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Ultra-Short-Term Multistep Wind Power Prediction Based on Improved EMD and Reconstruction Method Using Run-Length Analysis

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ABSTRACT With larger scale wind farm being connected to the power grid, the high-precision wind power prediction has become an important means which can ensure the safe operation of power system. The large fluctuations or abnormal data which exist in the local wind power sequences may lead to the phenomenon of over-iterative decomposition of the classical empirical mode decomposition (EMD). In response to this defect, first, the raw wind power sequences are decomposed using improved EMD with introducing the weight function and modifying the mean judgment condition in the classical EMD. Then, the reconstruction strategy based on run-test analysis is proposed based on the fluctuation characteristics of the decomposed components. Finally, the ultra-short-term prediction of the high-frequency item, the middle-frequency item, the low-frequency item, and the trend item in the reconstruction sequences are performed according to different prediction methods. The wind power data of three wind farms in northeast China were selected for forecasting analysis. The analysis shows that compared with other classical prediction methods, this method can effectively improve the prediction accuracy and verify the effectiveness of the proposed method.

INDEX TERMS Wind power, ultra-short-term multistep prediction, improved EMD, run length analysis.

I. INTRODUCTION

Wind power, as a type of renewable energy with strong economic competitiveness, will play a key role in the future to meet the growing energy needs in the world [1], [2]. In recent years, with the continuous expansion of the scale of wind farms and the increase of penetration power and installed capacity, the impact of wind power on the safe operation of power grids has become increasingly apparent [3]. Due to the intermittency and randomness characteristic of wind power, the large-scale wind power access to the grid which has caused many problems to the grid dispatching operation and increased the burden of grid frequency modulation [4]. Accurate and effective wind power prediction is the key to realizing conventional and large-scale wind power combined to the grid. It can make the power dispatcher timely adjust the scheduling plan and the control scheme of the wind turbines to reduce the reserve capacity and the operating cost of the power system, and ensure the stable operation of the power system and the reliability of the power supply [5], [6].

According to the different demand of power system for wind power combined to the grid, the prediction scale of wind power can be divided into medium and long-term prediction, short-term prediction and ultra-short-term prediction [7]–[9]. The forecasting cycle of the medium and long-term prediction is based on weekly, monthly or yearly. It is mainly used for regular maintenance and commissioning of wind farms, as well as the feasibility analysis of wind farm construction. The short-term prediction is based on a variety of numerical weather prediction (NWP) information to establish the forecasting model of wind power, then forecast tens of hours to several days of wind power. It is used to satisfy the demand of wind power price bidding and the reasonable dispatching of grid. The ultra-short-term prediction mainly utilizes the measured historical data of wind power and wind speed to establish the model, then rolling to predict the wind power at interval of 15 minutes in the next four hours, which is helpful to control the operating state of wind turbine in real-time.

The strong randomness and volatility of wind leads to large amplitude and frequent fluctuation of wind power, which makes power prediction difficult [10]. In this paper, we focus on improving the prediction accuracy of ultra-short-term wind power. In recent years, many scholars have put forward many prediction models based on historical measured data of wind power and wind speed around the problem of how to improve the ultra-short-term prediction accuracy of wind power [11]. The ultra-short-term multi-step wind power prediction is a real-time prediction based on time sequences. The commonly used methods in terms of the ultra-short-term multi-step wind power prediction can be divided into two major categories, one of which is the use of historical wind power data to build a combined mathematical model based on intelligent algorithms to forecast the target power. However, this kind of forecasting method does not directly study the structure of the data itself and simply obtains the predicted result by simulating the iteration through a large amount of historical data [12]. Commonly used prediction methods include least square method [13], autoregressive moving average (ARMA) [14], support vector machine (SVM) [15], Kalman filtering [16], and artificial neural network (ANN) [17]. A single prediction model is unable to satisfy the need of prediction accuracy, so the combined prediction models are the general trend [18]. Another type of forecasting method, firstly, analyzes and decomposes the historical wind power data to obtain the sub-sequences with periodic or strong regularity, and then performs the forecasting models on each sub-sequence. Finally, the target wind power is obtained by accumulating each forecast result. Giorgi *et al.*[19] introduced a combined forecasting method based on wavelet decomposition with least-squares support vector machine and artificial neural network to predict wind power. Zhang *et al.* [20] performed short-term wind power forecasting using a hybrid EMD-SVM model. Wu and Peng [21] proposed a hybrid wind power generation forecasting model which was combined the ensemble empirical mode decomposition with least squares support vector machine (LS-SVM). The simulation results revealed, overall, the proposed model outperformed the other single or hybrid models. Cui *et al.* [22] put forward a combining method of atomic sparse decomposition and artificial neural network to forecast short-term wind power. The atomic sparse decomposition (ASD), wavelet decomposition (WD) and empirical mode decomposition (EMD) all decompose the non-stationary the time series of wind power into multiple stationary components, and then the prediction models for each component are established, respectively. The atomic sparse decomposition is greatly affected by the choice of atom library. The wavelet decomposition has the difficulty of choosing wavelet bases and decomposition scales. However, the empirical mode decomposition overcomes the shortcomings of both, which has a maturity self-adaptive decomposition ability and does not need to preset the prior knowledge of the basis function for transformation [23]. EMD can theoretically be applied to any type of time series decomposition and has very obvious advantages for processing non-stationary and non-linear data [24]. The above method is to directly predict the components obtained by empirical mode decomposition, but the process of adaptively superposing the prediction results can introduce multiple random errors increase the workload of the prediction. In addition, when there is a wide range of fluctuations in the historical wind power or sudden surge in the value of abnormal data, the classical EMD may have an over-iteration in the decomposition process of the local data, which has a negative impact on the prediction result. In [25], Safari *et al.* proposed a novel decomposition approach to take the chaotic nature of wind power time series into account and to improve the accuracy of wind power prediction. For the IMF component obtained after Ensemble EMD (EEMD), there will be abnormal data of extremely rapid changes with low amplitudes. The chaotic time series analysis is used to determine which IMF components are chaotic, and then singular spectrum analysis (SSA) is applied to eliminate extremely rapid changes with low amplitudes. Thus several steps ahead wind power prediction with higher accuracy can be realized.

In view of the shortcomings of the above methods, an ultra-short-term multi-step wind power prediction method based on improved EMD and reconstruction method using run-length analysis is proposed. It is the first time that the historical wind power sequences are decomposed by the improved EMD and get a number of intrinsic mode functions (IMFs), then we use the reconstruction method using run-length analysis to analyze the fluctuation features of IMFs and reconstruct the components with similar fluctuation. Finally, the ultra-short-term multi-step prediction of the high-frequency item, the middle-frequency item, the low-frequency item and the trend item in the reconstruction sequences are performed by different prediction methods. In this paper, the measured historical data of three wind farms are used to test the proposed method and multi-day prediction are carried out for a certain wind farm. The results of the experimental show that the proposed method in this paper has higher prediction accuracy than the general method in the ultra-short-term multi-step prediction and shows good prediction performance.

The remainder of this paper is organized as follows. Section II describes introduces the implementation process of improved EMD and the reconstruction method using the run-length analysis. Section III establish the proposed model for ultra-short-term multi-step wind power prediction. Section IV presents the evaluation criteria of the results. Experiments are undertaken to evaluate the performance of the proposed model in Section V. Finally, the conclusions are drawn in Section VI.

II. METHODOLOGY

A. EMD

EMD is an adaptive time series decomposition technique proposed by Huang *et al.* [26]. After a complex time-series is decomposed by EMD, a finite series of intrinsic mode functions (IMFs) and one trend component (denoted as Res.) can be obtained [27]. Each IMF is independent of each other and contains an oscillation mode. The basic principle of the EMD is to use the sifting process (SP) to adaptively select the oscillation mode of the time series. The IMFs must satisfy the following two conditions: (1) in the whole time range of the function, the number of local extreme points and over zero must be equal, or the maximum difference is one; and (2) the mean value of the two envelopes formed by the local maxima and local minima, respectively, is zero at any points.

Given the original time series $x(t)$, the procedures of EMD are show as follows:

1) After all the local maximum and minimum points are determined, apply cubic spline interpolation to obtain the upper envelope $x_H(t)$ and lower envelope $x_L(t)$. The mean value $m(t)$ of two envelopes is calculated:

$$m(t) = \frac{x_H(t) + x_L(t)}{2} \tag{1}$$

2) Suppose $x_1(t)$ is the difference between $m(t)$ and the original $x(t)$. Identify whether $x_1(t)$ satisfies the two conditions of IMF. If it conforms, it can be considered as the first IMF and expressed in $c_1(t)$. Otherwise, repeat the above procedure until it meets the two conditions. Calculate the difference $r_1(t)$ between the original time series $x(t)$ and $c_1(t)$:

$$x_1(t) = x(t) - m(t) \tag{2}$$

$$r_1(t) = x(t) - c_1(t) \tag{3}$$

3) Let $r_1(t)$ be the new time series and continue with steps (1)–(2). The termination condition of the sifting process is that the standard deviation (SD) is less than the limit value:

$$SD = \sum_{t=0}^{\tau} \left[\frac{\left| c_{1(i-1)}(t) - c_{1i}(t) \right|^2}{c_{1(i-1)}^2(t)} \right], \quad i = 1, 2, \cdots \tag{4}$$

where the reference value of SD is generally set between 0.2–0.3. In addition, if $r_n(t)$ is a non-oscillatory monotonic function or less than the predetermined value.

4) Stated thus, the sifting process above will be repeated n times and the original time series $x(t)$ can be reconstructed as follows:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{5}$$

where $c_i(t)$ represents the IMFs, and $r_n(t)$ is the trend component.

B. IMPROVED EMD

Since the termination threshold of the sifting process is too low, as long as the mean of two envelopes in the local area is not small enough the entire signal will be over-iterated when the local signal is better approximated in the classical EMD [28]. Therefore, it has the drawback of contaminating other parts of the signal. In practice, the sifting process of the classical EMD is aimed at the entire data sequences, but it is impractical to decompose all the data in wind power prediction because there is a wide range of fluctuations in the historical wind power or sudden surge in the value of abnormal data. As it has been already mentioned, the phenomenon of over-iteration will occur in the decomposition process.

Here, based on above two shortcomings, the classical EMD is improved in two aspects using the improved strategy proposed by G. Rilling and Flandrin [29], and the improved EMD (IEMD) was obtained. In the first aspect, the termination criteria (standard deviation criteria, SD) for the sifting process of the classical EMD is improved. Propose a mode amplitude $a(t)$ and the evaluation function $\sigma(t)$:

$$a(t) = \frac{x_H(t) - x_L(t)}{2} \tag{6}$$

$$\sigma(t) = \left| \frac{m(t)}{a(t)} \right| \tag{7}$$

where the evaluation of how small is the amplitude of the mean value $m(t)$ has to be done in comparison with the mode amplitude $a(t)$.

Introduce a new criterion based on two thresholds θ_1 and θ_2, aimed at guaranteeing globally small fluctuations in the mean while taking into account locally large excursions. The termination criteria of the sifting process satisfy the following conditions: the sifting is iterated until $\sigma(t) < \theta_1$ for some prescribed fraction $(1-\alpha)$ of the total duration, while $\sigma(t) < \theta_2$ for the remaining fraction. One can typically set $\alpha \approx 0.05$, $\theta_1 \approx 0.05$ and $\theta_2 \approx 0.05$. This improvement appropriately relaxes the threshold of the termination criterion, which not only reflected the partial deviation, but also reduced the risk of excessive decomposition caused by over-iteration.

In the second aspect, the sifting process has been improved for the areas of the data where large fluctuations or abnormal data appear. These local areas in the raw data are individually identified and segregated and are additionally iterated. Here, to avoid excessive decomposition we introduce a weight function $\omega(t)$:

$$\omega(t) = \begin{cases} 1, & \sigma(t) > \theta_1 \\ 0, & \sigma(t) \le \theta_1 \end{cases} \tag{8}$$

For the time points where $\sigma(t) > \theta_1$, let (2) be $x_1(t) = x(t) - \omega(t)m(t)$; it softly decay to 0 outside those points.

C. RECONSTRUCTION METHOD USING RUN-LENGTH ANALYSIS

The principle of run-length analysis is defined as: the intrinsic mode function (IMF) corresponds to the time series $\{X(t), t = 1, 2, \cdots, N\}$, N is the number of sample time series, and the mean of the sample is $\bar{X} = \frac{1}{N}\sum_{t=1}^{N} X(t)$. Each value in the time series is tagged using the mean value $\bar{X}$ as a standard, the timing symbol S_t is defined as:

$$S_t = \begin{cases} 1, & X(t) > \bar{X} \\ 0, & X(t) \le \bar{X} \end{cases} \tag{9}$$

where S_t consists of a series of randomly arranged 0 or 1 sequences that are independent of each other. Each successive piece of the same sign (0 or 1) is defined as a run-length and finally the number of runs included in each IMF can be calculated. The size of the number of run-length for each IMF can reflect the degree of fluctuation of the component sequences. The more runs, the more violent fluctuations; conversely, the more stable fluctuations [30], [31].

According to this characteristics of run-length, the run-length analysis and IEMD are combined to propose the reconstruction idea of wind power sequences which is shown as follows:

1) The raw wind power sequences are decomposed by IEMD to obtain n IMF and one trend component.

2) The number of run-length for each component sample is calculated as $\{M_i, i = 1, 2, \cdots, n\}$, which is theoretically equal to the maximum number of samples of the wind power sequences. Then calculate the mean of the total number of run-length as $\bar{M} = \frac{1}{n}\sum_{i=1}^{n} M_i$.

3) The IMFs and one trend component are reconstructed according to the number of run-length for each component sample and $\bar{M}$. The component is reconstructed by comparing the size of $\bar{M}$ and the number of run-length for the IMF and the trend component. In this paper, the trend component obtained by IEMD is directly classified as the trend item and the first IMF is considered as the high frequency term; IMFs which lower than $\bar{M}$ are considered as low-frequency terms, and the rest are divided into middle-frequency terms.

It can be seen from the above that the sample size of wind power and the number of IMFs determine the result of reconstruction. Therefore, this method has certain objectivity.

III. PREDICTION MODEL BASED ON IEMD AND RUN-LENGTH ANALYSIS

In view of the fact that the existing single prediction method has already reached the bottleneck to the improvement of the prediction accuracy and the utility of the single prediction model is more insufficient for such a fluctuating and intermittent strong sequence of wind power. Based on the above analysis, IEMD can extract sub-sequences with different frequencies from a set of sequences, while the sub-sequences show the characteristics of volatility tend to be more regular. Therefore, we propose an ultra-short-term multi-step wind power prediction model based on IEMD and reconstruction method using run-length analysis which will be abbreviated as IEMD-R (IEMD-Run-length) model.

The number of IMFs varies depending on the fluctuations in the data. IEMD can adaptively decompose the non-linear and non-stationary raw wind power into stationary components with different time scales. It reduces the mutual influence and interference between different feature information and makes the prediction of stationary components more accurate. Predicting each IMF individually will increase the workload of the forecasting. At the same time, because all prediction methods have some errors, it will inevitably lead to the superposition of forecasting errors. According to the above analysis, forecasting the reconstructed IMF can not only reduce the prediction time, but also reduce the prediction error and meet the engineering requirements to the greatest extent.

The magnitude of the prediction error has a strong correlation with the fluctuation of wind power [32], [33]. The simplest linear prediction model can get a good prediction result when the wind power fluctuates more moderately, while which shows a big shortage for the wind power with more violent fluctuation. This shows that different forecasting models have different data types. Therefore, in the IEMD-R model, different prediction methods are used to predict the high-frequency item, middle-frequency item, low-frequency item and trend item after reconstruction. At present, the model of the ultra-short-term multi-step wind power prediction can be divided into one multi-step prediction and rolling multi-step prediction. One multi-step prediction refers to the one-time backward prediction of multiple time points starting from the prediction start moment. The rolling multi-step prediction is essentially the multiple single-step prediction [34]. If the higher accurate prediction is obtained at each step, the degree to which the backward prediction deviates from the true wind power is expected to decrease. In the process of rolling multistep wind power prediction, the prediction value at time t is introduced into the input data of the prediction model, and the first data of the input data is discarded and then the prediction of time $t + 1$ is performed. And so on, when all the steps of the multistep prediction are completed, the measured wind power are reintroduced into the next cycle. In this paper, according to the relevant provisions of National Energy Board of China on wind power prediction [35], we conducted the rolling multi-step wind power prediction of four hours ahead of schedule, the specific prediction process is shown in Fig.1.

If the accuracy of the prediction results of each step is high, the accuracy of the final prediction result will be higher. Therefore, the IEMD-R model in this paper adopts the idea of the rolling multi-step prediction, which is constructed as illustrated in Fig. 2. The prediction process of the single-day is as follows:

Step 1: The wind power series of length is decomposed into IMFs and one trend component. Calculate the run-length of each IMF and the mean run-length for all IMFs. The IMFs and Res. are reconstructed by the reconstruction method using run-length analysis.

Step 2: The reconstructed high-frequency item, middle-frequency item, low-frequency item and trend item are normalized and then predicted according to different forecasting methods. Artificial neural network (ANN) has good self-learning and self-adaptive ability, which can still give more accurate prediction results for the more volatile data types and has good fault tolerance. Therefore, it is suitable for the prediction of high-frequency item. Support vector machine (SVM) is fast in learning and good in generalization performance. Different kernel functions can be set for different

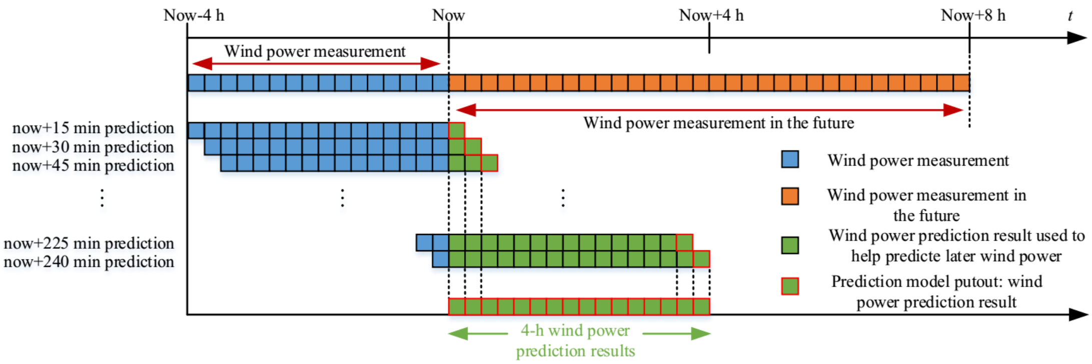

FIGURE 1. **Illustration of the process of one time rolling multi-step wind power prediction.**

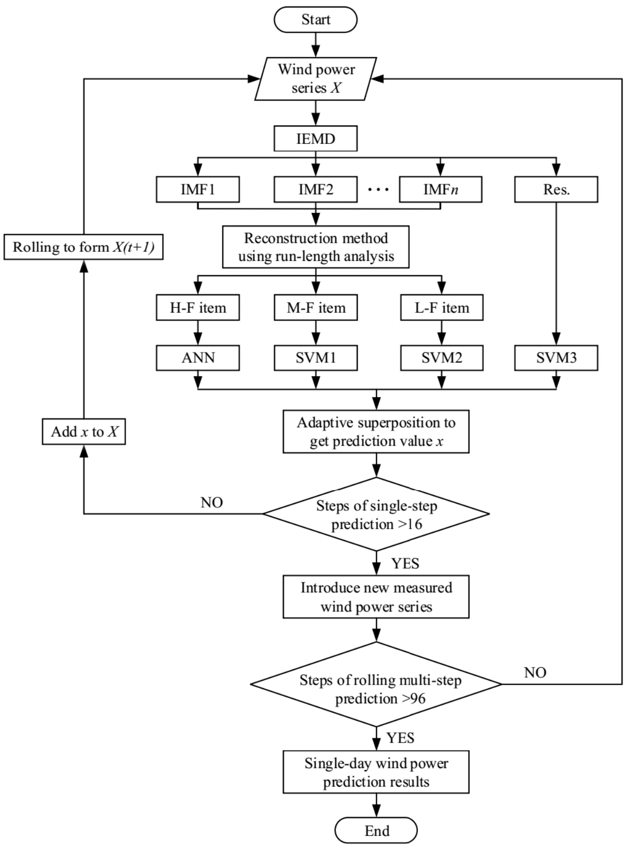

FIGURE 2. **The model structure of ultra-short-term multi-step prediction in the single-day.**

prediction data, which is very suitable for the prediction of middle-frequency item, low-frequency item and trend item.

Step 3: The prediction results of each prediction model are adaptively superposed to obtain the final single-step prediction result x as follows:

$$x = \sum_{i=1}^{4} x_i \tag{10}$$

where $\{x_1, x_2, x_3, x_4\}$ are the single-step prediction results of the high-frequency item, middle-frequency item, low-frequency item and trend item.

Step 4: Add the final single-step prediction result t to the input data of the prediction model to form a new sequence $X(t+1)$. Take $X(2) \sim X(t+1)$ as the new input data and the steps (1)–(4) are repeated until all the steps of one time rolling multi-step prediction is completed.

Step 5: After completing the first five steps, the measured power data until the prediction point $t+1$ is introduced and a new input data is established, and the steps (1)–(5) are repeated until the rolling completion of the 96 multi-step prediction to stop.

IV. EVALUATION CRITERIA OF PREDICTION PERFORMANCE

It is the primary issue to determine which prediction model outperforms the other models, and the accuracy of the proposed approach is evaluated according to the standard of error analysis of wind power forecasting which is set by Chinese government. Three criteria were employed for model evaluation and model comparison: the normalized root mean square error (NRMSE), the daily mean accuracy percent (DMAP), and the daily mean qualified percent (DMQP). The evaluation standard of error requires that the ultra-short-term multi-step prediction error of wind farm power should not exceed 15%, that is, the accuracy of DMAP should be greater than 85% and the NRMSE of all-day forecasting result should be less than 20%. These three error indexes are defined as follows:

$$NRMSE = \sqrt{\frac{1}{96\times 16}\sum_{i=1}^{96}\sum_{k=1}^{16}\left(\frac{P_{Mi}^{k}-P_{Pi}^{k}}{C}\right)^{2}} \times 100\% \tag{11}$$

$$R_{1i} = \left[1-\sqrt{\frac{1}{16}\sum_{k=1}^{16}\left(\frac{P_{Mi}^{k}-P_{Pi}^{k}}{C}\right)^{2}}\right] \times 100\% \tag{12}$$

$$R_C = \frac{1}{96}\sum_{i=1}^{96} R_{1i} \tag{13}$$

$$B_i^k = \begin{cases} 1, & \dfrac{\left|P_{Mi}^k - P_{Pi}^k\right|}{C} < 0.15 \\ 0, & \dfrac{\left|P_{Mi}^k - P_{Pi}^k\right|}{C} \geq 0.15 \end{cases} \tag{14}$$

where k is the number of forecasts each time, i is the number of forecasts in a day, and respectively, P_{Mi}^k and P_{Pi}^k represent the measured and prediction value at the k moment of the i prediction process. The accuracy percent of multi-step prediction at the i prediction process is represented as R_{1i}, R_C represents the mean daily accuracy percent. And B_i^k is a measure of whether each wind power forecasting meets the standard, the qualified percent of multi-step prediction at the i prediction process is denoted by R_{2i}, R_Q represents the mean daily qualified percent, and the installed capacity of wind farm is denoted by C.

V. CASE STUDY

A. DATA SETS

This paper collects the historical wind power data of three wind farms located in Northeast China in from August 1 to 30, 2012 as the experimental data samples. The sampling interval of the data samples is 15 minutes. The installed capacity of the three wind farms is shown in Table 1:

TABLE 1. Installed capacity of wind farms.

Wind farm	F-A	F-B	F-C
Installed capacity (MW)	265.5	99	49.5

B. EXAMPLE ANALYSIS

The model of this paper is tested with an example of the wind farm A with installed capacity of 265.5MW. The historical wind power sequences from August 1 to 30, 2012 (2880 sampling points) is shown in Fig. 3.

The sample points (1632) of the first 17 days are taken as the training samples, and the remaining sampling points (1248) are used as the test samples as the test samples. In this paper, the input of the wind power prediction model is set to 960, and the output is one data. After 16 steps of rolling prediction, we get the 4h prediction results, and update the real data in real time, so the matrix in 96 rows and 16 columns of prediction results is obtained in all day. With the prediction starting point 1460 as an example, the wind power of 1461–1476 points is predicted. Fig. 4 shows the historical wind power sequences of a set of 960 points (501–1460) in the input data.

IEMD is applied to decompose the training sample into seven independent IMFs and one trend component Res. and the results are shown in Fig. 5. As can be seen from the decomposition diagram, for wind power such a highly random and fluctuating time sequence, its waveform still shows the characteristics of strong volatility after the process of IEMD. However, the IMFs are no longer irregular fluctuations. The fluctuations of IMFs are gradually reflected in a

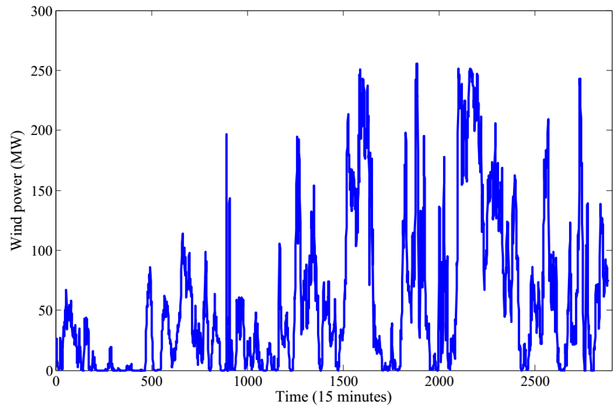

FIGURE 3. Historical wind power sequences of wind farm A.

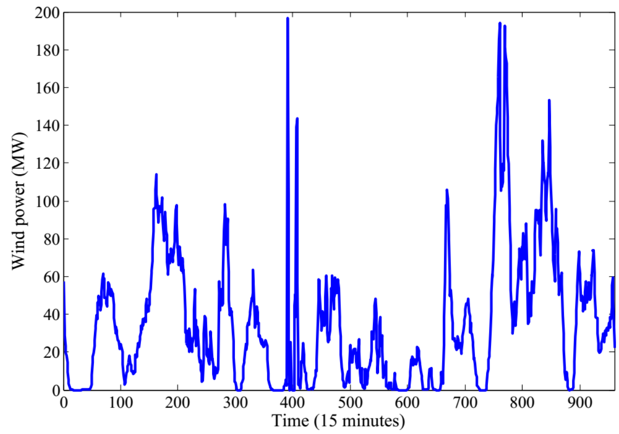

FIGURE 4. A set of input samples of wind farm A.

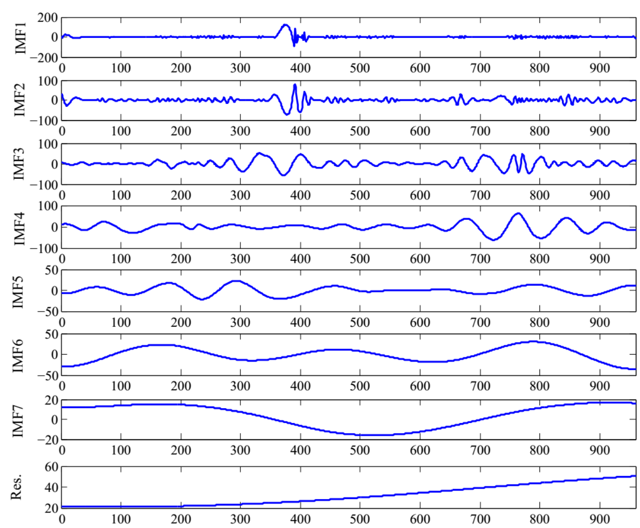

FIGURE 5. The IEMD results of a set of input samples of wind farm A.

periodic pattern, which is more stable than the raw sequences and the low-frequency sequences also shows a stable feature.

The run-length of each IMF is calculated respectively. The results are shown in Table 2. The total number of

TABLE 2. The Run-length of Each IMF.

IMFs	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7
Run-length	286	156	63	26	16	7	3

TABLE 3. The prediction results of different models (a).

Prediction Day	IEMD-R			EMD-R			EMD		
	R_C(%)	R_Q(%)	*NRMSE*(%)	R_C(%)	R_Q(%)	*NRMSE*(%)	R_C(%)	R_Q(%)	*NRMSE*(%)
1	91.86	79.86	15.31	90.90	78.15	16.35	88.94	76.28	19.02
2	87.16	57.12	22.43	86.75	56.79	24.90	83.96	52.24	25.63
3	89.58	69.39	19.04	89.18	69.29	20.00	85.96	69.10	21.29
Mean	89.53	68.79	19.75	88.61	68.07	20.66	86.29	65.87	20.91

TABLE 4. The prediction results of different models (b).

Prediction Day	ANN			PM		
	R_C(%)	R_Q(%)	*NRMSE*(%)	R_C(%)	R_Q(%)	*NRMSE*(%)
1	87.42	68.71	20.54	88.53	74.19	20.38
2	76.90	59.65	29.63	79.87	61.49	27.91
3	80.17	62.33	30.56	82.26	65.15	25.50
Mean	81.49	53.56	26.01	83.53	66.94	25.60

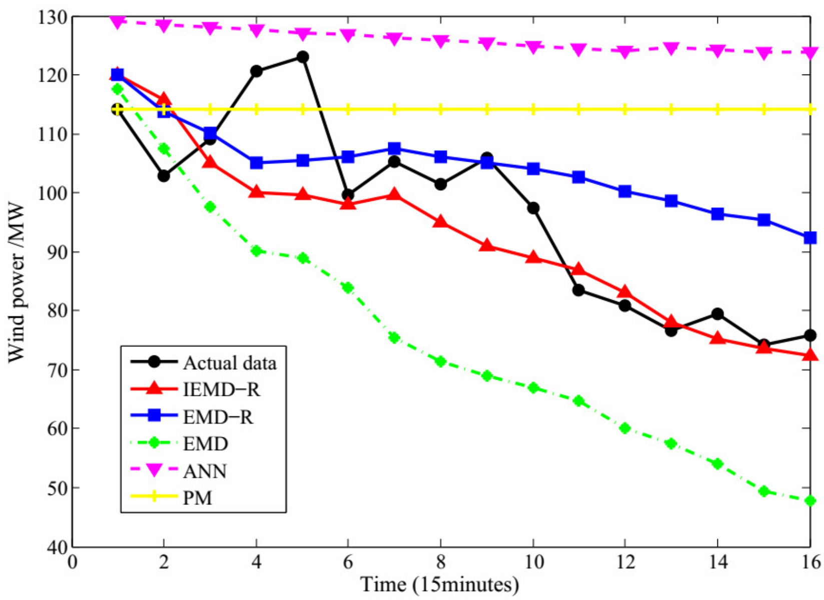

FIGURE 6. The rolling prediction results of five models at a certain point.

run-length for IMFs is 557, and the mean value is about 79.57. After normalizing each component, IMF1 is used as a high-frequency item according to the reconstruction method using run-length analysis that is proposed in this paper and ANN is used to predict it; IMF2 is used as an middle-frequency item and SVM1 is used to predict it; IMF3- IMF7 are used as a low-frequency item, and using SVM2 to predict it; the Res. as the trend item and using SVM3 for prediction. Here, The ANN prediction model is tested by a large number of data, and one hidden layers are selected. The number of neurons is set to 300. The transfer function of the hidden layer is the Sigmoid function. In view of the different characteristics of the middle-frequency item and low frequency item, the optimal parameters and kernel functions are selected, and SVM suitable for itself is established respectively. Aiming at the middle-frequency item with larger frequency and complexity, this paper uses radial basis kernel function (RBF) with strong generalization ability and good nonlinear sequences

TABLE 5. The prediction results of different wind farms.

Prediction models	F-A			F-B			F-C		
	R_C(%)	R_Q(%)	*NRMSE*(%)	R_C(%)	R_Q(%)	*NRMSE*(%)	R_C(%)	R_Q(%)	*NRMSE*(%)
IEMD-R	90.58	71.39	19.04	90.40	71.23	19.12	87.49	68.35	20.43
EMD-R	89.18	69.29	20.00	89.96	70.00	19.67	86.26	66.13	22.07
EMD	84.96	68.10	22.29	85.60	68.88	20.54	84.12	64.30	25.54
ANN	79.17	61.33	31.56	82.00	63.47	29.13	82.14	63.89	29.57
PM	81.91	65.17	28.28	83.24	66.59	27.57	83.21	64.08	28.63

effect to predict. The polynomial kernel function is used to predict the low-frequent item that changes steadily. The trend item is predicted using the linear kernel function, and other parameters can be determined by cross-validation. Finally, the forecasting results of each item are superimposed as a prediction result of the raw wind power.

In order to validate the effectiveness of the proposed method, the IEMD-R model (denoted as M1) and three classical prediction models are used to predict the same wind power. The forecasting results of three days are shown in Tables 3–4. In the tables, the EMD-R model (M2) indicates that the wind power sequences are directly decomposed by EMD and restructured using run-length analysis. The EMD model (M3) indicates that the wind power sequences are decomposed by EMD, and the artificial neural network (ANN) is used to predict each component sequences. The ANN model (M4) is a traditional artificial neural network method which predict the wind power directly without the process of empirical mode decomposition. The persistence model (M5) is a benchmark model for ultra-short-term wind power prediction, which is expressed as PM.

From the results in Tables 3–4, we can see that the three evaluation indexes of M1 are superior to other methods and the prediction results of three prediction days of M1 and M2 all satisfy the evaluation index. However, the prediction results of the second prediction days of M3-5 did not satisfy the demand of the evaluation index. Here, the second day of the five prediction models has the highest error and the worst effect due to the large drop in the forecasting accuracy of wind power on that day, but the DMAP of M1 increased by 0.41%, 3.2%, 10.26% and 7.29%, respectively, compared with the other four models.

The prediction result of M5 is better than that of M4, which shows that the persistence model has better prediction accuracy than the single ANN prediction model. It is worth stressing the fact that the accuracy of hybrid forecasting model outperformed the single prediction method. The DMAP and DMQP of M3 are all higher than M4 and the NRMSE of M3 is also small, which shows that the decomposition can effectively reduce the impact of volatility on the prediction results and improve the prediction accuracy. The DMAP of M2 is over 2% higher than M3, which indicates that the reconstruction strategy has a certain improvement in the DMAP of the prediction results. Compared with the M2, the DMAP of M1 is improved by 1%, which shows that the IEMD model can improve the large-scale fluctuation of local signals or the abnormal data with sudden increase of numerical value. Fig. 6 shows the rolling prediction results of five methods at a certain point. It can also be seen from the Fig. 6 that the proposed model in this paper is superior to the other four models.

TABLE 6. The prediction results of different wind power output.

Wind power output	R_C(%)	R_Q(%)	*NRMSE*(%)
High output	87.23	67.88	22.67
Middle output	89.16	72.01	19.02
Low output	91.45	78.14	16.36

In order to further verify the adaptability of the proposed method, other two wind farms with different installed capacity are selected to predict the wind power. The prediction results are shown in Table 5. It should be emphasized that the prediction date here is for the whole data set instead of the test set. As can be seen from Table 5, three wind farms with different installed capacity simultaneously are used the IEMD-R, EMD-R, EMD, ANN and PM models to prediction. The proposed method is superior to the other models in the DMAP, the DMQP and NRMSE, which shows that the reconstruction strategy using run-length analysis can improve the accuracy of wind power prediction. In summary, the proposed method in this paper has some practical value.

Under the condition of low wind power output, the same model will achieve good prediction effect. However, in the case of high wind power output, the prediction accuracy may be reduced and cannot satisfy the stipulated requirements. In this paper, wind farm A is selected as the research object and the ultra-short-term multi-step wind power prediction is carried out in wind power with high output, middle output and low output, respectively. The prediction results are shown in Table 6. As demonstrated in Table 6, as the output of wind power increases, the two indicators of the DMAP and DMQP gradually deteriorate, which shows that the output of wind turbine affects the prediction accuracy of wind power. However, the DMAP of the proposed method can reach more than 87% even under the condition of high wind power output, which shows that the proposed method has strong generalization ability and can content the power prediction under various conditions.

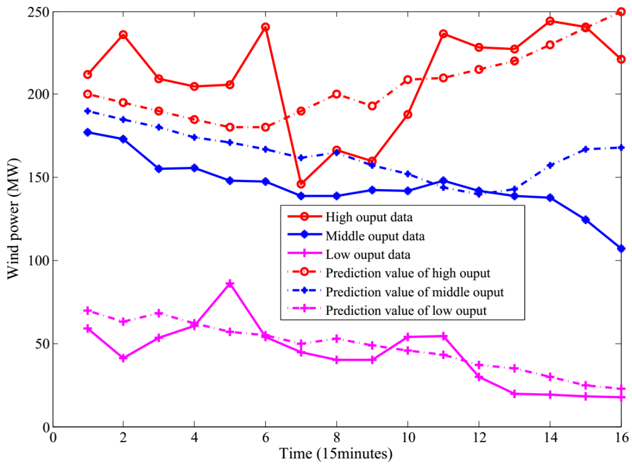

FIGURE 7. The rolling prediction results of different wind power output at a certain point.

One prediction result is selected randomly, as shown in Fig. 7. It is obvious from the figure that in the case of high wind power output, the forecasting results of the proposed method is not good at low and middle wind power output. This is a common phenomenon that the prediction accuracy is decreased due to the obvious fluctuation of wind power. How to improve the accuracy of the time-series prediction with obvious volatility is still a difficult problem and needs further study.

VI. CONCLUSION

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions. Considering the randomness, volatility and intermittency of wind power sequences, this paper proposes ultra-short-term multi-step wind power prediction based on improved EMD and reconstruction method using run-length analysis. Different prediction methods are used to predict the reconstructed sequences of IMFs. In this paper, we compared the prediction results of three wind farms with different installed capacities and studied the prediction effect of wind turbines under different output conditions. Major conclusions are summarized as follows: (a) compared with the EMD-R, EMD, ANN and PM models, the IMED-R model proposed in this paper has greatly improved the daily mean accuracy percent. In the case of high wind power output, the proposed model can still have a higher accuracy, reflecting the superiority of the IEMD-R model; (b) the DMAP of IEMD-R model is 1% higher than that of the EMD-R model, which shows that the improvement of EMD has a certain effect; (c) the DMAP of the EMD-R model than the EMD model increased by more than 2%, reflecting the need for reconstruction method using run-length analysis; (d) the DMAP of the EMD model to the ANN model is improved by $1\% \sim 5\%$ according to the different forecasting days, which indicates that the forecasting strategy of wind power decomposition before the prediction is helpful to improve the prediction accuracy. In addition, with the development of the intelligent algorithms, there will be more advanced models applied to predict the low accuracy of high wind power output prediction, which is our study direction in the future.

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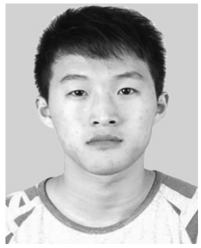

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