Short-term electricity price forecast based on long short-term memory neural network

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Abstract: Effective short-term electricity price forecasting is of great significance to reduce bidding risk and obtain stable income. In order to predict the timing price, this paper proposes a short-term electricity price forecasting model based on Long Short-Term Memory (LSTM) neural network. The model uses pauta criterion and Lagrange interpolation polynomial to process the historical data of electricity price, normalize the obtained data and input it into the LSTM network layer, using the Mean Squared Error as the loss function to measure the model forecasting. The effect is based on the loss function, and the weight coefficient of the LSTM neural network is updated by the Adam algorithm. Finally, the timing of the LSTM neural network is predicted. Using the real-time data of the California power market and the real-time data of the US PJM power market, it is proved that the accuracy of this method is higher than that of BP neural network, Cart regression tree and polynomial regression.

1. Introduction

The market-oriented reform of electric power industry has been carried out all over the world. As the basic element of electric power market, electricity price has changed from monopoly operation to market competition. Therefore, electricity price will directly affect the profits of market participants. Short-term electricity price forecasting is mainly to forecast the electricity price in the next few hours, days or a week. When the trend of future electricity price is known, market participants can formulate appropriate bidding strategies to reduce the risk of bidding and obtain stable revenue[1].

At present, there are mainly traditional methods and modern intelligent methods for electricity price forecasting. Traditional methods include regression model method and trend extrapolation method. Modern intelligent methods include Artificial Neural Network (ANN), Fuzzy Mathematics, Support Vector Machine, Expert System, etc.[2]. Among them, the neural network has a strong ability of self-learning and non-linear fitting[3]. At present, Back Propagation (BP) algorithm of artificial neural network is widely used in load forecasting and has achieved good results[4]. In reference [5], BP neural network is applied for the field of electricity price forecasting, and the artificial neural network is explored for the field of electricity price. In reference[6], Using the BP neural network parameters of particle swarm optimization (PSO), the market electricity price is effectively forecasted. In reference [7], the sigmoid function are replaced by mother wavelet, and the BP neural network is optimized by a genetic algorithm. In reference [8], According to artificial fish swarm algorithm, a flexible adaptive artificial fish swarm algorithm (RAAFSA) is proposed. The RAAFSA algorithm is used to train the BP neural network and optimize the parameters of the BP neural network. It can be seen that most of the methods adopted in the literature are improved on the basis of feed forward neural network (FNN), which can not completely to solve the defect of
correlation information on time series data. In reference[9], Recursive neural network is adopted. Although RNN solves the defect that it can not effectively connect the related information on time series data, RNN has the disadvantage that it can not remember the long-term information. For this reason, this paper uses the method of long Short-Term Memory (LSTM) neural network and sigmoid activation function to control the forgetting gate, input gate and output gate of LSTM network layer, so that the time series price data can be conditionally transmitted through the module, and an information flow representing long-term memory is added. These two improvements make LSTM have good long-term and short-term memory function. At the same time, electricity price forecasting model is constructed with electricity price data as input and output labels. This method makes use of the correlation between electricity price data and improves the accuracy of forecasting.

2. Relevant theories and methods

2.1. Principle of Recursive Neural Network
Compared with the ordinary neural network, Recursive Neural Network (RNN) adds the horizontal connection between the hidden layer units. Through a weight matrix, the value of the previous time series neuron units is transferred to the current neuron units, so that the neural network has the memory function, which is very helpful for processing the time series related data.

However, because RNN has no memory unit to store and output information, the problem of "gradient disappearance" will arise[10]. As a result, the influence of sequence information on output at a longer time either decreases slightly or increases exponentially, which makes the network layer parameters unable to be updated, so RNN can only be used for sequence information at a closer time.

2.2. Principle of Long-term and Short-term Memory Network
Long-term and Short-term Memory Network (LSTM) was proposed by Hochreiter & Schmidhuber in 1997[11]. An artificial intelligence method improved by Graves on the basis of recurrent neural network[12], LSTM uses memory cells to store and output information in order to solve the problem of "gradient disappearance" in RNN. The cell structure of LSTM is shown in fig.1:

![LSTM cell structure](image)

The cell unit of LSTM has three gates, they are Forget Gate, Input Gate, Output Gate. \( \sigma \) represents sigmoid activation function. LSTM cell unit parameters are updated as follows:

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

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

\[
C_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)
\]

\[
C_t = f_t \cdot C_{t-1} + i_t \cdot C_t
\]

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

\[
h_t = o_t \cdot \tanh(C_t)
\]

Among: \( h_{t-1} \) is output for the previous moment, \( x_t \) is input for the current moment, \( h_t \) is output for the current moment, \( i_t \) is output for input gates, \( f_t \) is output for forget gate, \( C_t \) is
cellular unit state for time, \( C_t \) is output for information flow, \( o_t \) is output for output gate, \( W_f, W_i, W_c, W_o, b_f, b_i, b_c, b_o \) is weight matrix for units.

3. Short-term electricity price forecasting model based on LSTM neural network

3.1. Data Preprocessing of Electricity Price

Due to the instability factors such as equipment failure and human disturbance in the process of data acquisition, there are usually abnormal data in the collected data sets. The existence of abnormal data will greatly affect the accuracy of prediction. Therefore, it is necessary to recognize and process the abnormal data in the sample before input training data.

Step 1: using pauta criterion\(^{[13]}\) to determine the threshold of outliers;

Step 2: eliminating outliers will lead to partial missing of time series data. In order to ensure the prediction effect, missing data need to be filled. Lagrange interpolation\(^{[14]}\) can be used to fill the missing values;

Step 3: the input is normalized:

\[
x' = \frac{x - \text{min}(x)}{\text{max}(x) - \text{min}(x)}
\]  

(7)

Among: \( x' \) is a normalized input variable; \( \text{max}(x) \) and \( \text{min}(x) \) are the maximum and minimum values of the variables to be normalized.

3.2. Short-term electricity price forecasting based on LSTM neural network

In order to improve the accuracy of electricity price forecast, the new electricity price data are processed as follows, using the correlation of electricity price data itself.(d is date, t is time interval):

- Electricity Price in the Prediction Period before 1h on the Day of the Prediction Period \( P(d,t−1) \);
- Electricity Price in the Prediction Period before 2h on the Day of the Prediction Period \( P(d,t−2) \);
- Electricity Price in the Prediction Period before 3h on the Day of the Prediction Period \( P(d,t−3) \);
- Electricity Price in the Prediction Period 1h before the Day before the Prediction Period \( P(d−1,t−1) \);
- Electricity price of the same period of time on the day before the forecast period \( P(d−1,t) \);
- Electricity Price in the Prediction Period 1h after the Day before the Prediction Period \( P(d−1,t+1) \).

Fig.2 shows the short-term price forecasting model of LSTM neural network:
The specific process is as follows:
Step 1: The input data is normalized, assuming a total of n training samples. Because the predicted input is six-dimensional and timesteps is one, that is, the price at a certain time in the future is predicted, the input data is stored in the form of a 3-dimensional tensor of n*1*6.
Step 2: The input data of training set is input into LSTM and the predicted value is obtained.
Step 3: The loss function is calculated according to the predicted value and the real value.
Step 4: Using Adam to update the weight of LSTM to realize supervisory learning of LSTM.
Step 5: The trained LSTM neural network is used to input the test set data and forecast the future electricity price data.

4. Forecast examples

4.1. Experimental scheme and parameter setting
Plan 1: The regional marginal price (LMP) data of California electricity market from January 2 to January 28, 2018 are selected as training samples for modeling. The short-term electricity price of California electricity market from January 29, 2018 to February 4, 2018 is selected to forecast and compared with the actual electricity price data.
Plan 2: The regional marginal price (LMP) data of American PJM power market from January 2 to January 27, 2017 are selected as training samples for modeling. The short-term electricity price of California electricity market from January 28, 2017 to February 3, 2018 is selected to forecast and compared with the actual electricity price data.

4.2. evaluating indicator
Evaluating indicator used Root Mean Square Error( RMSE), the formula is as follows:

$e_{\text{RMSE}} = \left( \frac{1}{24} \sum_{i=1}^{24} (Y_{\text{true}} - Y_{\text{pre}})^2 \right)^{0.5}$  \hspace{1cm} (8)

Among: $Y_{\text{true}}$ is real value of electricity price, $Y_{\text{pre}}$ is predicted value of electricity price.

4.3. Experimental results and analysis
California electricity market price data experiment results:
The test errors of LSTM neural network, BP neural network, Cart regression tree and polynomial regression (PR) test data are shown in Tables 1.
Table 1 Prediction Errors

| Date   | LSTM  | BP    | Cart  | PR    |
|--------|-------|-------|-------|-------|
|        | e_RMSE |       |       | order |       |       |       |       |
|        | 1order | 2order | 3order | 4order |
| 01-29  | 1.7760 | 1.8960 | 3.0220 | 2.9428 | 2.5357 | 2.2042 | 5.6971 |
| 01-30  | 1.4415 | 2.1876 | 2.7539 | 1.9619 | 1.5702 | 1.5879 | 2.1463 |
| 01-31  | 1.3225 | 2.1536 | 1.8090 | 1.5373 | 1.5431 | 1.4229 | 4.3126 |
| 02-01  | 1.3922 | 2.1540 | 2.6370 | 1.7252 | 1.4720 | 1.5467 | 2.4932 |
| 02-02  | 2.0373 | 3.5246 | 3.1460 | 2.3448 | 2.2076 | 2.1577 | 2.1587 |
| 02-03  | 2.3513 | 3.3701 | 3.2891 | 2.6593 | 2.5146 | 2.9913 | 4.9755 |
| 02-04  | 1.9542 | 3.2446 | 2.9271 | 2.5364 | 2.3180 | 2.5108 | 7.4309 |

Table 1 shows that LSTM's prediction is superior to other models. The experimental results of electricity price data of PJM electricity market in the US are as follows: The test errors of LSTM neural network, BP neural network, Cart regression tree and polynomial regression (PR) test data are shown in Tables 2.

Table 2. Comparison of Prediction Errors

| Date   | LSTM  | BP    | Cart  | PR    |
|--------|-------|-------|-------|-------|
|        | e_RMSE |       |       | order |       |       |       |       |
|        | 1order | 2order | 3order | 4order |
| 01-28  | 1.1679 | 1.1694 | 1.3225 | 1.3288 | 1.4614 | 1.3540 | 1.2148 |
| 01-29  | 0.6005 | 0.6612 | 0.8157 | 0.8602 | 0.8613 | 0.9709 | 0.7320 |
| 01-30  | 1.3005 | 1.4369 | 5.2933 | 1.4409 | 1.3719 | 1.5156 | 1.8861 |
| 01-31  | 1.4890 | 1.8775 | 6.0101 | 1.6560 | 1.9247 | 2.0182 | 2.1057 |
| 02-01  | 2.6608 | 3.5544 | 3.8685 | 2.9704 | 3.0741 | 3.2423 | 3.9504 |
| 02-02  | 1.7099 | 2.0323 | 4.8194 | 1.9114 | 1.9031 | 1.7468 | 2.5734 |
| 02-03  | 1.0469 | 1.1328 | 5.0998 | 1.2162 | 1.1918 | 1.3074 | 1.3965 |

Testing on different data sets shows that LSTM prediction is better than other models from Table 2. Analysis of experimental results: ①LSTM neural network is better than Cart regression tree and polynomial regression on the whole, which benefits from the better prediction effect of LSTM on time series data.②LSTM neural network is superior to BP neural network in forecasting effect, because LSTM solves the defect that ordinary neural network can not effectively connect the correlation information between time series data.③LSTM neural network model is more complex, and its training time is slightly more than that of single structure neural network model.

5. Conclusion

In this paper, a method of short-term price forecasting based on LSTM is proposed. Through the comparative analysis of simulation results, the following results can be obtained: when BP neural network, Cart decision tree and polynomial regression are used for short-term price forecasting, only part from the time period has a good fitting degree; when LSTM is used for short-term price forecasting, the forecasting curve is obtained. Fitting degree is improved greatly, and the overall prediction error is reduced. Therefore, the method proposed to this paper can effectively improve the prediction accuracy and provide a new idea about short-term price forecasting.

References

[1] ZHANG Xian, WANG Xifan.(2006) Summary of short-term electricity price forecast.J. Automation of Electric Power Systems, 30(3):92-101.
[2] SU Juan, DU Songhuai, ZHOU Xinghua.(2005) Summary of research status of forecast
methods for spot electricity price in electricity market. J. Power System Protection and Control, 2005, 33(16): 78-84.

[3] Simon Haykin. (2004) Neural network theory. Powered By SiteEngine.

[4] WANG Xiaobo, LIU Deqiang. (2011) Research on short-term load forecasting based on artificial neural network. J. Journal of Electric Power, 26(4): 287-289.

[5] Szkuta B.R., Sanabria L.A., Dillon T.S. (1999) Electricity price short-term forecasting using artificial neural networks. J. Power Systems, IEEE Transactions on, 14(3): 851-857.

[6] CHE Jinxing, WANG Guangfu. (2012) Short-term electricity price forecasting based on BP neural network under particle swarm optimization. J. Journal of Nanjing Institute of Technology, 31(1): 13-17.

[7] TU Qiyu, ZHANG Maolin. (2011) New improvement of forecasting electricity price by wavelet neural network. J. Proceedings of the Chinese Society of Universities for Electric Power System and Automation, 23(02): 157-160.

[8] SHI Biao, LI Yuxia, YU Xinhua, YAN Wang, LI Na, MENG Xin, LI Peng. (2010) Elastic adaptive artificial fish-BP neural network model and its application in short-term electricity price forecasting. J. Journal of Hydroelectric Engineering, 29(01): 106-113.

[9] ZOU Zhengda, SUN Yaming, ZHANG Zhisheng. (2005) Short-term load forecasting based on recurrent neural network based on ant colony optimization algorithm. J. Power System Technology, 29(3): 59-63.

[10] Kolen J, Kremer S, Frasconi P, et al. (2001) Gradient flow in recurrent nets: the difficulty of learning long-term dependencies. Wiley-IEEE Press, New York. 237-243.

[11] Hochreiter S, Schmidhuber J. (1997) Long Short-Term Memory. J. Neural Computation, 9(8): 1735-1780.

[12] Graves A, Mohamed A R, Hinton G. (2013) Speech Recognition with Deep Conference Recurrent Neural Networks. C//2013 IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE.

[13] YANG Jing, XIN Mingyong, OU Jiaxiang, et al. (2017) Method for judging data accuracy of metrology automation system based on pauta criterion. J. Power Systems and Big Data, 20(11): 74-78.

[14] ZHOU Jianwei, ZHANG Juan. (2016) Lagrangian interpolation model and statistical data testing and application. J. Statistics and Decision, 5: 78-80.