric heating appliances) of a specific user. In the future, some related technologies can be studied to further improve the accuracy of the prediction.

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