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Wind Speed Prediction Performance Based on Modal Decomposition Method

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***Abstract*—As wind energy and other renewable energy sources are valued by various countries, it is very important to estimate and predict the wind energy level. The accuracy of wind energy prediction mainly depends on the accuracy of wind speed prediction. Therefore, to seek ways of improvement the accuracy of wind speed prediction has become the most important issue. In this paper, three different decomposition methods and commonly used wind speed prediction methods are used to compose the corresponding combined models, and to study which combined prediction model has higher accuracy. According to data research conducted by the National Meteorological Science Center, experiments show that the prediction accuracy of the combined prediction model using the Variational mode decomposition (VMD) method is higher than that of the combined prediction model using empirical mode decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD).**

Keywords- Wind speed forecast, Modal Decomposition Method, BP neural network, support vector regression

I. INTRODUCTION

With the fluctuation of world climate and the dependence of countries on fossil fuels such as oil, the quantity of imported fossil fuels continues to increase, and the price of energy continues to rise. Various countries have realized this problem and began to focus on renewable energy. Among these renewable energy sources, wind energy is the most important renewable energy. However, the randomness and volatility of wind energy make it more complex for a high proportion of wind energy to enter the power grid system. In addition, the accuracy of wind energy prediction results mainly depends on the accuracy of wind speed prediction. Wind speed prediction can effectively reduce the risk caused by wind-related uncertainty [1,2].

For wind speed prediction, the main research can be divided into long-term forecasting, short-term forecasting and ultra-short-term forecasting [3,4]. For wind speed prediction methods, mainly divided into the following categories [5]: 1) statistical models: these model methods use time series models as the main representative. The various methods of wind speed time series are considered in Fortuna L. et. [6] and Su X. et.all [7]. In Kumar Kushwah A. et. all [8] authors consider linear and nonlinear data patterns and use autoregressive models for forecasting. 2) Deep learning model class, this model method has support vector machine as the main representative. 3) The machine learning model is mainly represented by artificial neural network. Li et al. [9] and Sinha et al [10] used different neural network models to predict agricultural products, and compared with the time series models in probability and statistics, the results showed that the prediction accuracy was better. However, they adjusted the parameters of the model manually, which made the selection of parameters too subjective. Hong et al. [11] used particle swarm optimization SVM to forecast precipitation, and compared with the deep learning model of recurrent neural network and other models. The experimental effect is better than the recursive neural network model, but they did not use the combination model. Liu Ming [12] and others used genetic algorithm to optimize the parameters of SVR, so as to predict the price of agricultural products and improve the prediction performance. However, they only considered the parameters of SVR model, but did not consider the influence of the length of prediction window on the price, so they had certain limitations. Similarly, He Pengfei [13] and others use particle swarm optimization to optimize the SVR model for price forecasting. Based on above study, this paper uses the combination of different decomposition methods and prediction methods to forecast the wind speed, so as to get a better combination forecasting model.

In this paper, artificial neural networks, support vector machine algorithms, and different decomposition methods (EMD, EEMD, VMD) are combined to forecast the wind speed, and which prediction model is more accurate is discussed. The organization of this paper is as follows: the second part mainly discusses the theoretical knowledge of decomposition and prediction methods, and the third part analyzes and discusses the corresponding combination forecasting model through experimental research. The fourth part introduces the corresponding conclusions of this paper.

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II. METHOD INTRODUCTION

A. Decomposition method

1) EMD Fundamentals:empirical mode decomposition (EMD) method [14,15] overcomes the problem that the basic function has no self adaptability. It can decompose any signal of different scales into relatively stable intrinsic mode functions (IMF) according to a segment of the signal.

EMD calculates the difference between the signal X(*t*) and empirical mode C*1*(*t*) to get the first order residual value r*1*(*t*). The original signal X(*t*) is replaced by r*1*(*t*) for corresponding processing. After *n* times of repetition, the n^{th} order modal function C*n*(*t*) and the final residual value $\mathrm{r}_n(t) = r_{n-1}(t) - c_n(t)$ can be obtained:

$$X(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

2) EEMD Fundamentals: Ensemble Empirical Mode Decomposition (EEMD) method [16,17] is to add a kind of noise aided signal processing (Nada) on the basis of EMD to solve the problem of mode component aliasing in EMD. By adding white noise to the signal to be decomposed, the signal has continuity in different scales, and the result of the integrated mean can be regarded as the final result, thus effectively suppressing the phenomenon of mixing among IMF components.

The steps of EEMD decomposition are as follows:

The noise signal $\mathrm{w}(t)$ is added to the original signal $X(t)$ to obtain the signal X'(*t*):

$$X^{'}(t) = X(t) + w(t) \tag{2}$$

The signal X'(t) is decomposed by EMD to obtain IMF component and residual component after decomposition:

$$X^{'}(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{3}$$

The IMF average value is calculated to the final IMF component $C_{\mathrm{n}}(t)$:

$$C_n(t) = \frac{1}{n} \sum_{i=1}^{n} C_i(t) \tag{4}$$

3) VMD Fundamentals: Variational mode decomposition(VMD) method is an adaptive, completely nonrecursive modal variation and signal processing method [18]. Its core idea is to construct and solve the variational problem. VMD method overcomes the problem of mode component aliasing in the EMD method and has a better mathematical theoretical basis.

B. Prediction method

1) BP neural network：BP neural network is the most basic neural network[19,20]. On its basis, there are PSO-BPNN and GA-BPNN. The output of the BP neural network adopts forward propagation and error adopts backpropagation. It is also one of the most widely used neural networks. However, the biggest problem of the BP neural network is that there is no effective method for the selection of input parameters.

GA-BPNN is mainly composed of three parts: decision tree-based classification contribution priority feature selection method, neural network weight initialization method based on genetic algorithm, and BP neural network for capacity prediction [21,22]. The core of GA-BPNN is BP neural network which can realize any complex nonlinear mapping.

PSO-BPNN in which PSO algorithm is an optimization algorithm, by updating the speed and position of particles for a global search to get the optimal solution [23]. The basic idea of the PSO algorithm to optimize BPNN is that the initial value of the connection weight and threshold value in the middle of BPNN is regarded as a particle in PSO, and the sum of the number of weights and the number of thresholds is the particle dimension. Then, the sum of squares of the difference between the output value of BPNN and the expected value of time is taken as the fitness function in the PSO algorithm. Then, continue to optimize the initial connection weights and thresholds of BPNN, and then use the output value of the optimized PSO algorithm as the initial connection weights and thresholds of BPNN to train the data.

2) SVR： SVR(support vector regression) is proposed as a branch of SVM(support vector machine), and SVM is proposed for binary classification [24,25]. The goal of SVM is to find a hyperplane so that the distance between the nearest sample points of the hyperplane is the better. However, SVR is different. SVR is to make the farthest sample points in the hyperplane as close as possible. The principle is that SVR has an interval region on both sides of the linear function. The loss is not calculated for the number of samples in the interval area, while the loss is calculated for the number of samples outside the interval area. Then the model is optimized by minimizing the width between the interval regions. SVM expects more sample points to be outside the interval area, while SVR expects more sample points to be within the interval area.

GA-SVR optimizes SVR model by genetic algorithm. Its main idea is from the biological evolution principle of the nature [26,27]. The algorithm is effective for solving multi-objective constraint problems. For GA-SVR, the most important thing is to find the best parameters for the samples through genetic algorithm, to ensure the accuracy of GA-SVR prediction model.

PSO-SVR is based on the PSO algorithm to optimize the SVR model [28]. PSO is an optimization algorithm proposed by Kennedy and Eberhart by observing the action of birds. After the kernel function of SVR is selected, the parameters are determined by the PSO algorithm.

III. EXPERIMENTAL STUDY

A. Data preparation

The data is from the National Meteorological Science Center. This paper selects Qingdao observation station in Shandong Province, which is located at (36.07 °N, 120.33 ° E), with an altitude of 76 m. The basic structure is shown in Figure 1.

B. Decompose

There are 300 sample data, which are divided into two groups: training set and test set. The first 80% is 240 data as the training set of the model, and the remaining 20% that is, 60 data are used as the test set of the model. Firstly, the original signal of wind speed is decomposed into IMF*1*, IMF*2*... IMF*n*. The decomposition results are shown in the fig.1-5:

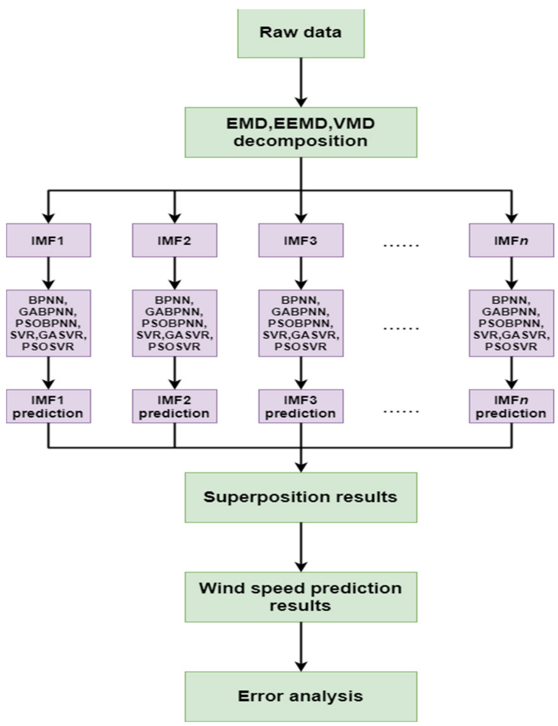

Figure 1. Basic structure of the model

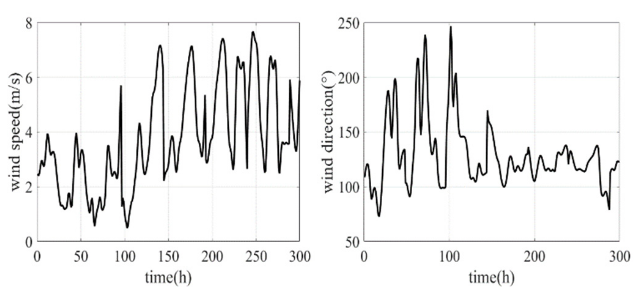

Figure 2. The original signal

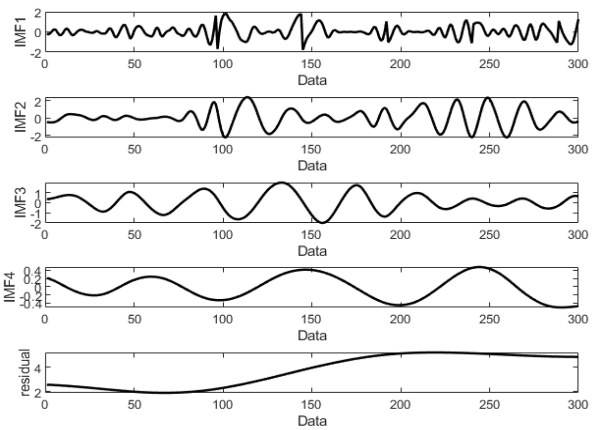

Figure 3. Decomposition of the original signal by EMD

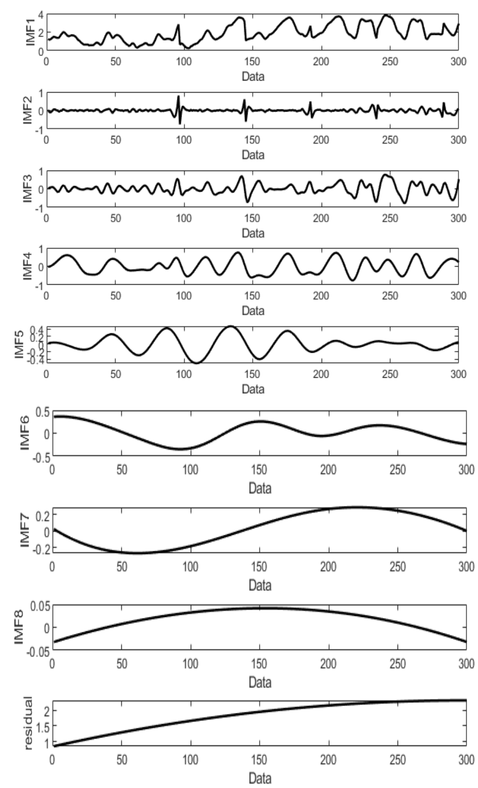

Figure 4. Decomposition of the original signal by EEMD

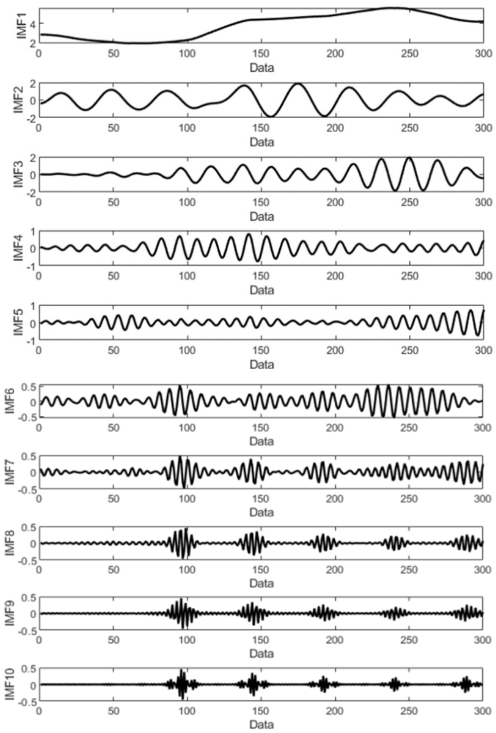

Figure 5. Decomposition the original signal by VMD

C. Prediction model

In order to get the optimal combination forecasting model in forecasting accuracy, this paper uses different decomposition methods (EMD, EEMD, VMD), artificial neural network (BPNN, GABPNN, PSOBPNN), and support vector machine (SVR, GASVR, PSOSVR) to make a combination comparison. Figures 6-8 are respectively correspound to the prediction results of EMD, EEMD and VMD combined models.

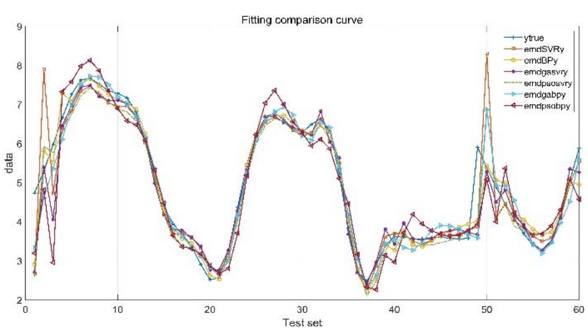

Figure 6. EMD combination forecasting model

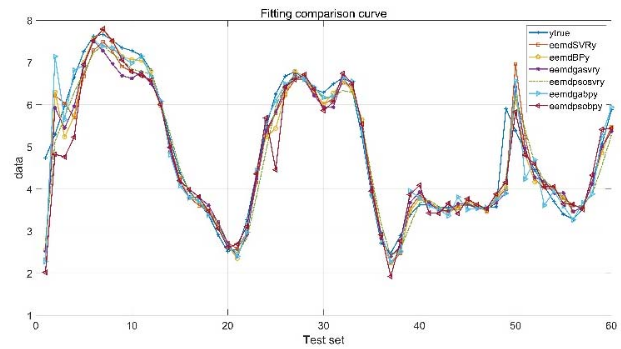

Figure 7. EEMD combination forecasting model

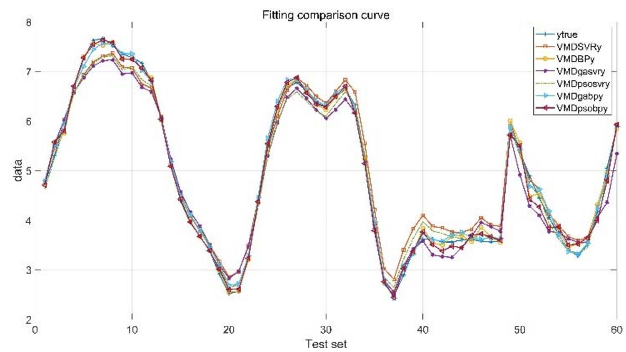

Figure 8. VMD combination forecasting model

D. Evaluation index

In this paper, mean absolute percentage error (MAPE), mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE)are used to measure the prediction accuracy. In order to evaluate the error quantitatively. The evaluation index ranges from $[0,+\infty)$. The smaller the error between the predicted value and the real value, the better the model is. When the predicted value is close to 0, it is a suitable model. The definition and formula of the four indicators are shown in the following figure:

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{5}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{6}$$

$$MAE = \sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{7}$$

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

Where n is the size of test samples, y_i and $\hat{\mathrm{y}}_i$ represent the real and the predicted value of the i^{th} moment, $i=\overline{1,n}$

E. Model error analysis

Table.1 is the error table of each combined prediction model. Thus, we can get the following conclusions:

From Table. 1, we can get the following conclusions:

1) For the combination models with different decomposition methods, it is easy to see that the error of the VMD combined forecasting model is much smaller than that of the EMD combined forecasting model and EEMD combined forecasting model, which indicates that the VMD combined forecasting model has better prediction effect. This also shows that VMD not only overcomes the mode aliasing problem of EMD, but also solves the residual noise produced by EEMD.

2) In the EMD combined forecasting model and EEMD combined forecasting model, the error of EMD combined with BPNN, GABPNN, and GASVR is smaller than that of EEMD combined with EEMD. However, the error of EEMD combined with PSOSVR, SVR, and PSOSVR is smaller than that of EMD combined with EMD. It shows that although EEMD overcomes the mode aliasing problem of EMD, the residual noise produced by its decomposition has a great impact on the prediction accuracy.

3) For the same decomposition method, when it is combined with the artificial neural network prediction method and the support vector machine prediction method in the combined model. Sometimes the error of the combined model composed of the decomposition method and the artificial neural network prediction method is smaller, and sometimes the error of the combined model composed of the decomposition method and the support vector machine prediction method is smaller. Therefore, we need to choose a suitable forecasting model according to our actual situation

4) In view of the good performance of the VMD combined forecasting model, it can be used for forecasting in other new energy fields, At the same time, we should pay more attention to emerging technologies.

TABLE 1. COMBINED FORECASTING MODEL ERROR BASED ON EMD, EEMD AND VMD

EMD/EEMD/VMD	MAPE(%)	MSE(m/s)	MAE(m/s)	RMSE(m/s)
BPNN	5.44/5.75/1.89	0.1784/0.2335/0.0127	0.2469/0.2752/0.0820	0.4223/0.4832/0.1126
GABPNN	6.11/6.27/1.99	0.2244/0.2964/0.0110	0.2863/0.2938/0.0852	0.4738/0.5445/0.1048
PSOBPNN	9.20/7.00/2.17	0.4299/0.3480/0.0158	0.4364/0.3419/0.0946	0.6557/0.5899/0.1256
SVR	6.83/6.65/5.08	0.4635/0.2903/0.0597	0.3345/0.3245/0.2058	0.6808/0.5388/0.2443
GASVR	5.44/6.25/4.95	0.2561/0.2527/0.0759	0.2631/0.3104/0.2291	0.5061/0.5027/0.2755
PSOSVR	6.42/6.14/3.04	0.2408/0.2386/0.1986	0.3000/0.2926/0.1419	0.4907/0.4456/0.1737

IV. CONCLUSION AND FUTURE WORK

This paper compares three different decomposition methods with artificial neural network prediction methods and support vector machine prediction methods. Experimental analysis and results showed: 1) The combined prediction model composed of the VMD decomposition method is more accurate than the combined prediction model composed of the EMD and EEMD decomposition methods. 2) There is not a certain method better than another method. A suitable model should be chosen according to the actual situation, so as to improve the prediction accuracy. 3) For the good performance of the VMD combined forecasting model, it can be used for forecasting in other new fields for preprocessing to forecast.

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