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A Hybrid EMD-SVM Based Short-term Wind Power Forecasting Model

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***Abstract*—This paper proposes a wind power forecasting model based on the empirical mode decomposition (EMD) and the support vector machine (SVM). In this model, the EMD is used to decompose wind power sequence into several intrinsic mode functions (IMF) and a residual component. Then, the SVM is used to train each component for the optimal parameters and kernel function. Finally, sum the prediction results of each component to obtain the wind power prediction values. Compared with the traditional forecasting methods, the hybrid EMD-SVM forecasting method can effectively reduce the root mean square error and the relative error, improve the forecasting accuracy and track the change of wind power.**

***Index Terms*—Empirical mode decomposition (EMD), forecasting model, support vector machine (SVM), wind power.**

I. INTRODUCTION

Wind power forecasting can help to increase the scheduling capacity of wind power and implement a reasonable control strategy to reduce the volatility of wind power, which is helpful to make the best use of wind energy and reduce the impact on the grid [1], [2].

Wind power forecasting methods are classified into statistical methods and physical methods [3]. Physical methods describe the physical conversion process of wind energy into electric energy. The numerical weather prediction (NWP) is a representative method, which establishes equations with thermodynamics and fluid mechanics, to describe the weather change according to the air pressure, wind direction, humidity, wind speed and other meteorological elements at different heights [4]. The statistical methods build up the map relationship between historical data and wind power output, and analyze the change rule of wind power, regardless of the physical performance during the change process of wind speed. The common statistical methods include spatial correlation method, genetic algorithm and support vector machine (SVM), Kalman filtering, artificial neural network (ANN), auto-regressive moving average method (ARMA), and so on [5]-[9]. The statistical method has the advantage of fast calculation without complex equation, but it needs a lot of historical data, which affects the forecast accuracy.

In this paper, a hybrid EMD-SVM forecasting model is proposed, based on the empirical mode decomposition (EMD) and the support vector machine (SVM), aimed at the non-stationary fluctuation of wind power with time and space. First of all, EMD is used to decompose wind power sequence into intrinsic mode functions (IMFs) and residual component. Then, each component is trained via SVM for the optimal parameters and kernel function. A case study is used to validate the proposed method.

II. THE EMD DECOMPOSITION OF WIND POWER

The wind power time series is decomposed with EMD into a corresponding number of IMFs and a residual component. IMFs are narrowband components should satisfy the following two conditions [11]:

1) The upper and lower envelopes of IMF are required locally symmetric on the timeline, namely the mean value of upper and lower envelopes defined by the local minimum value and the local maximum value, is equal to zero at any point. Assume that the upper and lower envelopes of the IMF component $x(t)$ are $a(t)$ and $b(t)$, respectively, and it is required that $a(t) + b(t) \equiv 0$. However the mean of the upper and lower envelopes is generally unequal to zero, so in order to satisfy the condition 1), the following equation (1) needs to hold [10]:

$$SD = \sum_{t=0}^{T}\left[\frac{|imf_{i(k-1)}(t) - imf_{ik}(t)|^2}{imf_{i(k-1)}^2(t)}\right] \leq \varepsilon \quad (1)$$

where ε is the sifting limit, which is general between 0.2 to 0.3; $imf_{ik}(t)$ is the signal after k times decomposition.

2) In the entire time series of IMF component, the number of the extreme points should be equal to the number of the zero-crossings or at most one difference.

Figure 1 shows the EMD decomposition process of wind power. First of all, find out all the maximum points and minimum points in the original wind power time series $x(t)$, and use

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cubic spline function to fit the upper envelope $e_+(t)$ and the lower envelope $e_-(t)$, respectively. The mean of upper and lower envelopes is treated as the mean envelope of original wind power $m_1(t)$, i.e.,

$$m_1(t) = \frac{e_+(t) + e_-(t)}{2} \tag{2}$$

$m_1(t)$ is also the low frequency component of original wind power time series, $imf_{11}(t)$ is the original wind power sequence after removing the low frequency component , which can be expressed as

$$imf_{11}(t) = x(t) - m_1(t) \tag{3}$$

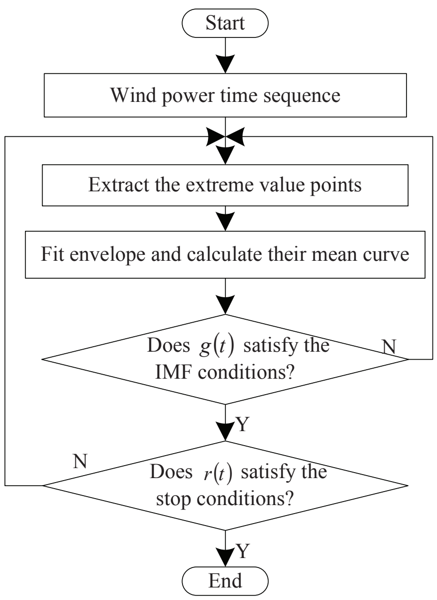

Figure 1. EMD decomposition flowchart of wind power

In general, $imf_{11}(t)$ is still non-stationary [12]. Repeat the decomposition process above to the new signal and after k times repeated decomposition, the first-order IMF component $c_1(t)$, which meets the above two conditions, can be is deduced as follows:

$$c_1(t) = imf_{1k}(t) \tag{4}$$

Another new signal removed the high frequency component $r_1(t)$ can be expressed as follows:

$$r_1(t) = x(t) - c_1(t) \tag{5}$$

Process $r_1(t)$ similarly, so can get the second-order IMF component $c_2(t)$. In this way, the n-order IMF component $c_n(t)$ and the residual component $r_n(t)$ can be deduced. When the residual component becomes a constant or a monotone sequence, the EMD decomposition is over. The decomposition process can be expressed as follows:

$$\begin{cases} r_1(t) - c_2(t) = r_2(t) \\ r_2(t) - c_3(t) = r_3(t) \\ \vdots \\ r_{n-1}(t) - c_n(t) = r_n(t) \end{cases} \tag{6}$$

where $c_i(t)$ is each IMF component of original wind power time series; $r_n(t)$ is the residual component.

The EMD decomposition results of original wind power can be expressed as

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{7}$$

III. SVM Based Wind Power Forecasting Model

The fundamental idea behind SVM forecast model is to train and analyze the time series of wind power, to find an optimal function $f \in F$ (F is the function set) [13],[14] so that the empirical risk function value $R(f)$ is minimized. Here, $R(f)$ can be expressed as follows:

$$R(f) = \int l(y - f(x)) dP(x, y) \tag{8}$$

where l is the loss function of original wind power sequence. It can be any convex function, which is commonly used in the form of $l(x) = |y - f(x)|^p$ where p is a positive integer.

Since the probability of wind power samples $P(x, y)$ is unavailable in advance, the expect risk minimum value cannot be calculated directly by (8).

According to the structural risk minimization principle [15], there is

$$R(f) \le R_{emp} + R_{gen} \tag{9}$$

where R_{gen} is a measure of complexity of $f(x)$; R_{emp} is the empirical risk, so the upper limit can be determined.

The given wind power sequence serves as the observation sample set $\{(x_1, y_1), (x_2, y_2), \cdots, (x_n, y_n)\} \in R^n \times R$, suppose the regression function is:

$$F = \{ f \mid f(x) = w^T x + b, w \in R^n \} \tag{10}$$

The structure risk function is used to realize the tradeoff between the model complexity and the empirical error. Such a function has the following form:

$$R_{reg} = \frac{1}{2} \| w \|^2 + C R_{emp}[f] \tag{11}$$

where C is a constant; $f(x)$ is the model complexity; $\|w\|^2$ is the describing function.

Transform the regression problem of (10) into the minimum cost functional problem, i.e.,

$$\min \frac{1}{2} w^T w + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*) \tag{12}$$

$$\begin{cases} \text{s.t. } y_i - w^T x_i - b \le \varepsilon + \zeta_i \\ w^T x_i + b - y_i \le \varepsilon + \zeta_i^* \\ \zeta_i, \zeta_i^* \ge 0 \end{cases} \tag{13}$$

where ζ_i and ζ_i^* are slack variables; ε is the estimation precision.

Since the wind power is a nonlinear sequence varies with space and time, it needs to map the wind power data into higher-dimensional feature space. The kernel function can be constructed to transform the nonlinear regression (lower-dimensional input space) into the linear regression (higher-dimensional feature space).

The minimum cost functional can be expressed as [16]

$$\begin{aligned} &\min_{\alpha,\alpha^*} \frac{1}{2}[\alpha,\alpha^*]\begin{bmatrix} Q & -Q \\ -Q & Q \end{bmatrix}\begin{bmatrix} \alpha \\ \alpha^* \end{bmatrix} \\ &+[\varepsilon I^T + y^T \quad \varepsilon I^T - y^T][\alpha\ \alpha^*]^T \end{aligned} \tag{14}$$

$$\text{s.t. } [I^T - y^T][\alpha \quad \alpha^*]^T = 0, 0 \le \alpha, \alpha^* \le C \tag{15}$$

where α and α^* are the Lagrange multipliers; $I=[1,\ldots,1]^T$; $Q_{i,j}=\phi^T(x_i)\phi(x_j)$.

The above (14) and (15) formulate the minimum cost functional into an expression of quadratic programming problem. By solving (14) and (15), the Lagrange multiplier α can be obtained. Also can deduce the equation (16):

$$w = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\phi(x) \tag{16}$$

Bring (16) into regression function can obtain the equation as follows:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i x) + b \tag{17}$$

where $(\alpha\text{-}\alpha^*)$ is the sample data of wind power that corresponds to the condition of non-zero; b is the constant deviation which can be calculated under the Karush-Kuhn-Tucker (KKT) condition [17]:

1) If $\alpha_i \in (0,C)$, b is expressed as follows:

$$b = y_j - \varepsilon - \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(x_i, x_j) \tag{18}$$

2) If $\alpha_i^* \in (0,C)$, b is expressed as follows:

$$b = y_j + \varepsilon - \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)K(x_j, x_i) \tag{19}$$

Figure 2 shows the flowchart of the SVM based forecasting model. More specifically, there are the following steps:

1) Normalize the original wind power data, and convert them into corresponding linear data in the interval [- 1, 1];

2) Data training: set up different SVM model with different parameters and kernel function to data;

3) Select the optimum kernel function and parameters by analyzing the comprehensive performance of different parameters and kernel functions;

4) Build up the training model with the optimum parameters and kernel function. If the accuracy of the predicted results cannot be satisfied, return to 3);

5) Perform the wind power forecasting.

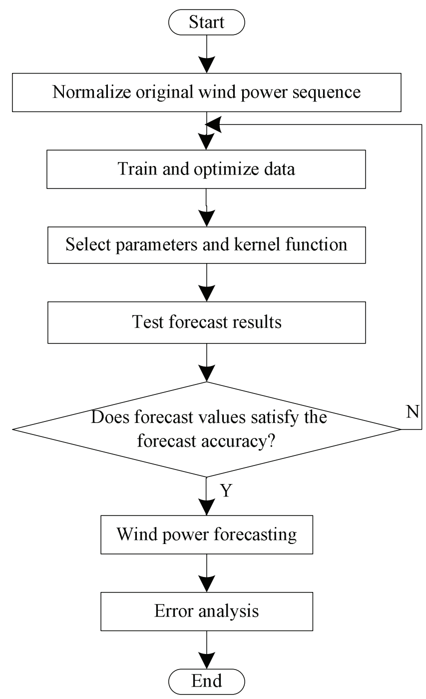

Figure 2. Flowchart of SVM based wind power forecasting

IV. HYBRID FORECASTING MODEL

Figure 3 shows the flowchart of the EMD-SVM based forecasting model, the steps are as follows:

1) Implement the EMD decomposition on the original wind power sequence, and then obtain a series of IMF components $c_i(t)$ and a residual component $r_n(t)$.

2) Do support vector training on $c_i(t)$ and $r_n(t)$, and then set up corresponding SVM prediction model with the selection of the optimal kernel functions and parameters to get the predicted value of each component.

3) Sum the above predictive values to get the wind power prediction result.

4) Calculate and analyze the forecast error.

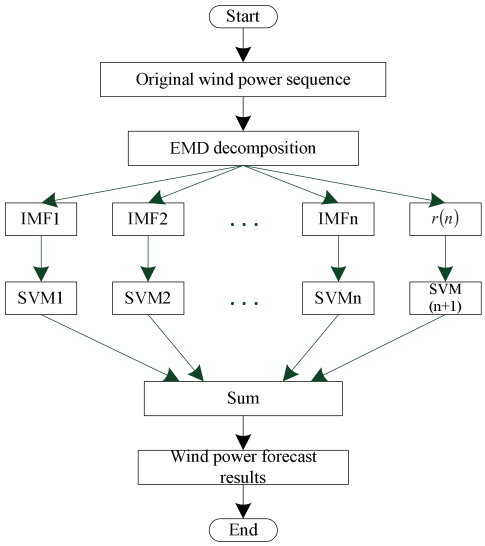

Figure 3. Flowchart of EMD-SVM based wind power forecasting

V. CASE SYUDY

The wind power data from a wind farm in China are utilized to validate the proposed forecasting model. Sample the data of three days with 15 minutes sampling time interval, namely 288 sampling points. Among them, the former 192 sampling points are the input data, while the later 96 sampling points are the test data, namely the actual wind power data.

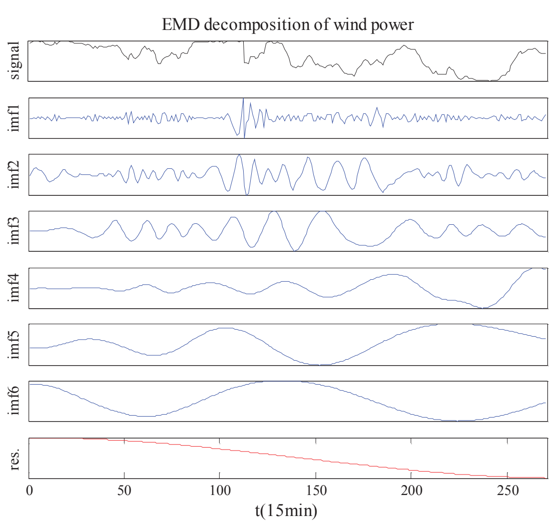

Figure 4. EMD decomposition results of wind power sequence

The original wind power data are decomposed into 6 IMF components and one residual component. The EMD decomposition results of the training sample data is shown in Figure 4. It can be seen that the volatility of these components are significantly lower than the original data, more and more stable from IMF1 to IMF6, and the last residual component is monotonous.

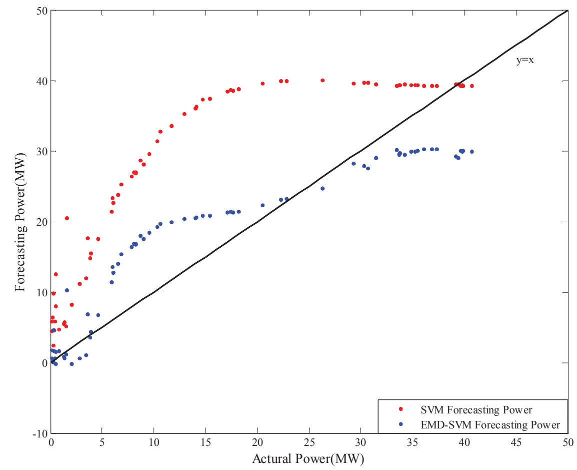

Figure 5. SVM and SVM-EMD based forecasting results of wind power

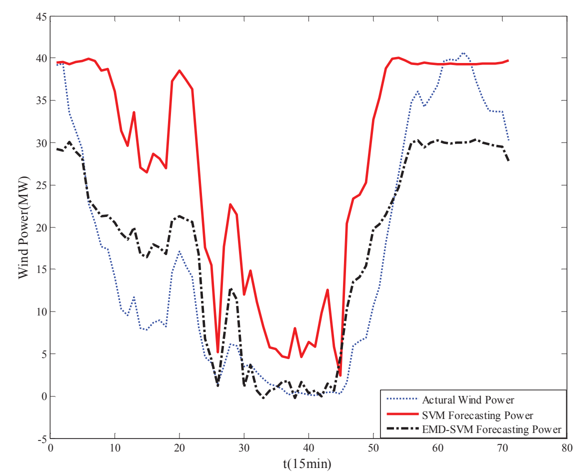

Figure 6. Comparison between forecasting results and actural wind power

Figure 5 shows the comparison between the traditional SVM based prediction model and EMD-SVM based forecasting model, which shows that the EMD-SVM based prediction results curve is closer to 1:1. Furthermore, Figure 6 gives a comparison between the experimental data and the forecasting results.

Figure 7 shows the error curves of different forecasting methods. Calculate the relative errors and the root mean square errors, of which the statistical results of the two forecast model are shown in Table I. It is clear that the proposed EMD-SVM based forecasting model can significantly reduce the forecast error and improve the forecast accuracy, compared with the traditional SVM based forecasting model.

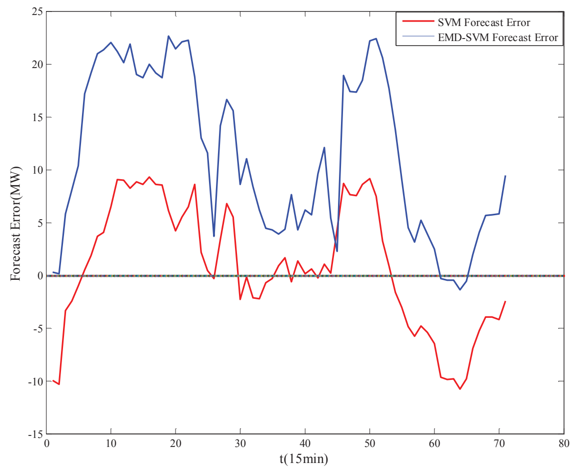

Figure 7. Comparison of forecast error between SVM and EMD-SVM

TABLE I. FORECAST ERROR OF DIFFERENT STATISTICAL METHODS

Forecasting methods	The probability distribution of relative error				RMS error
	≤10%	10%-20%	20%-30%	≥40%	
SVM	19.72%	23.94%	12.68%	43.66%	35.40%
EMD-SVM	46.48%	26.76%	26.76%	0	15.63%

VI. CONCLUSION

In this paper, a hybrid EMD-SVM forecasting model is established, which adopts SVM forecasting method and combines the advantages of EMD in nonlinear time series decomposition. With this model, the wind power sequence can be decomposed into a series of components of different scales and trends step by step, stabilizing the nonlinear and non-stationary sequence. SVM forecasting models are set up aiming at each stationary component with similar characteristics, respectively. So the effect of the nonlinear and non-stationary characteristics on wind power forecasting can be reduced. A case studied here also validates that this new model not only strengthens the regularity of the original data, but also improves the accuracy of wind power prediction, which is of great practical value.

VII. ACKNOWLEDGMENT

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