DOI:10.18686/ahe.v7i7.7607

Short-term Power Load Forecasting Based on LSTM Neural Network Model

Yanyan Wei
Zhengzhou College of Finance and Economics, Zhengzhou City, Henan Province, 450000

Abstract: This paper selects humidity, maximum temperature, minimum temperature, historical load data and holiday type as input variables, and constructs LSTM neural network model to predict the daily maximum load and daily minimum load of a place. The results show that LSTM is better than the minimum load in forecasting the daily maximum load.
Keywords: LSTM ; Power load forecasting; Meteorological factors

1. Introduction

Nowdays, electric energy is an indispensable energy. However,electric energy can't be stored on a large scale like other commodities, it's manufacturing, transportation and consumption are carried out simultaneously. Due to the high cost of power production, more production will be wasted, and less production can not meet the needs of users. Load is a key index in the power system, which plays a very important role in the process of power production, transportation and distribution. Therefore, the research of power load forecasting is very important to ensure the safe and efficient operation of power system.

Power load forecasting can be divided into medium-long term forecasting, short-term forecasting and ultra-short-term forecasting according to the forecasting cycle. Among them, medium and long term forecast generally refers to the forecast of load in the next one to five years, mainly used for long-term planning; Short-term forecast refers to the forecast of the load of each time period in the next day to week, which is mainly used for operation planning; Ultra-short term prediction refers to the prediction of the next few hours or even seconds, which is mainly used for online control. Therefore, short-term load forecasting is the key content of power system load forecasting research.

2. Literature review

In terms of power load forecasting models, relevant research can be divided into three categories:The first is classic forecasting method, which mainly uses traditional mathematical models such as regression analysis method, time series model, exponential smoothing method, etc. to carry out short-term load forecasting.G. Peter Zhang[1] combined the time series model with the neural network model to predict the power load, and the results show that the combined model has higher prediction accuracy.Charlton et al.[2] considered the impact of temperature, days and their product on the load, and analyzed the impact of temperature on energy use using regression model.The second is the traditional prediction method, mainly including fuzzy prediction method, grey prediction method, Kalman filter method, etc.DUSong-huai[3] and Grange[4] think that the grey model is suitable for power load forecasting, and the most commonly used grey forecasting model is GM (1,1) model.The third category is intelligent prediction method, mainly including expert system method, wavelet decomposition method, support vector machine, neural network prediction model and combination prediction method.HoKu-Long et al.[5] carried out short-term forecasting of Taiwan's load based on expert system, and the forecasting accuracy basically met the requirements. However, this method is prone to human errors, and it is difficult to accurately express and transform expert experience.Hong et al.[6]carried out short-term load forecasting based on artificial neural network model, and considered the impact of electricity price in the model, and achieved good forecasting results.Shafiul et al.[7]combined the convolution neural network model with the short-term and short-term memory network, and confirmed the effectiveness of the model.Goswami et al.[8]used a dynamic regression model to predict the power load of a city. The study showed that temperature had an impact on household and commercial load, but the impact on industrial load was very small, almost zero.

In summary,for the short-term load forecasting model, the classical forecasting methods have been continuously developed. However, with the development of society, the factors that affect the power load are gradually diversified. The classical forecasting method is relatively simple and cannot fully consider the impact of these factors on power load. The traditional prediction method also has some defects. With the development of computer technology and machine learning, there are more and more intelligent prediction methods, especially those based on neural network models. In addition, most studies have included short-term load factors.

3. Model

LSTM was proposed by German scientists Sepp Hockett and Jurgen Schmidt. It is good at learning from data with large time span, and its prediction accuracy is also higher than the traditional circular neural network model (RNN). It can model time series data and selectively "remember" the input information, avoiding the phenomenon that the neural network learning stops when there is too much input information. At present, it has been successfully applied in many fields such as graphics, natural language and speech processing.

Prediction error is the difference between the predicted value and the real value, which is used to measure the quality of the model. The prediction error formulas used in this paper is mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\% \quad (1)$$

4. Data source and preprocessing

4.1 Data source

The factors affecting short-term load include meteorological factors, date types, economic factors and random factors. However, due to the limited data, and some scholars' research shows that economic factors are more important in the medium and long term power load forecasting, while this paper studies the short-term power load forecasting, so this paper does not add economic factors to the model. In addition, due to the unpredictable nature of random factors, this paper has not included them in the model.

Thus, this paper mainly selects six indicators from two aspects of meteorological factors and date types: maximum temperature, minimum temperature, average temperature, humidity, precipitation, and date type(workday is 0,otherwise is 1). In addition, The data of daily maximum and minimum loads have autocorrelation,and because the current power load is correlated with the same period last year, this paper also adds the load data with a lag of one year to the model as input.

The data is the real data of power load and meteorological factors in a certain area from January 1, 2012 to January 10, 2015. Among them, the sampling interval of power load is 15 minutes, but because no real-time meteorological factors are given, this paper only forecasts the maximum and minimum load every day.

4.2 Data preprocessing

This paper mainly deals with outliers and standardization of data.

4.2.1 Handling of outliers

Some load values are negative, and such data is obviously abnormal. With regard to these outliers, this paper adopts the mean value of the four adjacent sampling points to correct them. That is, if the load value at the moment is abnormal, the corrected value is:

$$\hat{P}t = \frac{P_{t+2} + P_{t+1} + P_{t-1} + P_{t-2}}{4} \quad (2)$$

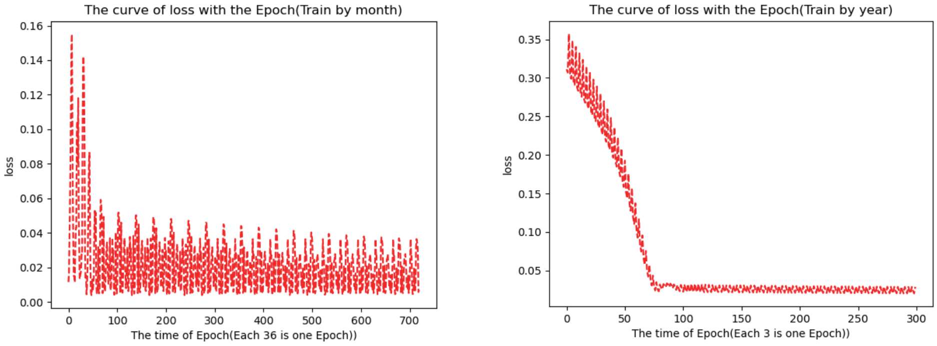
4.2.2 Standardization

The unit of different types of variable are also different, and the order of magnitude may vary greatly, which may affect the prediction effect of the model and slow down the convergence speed of the model. In order to avoid this situation, it is usually necessary to standardize the data. The standardization formula used in this paper is:

$$Z_i = \frac{X_i - \min(X_i)}{\max(X_i) - \min(X_i)} \quad (3)$$

5. Experimental process

This paper takes the data from January 1, 2012 to December 31, 2014 as training data, and the data from January 1, 2015 to January 10, 2015 as test data, and the LSTM neural network model is built through PYTHON 3.6 for empirical analysis. Figure 2 (a) and (b) are the loss functions obtained by training the model by month and year respectively.Since the loss of the monthly training model is less than that of the annual training model, this paper will train the monthly training model (Figure 1).

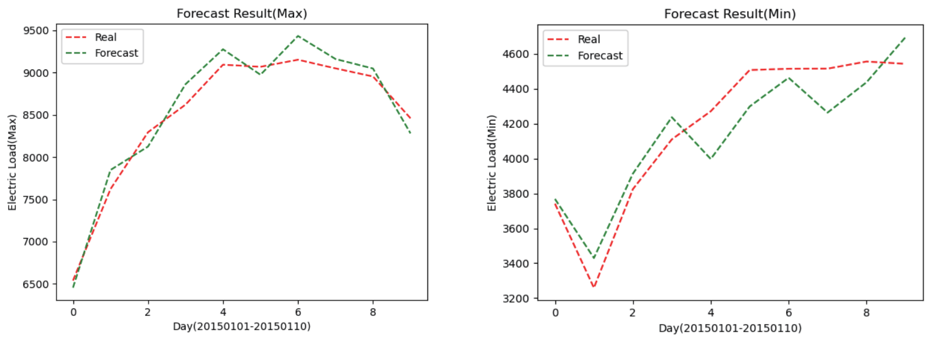


(a) (b)

Figure 1 Loss function of training model

6. Results

The MAPE of the maximum load forecast(2.165%) is smaller than that of the minimum load forecast(3.508%)(table 1), which indicates that the LSTM model has a better prediction effect on the daily maximum load than the minimum load. This may be because the maximum load is greatly affected by meteorological factors, date type and historical load, so the forecast is relatively arbitrary. However, the minimum load may be greatly affected by random factors, so it is relatively difficult to predict (Figure 2).



(a) (b)

Figure 2 Predicted and true values

Table 1 Model prediction error

Type	ME	MAE	RE	MAPE
Max	43.001	184.340	21.649	2.165
Min	-33.893	146.996	35.084	3.508

References:

[1] Peter G Z. Time series forecasting using a hybrid ARIMA and neuralnetwork model[J]. Neurocomputing, 2003(50): 159-175.

[2] Charlton N, Singleton C. Arefined parametric model for short term load forecasting. International Journal of Forecasting[J].2014(30) : 364-368.

[3] Du Songhuai, Hou Zhijian, Jiang Chuanwen. Grey forecasting price, utation and its simulation[J]. Journal of Grey System, 2003(1): 43-48.

[4] Granger C. Combining forecasts-twenty years later[J]. Journal of Forecasting, 1989, 8(3): 167-173.

[5] Ho Ku Long, Hsu Yuan Yih, Lee C E, etal. Short-term load forecasting of Tai-wan power system using aknowledge-based expert system[J]. IEEE PWRS, 1990, 5(4): 46-57.

[6] Hong C, Canizares C Z, Singh A. ANN-based short-term load forecasting in electricity markets[C]. 2001 IEEE Power Engineering Society Winter Meeting. Conference Proceedings, 2001(2): 411-415.

[7]RafiS.H,Nahid-Al-Masood,DeebaSR,etal.Ashort-termloadforecastingmethodusingintegratednnandlstmnetwork[J].IEEE Access,2021(9):32436-32448.

[8] Goswami K, Ganguly A, et al. Day ahead forecasting and peak load management using multivariate auto regression technique[C]. 2018 IEEE Applied Signal Processing Conference (ASPCON), 2018.