Short term wind power interval prediction based on VMD and improved BLS

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Abstract. Aiming at the problem of wind power interval prediction, a short-term wind power interval prediction model based on VMD and improved BLS is proposed. Firstly, the complex wind power time series are decomposed by variational mode decomposition to reduce the non-stationarity of wind power. Then an improved broad learning system (BLS) is established to predict the power and error of each component, and a weight is given to the prediction error of each component. The sparrow search algorithm (SSA) is used to optimize the weight, and the width of the prediction interval is obtained by adding the power and error prediction values. The experimental data show that the proposed model improves the accuracy of prediction interval.

1. Introduction

Due to the intermittence, randomness and volatility of wind power itself, point prediction cannot be accurately carried out. Therefore, it is also very important to obtain the predicted wind power fluctuation range for power system planning and operation decision-making.

At present, many literatures have studied the interval prediction of wind power. In reference [1] Deterministic and probabilistic interval prediction for wind farm based on VMD and weighted LS-SVM can effectively improve the prediction accuracy and reduce the prediction width. In reference [2] a broad learning system is proposed. The model has the advantages of simple structure, fast training time and high prediction accuracy. In reference [3] proposed Wind Power Interval Prediction Based on Improved PSO and BP Neural Network, but particle swarm optimization has poor search ability and is easy to fall into local optimal solution. In reference [4] proposes the wind speed interval prediction based on the error prediction method. The point prediction is carried out through the combination of vmd-gru. On this basis, the prediction error interval is constructed, and the value parameters are optimized by PSO algorithm. This method does not depend on the distribution characteristics of prediction error.

Based on the above research, this paper proposes a short term wind power interval prediction based on VMD and improved BLS, Improved BLS has the characteristics of low complexity and strong generalization ability. VMD and improved BLS combined model can obtain higher precision point prediction value and prediction error. On this basis, the wind power interval prediction model is constructed, and the sparrow algorithm optimizes the prediction interval. The simulation results show that the proposed model has low complexity, strong robustness and can obtain better interval width.
2. Variational mode decomposition

VMD is an adaptive and non recursive decomposition method [5]. The main idea is to construct the variational problem and solve it iteratively. The complex signal \( f(t) \) is decomposed into modal components \( u(k) \) with different bandwidths and center frequencies by setting the modal number \( K \) in advance, and each modal component and its center frequency are updated. When the sum of the estimated bandwidths of each modal is the smallest, the update is completed to obtain the optimal solution. The process is as follows:

- The unilateral spectrum of each modal component is calculated by Hilbert transform, and the corresponding center frequency \( \omega_k \) is estimated.
- The exponential term \( e^{-j\omega_k t} \) of the center frequency of each modal analysis signal is aliased, and the spectrum of each modal is converted to the corresponding fundamental frequency band.
- The bandwidth of each mode is estimated by Gaussian smoothing method and transformed into a variational solution problem with constraints:

\[
\begin{align*}
\min_{\{\delta(t), \{u_k(t)\}_{k=1}^K\}} & \left\{ \left\| \mathcal{E}_1 \left( \delta(t) + \frac{1}{\pi t} * u_k(t) \right) e^{-j\omega_k t} \right\|_2 \right. \\
\left. + \sum_{k=1}^K \left| u_k(t) \right| e^{-j\omega_k t} = f(t) \right\}
\end{align*}
\]

where; \( \delta(t) \) is the unit pulse function; \(*\) represents convolution; \( \hat{\delta}(t) \) represents partial derivative; \( u_k(t) \) represents \( K \) components; \( \omega_k \) represents the center frequency of \( K \) components; \( f(t) \) represents the time data of wind power.

Lagrange multipliers \( \lambda \) and penalty factors \( \alpha \) are introduced into the constrained problem in the above equation (1) above to change it into an unconstrained variational problem, as shown in equation (2):

\[
\zeta(\lambda, \{u_k\}, \{w_k\}) = \sum_{k=1}^K \left\{ \mathcal{E}_1 \left( \delta(t) + \frac{1}{\pi t} * u_k(t) \right) e^{-j\omega_k t} \right\}^2 + \left\| f - \sum_{k=1}^K u_k \right\|^2 + \langle \lambda, f - \sum_{k=1}^K u_k \rangle
\]

The saddle point in equation (2) is solved by alternating direction multiplier method (ADMM), and the updated formulas of corresponding variables \( u_k, \omega_k \) and \( \lambda \) are obtained, as shown in equation (3-4):

\[
\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{k=1}^K \hat{u}_k^n(\omega) - \sum_{k=1}^K \hat{\omega}_k^n(\omega) + \lambda^n(\omega)}{1 + 2\alpha(\omega - \omega_k^n)^2}
\]

\[
\hat{\omega}_k^{n+1} = \int_0^{\infty} \frac{\hat{u}_k^{n+1}(\omega)}{\sqrt{\int_0^{\infty} \left| \hat{u}_k^{n+1}(\omega) \right|^2 d\omega}} d\omega
\]

where: \( \Lambda \) is Fourier transform; \( n \) is the number of iterations.

3. Improved broad learning system

In this paper, based on the structure of improved BLS as shown in Figure 1. In view of the flexibility of BLS structure, the feature layer of BLS is connected in a cascade way, which can improve the recognition ability of the network to data features. Generate \( m \) group feature mapping as \( \{Z_1, Z_2, \ldots, Z_m\} \). The feature mapping node \( Z_i \) is defined as:

\[
Z_i = \phi(XW_{i1} + \beta_{i1})
\]

where: \( X \) is the input data, \( \phi(\cdot) \) is the linear activation function, and \( W_{i1} \) and \( \beta_{i1} \) are the weights and offsets of group 1 random initialization.

Group 2 feature node \( Z_2 \) takes \( Z_1 \) as the input through cascading. The generated \( Z_2 \) is:
\[ Z_2 = \phi(Z_1 \cdot W_{f2} + \beta_{f2}) = \phi(\phi(X \cdot W_{f1} + \beta_{f1})W_{f2} + \beta_{f2}) = \phi^2(X; \{W_{\beta_i}, \beta_{\beta_i}\}) \] (6)

Therefore, the m-th mapping feature is represented as:

\[ Z_i = \phi(F_{i-1} \cdot W_i + \beta_i) = \phi^i(X; \{W_{\beta_i}, \beta_{\beta_i}\}), i = 1, 2, \ldots, m \] (7)

At the same time, in order to enhance the dynamic capture characteristics of the system, this paper introduces the reserve pool layer in ESN network[6] into the enhancement layer of BLS, so that the network has the function of memory. The state matrix of the output h of the enhancement layer is shown in equation (8):

\[ H(t+1) = \xi(W_{\beta_i}^{(i)}Z^{(i)}(t+1) + W_iH(t) \] (8)

where, \( t = 1, 2, \ldots, l \) (l is the number of data samples), \( \xi(\cdot) \) Represents the nonlinear activation function, \( W_{\beta} \) is the weight matrix from the mapping layer to the reserve pool layer, and \( W_i \) is the neuron connection matrix of the reserve pool.

The output y of improved BLS is shown in equation (9), and the output weight is also calculated by ridge regression, as shown in equation (10):

\[ Y = [Z_1, Z_2, \ldots, Z_m, H]W = AW \] (9)
\[ W = [(A^T A + \alpha I)^{-1}(A^T Y \] (10)

where, \( W \) is the output weight matrix, \( \alpha \) is the regularization parameter

4. Construction and optimization criteria of short-term wind power range

4.1. Interval construction

The wind power and its error are predicted by VMD and improved BLS. Then the wind power is included in the \((U_{pre}, L_{pre})\) interval composed of power prediction value and prediction error as much as possible. In order to further improve the level of prediction interval. The prediction error \( E_{pre} \) is given a weight to adjust the interval width. The interval mathematical model is constructed as follows:

\[ U_{pre} = \sum_{i=1}^{k} W_{pre}^{i} + \sum_{i=1}^{k} w_i |E_{pre}^{i}| \]
\[ L_{pre} = \sum_{i=1}^{k} W_{pre}^{i} - \sum_{i=1}^{k} w_i |E_{pre}^{i}| \] (11)

where \( W_{pre}^{i} \) and \( E_{pre}^{i} \) represent the wind power prediction and error prediction of the ith mode respectively. \( w_i \) is the corresponding weight of \( E_{pre}^{i} \).
4.2. Evaluation interval prediction criteria
The prediction interval coverage (PICP) and normalized root mean square width (PINRW) are used to test the interval prediction effect of the proposed model.

1) Forecast interval coverage (PICP)
It is used to evaluate the probability of the test set falling within the prediction interval, that is, the probability between interval $U_{pre}$ and $L_{pre}$. The larger the value of PICP, the more the test set falls into the prediction interval, and the better the prediction effect.

$$\text{PICP} = \frac{1}{n} \sum_{i}^{n} c_{i}$$  \hspace{1cm} (12)

Where: $n$ represents the number of test sets, and $c_{i}$ represents Boolean value

2) Normalized root mean square width of prediction interval (PINRW)
In order to prevent the prediction interval from being too wide and meaningless by only seeking the coverage of the prediction interval, the PINRW value is used to evaluate the prediction interval. The smaller the PINRW value, the narrower the prediction width and the better the prediction.

$$\text{PINRW} = \frac{1}{R} \sqrt{\frac{1}{n} \sum_{i}^{n} (U_{pre,i} - L_{pre,i})^2}$$  \hspace{1cm} (13)

where: $U_{pre,i}$, $L_{pre,i}$ is the upper limit and lower limit of the $i$th prediction interval respectively

4.3. Short term wind power interval prediction model
In order to obtain higher quality wind power interval width, SSA is used to optimize parameter $w$ of interval prediction model. The fitness of sparrow optimization algorithm is selected as follows:

$$\begin{align*}
\min & \quad \text{PINRW}(w) \\
\text{s.t} & \quad \mu \leq \text{PICP}(w) \leq 100\%
\end{align*}$$  \hspace{1cm} (14)

where $\mu$ is the nominal confidence level and $w = (w_1, w_2, \cdots, w_k)$.

The basic flow of VMD and improved BLS interval prediction model is shown in Figure 2. The specific steps are as follows:

- VMD is used to decompose the original wind power data into a series of subsequences. Each sub serialization is divided into training set and test set.
- The improved BLS model is used to predict the wind power and calculate the training error of each sub sequence.
- The improved BLS model is established for the error sequence to predict the error.
- The prediction interval is composed of wind power prediction, error prediction and corresponding weight of each subsequence. The sparrow algorithm[7] is used to search the optimal value of the weight $w_i$
- The performance of the proposed model is evaluated by PICP and PINRW.
5. Example analysis

A total of 3072 samples were selected from the actual data collected in July 2012 with a wind farm capacity of 16mw and a sampling interval of 15min in Northeast China to verify the effectiveness of the proposed model. Firstly, the samples are processed by hourly averaging. For the 803 processed samples, the data of the first four times are selected as the input, the prediction point is the fifth time, and so on. 803 data samples were processed into 799 groups of data, of which the training data set was the first 703 groups of data and the test data set was the last 96 groups.

VMD decomposition is performed on the processed original wind power time series. During VMD decomposition, the value of modal number $K$ needs to be determined. Excessive $K$ value will over decompose the signal modal component, and too small $K$ value will under decompose the signal modal component. The penalty factor $\alpha$ can effectively avoid the phenomenon of mode aliasing of each component. In this paper, the values of $K$ and $\alpha$ are determined by instantaneous frequency and overall orthogonality index. $K$ is 11 and $\alpha$ is 644. The grid search method is used to optimize the parameters of improved BLS. Finally, the prediction model established in this paper is used to predict the test data set, and the prediction results are shown in Figure 3.

In order to verify that the model in this paper has good interval prediction effect. Compared with VMD and ELM model and VMD and BLS model, The prediction results of each model are shown in Figure 4–Figure 5.
According to the interval prediction results in Fig. 4 and Fig. 5, the prediction interval of the proposed model has the smallest width and contains the most actual power, and its fluctuation trend is around the actual output value. The effect is most obvious at the inflection point of wind power series change. Therefore, the proposed model further improves the prediction accuracy of wind power intervals. The interval prediction performance index results of the three models are shown in Table 1.

Table 1. Interval prediction and evaluation indexes of each model

| Interval prediction model   | PICP  | PINRW  |
|-----------------------------|-------|--------|
| VMD and ELM                 | 0.9375| 0.4454 |
| VMD and BLS                 | 0.9479| 0.3002 |
| VMD and improved BLS        | 0.9587| 0.2590 |

As can be seen from table 1, compared with VMD and ELM interval prediction model and VMD and BLS interval prediction model, PICP of the model in this paper is improved, PINRW is reduced, and the interval width is narrowed. Therefore, the proposed model can well reflect the change of wind power uncertainty in wind power interval prediction.

6. Conclusion
The proposed model is compared with VMD and ELM and VMD and BLS. It is verified that the proposed model has better prediction effect on wind power range. VMD can adaptively decompose and reduce the non stationarity of data, and improved BLS model can improve the prediction ability. SSA algorithm has strong optimization ability for interval model parameters.

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