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Research on Electric Load Forecasting Method

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Abstract

Accurate power load forecasting has far-reaching significance in the daily operation and maintenance of the power grid, long-term decision-making and user power management. However, due to various uncertain factors and the nonlinear and random behavior of users, the difficulty of power load forecasting is further increased. Even though domestic and foreign scholars have conducted a lot of research in this area, we still need a more accurate And a stable power load forecasting model. To further alleviate this problem, this paper adopts a novel power load forecasting model: Long-Short-Term Time Series Network (LSTNET). The model adopts convolutional neural network (CNN) to form convolutional layers to capture the short-term characteristics of loads and short-term dependencies of variables, while recurrent layers composed of gated recurrent neural network (GRU) and long short-term memory network (LSTM) and The loop skip layer is used to capture the long-term characteristics and variables of the long-term dependence of the load, and the adaptive regression part of the autoregressive model (AR) is formed to improve the robustness of the model. The experimental results show that the LSTNET network model has better accuracy.

Keywords

Load Forecasting; CNN;LSTM;LSTNET.

1. Introduction

With the continuous development of the national economy, the demand for electricity and energy in the whole society is increasing day by day, and the situation of insufficient electricity supply appears. Therefore, the entire power system needs to analyze and select an appropriate model or method for power load forecasting based on the existing detailed load data at the same time as the characteristics of the actual power consumption on the ground. Only by clarifying the specific power loads in different regions and intervals, can a reasonable power supply plan be carried out based on the existing load data, so as to achieve a balance between power supply and demand, fully guarantee the actual power demand of each end user, and thus ensure the power supply of the entire power system. Safe and reliable operation, in order to lay a theoretical foundation for the local planning of electric energy demand.

2. Research purpose, significance and development trend

As a kind of secondary energy, electric energy is the prerequisite for the stable development of all walks of life, the cornerstone of the healthy development of the country, and an important guarantee for the advancement of the entire society. The "Guiding Opinions on Actively Promoting "Internet +" Actions issued by the State Council in 2015 clearly pointed out the future development direction of "Internet +" smart energy [1]. At present, my country's national economy is undergoing changes from a high-speed growth stage to high-quality development. With the vigorous development of all walks of life, electric energy, as an indispensable and important link in national economic construction and people's lives, also needs to be further

developed. In order to ensure stable power supply and power supply quality, higher requirements are put forward for the safe and efficient operation of the power grid [2].

Since the storage of electric energy will be lost over time, and the large-scale electric energy storage technology is not yet mature and difficult to achieve, an ideal solution at this stage is to ensure that the power generation and consumption are in a dynamic balance. , in order to ensure the safe, reliable and efficient operation of the power grid [3]. As a part of the power system, power load forecasting is based on the establishment of the power grid and maintaining its normal use and operation. While improving the quality of power supply services, it is also natural to put forward higher requirements for power load forecasting. That is to make more accurate power load forecasting. A research result from abroad shows that even if the error of power load forecast increases by only 1%, it will obviously increase the cost of grid operation [4]. With the increase of power demand year by year, the accuracy of power load forecasting will have a direct impact on the safe operation, efficiency and power supply quality of the entire power system [5]. How to accurately predict the power load is of great significance to the arrangement of the unit maintenance plan, the planning of the power grid operation mode and the grasp of the market trend. It will help promote social stability, solve various problems, and will also help the relevant departments to improve the market in the market. To compete well, to better serve the society, and to improve the economic level. Accurate power load forecasting has many meanings, mainly as follows:

(1) Power load forecasting is an important issue for the power system to improve the management efficiency of the power grid system, reduce the cost of power generation, power supply and transmission, and reduce power loss, and to predict and judge future power demand [6];

(2) Accurate power load prediction can more reasonably control the stop and start of the generator set, which is conducive to reducing energy consumption, so as to meet the social demand for electricity as much as possible, and at the same time, the maintenance work of the generator set is effective. Some help [7];

(3) Long-term power load forecasting in my country can effectively reduce the cost of thermal power plants to a large extent, which is in line with my country's strategic goal of sustainable energy development [8];

(4) The quality of the power load prediction results can provide guidance for the local power department whether to add generator sets and determine the capacity of the generator sets. At the same time, according to the prediction results between regions, it can also provide a reference for the site selection and reconstruction of power plants, which is conducive to rationally arranging the operation mode of the power grid;

(5) Accurate power load forecasting can maximize the power supply quality of the power system, is an important guarantee to ensure the safe operation of the national grid, and greatly improves the economic and social benefits of the entire power industry to society.

Reference [9] used artificial neural network (ANN) in 1991 to predict the load problem in power system. Literature [10] Hochreiter S et al. in 1991 used long short-term memory network (LSTM) to improve the problem of long-term dependence in RNN and perform load prediction. Reference [11] Vermaak J et al. used a recurrent neural network (RNN) to predict the short-term load of the power system in 1998, and obtained a relatively satisfactory prediction accuracy, but the problems of gradient disappearance and explosion in the model could not be solved. Reference [12] applied support vector machine (SVM) to power system to forecast load in 2003, and achieved ideal results. Reference [13] Alex Graves et al. proposed a bidirectional long short-term memory network (vanilla LSTM) in 2005, and finally formed a widely used LSTM model. The LSTM neural network has greatly improved the gradient

disappearance and explosion problems that RNN is prone to. , the prediction accuracy is greatly improved. Literature [14] KCho et al. proposed Gated Recurrent Neural Network (GRU) in 2014.

The combined forecasting method takes into account the advantages of each model, so the combined forecasting method has become the development direction of the research on load forecasting methods at home and abroad. Reference [15] used a recurrent neural network-based power load forecasting model to predict power load using the long-term correlation of memory sequences of LSTM networks. Literature [16] Sun Yaming et al. proposed a short-term load forecasting method based on ant colony optimization algorithm recurrent neural network, which alleviated the problem of slow convergence speed of BP algorithm and easy to fall into local minimum to a certain extent. Literature [17] Fang Na et al. used empirical mode decomposition (EMD) and gated recurrent unit (GRU) combined model to forecast the power load in the short-term, which can effectively improve the short-term power load forecasting accuracy. Reference [18] proposed an optimized least squares support vector machine (LSSVM) prediction model ISSA-LSSVM based on the improved sparrow search algorithm (ISSA). In [19], scholars proposed a short-term load forecasting (STLF) method based on fuzzy time series (FTS) and convolutional neural network (CNN). Reference [20] applied the combined modeling method of CNN-BiLSTM to short-term power load forecasting. The combined model constructed by this method can improve the short-term forecasting accuracy of multi-dimensional power load data. Reference [21] proposed an attention-based CNN-LSTM-BiLSTM model for power load forecasting. CNN can effectively extract features, and attention mechanism can assign weights to features, highlighting the importance of different features in load prediction models. LSTM-BiLSTM can predict the load based on the extracted features. Reference [22] proposed the LSTNET forecasting model, which improved the power load forecasting accuracy.

3. Features of Electric Load Forecasting

The load of the power system changes with time. In the long run, the power consumption of end users, the level of local economic development, working days and holidays, and the alternation of four seasons (spring, summer, autumn and winter) usually have a huge impact on the load. At the same time, it is affected by climatic factors (temperature, rainfall, sunshine, etc.) and various other uncertain factors, which show randomness and time-varying [23].

3.1. Continuity and periodicity

The power consumption of end users, the level of local economic development, working days and holidays, and the alternation of four seasons (spring, summer, autumn and winter) usually have a huge impact on the load and show a certain continuity and periodicity. Time is one of the most important factors affecting electric load forecasting. The load in the same period in the future can be predicted by comparing the load in the historical period.

3.2. Randomness

Compared with periodic power load forecasting, it can be predicted more accurately. However, the occurrence of various uncertain events adds certain difficulties to power load forecasting, because these are completely unpredictable and unpredictable random events. Therefore, we can only predict the power load as accurately as possible.

3.3. Time-varying

Due to the characteristics of the power system itself and the vague and uncertain power demand of end users, the time-varying data of power load data is very significant. Power load forecasting usually requires a comprehensive forecast based on existing data and combined with objective uncertain factors. Therefore, it is necessary to clarify the time period of historical

data and the time range of future prediction before forecasting. When establishing the forecast model, it is necessary to consider the time-varying power load and dynamic compensation to carry out the load modeling of the power system [24].

4. Electric load forecast classification

Due to the different classification standards of power load forecasting, the classification methods are also different, but people are usually divided into the following four categories according to the length of the forecasting time period [25].

4.1. Ultra-short-term power load forecast

The general forecasting time interval is 0 to 60 minutes, with a maximum of 24 hours. The appropriate time is selected in seconds or minutes to forecast future power loads. It is usually used to monitor and dispatch the security state of the power system and handle emergency situations. .

4.2. Short-term power load forecast

Generally, it is mainly used in daily load forecasting or weekly load forecasting. It is often used to guide the power dispatching of the power system, plan the complementary plan of thermal power and hydropower power, and optimize the running time of generator sets. It is the most common type of power load forecasting.

4.3. Medium-term power load forecast

The time horizon for forecasts varies from a few weeks to a few months. It is mainly used to determine the operation mode of the generator set, and to formulate plans for monthly maintenance, reservoir dispatching and thermal coal. The high-accuracy forecast of power load in the medium term plays an important role in formulating the procurement plan for the energy source material inventory of thermal power generation, scientifically and rationally arranging the power generation dispatch and rationally arranging the rotating maintenance cycle of the power plant.

4.4. Long-term power load forecast

The forecast time interval is generally the next few years, which mainly provides a scientific decision-making basis for the development of the power system, the medium and long-term transformation and expansion planning of the power grid, and has far-reaching significance. The forecast must not only consider the development characteristics of the power system itself, but also must consider the relevant factors outside the power system, such as the development trend of the national economy and the adjustment of industrial layout.

5. Common methods of power load forecasting

After a long period of research and development, power load forecasting has developed various forecasting models and methods. In the final analysis, it can be roughly divided into the following three categories according to the time line:

5.1. Artificial experience prediction method [26-27]

Before the 1970s, due to the backward technology level in my country, the power load forecasting could only be carried out by experienced technicians with years of experience combined with the current actual situation. Obviously, the accuracy of this load forecasting method cannot meet the requirements. society's needs.

5.2. Traditional prediction method [28]

5.2.1. Regression analysis method

According to the number of characteristic variables, regression analysis can be divided into two categories: univariate regression and multiple regression [29]. As one of the most basic methods, the relationship between the factors affecting the load is first analyzed and summarized, and then a regression model is established according to the relationship between the factors to achieve the expectation of power load forecasting. The model is simple and reliable, and the operation speed is Faster and more accurate predictions as the number of variables increases. However, the relationship between nonlinear factors cannot be analyzed.

5.2.2. Time series method

The historical load data is analyzed and summarized as the time line changes, and then a mathematical model is built to predict the power load for a period of time in the future. The relevant models of the time series method are represented by the autoregressive moving average model, which also includes the autoregressive model and the sliding-average model. The advantage of this method is that it uses less data to model and can make predictions quickly, but it also has disadvantages. The disadvantage is that the accuracy of power load forecasting will decrease with the increase of uncertain factors, resulting in the forecast results not meeting the predetermined expectations.

5.2.3. Grey prediction method

In the 1980s, Professor Deng Julong of my country first proposed the grey theory. The grey prediction method is to build a prediction model after internal analysis of the power load data on the basis of the grey theory. The advantage of this method is that it is suitable for nonlinear load index prediction, does not need to calculate and analyze the characteristics of variables, and does not consider the distribution law and change trend, and can use less data to build the model. However, the data is required to conform to the law of exponential function growth, and the data quality is required to be high. At the same time, the prediction accuracy will decrease with the increase of the degree of data dispersion.

5.2.4. Trend extrapolation

Analysis and induction Draw a function curve according to the existing historical load data, so that the curve can reflect the growth trend of the load itself. In the forecasting process, the load level at a certain time in the future is predicted according to the growth curve, so that the curve can reflect the increasing trend of the load itself. Trend extrapolation is usually used in medium and long-term load forecasting, and is also used in short-term, especially ultra-short-term forecasting. The advantage is that the amount of data required is small and the working time is minimal, but the disadvantage is that the prediction efficiency is not ideal in the period of complex changes in the long-term load curve, especially at its turning point.

5.3. Modern intelligent prediction method

5.3.1. Neural network model

Artificial neural network is a method of simulating the thinking mode of the human brain, so as to think about things and get results, including convolutional neural networks, recurrent neural networks, and forward neural networks. The artificial neural network method sets up a large number of neurons to form a complex nonlinear system. The output value of each neuron is set internally by a linear function and amplified by the function, multiplied by the corresponding weight coefficient, and superimposed with other neurons of the same level and transmitted to the next level of neurons. Even though the internal structure of a single neuron is relatively simple, the model formed by different combinations of many neurons becomes relatively complex. The method has good fault tolerance and memory storage ability, and at the same time, it can improve and optimize the mapping ability and complex information processing ability to

a certain extent. Of course, this method also has shortcomings. It is prone to local minima, and the convergence speed is slow, the memory storage will be chaotic, and the data demand is relatively large.

5.3.2. Combined prediction method

This method is a prediction method that selects two or two methods to combine according to the characteristics of the load data. This method can avoid the shortcomings of a single model and can also take advantage of the advantages of multiple models. The linear and nonlinear features in the data samples are effectively processed, so that the power load prediction accuracy can be further improved.

6. LSTNET prediction mode

6.1. LSTNET

6.1.1. Combined prediction method

The first layer of LSTNet is a convolutional neural network (CNN) without pooling layers, using convolutional layers composed of convolutional neural networks (CNN) to capture short-term features of the load and short-term dependencies of variables.

$$h_k = RELU\left(W_k * X + b_k\right) \tag{1}$$

Here $*$ represents the convolution operation, the output is a vector, and the $RELU$ function is $RELU(x) = \max(0, x)$. We generate each vector of length T by padding the left side of the input matrix X with zeros. The size of the output matrix of the convolutional layer is $d_c \times T$, where d_c represents the number of filters.

6.1.2. Recurrent Component

The output of the convolutional layer is fed into both the recurrent layer and the recurrent skipping layer. The recurrent part is a recurrent layer with a gated recurrent neural network and uses the ReLU function as the hidden update activation function. The hidden state of the time period unit is calculated as follows:

$$r_t = \sigma\left(W_{xr}x_t + W_{hr}h_{t-1} + b_r\right) \tag{2}$$

$$u_t = \sigma\left(W_{xu}x_t + W_{hu}h_{t-1} + b_u\right) \tag{3}$$

$$c_t = RELU\left(W_{xc}x_t + r_t \odot \left(W_{hc}h_{t-1}\right) + b_c\right) \tag{4}$$

$$h_t = h_{t-1} \odot \left(1 - u_t\right) + u_t \odot c_t \tag{5}$$

$\odot$ is the product of the elements, σ is the sigmoid function, and x_t is the input to the layer at time t. The output of this layer is the hidden state for each timestamp. Although researchers are accustomed to using hidden update activation functions, ReLU has more reliable performance, in this way gradients are more easily back-propagated.

6.1.3. Recurrent-skip Component

Recurrent layers with GRU and LSTM units are carefully designed to memorize historical information and thus memorize relatively long-term dependencies. However, due to vanishing gradients, GRUs and LSTMs usually cannot capture long-term correlations in practical applications, and recurrent skip layers can alleviate this problem well.

$$r_t = \sigma\left(W_{xr}x_t + W_{hr}h_{t-p} + b_r\right) \tag{6}$$

$$u_t = \sigma\left(W_{xu}x_t + W_{hu}h_{t-p} + b_u\right) \tag{7}$$

$$c_t = RELU\left(W_{xc}x_t + r_t \odot \left(W_{hc}h_{t-p}\right) + b_c\right) \tag{8}$$

$$h_t = h_{t-1} \odot \left(1 - u_p\right) + u_t \odot c_t \tag{9}$$

$$h_{t,i}^{L} = \sum_{k=0}^{q^{ar}-1} W_k^{ar} y_{t-k,i} + b^{ar} \tag{10}$$

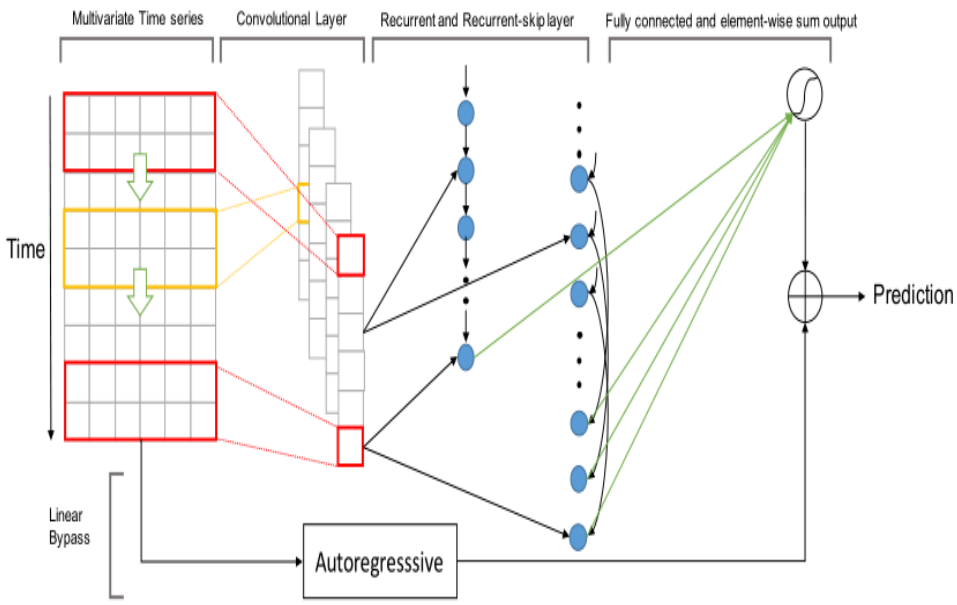

Figure 1 LSTNET structure diagram

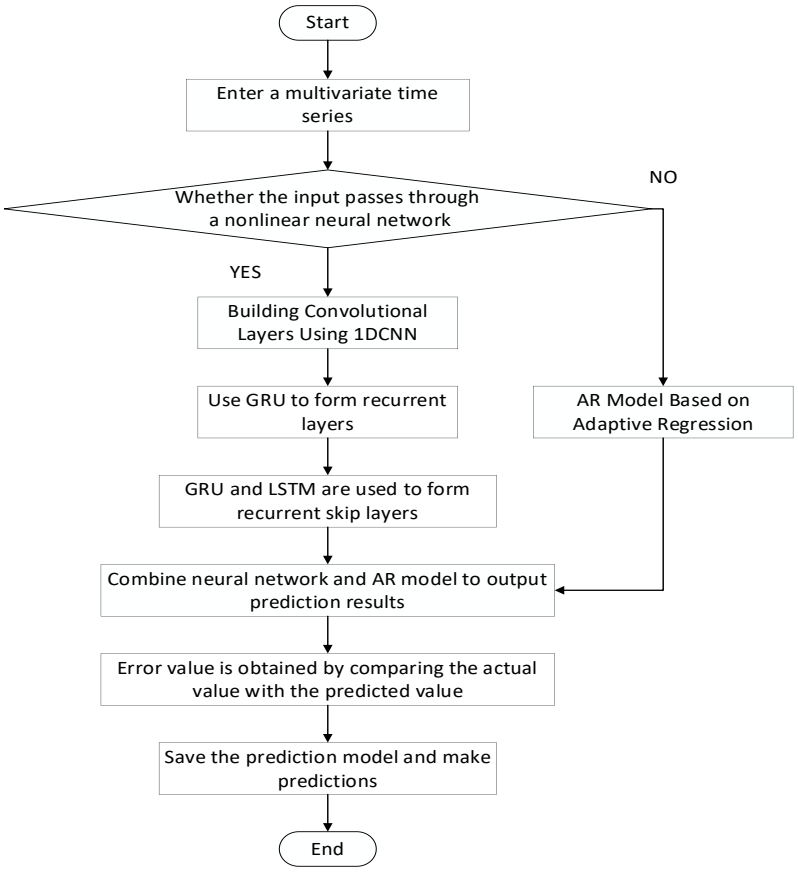

Figure 2 Prediction flow chart

6.1.4. Autoregressive Component

Due to the nonlinear nature of the convolutional layer and the recurrent layer, it is insensitive to the scale of the input. The autoregressive model (AR) composed of the adaptive regression part solves the scale insensitivity problem of the neural network model and improves the robustness of the model. sex.

6.2. Forecast Result

The whole prediction consists of two parts, nonlinear prediction and linear prediction.

6.3. Optimization Strategy

The optimization strategy is the same as the traditional time series forecasting model, and the optimization can be done by Stochastic Gradient Quadrant (SGD) or its variants such as Adam.

6.4. Performance Evaluation Index

In this paper, the mean absolute error (MAE), the mean absolute percentage error (MAPE) and the root mean square error (RMSE) will be selected as the indicators to evaluate the experimental prediction results. The lower the value of the three indicators, the more accurate the prediction. The formulas for these metrics are as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{11}$$

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{12}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{13}$$

Where $\hat{y}_i$ and y_i represent the predicted value and the actual value at time t=i, respectively.

6.5. Data Selection

This paper selects the public data set Australia's electricity load and price forecast data from 2006 to 2010, extracts the load data information every 30 minutes, a total of 87648 sets of data, and uses the LSTNET model to predict the power load. The four models were compared with each other.

6.6. Experimental Results and Analysis

The prediction results based on the LSTNET model are shown in Figure 3, the prediction results based on the four models of LSTM, GUR, CNN_LSTM and CNN_BILSTM are shown in Figure 4, and the evaluation indicators of the above five prediction models are shown in Table 1. It can be seen that the LSTNET model has MAE=52.068, MAE=0.672%, and RMSE=69.644. Compared with the other four models, the evaluation indicators of this model are reduced to varying degrees, which shows that the model has better prediction accuracy.

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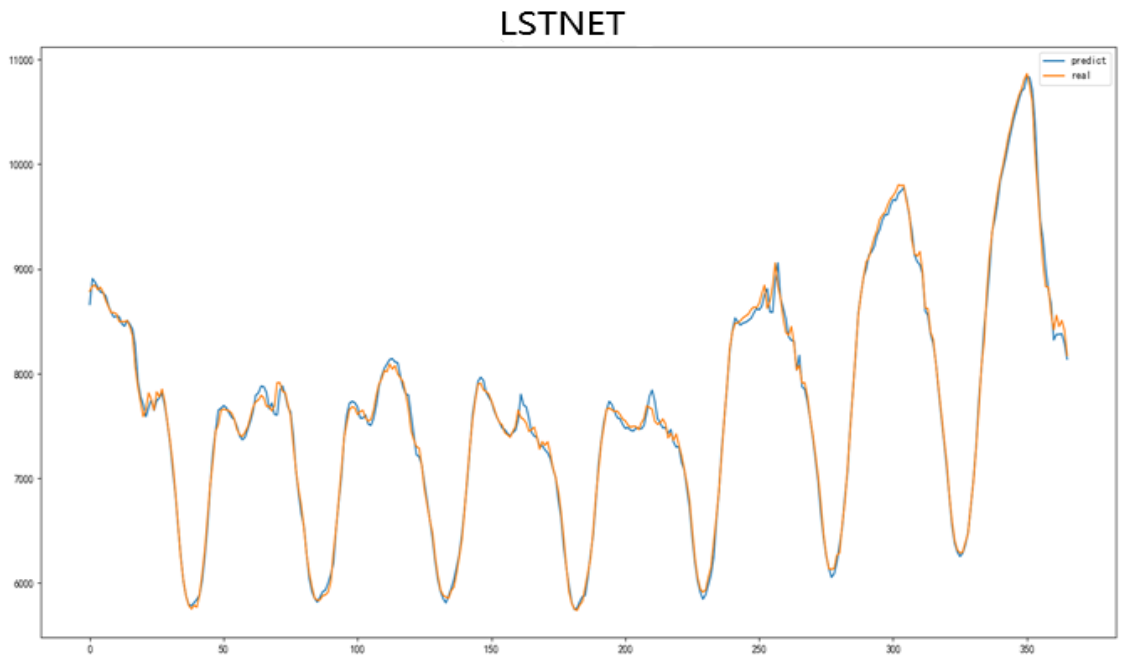

Figure 3 LSTNET prediction experimental results

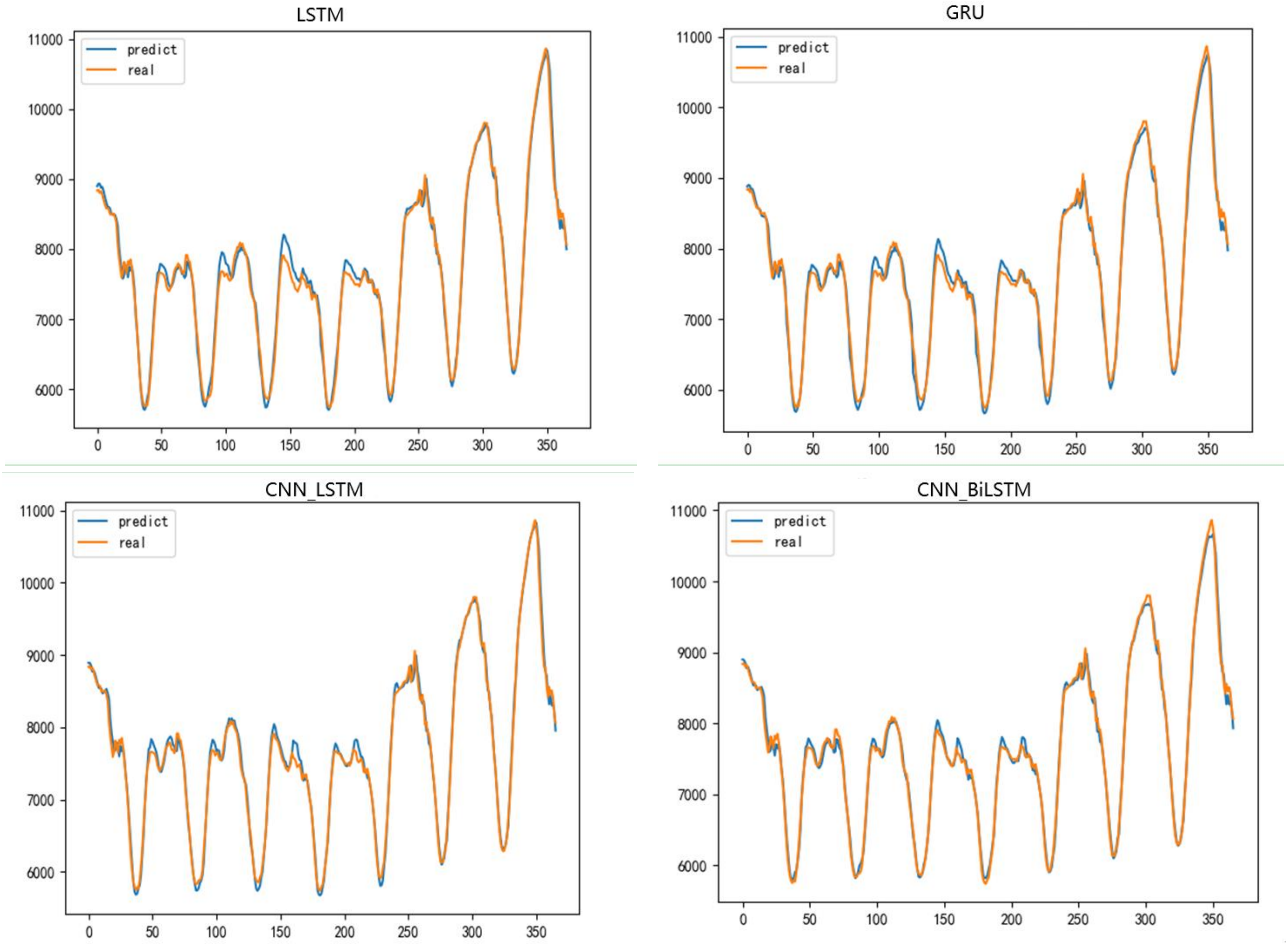

Figure 4. Other models predict the experimental results

Table 1 Model error comparison

Error comparison of different models			
Model	MAE	MAPE(%)	RMSE
LSTM	93.097	1.231	116.633
GUR	92.750	1.224	114.953
CNN_LSTM	71.980	0.953	94.681
CNN_BILSTM	67.992	0.881	89.375
LSTNET	52.068	0.672	69.644

7. Summarize

This paper analyzes and summarizes the characteristics of power load forecasting, the factors affecting load forecasting and some common load forecasting methods. Obviously, power load forecasting has significant complexity, so accurate power load forecasting methods are usually completed on the basis of multiple combined forecasting models, so as to ensure that the forecast results meet social needs as much as possible. This paper compares the four models of LSTNET and LSTM, GUR, CNN_LSTM and CNN_BiLSTM. The LSTNET model has MAE=52.068, MAE=0.672%, RMSE=69.644. According to the experimental results, it can be seen that the prediction model accuracy of the LSTNET neural network is significant. It has achieved the expected forecasting effect, improved the accuracy of short-term load forecasting, and laid a foundation for the development of the power system.

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