A Hybrid Model for Short-Time Wind Power Forecasting Base on Ensemble Empirical Mode Decomposition and Volterra Neural Networks

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***Abstract*—In view of excavating the non-stationary and nonlinearity of wind power，a hybrid model based on ensemble empirical mode decomposition (EEMD) and Volterra neural networks(VNN) is introduced. Firstly, the end issue of EEMD is dealt with by using the largest Lyapunov prediction. Secondly, the new gained time series is decomposed into a series of sequences of different time scale by the EEMD to reduce its non-stationary. Then the VNN model of each component is established on the basis of important parameters including embedded dimensions ,delay time and maximum Lyapunov exponent ,after mining the sequences chaotic characteristics by means of phase space reconstructed. Finally, the predicting results of each subsequence are superimposed to gain the final estimating result. Calculation example results show that the proposed model is able to excavate power time series features effectively and obtain higher prediction accuracy.**

***Index Terms*—wind power, ensemble empirical mode decomposition, Volterra neural networks, combined forecasting model**

I INTRODUCTION

WITH the increase of wind power installed capacity, wind energy has adverse effects on power systems of stability, quality and reliability, due to the variability and fluctuation of the wind. It was proved that the accurate prediction of wind power provided an important basis for the dispatching department to formulate the scheduling plan and operation mode, effectively decreasing spinning reserve capacity and operating cost of power system, and enhancing the economy of wind power in reference [1, 2].

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Common wind power prediction methods are divided into two categories: physical modeling techniques based on numerical weather prediction (NWP) and statistical modeling techniques based on historical data, as illustrated in [3]. The former can predict short-term wind power of 1-3 days, but it needs to consider complex factors such as topography, air pressure and temperature, which makes the forecasting calculation large and costly. The latter mainly includes: time series method [4], Kalman filter method [5], support vector machine method [6], artificial neural network method [7], Volterra adaptive prediction method [8] and some of combination forecasting models, as proposed in [9-13].

In order to overcome the shortcomings of the single method, a variety of combined prediction methods in reference [12,13] are introduced. Other intelligent algorithms to predict wind power has become a research hotspot.

In addition, the non-stationary of wind power has a serious impact on the prediction accuracy. The current methods to reduce the non-stationary power of wind power main consist: Fourier decomposition method [14], wavelet decomposition method [11,15] and empirical mode multi-scale decomposition method[11].

Through mining the non-stationary and nonlinear of wind power time series, this paper puts forward a new wind power short-term prediction model based on EEMD and VNN. This paper is structured as follows. Section II mainly describes the correlation between the Volterra functional model and the 3-layer feedforward neural network, and solves the problem of how to solve the kernel function. Section III proposes a predictive combination model of wind power based on EEMD-VNN. In Section IV, a calculation example is described. Finally, in Section V, performance indicators of the prediction models are analyzed and discussed.

II BASIC THEORY

II.I Phase Space Reconstruction

Wind power time series has chaotic characteristics proved in reference [16]. The wind power timing is known as $\{x(i)\}$, $i=1,2,\cdots n$ .Construct an m-dimensional attractor by reconstructing the phase space vector $\boldsymbol{X}(t)$.

$$\boldsymbol{X}(i)=[x(i),\mathrm{x}(i+\tau),\mathrm{x}(i+2\tau),\cdots,\mathrm{x}(i+(\mathrm{m}-1)\tau)]^{\mathrm{T}} \quad (1)$$

Where: m is embedding dimension and τ is time delay, $i=1,2,\cdots,N$, $N=n-(\mathrm{m}-1)\tau$. Based on Takens' Embedding Theorem, when $m\ge 2d+1$, the reconstructed phase space will remain equivalent to the chaotic attractor of original dynamical system.

In this paper, the C-C (correlation-integral, C-C) method, as illustrated in [17], is used to solve the embedding dimension and delay time; then the largest Lyaunov exponent λ is calculated by using the Wolf method or the small data amount method, the positive and negative values of which can be used as the criterion for judging whether the time series is a chaotic system.

II.II Ensemble Empirical Mode Decomposition

II.II.I End Extension of Wind Power Time Series

In order to suppress the inward propagation of the endpoint error, the largest Lyapunov exponential method is used to predict the endpoint value and to realize the extension of the extreme point at the endpoint. A detailed description of the specific principles and steps can be seen in reference [18].

II.II.II EEMD *on Wind Power Time Series*

The process of EEMD decomposition is as follows:

(1) A new sequence $\{\tilde{x}(t)\}$ is obtained by adding a white noise sequence obeying the normal distribution $(0,(\alpha\varepsilon)^2)$ to the wind power data, where α is the noise intensity and ε is the standard deviation.

(2)The new sequence $\{\tilde{x}(t)\}$ is decomposed into several IMF components $C_i(t)$ and a residual signal $r_n(\mathrm{t})$ using EMD.

(3) Repeat steps (1) and (2) r times, each time adding a white noise sequence of different amplitudes.

(4) The average value of each IMF component obtained by decomposing a total of r times is taken as the IMF component of the original wind power timing.

II.III Volterra Neural Network Prediction Model

II.III.I Volterra *Functional Model*

The Volterra functional model has high prediction accuracy and clear physical meaning with limited memory, that is, at a point $k-k_0$ far from the predicted time point- k, the system input does not affect the output. The model applied in this paper is:

$$\begin{aligned}y(k)&=h_0+\sum_{l_1=0}^{m-1}h_1(l_1)x(k-l_1\tau)+\\&\sum_{l_1=0}^{m-1}\sum_{l_2=0}^{m-1}h_2(l_1,l_2)x(k-l_1\tau)x(k-l_2\tau)+\cdots+\sum_{l_1=0}^{m-1}\sum_{l_2=0}^{m-1}\cdots\\&\sum_{l_m=0}^{m-1}h_m(l_1,l_2,\cdots,l_m)x(k-l_1\tau)x(k-l_2\tau)\cdots x(k-l_m\tau)\end{aligned} \quad (2)$$

where: i、l_m、$k\in\mathbf{R}$, $h_m(l_1,l_2,\cdots,l_m)$ is the m-order kernel function; m is the memory length of the model, the value of which is the minimum embedding dimension of wind power chaotic timing; τ is the delay time, whose physical meaning are detailed in Section 2.1 of this paper.

II.III.II Combination of Volterra Functional Model and BP *Neural Network*

Based on the equivalence of the Volterra functional model and the 3-layer feedforward neural network, a wind power time series VNN prediction model is established. The model is shown in Figure 1.

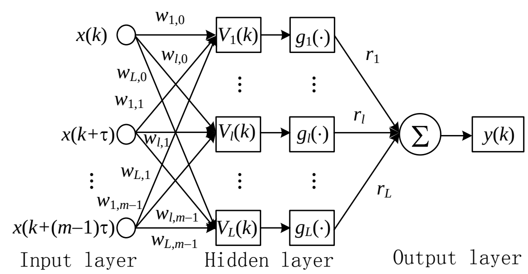

Fig. 1 Volterra neural network model

$$V_l(k)=\sum_{j=0}^{m-1}w_{l,j}x(k+\mathrm{j}\tau) \quad (3)$$

$$g_l(\cdot)=a_{0,l}+a_{1,l}\mathrm{x}+a_{2,l}x^2+\cdots+a_{i,l}x^i+\cdots \quad (4)$$

where: $\boldsymbol{X}^{\mathrm{T}}=[x(k),x(k+\tau),\cdots,x(k+(m-1)\tau)]$ is an m dimensional input vector; $w_{l,n}$ is the network weight of the hidden layer; $V_l(k)$ is the convolution of the wind power input signal; $g_l(\cdot)$ $(l=1,2,\cdots,L,L\in\boldsymbol{R})$ is the activation function, taking the form of a polynomial, with $a_{i,l}\in\mathbf{R}$ being Polynomial coefficient.

The input formula for the wind power time series is:

$$\begin{aligned}y(k)&=\sum_{l=1}^{L}r_l g_l(V_l(k))=\sum_{l=1}^{L}r_l\sum_{i=0}^{\infty}a_{i,l}(V_l(k))^i=\\&\sum_{l=1}^{L}\sum_{i=0}^{\infty}r_l a_{i,l}(\sum_{j=0}^{m-1}w_{l,j}x(\mathrm{k}+\mathrm{j}\tau))^i=\\&\sum_{l=1}^{L}\sum_{i=0}^{\infty}r_l a_{i,l}\sum_{n_1=0}^{m-1}\cdots\sum_{n_i=0}^{m-1}[w_{l,n_1}\ldots w_{l,n_i}x_{k,n_1}\ldots x_{k,n_i}]\end{aligned} \quad (5)$$

Where: r_l is the network weight of the output layer. Comparing the coefficient relations of equations (2) and (5), the i-th order Volterra kernel function is obtained:

$$h_i(z_1,z_2,\ldots,z_i)=\sum_{l=1}^{L}r_l a_{i,l}w_{l,z_1}w_{l,z_2}\ldots w_{l,z_i} \quad (6)$$

After obtaining the network weights $w_{l,n}$ and r_l by training the VNN of Fig. 1, we can solve Volterra kernel function according to equation (6), and then the Volterra neural network model is obtained.

II.III.III *The* VNN *Model Learning Algorithm of Wind Power*

1) Based on C-C method, the embedding dimension- m and delay time- τ of wind power time series are solved. Reconstruct phase space, and we will get space vectors, a total of $N = n-1-(m-1)\tau$. Take the first N' as a network training, and normalize it to map its value to [0,1].

2) The number of neurons in the input layer is the embedded dimension, which is m; the number of neurons in the hidden layer is obtained by the gray correlation analysis method, which is L; the output layer is a single output layer, that is, we create a VNN model with structure $m-L-1$.

3) Initialize the hidden layer network parameter matrix $\boldsymbol{W}=(w_{1,j})_{L\times m}$, ($j$=1,2, · · · , m) and output layer network coefficient r_l . Perform the first network calculation according to formula (6), using the data obtained by 1) and 2).

4) Calculate the target error function E:

$$E = \frac{1}{2}\sum_{k=1}^{N'}(y(k)-\tilde{y}(k))^2 \tag{7}$$

Where: $y(k)$ is the true value and $\tilde{y}(k)$ is the estimated value. Maximum target error $E_{\max}$ is set to 0.025. If $E < E_{\max}$, stop the calculation, meanwhile store the network parameters $\boldsymbol{W} = (w_{l,j})_{L\times m}$ and r_l .Comparing the polynomial coefficient $a_{i,l}$ $(i = 1, 2, \cdots, m)$, calculate and store each order kernel function $h_i(l_1, l_2, \cdots, l_i)$ according to formula (6). Otherwise, proceed to the next step.

3) Calculate the local gradient $\delta_l(k)$ and the network weight parameter correction $\Delta w_{l,j}(k)$ .The formula is as follows:

$$\delta_l(k) = -\frac{\partial E}{\partial y(k)}g_l'(V_l(k)) \tag{8}$$

$$\Delta w_{l,j}(k) = \alpha\Delta w_{l,j}(k-1) + \eta\delta_l(k)y(k) \tag{9}$$

Where: $\alpha\Delta w_{l,j}(k-1)$ is the introduced motion vector ($0 < \alpha < 1$); η is the learning rate.

6) Correct the network weight and train the network again, then calculate the network output $\tilde{y}(k)$ and the target error E , and repeat training until $E < E_{\max}$ ($E_{\max}$ is set to 0.025 in this paper) is satisfied.

7) Predict the wind power by using the Volterra-kernel functions.

III SHORT-TERM WIND POWER FORECASTING BASED ON EEMD-VNN

This paper proposes a predictive combination model of wind power based on EEMD-VNN.

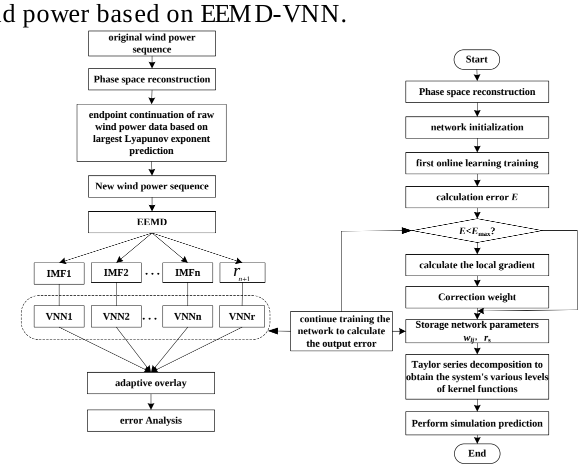

Fig. 2 Structure of the wind power prediction model based on EEMD-VNN

Firstly, based on the largest Lyapunov exponent prediction, endpoint extension is utilized to eliminate the endpoint effect. Then the EEMD is used to decompose the new sequence obtaining IMF components of different scales and residual residuals, which realizes the smoothing of wind power signals. In this paper, the largest Lyapunov exponent is obtained by the small data volume method. Secondly, phase space reconstruction is performed for each component, and the appropriate number of truncated items and truncated order are selected to establish VNN neural network model for wind power prediction. Finally, the predicted values of the components are adaptively superimposed to obtain a final prediction value. The modeling process is shown in Figure 2.

IV ANALYSIS OF EXAMPLES

IV.I *Sample Treatment*

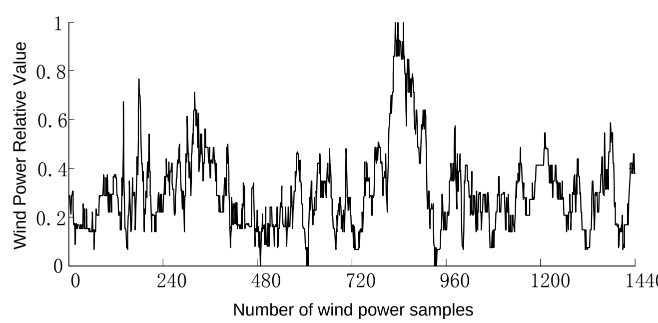

Fig. 3 Time series of wind power

The wind power data in this paper is from the continuous measurement data of 1440h from May 10th to July 8th of a wind turbine provided by a certain wind farm which contains 58 G58-850 kW units with a total installed capacity of 49.3

MW. The sampling period of the unit is 10min. For the convenience of research, the samples are averaged in hours, and a total of 1440 data are obtained after processing, as shown in Fig. 3.Take the first 1340 data as learning data, and the remaining 100 data as test data.

Following the prediction steps mentioned in this paper, a total of 9 IMFs (IMF1~IMF9) and one residual sequence r_{10} are obtained, as shown in Fig. 4. （r takes 100, α takes 0.25）

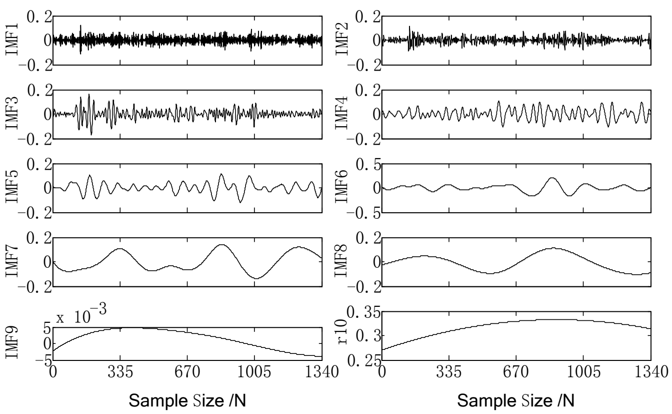

Fig.4 EEMD results after terminal extension

IV.II Evaluation Index

In this paper, the performance indicators are: normalized absolute mean error e_{NMAE}, normalized root mean square error e_{NRMAE}, maximum relative error e_{MAE} and time cost t_{MAX} to evaluate the performance of the model. The expressions of the four indicators are as follows:

$$e_{\text{NMAE}} = \frac{1}{P_{\text{cap}}} \cdot \frac{1}{M} \cdot \sum_{k=1}^{M} | \tilde{y}(k) - y(k) | \tag{10}$$

$$e_{\text{NRMAE}} = \frac{1}{P_{\text{cap}}} \cdot \sqrt{\frac{1}{M} \sum_{k=1}^{M} (\tilde{y}(k) - y(k))^2} \tag{11}$$

$$e_{MAE} = \frac{1}{P_{\text{cap}}} \cdot \max_{k=1,2,\cdots M} (| \tilde{y}(k) - y(k) |) \tag{12}$$

$$t_{\text{MAX}} = \max_{i=1,2,\cdots,n} (t_i) \tag{13}$$

Where: M is the number of predicted points; P_{cap} is the rated capacity of the fan. The t_i is the optimal training time of the i th subsequence.

IV.III Analysis of Prediction Results

The parameters of each sub-sequence VNN model are as shown in Table 1. In order to compare with the prediction performance of the EEMD-VNN model, this paper also performs predictive simulation based on the other three models. The prediction results and errors of the four models are shown in Figure 5 and Figure 6 respectively; the prediction indicators are shown in Table 2

TABLE I
PARAMETERS OF SUBSEQUENCE COMPONENT

SUB-SEQUENCES	EMBEDDING DIMENSION m	OPTIMAL DELAY τ
IMF1	3	7
IMF2	7	5
IMF3	8	4
IMF4	5	6
IMF5	7	10
IMF6	9	14
IMF7	4	16
IMF8	6	14
IMF9	4	12
r_9	3	5

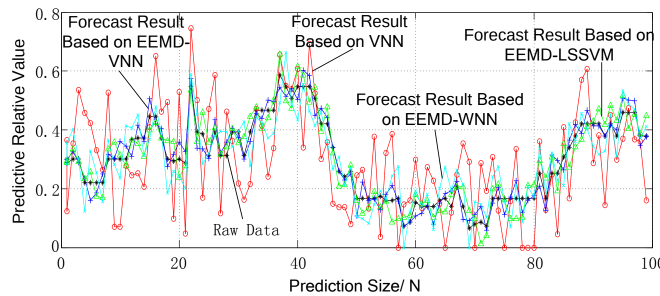

Fig.5 Comparison of actual wind power and the predicted results

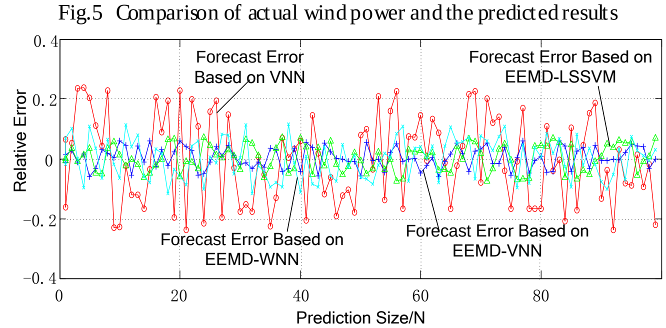

Fig.6 Curves of wind power forecast error

TABLE II
COMPARED ERROR INDEXES OF THE FORTH MODELS

PREDICTIVE MODELS	ERROR INDEXES (%)			
	e_{NMAE}	e_{NRMAE}	e_{MAE}	t_{MAX}(s)
VNN	6.916	9.538	23.8863	119.4849
EEMD-VNN	2.98	3.524	6.0834	123.1993
EEMD-LSSVM	3.78	4.365	7.4481	973.3573
EEMD-WNN	5.719	6.619	11.5886	57.5786

V CONCLUSION

The nonlinear and non-stationary nature of wind power makes it difficult to achieve high-precision prediction with a single prediction method, but combined prediction can integrate advantages and achieve satisfactory prediction results. As seen from Fig. 5, Fig. 6 and Table 2, all four models show good prediction results, but their prediction performance is different.

(1) The EEMD is used to decompose the wind power time series after endpoint extension into sub-sequences at different time scales to achieve sequence smoothing and avoid distortion of sub-sequences, which provides a basis for further prediction.

(2)The error index of the EEMD-WNN and the EEMD-LSSVM is higher than that of the EEMD-VNN. It is because that the combination of the Volterra functional model and the neural network not only overcomes the difficulty of solving Volterra high-order kernel functions, but also the order of kernel functions of each sub-sequence is completely determined by its own chaotic characteristics, thus avoiding blind selection. Thereby accurate modeling and high-precision prediction of nonlinear systems are realized

(3) From the perspective of time cost, the EEMD-LSSVM is the longest because it needs to optimize the super parameter, while the EEMD-WNN takes the shortest time. The learning time of the EEMD-VNN and the VNN are almost the same, about twice that of the EEMD-WNN model, but much smaller than the EEMD-LSSVM model (the latter is 8 times that of the former).

In short, taking into account the prediction accuracy and cost time, it can be seen that the EEMD-VNN model proposed in this paper has better prediction performance, time cost is more compromised, and engineering development potential is large.

REFEENCES

[1] Ma Xiyuan，Sun Yuanzhang，Fang Hualiang. Scenario generation of wind power based on statistical uncertainty and variability[J]. IEEE Transaction on Sustainable Energy，2013，4(4)：894-904.

[2] Zhang Liying，Ye Tinglu，Xin Yaozhong，et al. Problems and measures of power grid accommodating large scale wind power[J]. Proceedings of the CSEE，2010，30(25)：1-9(in Chinese).

[3] Feng Shuanglei，Wang Weisheng，Liu Chun，et al. Study on the physical approach to wind power prediction[J]. Proceedings of the CSEE，2010，30(02)：1-6.

[4] Peiyuan C，Pedersen T，Bak J B，et al. ARIMA-based time series model of stochastic wind power generation[J]. IEEE Transactions on Power Systems，2010，25(2)：667-676.

[5] P Louka，G Galanis，N Siebert，et al. Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering[J]. Journal of Wind Engineering and Industrial Aerodynamics，2008，96(12)：2348-2362.

[6] Sancho S，Emilio G，Angel M，et al. Short term wind speed prediction based on evolutionary support vector regression algorithms[J]. Expert Systems with Applications，2011，38(4)：4052-4057.

[7] Hao Quan，Srinivasan D，Khosravi A. Short-time load and wind power forecasting using neural network-based prediction intervals[J]. IEEE Transaction on Neural Networks and Learning Systems，2014，25(2)：303-315.

[8] Meng Yangyang，Lu Jjping，Wang Jian，et al. Wind power chaos prediction based on Volterra adaptive filter[J]. Power System Protection an Control，2012，40(04)：90-95.

[9] Wang He，Hu Zhijian，Zhang Yihui. A hybrid model for short-Term wind speed forecasting based on ensemble empirical mode decomposition and least squares support vector machines[J]. Transactions of China Electrotechnical Society，2014，29(04)：237-245.

[10] Li Jin，Liu Jinpeng，Wang Jianjun. Mid-long term load forecasting based on simulated annealing and SVM algorithm[J]. Proceedings of the CSEE，2011，31(16)：63-66.

[11] Wang He，Hu Zhijian，Chen Zhen，et al. Hybrid model for wind power forecasting based on ensemble empirical mode decomposition and wavelet neural networks[J]. Transactions of China Electrotechnical Society，2013，28(9)：137-144.

[12] Catalao J P S，Pousinho H M I，Mendes V M F. Short-term wind power forecasting in Portugal by neural networks and wavelet transform[J]. Renewable Energy，2011，36(4)：1245-1251.

[13] Amjady N，Keynia F，Zareipour H. Wind power prediction engine composed of modified hybrid neural network and enhanced particle swarm optimization[J]. IEEE Transaction on Sustainable Energy，2011，2(3)：265-276.

[14] Sang Bingyu，Wang Deshun，Yang Bo，et al. Optimal allocation of energy storage system for smoothing the output fluctuations of new energy[J]. Proceedings of the CSEE，2014，34(22)：3700-3706.

[15] Liu Hui，Tian Hongqi，Li Yanfei. Short-term forecasting optimization algorithm for wind speed from farms based on wavelet analysis method and rolling time series method[J]. Journal of Central South University(Science and Technology)，2010，41(1)：370-375.

[16] Zhang Xueqing，Liang Jun. Chaotic characteristics analysis and prediction model study on wind power time series[J]. Acta Physica Sinica，2012，61(19)：70-81(in Chinese).

[17] Yang Yongfeng，Wu Yafeng，Ren Xingmin，et al. The largest lyapunov prediction method for the end issue of empirical mode decomposition[J]. Acta Physica Sinica，2009，58(06)：3742-3746.

[18] Lu Zhenbo，Cai Zhiming，Jiang Keyu. Determination of embedding Parameters for phase space reconstruction based on improved C-C method[J]. Journal of System Simulation，2007，19(11)：2527-2538.

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