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Short-term Electricity Price Forecast and Analysis Based on LSTM in Spot Electricity Market

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Abstract: Aiming at the problem of short-term electricity price forecasting in the spot electricity market, this paper proposes a short-term electricity price forecasting algorithm based on LSTM neural network. Firstly, the algorithm constructs the electricity price correlation factor matrix, and then uses the LSTM model to forecast the electricity price. In the LSTM model, the Adam gradient descent method is used to estimate the input, forgetting and output of the LSTM model, and the node price data in the forecasting time interval are obtained. Using the PJM-RTO actual node price data of PJM website, the simulation results show that the proposed method can accurately predict the node price. Compared with the prediction interval of one week, two weeks and two months, the accuracy is the highest when the prediction interval is one month, the average absolute error percentage and average absolute error are the minimum, and the prediction effect is the best.

1. Introduction

Due to the volatility and uncertainty in the operation of the electricity market, the transaction price in the electricity market will also appear certain volatility, and the prediction and analysis of electricity price can effectively ensure the economy and security of the market operation. At the same time, the prediction and analysis of electricity price provide effective guidance and reference for trading subjects and government regulatory departments, and play an important role in maintaining market security and stability.

Scholars at home and abroad have done a lot of research on the application of artificial intelligence in power system. However, as the domestic spot market is now generally in the trial operation stage, so the research on the power spot market at this stage. However, some progress has been made in load forecasting. Reference [1] adopts a short-term electricity price forecasting method combined with ATT-CNN-LSTM, which achieves higher forecasting accuracy and computational efficiency than LSTM algorithm and CNN-LSTM algorithm. Wei Qin and others use the spot market clearing price prediction method based on random forest, which is more accurate and more stable than support vector machine and traditional neural network [2]. Reference [3] adopts the electricity price forecasting method based on Kalman filter, genetic algorithm and neural network, which can effectively forecast the electricity price. In reference [4], a good prediction effect has been achieved by using support vector machine as the prediction model. Bai Rui and others use genetic algorithm to forecast electricity price, and the final result is in good agreement with the real electricity price [5]. Literature [6] combines annealing algorithm and neural network algorithm to predict electricity price, and the prediction accuracy of electricity price is higher than that of traditional methods. Li Haiping and others proposed to divide the time into working days and holidays to establish ARMA-GARCH models to achieve segmented prediction. The results show that the prediction idea of different periods can obviously improve the prediction accuracy [7].

To sum up, at present, for the research of electricity price forecasting, a variety of methods are widely used to achieve more accurate electricity price forecasting, while for dealing with typical time series forecasting problems, LSTM algorithm can achieve better results. In this paper, the relatively mature neural network algorithm is used to realize the electricity price forecast, and the more accurate point price forecast is realized. The specific implementation steps are as follows: the first is to find the load correlation factors to construct the input matrix; secondly, to standardize the data; then to get the point prediction data; thirdly, to iterate the LSTM network to determine the weight; finally, to use the data of the American PJM website to verify the feasibility of the scheme.

2. Electricity Price Forecasting Model Based on LSTM Algorithm

In this paper, firstly, the load correlation factor matrix is constructed, which is standardized and introduced into the LSTM model, and the electricity prices at different times are obtained by neural network iteration, and then the forecasting accuracy of electricity prices is analyzed according to the corresponding evaluation indicators. Figure 1 is the flow chart of electricity price forecasting based on LSTM algorithm.

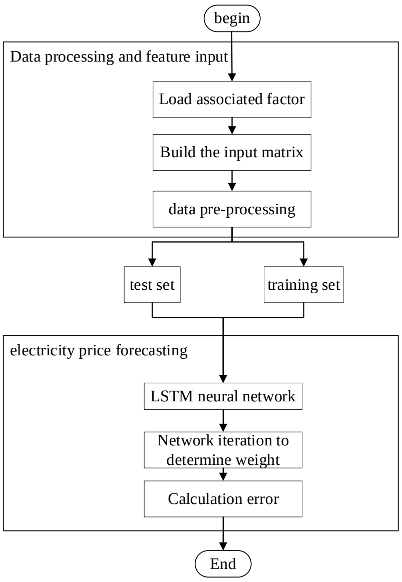

Figure 1: Flow chart of electricity price forecasting based on LSTM algorithm

2.1. Prediction Model Based on LSTM Neural Network

RNN algorithm is a kind of neural network model which can be used to predict time series. The neural network levels are connected by weights to achieve accurate prediction [8]. Although RNN algorithm can be used to predict time series, the situation of gradient explosion will affect its prediction accuracy to a certain extent. LSTM neural network algorithm is an improved algorithm of RNN algorithm, which successfully solves the problem of gradient disappearance in RNN, and has a better effect on the prediction of long series data. Although there are many derivative algorithms of

LSTM based on LSTM in recent research, LSTM algorithm is still the most mature and widely used time prediction algorithm.

2.2. Basic Cyclic Neural Network (RNN)

Compared with the ordinary neural network structure, the RNN neural network model is not only closely related to the hidden units, but also its output is related to the input sequence of the hidden units in the structure. Figure 2 shows the structure of the hidden layer unit of the neural network.

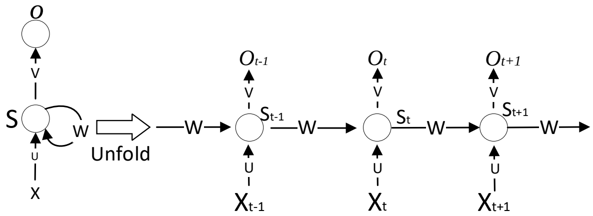

Figure 2: RNN Hidden layer Unit unfold Diagram

Among them, V represents the weight matrix between the hidden layers in the RNN neural network, X represents the input function in the network, St represents the current state of the hidden layer, U represents the input weight matrix in the network, W represents the weight matrix from the output layer to the input layer, and O represents the output of the network output layer. In RNN neural network, the parameters U, V and W of hidden layers can be shared, which can greatly shorten the training time while ensuring the training accuracy.

2.3. Long-and Short-term Memory Circulation Neural Network (LSTM)

Figure 3 is a neural network cell diagram. Although RNN can greatly shorten the training time while ensuring the training accuracy, there is a problem of gradient explosion in the operation of RNN neural network, and the emergence of LSTM solves the situation of gradient explosion in RNN. The core idea of the LSTM model is that the units similar to the cell state are transferred to each other. The final output value is a filtered version based on the previous cell state. The part that needs to be output is determined by sigmoid, and then the output value is processed with tanh and sigmoid, and finally the part that we need to output is output.

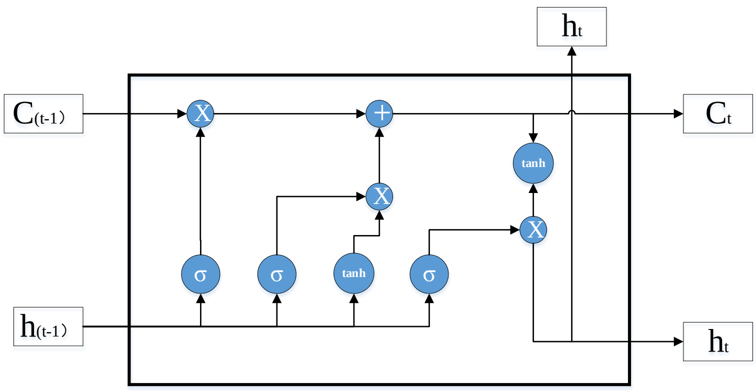

Figure 3: Neural network schematic diagram

In LSTM neural network, there are three types of gates: input gate, forgetting gate and output gate. In addition, there is a transmission line. he state of each unit in the LSTM neural network can be expressed by the following formula:

$$C_t = f_t \otimes C_{t-1} + i(t) \otimes C(t) \tag{1}$$

Forgetting gate: part of the characteristic information of the unit state C_{t-1} is retained in the current C_t by multiplication. The commonly used activation function is the sigmoid function. The output of Sigmoid is a value in the interval [0,1], and the calculation formula is shown below.

$$s(X_t) = \frac{1}{1+e^{-X_t}} \tag{2}$$

Input gate: part of the characteristic information of the input X_t of the current network is saved to the unit state C_t by operation. The activation function that updates the state of the unit usually uses the tanh function.

$$C_t = \tanh(W_c[h_{t-1}, X_t]) + b_c \tag{3}$$

$$\tanh(X_t) = \frac{\sinh X_t}{\cos X_t} = \frac{e^{X_t} - e^{-X_t}}{e^{X_t} + e^{-X_t}} \tag{4}$$

Output door: the current output value h_t of how much LSTM the unit state C_t has is determined by operation.

$$\begin{aligned} o_t &= \sigma(W_o[h_{t-1}, x_t] + b_0) \\ h_t &= o_t * \tanh(C_t) \end{aligned} \tag{5}$$

Among them, C_t controls the degree to which the previous unit is forgotten, with a valve of [0,1] , o_t represents the final output value, h_{t-1} is the previous output value of the amnesia door, W_c and W_o are weight parameters, and b_c and b_o are biased parameters.

3. Evaluation Index of Prediction Model

In order to improve the prediction accuracy of the model, the super parameters need to be adjusted, and Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error(SMAPE) and are selected as the basis for parameter adjustment and evaluation.

(1) Mean Absolute Percentage Error—MAPE

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_{(i)} - f(x_{(i)})}{y^{(i)}}\right| \tag{6}$$

The range of the error of the average absolute percentage is $[0,+\infty)$. When MAPE is 0%, it means that the error is the smallest, and the predicted value is completely consistent with the real value. When the MAPE is 100%, the error is the largest. The smaller the value of MAPE is, the better the model is.

(2) Symmetric Mean Absolute Percentage Error—SMAPE

$$SMAPE = \frac{1}{N}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{(|\hat{y}_i| + |y_i|)/2} \tag{7}$$

The range of symmetric average absolute percentage error is also $[0,+\infty)$. The smaller the value of SMAPE is, the higher the prediction accuracy of the given model is. The greater the value of SMAPE, the greater the error. The smaller the value of SMAPE, the better the effect of the model.

(3) Mean Absolute Error—MAE

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{8}$$

MAE is an indicator of average absolute error, that is, the greater the error of the predicted value, the greater the value of MAE, and the smaller the value of MAE, the better the effect of the model.

4. Example Analysis

Due to the lack of domestic electricity price data, this paper chooses to use the node price data of the American PJM platform. In this platform, the hourly real-time marginal node price (LMPs) of PJM-RTO [9] is selected as the data set from 5:00 on January 1, 2018 to 3:00 on September 1, 2022, including the node price and load at the corresponding time. The data of one year was used as the training set, and seven days, fourteen days, one month and two months after the training set were used as the test set to compare the three indicators given above.

4.1. Feature Selection

Because the spot electricity market has volatility and uncertainty, it brings a certain degree of complexity to the electricity price forecasting. Therefore, it will produce a large error to forecast the electricity price only based on the historical electricity price data. Therefore, this paper considers the relevant factors of electricity price-power load to forecast electricity price.

4.2. Data Preprocessing

In order to reduce the difference between different data, this paper adopts the maximum-minimum normalization processing, and the total data set is normalized, and the normalization formula is as follows.

$$\tilde{X}_t = \frac{X_t - X_{\min}}{X_{\max} - X_{\min}} \tag{9}$$

Among them: X_{max} and $X_{\min}$ are the maximum and minimum values in the sample, respectively. Through max-min normalization, all data can be compressed in the range of [0, 1], keeping the consistency between the mathematical units of the data.

4.3. Analysis of Short-Term Electricity Price Forecast Result of LSTM

Table 1: Shows the neural network structure parameters of LSTM

Number of hidden layer nodes	（128，64，64）
Number of training samples	24
Epoch	200
Loss value	mean_squared_error
Optimizer	Adams

This part mainly analyzes the effect of LSTM neural network on electricity price forecasting. The simulation experiment in this paper is written by Pycharm, the CPU serial number is i7-12700, and the memory is 32G. Table 1 shows the structural parameters of the LSTM neural network. The setting of the parameters affects the training effect of the neural network.

The prediction results of different training sets under the neural network are shown in Figure 4 to Figure 7.

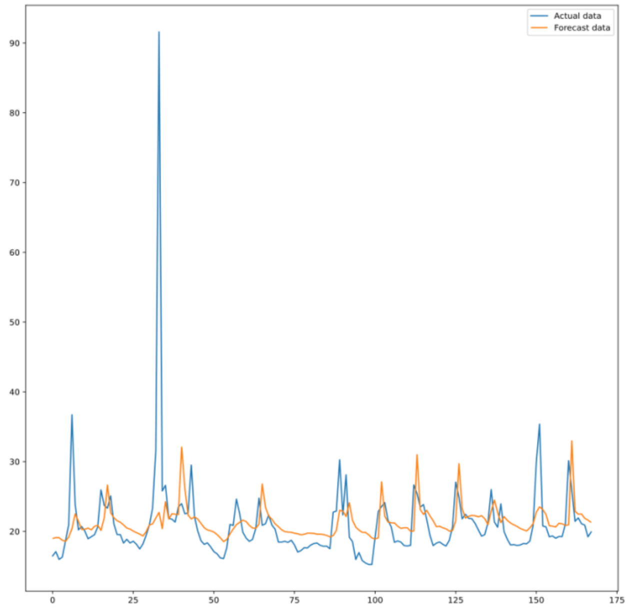

Figure 4: Fitting result when the test set is one week

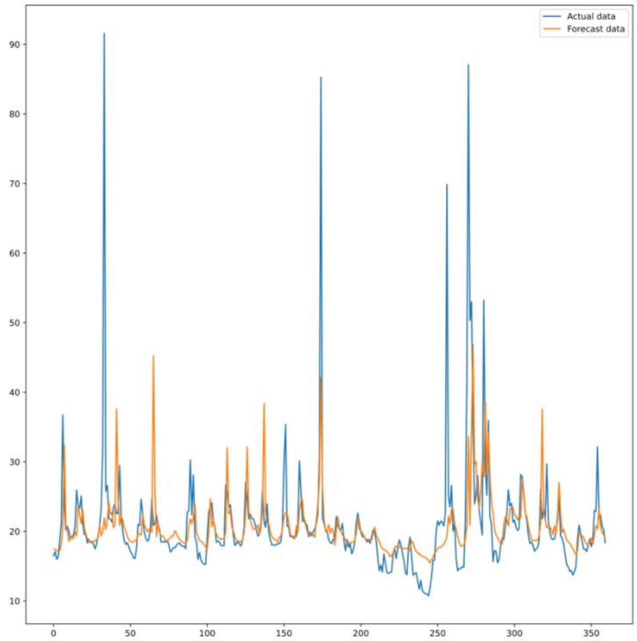

Figure 5: Fitting results when the test set is two weeks

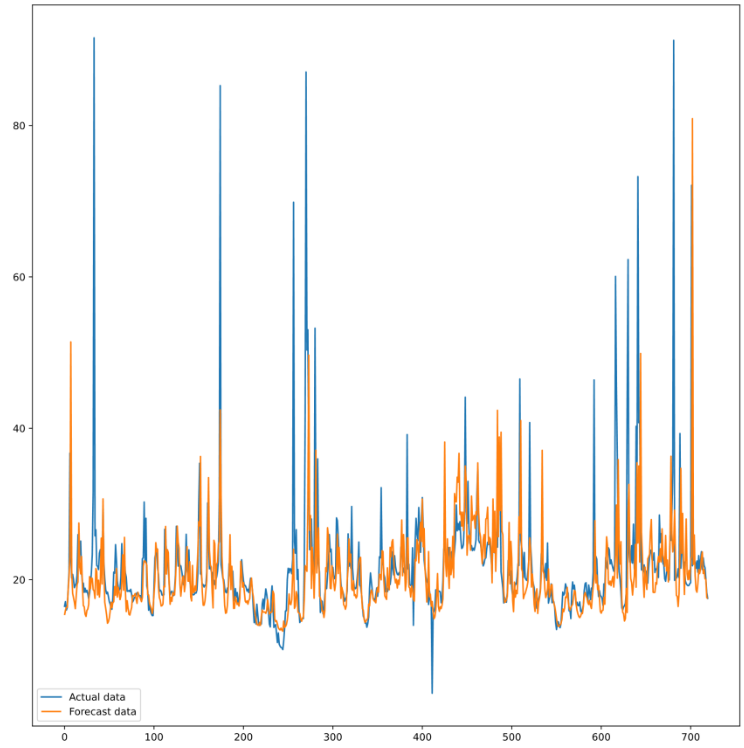

Figure 6: Fitting results when the test set is one month

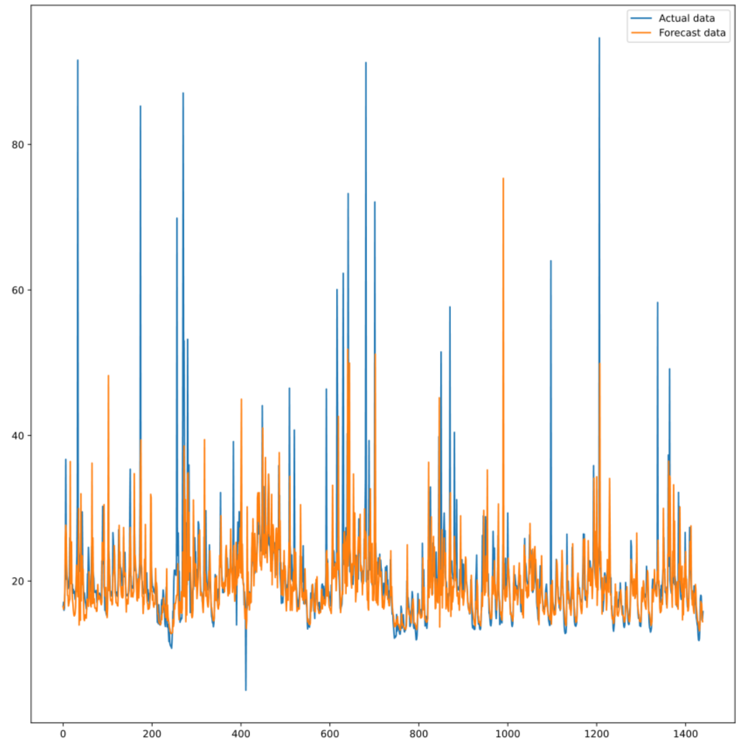

Figure 7: Fitting results when the test set is two months

It can be seen from the chart that there is a great correlation between the load usage and the electricity price level. Except for the peak electricity price, the remaining points can achieve better forecasting results. The results show that good forecasting results have been achieved by using LSTM neural network training. The calculated values of specific indicators under different test sets are shown in Tables 2 to Table 5.

Table 2: Calculated values of LSTM indicators when the test set is one week

Mae	3.08582007
Smape	0.123106047
Mape	0.137276595

Table 3: Calculated values of LSTM indicators when the test set is two weeks

Mae	3.569005753
Smape	0.136682599
Mape	0.158647069

Table 4: Calculated values of LSTM indicators when the test set is one month

Mae	2.851108909
Smape	0.119611171
Mape	0.131076661

Table 5: Calculated values of LSTM indicators when the test set is two months

Mae	3.0468927384
Smape	0.1257983447
Mape	0.141995711

Further analysis of the algorithm results shows that under the conditions of four different test sets, the average absolute error percentage and symmetrical average error percentage are controlled within 85%, and the average absolute error is controlled at about 3, indicating that LSTM neural network can play a better performance in electricity price forecasting.

4.4. Comparison of Algorithm Results

In this paper, by comparing the four groups of experimental results of the algorithm index analysis, LSTM algorithm for short-term forecasting can play a better prediction effect, whether it is to predict one-week, two-week or one-month two-month electricity price, has a very good applicability. By comparison, it can be found that when the test set is one month, all the indexes of the LSTM neural network model are the minimum of the four groups of experimental results. It is proved that in the four short-term prediction models, when the training set is two years and the training set is one month, the LSTM neural network model can achieve the best prediction effect.

5. Conclusions

At present, the construction of electric power spot market in China has been promoted rapidly, and many provinces have carried out the trial operation of the spot market. Based on LSTM neural network and considering load factors, this paper trains the electricity price and load data of American PJM website from January 1, 2018 to January 1, 2020. Through the comparative analysis of different test sets, it is found that using the first two years as the training set and the latter month as the test set has the best prediction effect and has strong practicability and reference.

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