Research on Electricity Load Forecasting Based on LSTM Networks and BP Networks

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Abstract. The aim of this study is to compare the performance of Long Short-Term Memory (LSTM) network with Back Propagation Neural Network (BP network) for electricity load forecasting. Two prediction methods are used in the study: the first one uses a sliding window approach to predict the load of the next hour using the electricity load data of the past 24 hours and external factors such as temperature and humidity; the second one uses the data of the same time point of the past 24 days to predict the load of the corresponding time point of the next day. The results show that in the first method, the BP network outperforms the LSTM in prediction; while in the second method, both networks perform poorly, but the LSTM network outperforms the BP network in prediction. This finding provides new insights into power load forecasting, which is important for power system efficiency and reliability improvement.

Keywords: Short-term load forecasting, LSTM network, BP network.

1. Introduction

The accurate prediction of power load is of great significance for the electric power production and the safe operation of the power grid and the national economy [1]. Short term load forecasting is an important part of energy management system. The prediction error directly affects the analysis results of subsequent safety check of power grid, which is of great significance for dynamic state estimation, load scheduling and cost reduction [2-4]. Traditional prediction methods are based on linear regression, such as time series method, analysis method and pattern recognition method has defects of respectively [5-7].

In recent years, with the rapid development of artificial intelligence technology, power load forecasting methods based on machine learning have gradually become a research hotspot [8]. In particular, neural network models such as Long Short-Term Memory (LSTM) networks and Back Propagation Neural Networks (BP networks) have shown strong potential in the field of power load forecasting due to their excellent nonlinear modeling capabilities and self-learning characteristics. Compared with traditional methods, these neural network-based methods are able to process and learn patterns from large amounts of historical data more efficiently, improving the accuracy and reliability of forecasts.

The results of the study show that when dealing with short-term data, the BP network slightly outperforms the LSTM in terms of prediction accuracy, demonstrating its ability to quickly adapt and deal with shorter time series data. However, when dealing with long-term data, LSTM significantly outperforms BP network, reflecting the strong ability of LSTM in capturing long-term dependencies. Compared to traditional methods, these two neural network models demonstrate higher flexibility and accuracy in processing complex and dynamic power load data.

By studying and analyzing LSTM and BP networks, this paper not only reveals the applicability and effectiveness of these advanced models under different time scales and data characteristics, but also provides a new perspective and tool for enhancing the accuracy and reliability of power load forecasting. This is of great practical significance for optimizing the allocation of power resources,

enhancing the operational efficiency of the power grid, and realizing the intelligent management of the power system.

2. Principles of short-term load forecasting

Short-term electricity load forecasting is the use of historical load data and related influencing factors to predict electricity demand over the next few hours to days. [9-10] Such forecasts are usually based on time series analysis of historical load data, combined with factors such as weather conditions (temperature, humidity, wind speed, etc.), type of date (weekday or holiday), social activity patterns, etc.

The principles of short-term load forecasting are mainly based on statistical and machine learning methods. Among the statistical methods, commonly used techniques are autoregressive moving average (ARMA) models, seasonal decomposition, etc., which focus on analyzing the statistical properties of time series data. Whereas, in the field of machine learning, methods such as Support Vector Machines (SVMs), neural networks (e.g., BP networks and LSTMs), etc. are used to identify and learn complex patterns and relationships in historical data.

The key to these forecasting models is the ability to learn from historical data the patterns of change in loads over time, as well as the correlation between loads and various influencing factors, such as temperature changes. For example, higher temperatures may lead to increased air conditioning use, which in turn increases electricity load. By analyzing these patterns and relationships, the forecasting model can estimate future electricity demand, thus helping grid operators to effectively plan resources and ensure the stability of power supply.

3. Model building

In this paper, Matlab is used to build the required neural network model. Both the LSTM network and BP network used are multi-input, single output structures. In the first method, the sliding window size is set to 24 hours i.e. the input of the model is 24 hours of historical power load data, the sliding step is 1 hour, and the output of the model is 1 hour of future power load data. The second method is to utilize the power load data at the same point of time in the past 24 days (e.g. 1:00 every day) to predict the power load at the same point of time in the future day, the input is the power load data at a certain point of time in the past 24 days, and the output is the power load data at the same point of time in the future day. The LSTM network used in this paper consists of one input layer, one LSTM layer, and one output layer.The BP network consists of one input layer, one fully connected layer as hidden layer, and one output layer as shown in Figure 1.

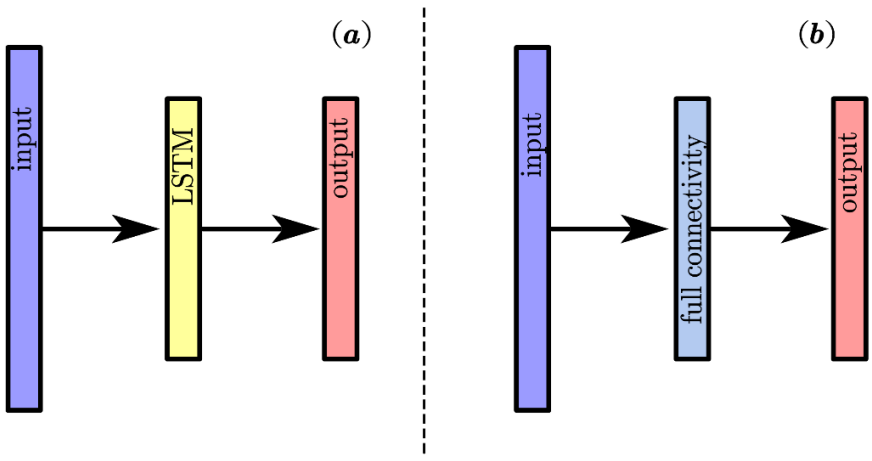


Fig 1. Network composition of LSTM network and BP network used in this paper ((a) is LSTM network, (b) is BP network)

4. Experiments and Analysis of Short-term Forecasting of Electricity Load

In this paper, we use the constructed LSTM network and BP network to randomly select part of the data from the dataset for short-term power load prediction, and compare the prediction results of the two models using the two prediction methods respectively.

4.1. Acquisition and processing of data

The dataset is load data for the country of Panama, with a total collection period of 03/01/2015 a 06/27/2020. The sampling interval of the load data is 60 min and the data has 48,048 electric load samples, which also includes external influences such as humidity, temperature, wind speed, etc. in the cities of Santiago, David, and Panama City in the country of Panama at each point in time. Selected portions of the data were plotted through Origin as in Figure 2.

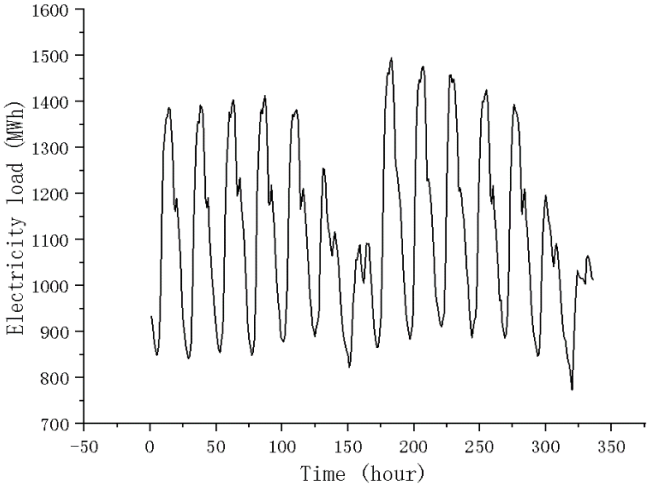


Fig 2. Electricity load map for a randomly selected two-week period in the country of Panama

Prior to utilizing neural networks for power load forecasting, the raw data set is adequately preprocessed. This process typically involves filling in missing data, identifying and processing anomalous data points, and performing data normalization operations. Data normalization helps to prevent the model from over-reliance on certain features during the training process, which may lead to overfitting, making the model perform well on the training set but fail to generalize to new datasets. In this study, this paper divides the dataset into two parts: 80% of the data is used as a training set for model learning and 20% of the data is used as a test set.

4.2. Model Parameter Setting

The accuracy of short-term forecasting of electricity loads depends mainly on the quality of the dataset and the appropriateness of the model parameters. The effectiveness of model training is largely determined by the parameter configuration, and the optimization of these parameters is directly related to the accuracy of the prediction results.

In this paper, the initial learning rate is set to 0.003 in the LSTM network, and a total of 1000 iterations are performed, and the learning rate decreases to 20% of the original after every 125 iterations after the start of training. In the BP network, the learning rate is fixed at 0.0001, the maximum number of iterations is 1000, and training is also stopped if the target error is reached, which is 0.0001.

4.3. Results and Analysis of Short-term Forecast of Electricity Load

4.3.1 Indicators for evaluating projected results

In order to verify the effectiveness of the two models when using the two methods respectively, short-term forecasting of the same electricity load data is performed using the two models proposed in this paper, and the forecasting results are compared. The three types of mean square error (MSE), mean

absolute error (MAE) and root mean square error (RMSE) are used as the metrics for error evaluation. The mathematical expressions for MSE, MAE, and RMSE are as follows [11].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|^2 \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{3}$$

4.3.2 Forecast results and analysis

BP network and LSTM network are used to predict the power load through the first method respectively, for both the models are utilized in the form of sliding window with a window size of 24, 24 hours of historical data as input and one hour of future power load data as output, such that the total number of data pairs is 1200 pairs. After the training of both the models is completed, Figure 3 is plotted using the predicted and real data.

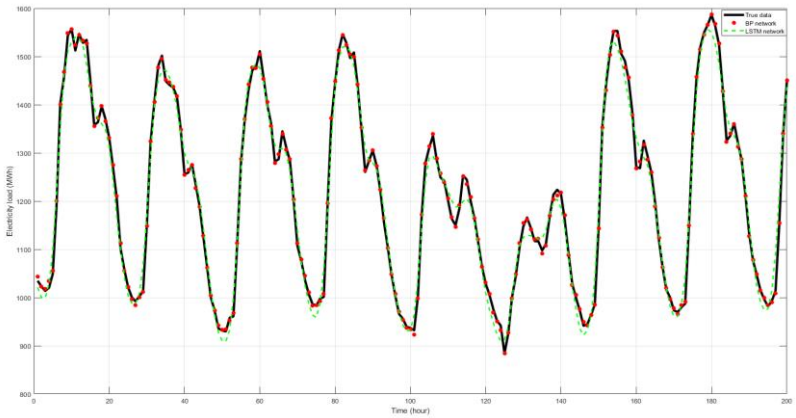


Fig 3. Comparison chart of prediction results (the black solid line is the real data, the red dots are the prediction results of the BP network, and the green dotted line is the prediction results of the LSTM network)

Table 1 shows the comparison of the errors of the electricity load forecasting results obtained by the first method using the two models, and Figure 4 shows the visualization of the errors between the predicted and true values of the two models.

Table 1. Comparison of the prediction errors of the two models

predictive model	MSE/MWh	MAE/MWh	RMSE/MWh
BP network	31.67	4.41	5.63
LSTM network	618.12	20.07	24.86

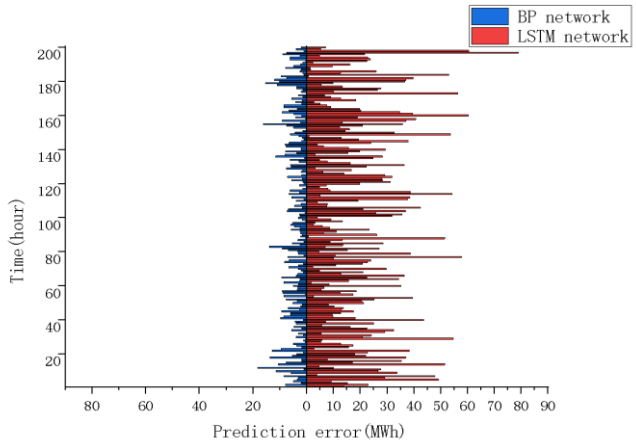


Fig 4. Visualization of prediction error comparisons

From Figure 3,Figure 4 and Table 1, it can be seen that when the original power load data changes drastically, the results predicted by the BP network can always follow the changes well, while the prediction results of the LSTM network can fit well with the power load data when the data is relatively smooth, and when the power load data changes drastically, the prediction results of the LSTM network are poorer in comparison with the prediction results of the BP network.

The power load is predicted by the second method using BP network and LSTM network respectively, for both models the power load data of the corresponding time point of the future day is predicted based on the same time point of 24 days of history, the power load data of the same time point of the 24 days of history is taken as the input, and the corresponding power load data of the future day is taken as the output, such that there are a total of 24 pairs of data pairs. After the training of the two models is completed, Figure 5 is plotted using the predicted and real data.

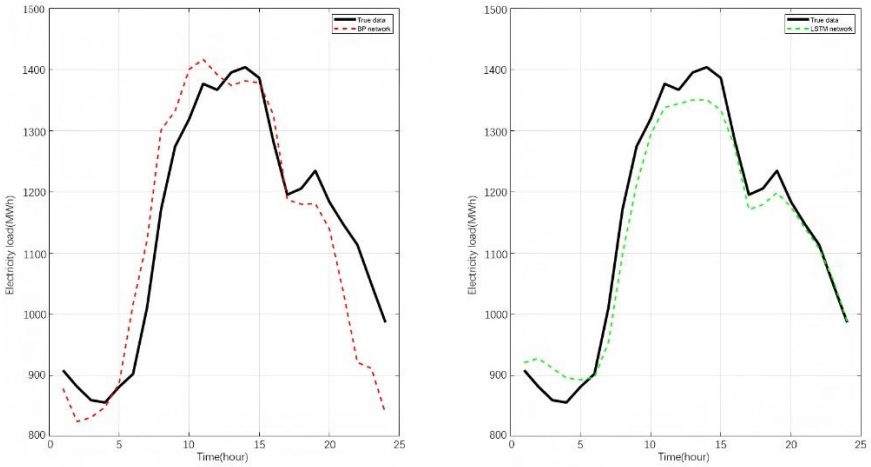


Fig 5. Comparison of prediction results when using the second method

Table 1. Comparison of the prediction errors of the two models when using the second approach

predictive model	MAE/MWh	RMSE/MWh
BP network	62.59	81.09
LSTM network	30.25	36.83

From Figure 5 and Table 2, it can be seen that the prediction results of both models are poor, but in contrast, the prediction results of LSTM are better than those of BP network. In this paper, we believe that there may be two reasons for the poor prediction results of the second method. (1) This method can only have 24 groups of data for prediction, and can only increase the amount of data in each group but not the number of groups. (2) This method does not consider external factors such as temperature and humidity.

5. Conclude

In this study, this paper draws some key findings and conclusions by comparing the prediction performance of two mainstream deep learning models, backpropagation neural network (BP network) and long-short-term memory network (LSTM network), for the short-term power load forecasting problem. Although LSTM networks are widely used in various types of time series prediction tasks due to their ability to capture long-term dependencies, BP networks show more superior performance in this specific scenario of short-term prediction.

Through empirical analysis, when using the first method for forecasting, this paper finds that the BP network outperforms the LSTM network in terms of forecasting accuracy. This may be attributed to its high efficiency and faster convergence speed when dealing with shorter time series data.The BP network is able to quickly adapt to data changes and accurately capture short-term fluctuations in loads, thus providing more accurate information for load scheduling in power systems. In addition, the structure of the BP network is relatively simple and the training process is faster, which is a non-

negligible advantage for the power load forecasting system that requires rapid response. The results obtained by using the second method for prediction are overall worse than those obtained through the first method, and this paper suggests that this may be due to the fact that the number of groups of data is too small or external influences are not taken into account when using the second method for prediction.

In summary, although LSTM networks have theoretically unique processing advantages for long-term time series data, BP networks have been shown to be a more suitable choice for specific short-term power load forecasting tasks due to their excellent predictive ability and fast response characteristics. This finding emphasizes the importance of selecting a neural network model suitable for the needs of a specific forecasting task and provides a valuable reference for future research in similar short-term forecasting areas.

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