Short-term Load Forecasting Based on Electricity Price in LSTM in Power Grid

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Short-term Load Forecasting Based on Electricity Price in LSTM in Power Grid

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Abstract: In the electricity market, accurate short-term load forecasting can ensure the safe and stable operation of the grid, but the real-time fluctuation of electricity price increases the complexity of load changes and increases the difficulty of forecasting. In response to this problem, this paper studies the correlation between electricity price and power load, and provides a basis for the prediction of short-term load in the active distribution network. Based on the correlation between electricity price and power load, this paper proposes a short-term load forecasting model for long-term and short-term memory-cycle neural networks. Taking the power data of a certain area as an example, the LSTM model and other models were used to carry out simulation experiments. The results show that the proposed method outperforms other models in terms of prediction accuracy and stability.

1. Introduction

With the development of science and technology and economy, the position of electricity in production and life is more and more important, and load forecasting is the basis for efficient and stable operation of power systems.[1-2] Short-term load forecasting of power systems can be divided into ultra-short-term, short-term, medium-term and long-term forecasts, where short-term forecasting is an important component of load forecasting. Short-term load forecasting methods can be mainly divided into traditional forecasting method and intelligent forecasting method.[3-5] Traditional methods mainly include time series method, regression analysis method, etc. Intelligent methods mainly include neural networks, decision trees, wavelet analysis, random forests, support vector machines, and cloud computing.[6]

2. Analysis of electricity price and load correlation

In the electricity market environment, the fluctuation of electricity price will affect the size of the load, and the fluctuation of the load will also affect the size of the electricity price, and reach a balance in the process of mutual influence. This paper directly analyzes the correlation between the load after reaching steady state and the real-time electricity price. The following figure shows the load curve and the real-time electricity price curve. The data comes from the total load of an energy company in the United States and its real-time electricity price.
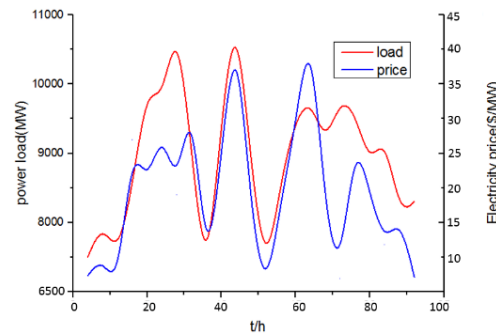
Fig.1 Hourly load and electricity price curve

It can be seen from the figure that the real-time electricity price and the load trend and cycle are almost the same, and the positions of the peaks and valleys are also relatively consistent, showing a greater correlation. The following is a sample of the 2016 full-year load data and real-time electricity price data for correlation analysis which the Pearson correlation analysis and the Spearman correlation analysis. The results are shown in the following table:

Tab.1 Correlative analysis of load and electricity price

Correlative Analysis	Correlation coefficient	Significant
Pearson	0.452	0.000
Spearman	0.598	0.000

The significance is 0.000, indicating that the load is related to the real-time electricity price. The correlation coefficients are 0.452 and 0.598, indicating that the real-time electricity price is moderately related to the load. When carrying out load forecasting, the influencing factor of real-time electricity price should be considered.

3. LSTM-based predictive model

3.1 LSTM network structure

Traditional cyclic neural networks have gradient disappearance and gradient explosion problems in practical applications. Hochreiter proposed an improved RNN, LSTM neural network, which can solve the problem that RNN can't handle long-distance dependence, make full use of historical information, and have stronger adaptability in time series data analysis. [7-9] The unit structure of the LSTM is shown in Figure 2.
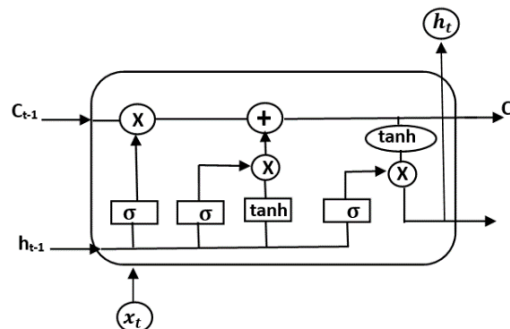

Fig.2 LSTM unit structure

In Figure 2, xt, ht and yt represent the input vector at t, the hidden layer state value, and the output vector, respectively. The memory unit is a memory of the state of the neuron and is used to record the current state of time. Input gates and output gates are used to read, output, and correct parameters. The forget gate is used to selectively forget the correction parameters of the unit state at the previous moment.[10]

$$h_t = O_t * \tanh(C_t) \qquad （1）$$

$$f_t = \text{sigmoid} \left(W_f \cdot \left[h_{t-1}, \; x_t \right] + b_f \right) \quad （2）$$

$$i_t = \text{sigmoid} \left(W_i \cdot \left[h_{t-1}, \; x_t \right] + b_i \right) \quad （3）$$

$$O_t = \text{sigmoid} \left(W_o \cdot \left[h_{t-1}, \; x_t \right] + b_o \right) \quad （4）$$

Where: f、i、g、C、o represent the forgotten gate, the input gate, the alternate cell state for updating, the updated cell state, and the output gate; W and   b are the corresponding weight coefficient matrix and bias term, respectively; σ and tanh represent the sigmoid activation function and the hyperbolic tangent activation function, respectively.

3.2 LSTM structure and training

The LSTM model includes input vectors, two LSTM hidden layers, fully connected layers, and predicted values for the output. The input vector starts from the input layer and passes through two layers of LSTM hidden layers to output the processed vector. First, the weight vector is calculated according to the current layer input vector, and then the weight vector is merged with the current layer input vector to obtain a new vector, which is input into the fully connected layer, and finally the predicted value is calculated. The LSTM model is shown in Figure 3.
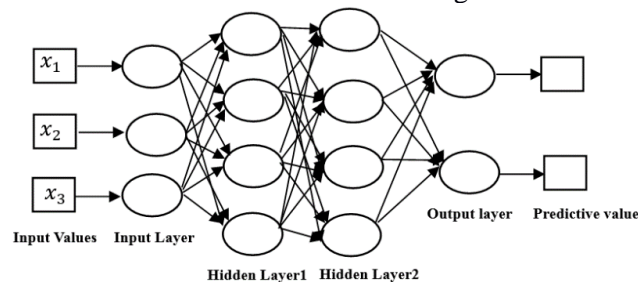

Fig.3 LSTM model

The role of the LSTM layer is to choose to remember important information and forget information that is not important. In this model, the more layers it has, the stronger the nonlinear fitting ability of the model, and the better the learning effect. However, since training requires a lot of time, it is generally preferred to choose a solution that is better and less time consuming. This experiment sets up two layers of LSTM to get good results in less time. Therefore, the number of neurons in the first layer of LSTM is 128.   Layer 2 LSTM sets the number of neurons to 64. Since the parameters of the fully connected layer are multiplied as the input data increases, it is necessary to properly compress the data.

4. Analysis of results

In order to reflect the correctness and feasibility of the method, BP neural network, RNN and LSTM neural network are used to calculate the load without considering the price of electricity and the price of electricity, using the same data. LSTM* is a prediction of the electricity price relationship in LSTM. The annual error pairs predicted by different models are shown in Table 2, and the different model prediction curves are shown in Figure 4.

Tab. 2 Comparison of prediction error between different models for two years

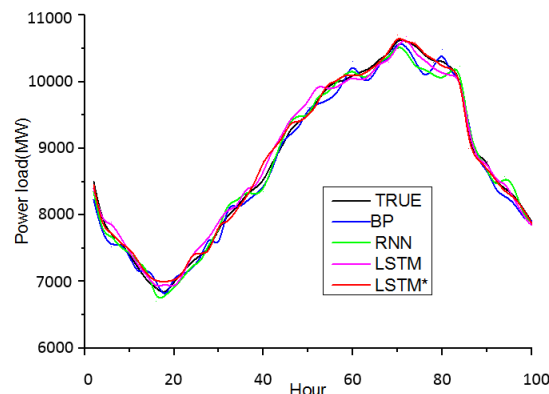| Years	2015			2016		
Models	eMAPE/%	eRMSE/MW	6MAPE	eMAPE/%	eRMSE/MW	6MAPE
LSTM*	0.531	59.691	0.024	0.463	60.052	0.021
LSTM	0.578	67.876	0.036	0.669	64.256	0.037
RNN	0.761	83.320	0.067	0.792	87.214	0.069
BP	1.345	152.675	0.079	1.659	149.309	0.086

Fig.4 Curve of load forecasting

It can be seen from the prediction results that in the same prediction model, the prediction accuracy of the electricity price is higher than the prediction accuracy without the electricity price. When considering electricity price, LSTM neural network is better than RNN than BP neural network. This shows that LSTM is more suitable for dealing with short-term load forecasting, and in the real-time electricity price environment, considering the influence of electricity price, it is beneficial to improve the accuracy of prediction.

5. Conclusions

In the context of power market reform and smart grid, it has a great correlation with the load. Therefore, when carrying out load forecasting, it is necessary to consider its impact. Aiming at this problem, this paper proposes a short-term load forecasting model that combines electricity price and historical load data. The actual example shows that the prediction accuracy of electricity price is higher than that of electricity price, and it has good stability and Higher prediction accuracy. On this basis, the predictive model will continue to be optimized to make it more widely used and more accurate.

References

[1] Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. (2014). Empirical evaluation of gated recurrent neural networks on sequence modeling. In NIPS 2014 Workshop on Deep Learning, December 2014

[2] W. Kong et al., "Effect of automatic hyperparameter tuning for residential load forecasting via deep learning," 2017 Australasian Universities Power Engineering Conference (AUPEC), Melbourne, VIC, 2017, pp. 1-6.

[3] N. Kim, M. Kim and J. K. Choi, "LSTM Based Short-term Electricity Consumption Forecast with Daily Load Profile Sequences," 2018 IEEE 7th Global Conference on Consumer Electronics (GCCE), Nara, 2018, pp. 136-137.

[4] T. Hossen, A. S. Nair, R. A. Chinnathambi and P. Ranganathan, "Residential Load Forecasting Using Deep Neural Networks (DNN)," 2018 North American Power Symposium (NAPS), Fargo, ND, 2018, pp. 1-5.

[5] D. L. Marino, K. Amarasinghe and M. Manic, "Building energy load forecasting using Deep Neural Networks," IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, 2016, pp. 7046-7051.

[6] T. Panapongpakorn and D. Banjerdpongchai, "Short-Term Load Forecast for Energy Management Systems Using Time Series Analysis and Neural Network Method with Average True Range," 2019 First International Symposium on Instrumentation, Control, Artificial Intelligence, and Robotics (ICA-SYMP), Bangkok, Thailand, 2019, pp. 86-89.

[7] Jian Zheng, Cencen Xu, Ziang Zhang and Xiaohua Li, "Electric load forecasting in smart grids using Long-Short-Term-Memory based Recurrent Neural Network," 2017 51st Annual Conference on Information Sciences and Systems (CISS), Baltimore, MD, 2017, pp. 1-6.

[8]Á. F. Gambín and M. Rossi, "Smart Energy Policies for Sustainable Mobile Networks via Forecasting and Adaptive Control," 2018 IEEE Globecom Workshops (GC Wkshps), Abu Dhabi, United Arab Emirates, 2018, pp. 1-6.

[9] S. Ai, A. Chakravorty and C. Rong, "Evolutionary Ensemble LSTM based Household Peak Demand Prediction," 2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), Okinawa, Japan, 2019, pp. 1-6.

[10] Xi Chen，Jing Qu，Zhao Yangdong．An Improved Load Forecast Model Using Factor Analysis ： An Australian CaseStudy[C]//Proceedings of the 2017 IEEE International Conference on Information and Automation (ICIA)．Macau SAR，China：IEEE，2017：903-908．

[11] He Yaoyao ，Liu Rui，Han Aoyang．Short-Term Power Load Probability Density Forecasting Method [1] Based On Real Time Price And Support Vector Quantile Regression[J]．Proceedings of the CSEE，2017，37(3)：768-774．

[12] Schmidhuber, J.: Deep learning in neural networks: An overview. Neural Networks,61, 85–117 (2015)