Short-term load forecasting model based on EEMD-LSTS-ARIMA

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Abstract. To improve the accuracy of the short-term power load forecasting, this paper designed a model, namely, the first to use based on empirical mode decomposition (EMD) method based on the collection of ensemble empirical mode decomposition (EEMD) in order to improve signal decomposition in the process of modal aliasing phenomenon and false component, and using the decomposition method of power load data decomposition, modal components with different characteristics, and according to its characteristics can be divided into high frequency components, intermediate frequency and low frequency components, Then the Long Short-Term Memory network (LSTM) is used for load forecasting. Using the autoregressive Integrated moving average model (Arima) to correct the predicted residual error, the load forecasting model based on EEMD-LSTM-ARIMA is established. Finally, the data of Queensland, Australia is used as the research sample. On the above prediction model, the data of this region is input into the model for power load prediction. At the end of the prediction, the final prediction results are compared with the EEMD-LSTM model through root mean square error (RMSE) and mean absolute percentage error (MAPE). Through comparison, it is found that the method used in this paper has a high prediction accuracy.

1. Introduction
Short-term power load prediction refers to the prediction of the power load data in the next few hours, a day or a week. Accurate load prediction can improve the real-time dispatching and operation planning of the power system, thus reducing energy consumption and promoting the development of society and economy [1]. As electric energy is difficult to be stored in large quantities, the dynamic balance of electricity consumption and generation can improve the reliability of power system operation [2].

Power load data is a special time series with certain randomness, fluctuation and periodicity, and is usually non-stationary and non-linear data [3]. The methods currently used are usually divided into traditional predictive methods and machine learning predictive methods. The traditional methods are represented by regression analysis [4], time prediction [5-6], etc. Although the calculation is simple and easy to realize, the prediction accuracy is not high due to its poor ability to deal with a large number of nonlinear data. Machine learning methods, represented by neural network and support vector machine, have been gradually applied in load forecasting with good predictive effect [7-8]. In literature [9], empirical mode decomposition (EMD) was used to decompose the micro-grid load time series into multiple components of inherent mode functions, and then the components with different characteristics were predicted. Although the above methods can fit nonlinear data well, most of them treat load data as a static regression problem and do not fully consider the temporal correlation of load data. Moreover, EMD decomposition tends to cause the phenomenon of modal mixing, which affects the prediction.
accuracy. Therefore, this paper proposes to firstly adopt EEMD model to carry out multi-dimensional decomposition of load data, then use LSTM neural network to predict each dimension sequence, and then add the prediction results of each dimension sequence to obtain the preliminary load prediction results. Finally, Arima model is used to correct the prediction error, so as to improve the prediction accuracy.

2. Basic principle

2.1. Principles of the EMD model

EMD decomposition method, proposed by Huang, is a signal decomposition method based on the time-scale characteristics of the data itself without presetting the basis function. Therefore, it plays a good role in dealing with nonlinear and non-stationary data. The method decomposes the complex signal into a finite Intrinsic Mode Function (IMF). The IMF must meet two conditions:

1. In the whole time frame, the number of local extremums and zero crossings of IMF must be equal or at most one different.
2. At any moment, the average of the upper envelope (the local maximum) and the lower envelope (the local minimum) is zero.

Based on the above features, the process of EMD decomposition of time series x(t) is shown in Figure 1.

![EMD flowchart](image)

2.2. Principles of the EEMD model

Caused by the emd decomposition signal easy modal aliasing, therefore, adding white noise to decompose signals, using the uniform distribution of white noise spectrum, when the signal to add on the uniform distribution of white noise background, the different time scale of signal automatically distributed to the appropriate reference scale, and due to the nature of the zero-mean noise, after many
times the average noise will offset each other, integrate the results of the average as the final result. This is the EEMD method. The process is shown in Figure 2.

![EEMD flowchart](image)

**Figure 2. EEMD flowchart**

### 2.3. Principles of the LSTM model

Long Short-Term Memory (LSTM) is a kind of improved network based on recurrent neural network (RNN), because the RNN neural network with the increase of time, easy to lose the ability to get more information from the past, explode gradient disappeared and gradient phenomenon\[^{10}\]. LSTM through additional memory unit, memories of the past information, stored for a long time. LSTM has strong generalization ability and good learning ability for both large and small data sets, and has a strong advantage in dealing with nonlinear problems\[^{11}\]. The basic unit structure of LSTM is shown in Figure 3.

![LSTM neural network structure](image)

**Figure 3. LSTM neural network structure**

The process of LSTM neural network is to combine the input data at time $t$ with the output data at time $t-1$, then select the memory variable that needs to be retained for a long time through the forgetting gate, and then get the new memory state variable by superimposing the long-term state of the previous moment with the current state through the input gate. Finally, the long-term memory state variable gets the output at time $t$ through the action of the output gate.

The operational process of LSTM memory cells is shown as follows:

$$i_t = \sigma(W_i[y_{t-1}, x_t] + b)$$

(1)
\[ f_t = \sigma(W_f[y_{t-1}, x_t] + b) \] (2)
\[ o_t = \sigma(W_o[y_{t-1}, x_t] + b) \] (3)
\[ \tilde{s}_t = \tanh(W_s[y_{t-1}, x_t] + b) \] (4)
\[ s_t = f_t s_{t-1} + \tilde{s}_t o_t \] (5)
\[ y_t = o_t \tanh(s_t) \] (6)

Where \( x_t \) is the input, \( y_t \) is the output, \( i_t \) is the output of the input gate, \( f_t \) is the output of the forgetting gate, \( o_t \) is the output of the output gate, and \( W \) and \( b \) are the parameter matrices. \( \sigma \) uses Sigmoid activation function.

2.4. Principles of the ARIMA model

The predicted load values are obtained by using EEMD-LSTM model, and the error sequences can be obtained by comparing the predicted load values with the measured load values. In order to improve the prediction accuracy, this paper uses Arima model for error correction, and takes the error series as the original time series to establish Arima model for correction. The formula of Arima \((p, d, q)\) model is as follows.

\[
\left[1 - \sum_{i=1}^{p} \phi_i L^i\right](1-L)^d X_t = \left[1 + \sum_{i=1}^{q} \theta_i L^i\right]\epsilon_t
\] (7)

Where, \( X_t \) is the input error sequence, \( d \) is the order required for differential to obtain stationary time series, \( p \) is the order of autoregression, \( q \) is the order of sliding average, \( L \) is the lag operator, and \( t \) is the residual sequence. When Arima is used for error correction, if the \( \epsilon_t \) of the residual sequence is the white noise sequence, it passes, otherwise, the parameter is modified until it passes.

3. Model flowchart and modeling algorithm

3.1. Model flowchart

The modeling process of EEMD-LSTM-ARIMA model is shown in Figure 4.

3.2. Model modeling algorithm

(1) The input load was decomposed into a finite number of IMF components and a trend component using EEMD decomposition technique, as shown in Figure 5. The decomposed subsequence is divided into training set and test set.
LSTM models were established for each component and load data were predicted. The predicted values of each model were accumulated to obtain the predicted results of the training set, as shown in Figure 6.

The error sequence can be obtained by comparing it with the real value, and the error sequence can be modified by constructing Arima model as the original time series.

Finally, the data of the test set is input into the whole model, and the predicted results are shown in Figure 7.

3.3. The evaluation index

In this paper, root mean square error (RMSE) and mean absolute percentage error (MAPE) are used to evaluate the prediction effect of the model.

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \tag{8}
\]

\[
\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \tag{9}
\]

Where, \( y_i \) actual values for the case of a prediction sample \( i \), \( \hat{y}_i \) for the case of a prediction sample \( i \) predicted. The smaller RMSE and MAPE, the smaller the deviation between the predicted value and the actual value, the higher the model accuracy, and vice versa, the poorer the prediction results.

4. Numerical example analysis

4.1. Data processing

In order to verify the accuracy of the model, the power load data of 1 solstice in June 2019 and 31 August 2019 in Queensland, Australia is selected as the data set. The load data is sampled every 0.5 hour, and there are 48 sampling points in a day, with a total of 4416 load data as the research object. The training set and test set were divided in a scale of 0.9:0.1. RMSE and MAPE were used as indicators to evaluate the prediction effect of the model. Finally, the prediction results of the EEMD-LSTM model and the EEMD-LSTM-ARIMA model were compared.

There are outliers and missing values in historical power data due to data omission, collector failure and other factors. The outliers can be treated as missing values, and then the missing values can be supplemented by the mean value method, which can effectively improve the prediction accuracy of the model. Finally, the data is normalized, and the normalization formula is as follows:

\[
x_{\text{norm}}^i = \frac{x^i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \tag{10}
\]

4.2. Results analysis

The preprocessed load is decomposed by the decomposition method of EEMD, and the high frequency signal with noise and the relatively stable low frequency signal are decomposed. The decomposition results are shown in Figure 5. It can be seen that the top sequence is the original sequence, which is decomposed into 6 modes. IMF1 has the highest frequency and the sequence is complex and disordered. IMF2-imf5 gradually changed from high frequency to low frequency, and the complexity of the sequence decreased. IMF6 is the residual component and the trend of reaction load time series. Compared with the original sequence, the decomposed components become more stable.
All components were input into the LSTM network for prediction, and the predicted values of each model were accumulated to obtain the prediction results of the training set, as shown in Figure 6. It can be seen that although the predicted results were close to the actual load value, there were still large errors in 2h-4h and 9h-12h. Then, the error is corrected by using Arima model, and the prediction results of EEMD-LSTM-ARIMA model and EEMD-LSTM model are obtained, as shown in Figure 7.

It can be seen from Figure 7 and Table 1 that compared with the EEMD-LSTM model, the prediction curves of 2h-4h and 9h-12h of EEMD-LSTM model are greatly improved, and the errors are significantly reduced. Moreover, both RMSE and MAPE of EEMD-LSTM-ARIMA model are smaller than that of EEMD-LSTM model, indicating that the prediction accuracy of the proposed model is relatively high and has better prediction effect.
5. Conclusion
The short-term load forecasting model based on EEMD-LSTM-ARIMA proposed in this paper firstly decomposes load data by EEMD. Then, LSTM model is used to predict each decomposition sequence, and the error sequence can be obtained by comparing the prediction result with the real value. The error sequence is used as the original time series to build an Arima model for correction. Finally, the data of the test set is input into the whole model to obtain the final prediction result.

Experiments show that the model proposed in this paper has higher prediction accuracy, can meet the demand of short-term prediction of power system, promote the smooth operation of power grid, and realize the reasonable dispatching of power generation capacity.

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