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Short Term Wind Power Prediction Based on CEEMDAN-LSTM

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Abstract: To improve the accuracy of wind power prediction, a wind power prediction method based on time series decomposition and error correction is proposed. Firstly, the maximum information coefficient (MIC) method was used to select the features that have strong correlation with wind power to reduce the complexity of the original data; Then, according to the non-stationary characteristics of wind power, complete ensemble empirical mode decomposition with adaptive noise(CEEMDAN) was used to decompose wind power into several stationary subsequences; Finally, the long short memory network (LSTM) was used to dynamically model the wind power multivariable time series; Add the predicted values of each subsequence to get the final predicted value. Combined with the measured data of a domestic wind farm, the simulation results showed that the proposed method had higher short-term wind power prediction accuracy compared with other prediction models.

Keywords: Wind power prediction, CEEMDAN, Deep Learning, LSTM; MIC.

1. Introduction

By the end of 2020, China's installed wind power capacity was 281 million kilowatts, and the wind power generation capacity is 466.5 billion kilowatt hours, accounting for 6.1% of the total power generation [1]. Wind power gradually changes from 'auxiliary power supply' to 'main power supply' [2]. However, due to the time-varying characteristics of wind, wind power has strong randomness, intermittency and uncertainty [3]. Therefore, accurate prediction of wind power was of great significance to the safe and economic operation of power system [4].

Wind power time series data were non-stationary series, and it was difficult to capture their change characteristics and autocorrelation in time series. Therefore, the direct prediction of wind power data is not ideal[5]. In view of the random volatility of wind power data, the literature[6] used the Complex Ensemble Empirical Model Decomposition (CEEMD) to decompose the wind power sequence, and used the Satin Gardener algorithm to optimize the least squares support vector machine to predict the wind power. In reference[7], the serial information such as historical wind power was decomposed into modal components of specified layers by using variational mode decomposition(VMD).Different modal components represent features of different scales. Weight sharing gate recurrent unit (WSGRU) was used for modeling. Finally, ANN was used to correct and obtain the prediction results of wind power. In reference[8], for the low adaptability of VMD method, the Enhanced Colliding Bodies Optimization (ECBO) algorithm was used to optimize the core parameters of the variational mode. After decomposition, the wavelet kernel limit learning machine prediction model is used for prediction.

In order to improve the accuracy of wind power prediction, a short-term wind power prediction method based on fully adaptive noise ensemble empirical decomposition (CEEMDAN) and long short memory network (LSTM) prediction was proposed in this paper. The CEEMDAN was used to decompose the wind power into several subsequences, establish the LSTM wind power prediction model of subsequences, and stack the predicted values of subsequences to obtain the final predicted value. The proposed method was compared with LSTM and EMD-LSTM to verify that the proposed model has higher accuracy.

2. Data Preprocessing

2.1. MIC feature selection

Reshef et al. proposed the maximum information coefficient (MIC) method basedon mutual information [9]. Mutual information is a measure that describes the mutual relationship between two random variables x and y. The greater the mutual information value, the stronger the correlation between the two variables. Mutual information is defined as:

$$I(x,y)=\sum_{x\in X}\sum_{y\in Y}p(x,y)\log\frac{p(x,y)}{p(x)p(y)} \tag{1}$$

In the formula: *p(x,y)* is the joint probability density function of x, y; *p(x)* and *p (y)* are edge density functions of x and y, respectively.

The maximum information coefficient is defined as follows: assuming that *D(x,y)* is a finite two-dimensional data set, the current two-dimensional space was divided into m intervals and n intervals in the x and y directions, respectively, to form a grid of $m * n$. There are multiple ways to divide grids with the same interval [9]. Under grids of different scales, the maximum mutual information value was selected for calculation, and the maximum information coefficient is defined as:

$$MIC(x,y)=\max_{m\times n<B}\frac{I(x,y)}{\log(\min(m,n))} \tag{2}$$

In the formula, $m*n<B$ represents the constraint condition of the total number of grid divisions. It can be seen from literature[10] that the optimal effect can be achieved when it is set to the 0.6th power of the total amount of data. Therefore, this setting method was also used in this paper.

2.2. Normalization

When using multivariate time series to predict wind power, the dimensions of different variables are different, and the numerical differences are also large [11]. In orderto make the prediction model consider the effect of variables on wind power equally, the wind speed, temperature,wind direction angle and active power in the wind power data are normalized to the [0,1] range.

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

In the formula: X_{min} and X_{max} are the minimum and maximum values of variables respectively.

3. Prediction Model Analysis

3.1. CEEMDAN principle

CEEMDAN is based on EMD decomposition. In the process of decomposing wind power signals, it adaptively adds white noise to weaken the mode aliasing problem, and the decomposition process is characterized by integrity and almost no reconstruction error [12].

The CEEMDAN decomposition algorithm is implemented as follows:

1) CEEMDAN decomposition algorithm makes use of EMD for signal $X(t)+\varepsilon^{i}_{0}n(t)$is decomposed repeatedly for N times, and the first modal component is obtained through mean value calculation:

$$\overline{IMF_1(\mathrm{t})} = \frac{1}{N}\sum_{i=1}^{N} IMF_1^{i}(t) \tag{4}$$

2) Calculate the first residual signal $r_1(t)$ decomposed by CEEMDAN as:

$$r_1(t) = X(t) - \overline{IMF_1(t)} \tag{5}$$

3) The signal $r_1(t) + \varepsilon_1 E_1(n^i(t))$ is decomposed repeatedly for N times to obtain the second modal component:

$$\overline{IMF_2(t)} = \frac{1}{N}\sum_{i=1}^{N} E_1(r_1(t) + \varepsilon_1 E_1(n^i(t))) \tag{6}$$

4) For $k=2,...,K$, calculate the kth residual signal:

$$r_k = r_{k-1} - \overline{IMF_K(t)} \tag{7}$$

5) Repeat the calculation process in step 3) to obtain the k+1 modal function:

$$\overline{IMF_{k+1}(t)} = \frac{1}{N}\sum_{i=1}^{N} E_1(r_k(t) + \varepsilon_k E_k(n^i(t))) \tag{8}$$

6) Repeat steps 4) and 5) until the residual signal meets the termination condition of decomposition, and finally obtain k modal components. The final residual signal decomposed is:

$$R(t) = X(t) - \sum_{k=1}^{k} \overline{IMF_k(t)} \tag{9}$$

The original signal can be decomposed into:

$$X(t) = R(t) + \sum_{k=1}^{k} \overline{IMF_K(t)} \tag{10}$$

3.2. LSTM network model

LSTM is a variant of the cyclic neural network, which can effectively capture the dependencies in the time series, and is suitable for modeling the wind power time series data[13]. Its basic unit structure is shown in Figure 1.

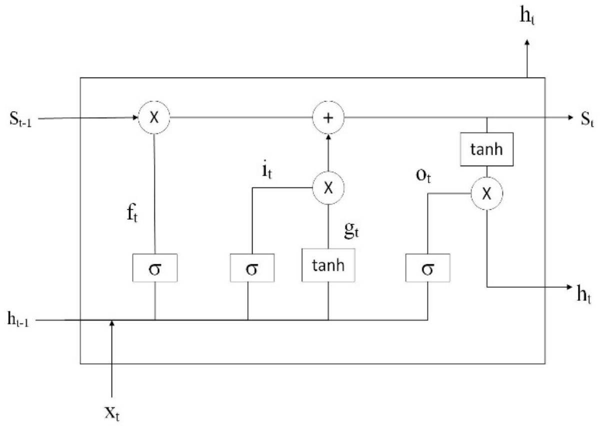

Figure 1. LSTM basic unit structure diagram

As shown in the figure above, the calculation formula is as follows:

$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f) \tag{11}$$

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \tag{12}$$

$$g_t = \Phi(W_{gx}x_t + W_{gh}h_{t-1} + b_g) \tag{13}$$

$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \tag{14}$$

$$S_t = g_t \,\mathrm{Z}\, i_t + S_{t-1} \,\mathrm{Z}\, f_t \tag{15}$$

$$h_t = \Phi(S_t) \,\mathrm{Z}\, o_t \tag{16}$$

In the formula: f_t、i_t、g_t、o_t、S_t、h_t are the states of forgetting gate, input gate, input node, output gate, intermediate output and state unit respectively; S is the activation function sigmoid; W_{fx}、W_{tx}、W_{gx}、W_{ox} are weight matrices; b_f、b_i、b_g、b_o offset terms; F Is the change of tanh function.

4. Wind Power Prediction Model

4.1. Forecast process

The flow of short-term wind power prediction method proposed in this paper is as follows:

(1) MIC method was used to select the features of wind power data, and the features with strong correlation with wind power were selected to accelerate network training;

(2) Based on CEEMDAN decomposition algorithm, wind power time series data was decomposed to obtain several stable sub sequences;

(3) LSTM network prediction model is established for each subsequence. After training, the prediction results of each

subsequence were obtained, and the prediction values were obtained after superposition.

The flow chart was shown in Figure 2:

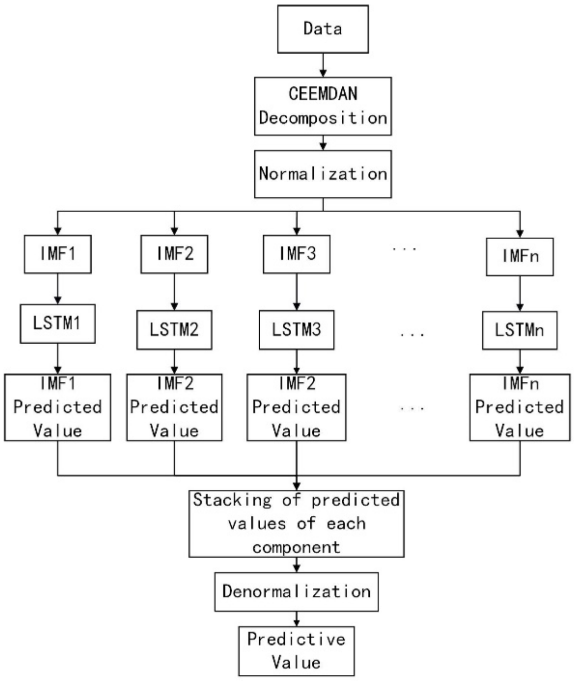

Figure 2. Algorithm flow chart

4.2. Evaluation index

In this paper, three evaluation indicators, mean absolute error (MAE), mean relative error (MRE) and root mean square error (RMSE), are used to analyze the wind power prediction results. The evaluation indicators are as follows:

$$MAE = \sum_{t=1}^{n} \frac{|p_t - \hat{p}_t|}{np_N} \tag{17}$$

$$MRE = \sum_{t=1}^{n} \frac{|p_t - \hat{p}_t|}{np_t} \tag{18}$$

$$RMSE = \frac{1}{p_N}\sqrt{\sum_{t=1}^{n} \frac{(p_t - \hat{p}_t)^2}{n}} \tag{19}$$

In the formula: n is the total number of forecasts; P_N is the capacity of wind turbine; P_t is the Actual power of wind turbine; $\hat{p}_t$ is the predictive value of wind turbine power.

5. Example Analysis

5.1. Data preparation

The measured data of a domestic wind farm was used for simulation experiments. Two adjacent wind turbines in the wind farm are selected and divided into wind turbine A and wind turbine B. The data collected in the wind farm include wind turbine ID, wind speed, wind direction angle and ambient temperature, with a sampling period of 10 minutes.

The 15 day continuous SCADA data of wind turbine in September 2015 was used to predict the wind power of wind turbine A on the 15th day. The raw data of wind turbine A was shown in Figure 3.

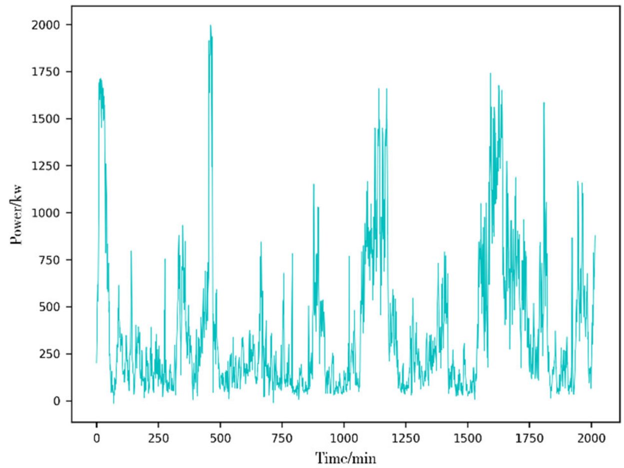

Figure 3. Raw data

5.2. MIC feature selection

There are many types of parameters of wind power SCADA data setted recording units. If all dimensions of the data setted are input into the prediction model, a large number of parameters will be generated in the network model, and the training speed will be slow, affecting the prediction accuracy. The maximum information coefficient method was used for feature selection of wind turbine multivariable time seriesto reduce the data scale and complexity.

Table 1. MIC feature selection results

influence factor	*WS*	*GS*	*RS*	*WD*	*GT*	*T*
MIC coefficient	0.982	0.965	0.971	0.250	0.810	0.143

In Table 1, six variables with the strongest correlation with output power were selected by using the maximum information coefficient method for feature selection. *WS* represented wind speed; *GS* represented the generator speed; *RS* stands for impeller speed; *WD* represented wind direction angle; *GT* standed for gearbox temperature; *T* were the ambient temperature.

5.3. CEEMDAN decomposition results

In this paper, CEEMDAN algorithm was used to decompose the wind power time series data. The white noise group number NR=100, the noise standard deviation Nstd=0.05, and the maximum iteration number MaxIter=300 were added. Nine subsequences were obtained from the decomposition shown in Figure 4.

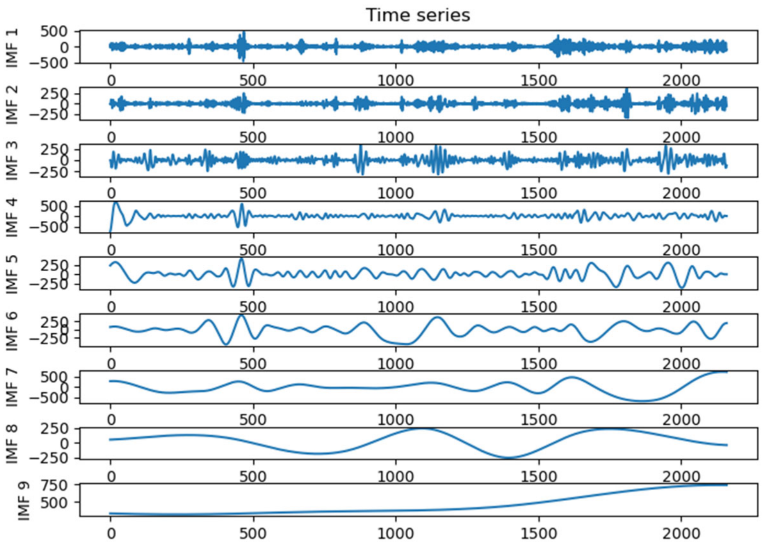

Figure 4. CEEMDAN decomposition sequence

5.4. Results

Figure 5 showed the power change curve of wind turbine A predicted by each model on September 15, with a prediction resolution of 10 minutes and 144 data points in total.

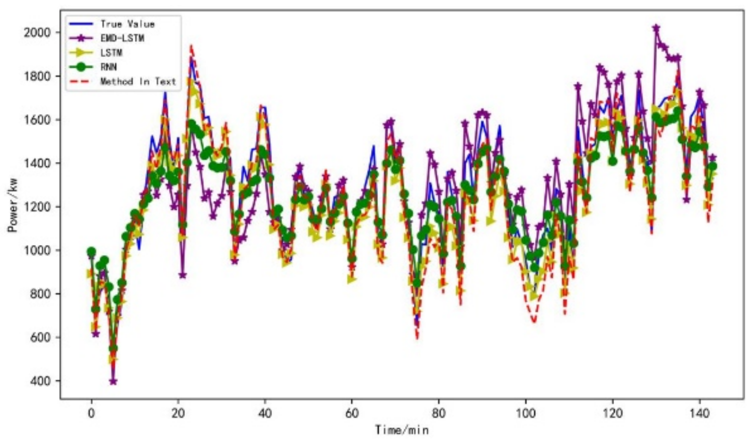

Figure 5. The effect of each prediction model

The *MAE*, *MRE* and *RMSE* indexes of each model were calculated for evaluation and analysis, as shown in Table 3.

Table 2. Evaluation index of each prediction model

Model name	*MAE*/%	*MRE*/%	*RMSE*/%
RNN	7.94	8.99	9.96
LSTM	7.13	8.63	9.37
EMD-LSTM	6.94	7.44	8.21
CEEMDAN-LSTM	5.54	5.88	5.53

After training the model with the same data, it can be seen from Table 2 that the time series decomposition algorithm can effectively reduce the impact of wind power uncertainty. After decomposition, the prediction accuracy becomes higher. With LSTM as the benchmark model, CEEMDAN has a better prediction effect than EMD. *MAE*, *MRE* and *RMSE* have decreased by 1.40%, 1.56% and 2.68% respectively. The evaluation index showed that the method in this paper has higher prediction accuracy compared with LSTM, RNN and EMD-LSTM models.

6. Conclusion

A wind power prediction model based on CEEMDAN-LSTM was proposed. Through the verification of the measured data of a domestic wind farm, the proposed model had a more accurate prediction effect. The main conclusions were as follows:

(1) According to the fluctuation characteristics of wind power, CEEMDAN algorithm was used to decompose the wind power time series data into relatively stable subsequences, which can effectively improve the stability of prediction data and reduce the difficulty of prediction.

(2) The forgetting gate in LSTM can update the effective information in the time series, enhanced the ability to capture the nonlinear dependencies in the wind power time series data, and had higher prediction accuracy than RNN.

(3) The time series modeling method based on CEEMDAN-LSTM proposed in this paper had higher prediction accuracy, had some room for improvement, and can be applied to other time series prediction scenarios.

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