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Short term Wind Power Prediction based on Parameter Optimization of the Variational Modal Decomposition and Support Vector Regression

Zhen Chenggang[1,*], Yin Tai[1]

[1]School of control and computer engineering, North China Electric Power University, Baoding 071000, Hebei, China.

Abstract

In order to solve the problem of low adaptive in wind power time series by using the method of variable mode decomposition (VMD), a new parameter optimization method is proposed for VMD method. Firstly, particle swarm optimization algorithm based on the algorithm of searching for optimization of tianniu is used to optimize the parameters of the variational mode decomposition, and the fitness function is calculated by using fuzzy entropy, Then, the VMD model is used to decompose the short-term wind power time series, and then the SVR prediction model is established for each decomposition eigenmode and the final prediction results are obtained by recombining. The experimental results show that the prediction accuracy of the combined prediction model based on parameter optimization and variational mode decomposition is much higher than that of the traditional time series based combination prediction method.

Keywords

Wind-power Generation; Short-term Fore-casting; Time Series; Combination Optimization; Variational Mode Decomposition; Support Vector Regression (SVR).

1. Introduction

In recent years, the state has gradually strengthened the remediation of environmental problems, and wind power generation plays an increasingly important role in the energy system. If there is a large wind power fluctuation, it will have a serious impact on the power balance and frequency regulation of the power grid. Therefore, improving the accuracy of wind farm power prediction is of great significance to ensure the planned dispatching of power dispatching department and the stability and operation safety of power grid.

At present, the common wind power prediction methods can be divided into physical model, statistical learning model, deep learning model and combined prediction [1]. It is a common method to build physical models by combining NWP data of numerical weather forecast with various spatial physical quantities such as wind speed, geographical location of wind farm and fan parameters; The statistical method is to induce the model from the historical data of wind farm and construct the learning model including time series analysis, machine learning method and so on [3]; The deep learning method uses the model fitting ability of neural network functions, such as long short term memory (LSTM) and convolutional neural networks (CNN), to predict the wind power [4]. Considering that the wind power series is greatly affected by environmental factors and has strong random volatility, most models cannot mine all the characteristic information when processing the original signal series, so the combined prediction model is usually constructed by the method based on signal processing before modeling. The research shows that the combined prediction method has lower prediction root mean square error [5].

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There are various signal processing methods, such as wavelet decomposition, empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD) and variational mode decomposition (VMD). Compared with the traditional signal processing methods EMD and EEMD, the variational modal decomposition technology VMD effectively solves the problems of endpoint effect and modal component aliasing, and the VMD method can better reduce the non stationarity of time series with high complexity and strong nonlinearity, and decompose a non-stationary time series into multiple relatively stable subsequences [6]. Based on the above advantages, VMD method is more suitable for non-stationary time series such as wind power. However, VMD often depends on empirical selection in the selection of modal number and penalty term parameters, and there is no criterion, and different parameter selection has an obvious impact on the decomposition effect. In view of the above problems, some adaptive learning algorithms are introduced into VMD optimization. For example, literature [7-8] respectively introduces particle swarm optimization algorithm and multi-scale arrangement entropy to optimize VMD parameters or decomposed modal components.

Based on the above research, an optimization algorithm based on particle swarm optimization (PSO) under longicorn whisker search (BAS) optimization is proposed in VMD parameter optimization. The fuzzy entropy algorithm is selected as the fitness function of the optimization process, the decomposed modal components are obtained by VMD, and the support vector regression (SVR) is introduced to predict each decomposed sub sequence, and the final predicted value is obtained after superposition. Simulation results show that VMD method combined with parameter optimization can greatly improve the prediction accuracy of SVR model.

2. Parameter optimization of the Variational modal decomposition

2.1 Variational modal decomposition

The variational mode decomposition algorithm is an adaptive and completely non recursive signal processing method. When obtaining the intrinsic mode component (IMF), the algorithm can adaptively match the optimal center frequency and limited bandwidth of each mode, and can realize the effective separation of IMF and the division of signal frequency domain, so as to obtain the effective decomposition component of a given signal, Finally, the optimal solution of the variational problem is obtained [9].

When constructing the variational problem solution, the variational modal decomposition shall ensure that the decomposition sequence is the modal component with limited bandwidth with central frequency, and the sum of estimated bandwidth of each mode is the smallest. The constraint condition is that the sum of all modes is equal to the original signal. The corresponding constrained variational model can be expressed as:

$$\begin{cases} min\{\sum_k || \partial_t[(\delta(t)+j/\pi t)u_k(t)]e^{-j\omega_k t}||_2^2\} \\ s.t. \sum_{k=1}^{K} u_k = f \end{cases} \tag{1}$$

K refers to the total number of decomposed modes, {uk} refers to the modal frequency domain of the decomposed K IMF components$\{\omega_k\}$ Refers to the frequency center of each component. In order to solve the optimal solution of the above constrained variational problem, the Lagrange multiplier method is used and the operator is introduced λ The constrained variational problem is expressed as an unconstrained variational problem, and the Lagrange function is expressed as shown in (2):

$$L = a\sum_k | \partial_t[(\delta(t)+j/\pi t)u_k(t)]e^{-j\omega_k t}||_2^2 + ||f(t)-\sum_k u_k(t)||_2^2 + \langle\lambda(t), f(t)-\sum_k u_k(t)\rangle \tag{2}$$

among α It refers to the quadratic penalty factor, which can reduce the interference of Gaussian noise. Using Fourier equidistant transform, the formula is transformed into frequency domain, and the frequency domain and frequency center $\{u_k\}$ sum of each modal component are obtained$\{\omega_k\}$:

$$\begin{cases} u_k^{n+1}(\omega) = \frac{f(\omega)-\sum_{i\neq k} u_i(\omega)+\lambda(\omega)/2}{1+a(\omega-\omega_k)^2} \\ \omega_k^{n+1} = \frac{\int_0^\infty \omega|u_k^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |u_k^{n+1}(\omega)|^2 d\omega} \end{cases} \tag{3}$$

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The VMD decomposition process is shown in Figure 1. A large number of studies show that the modal component parameter K and the penalty term parameter α The component K directly determines the number of eigenmode functions (IMF) after modal decomposition. Different values of K will lead to different processing results; Penalty parameter α Represents the initial center constraint strength of each eigenmode function, α The larger, the smaller the signal bandwidth of each IMF component, α The smaller, the larger the component signal bandwidth [10]. How to reasonably determine K value and α Value becomes the key step of using VMD algorithm to process wind power sequence.

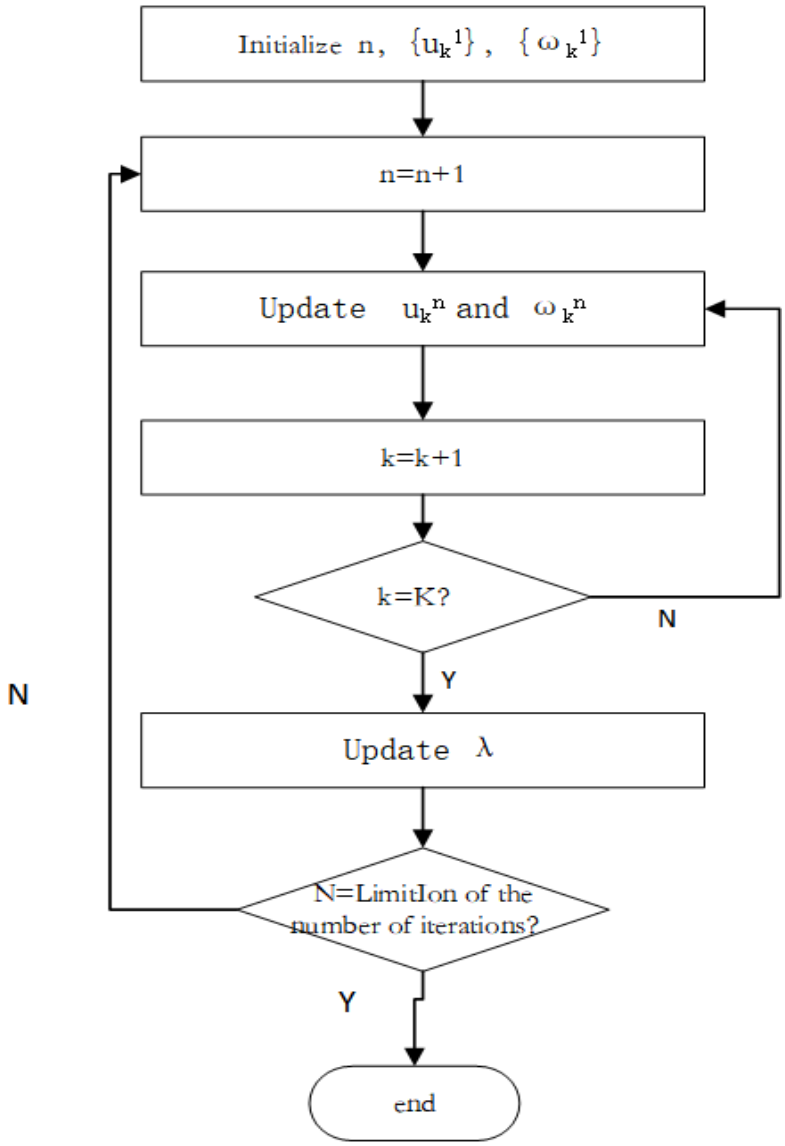

Fig. 1 The VMD decomposition process

2.2 Optimize VMD parameters based on BAS-PSO combination algorithm

2.2.1 Principle of particle swarm optimization algorithm

Particle swarm optimization (PSO) is a swarm intelligence optimization algorithm realized by simulating the foraging behavior of birds. In the process of solving the optimal solution, PSO algorithm sets particles with only two attributes of speed and position to simulate birds in birds. Each particle searches for the optimal solution separately in the search space and records it as the current individual extreme value, shares the individual extreme value with other particles in the whole particle swarm, finds the optimal individual extreme value as the current global optimal solution of the whole particle swarm, and all particles in the particle swarm adjust their speed and position according to the

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current global optimal solution, Finally, the whole particle swarm can gather near the optimal solution. Particle swarm optimization algorithm has the advantages of fast local convergence speed and less parameters to be set. However, due to the lack of the ability to adjust the particle speed in the convergence process, the later convergence accuracy of the algorithm is low, and the particles are easy to fall into the local optimal solution [11].

2.2.2 Principle of longicorn whisker search algorithm

Longicorn beetle whisker search algorithm bas is an optimization algorithm developed based on the foraging principle of longicorn beetles. When searching for food, longicorn beetles perceive the food smell in the air through the left and right antennae on their heads. According to the different distance between the food and the two antennae, longicorn beetles can perceive the concentration difference and move randomly towards the side with strong concentration. Through iteration after iteration, finally find the location of the food. The code of longicorn whisker search algorithm is simple. By constantly modifying the search compensation, the particles have better global search ability. When dealing with low-dimensional optimization objectives, longicorn whisker search algorithm has the advantages of fast search speed and high solution accuracy [12].

2.2.3 VMD parameter selection and optimization

In this paper, in order to improve the global optimization ability of PSO algorithm and ensure that longicorn whisker search algorithm is used to improve particle swarm optimization algorithm, bas-pso is used to improve the two parameters K and K that affect the decomposition effect of VMD α The optimal parameters are automatically selected without subjective influence to ensure the accuracy of VMD decomposition results.

The idea of bas-pso combined optimization algorithm is to treat a single particle as a single longicorn at the same time. Combined with the longicorn whisker search idea, when updating the position of each particle in the iterative process, it must also compare the fitness function values of the left and right whiskers, and adjust the particle position coordinates in real time, so as to avoid the particle gradually falling into local optimization in the convergence process. Determining the fitness function is an important work in the improvement of this algorithm. As a good standard for evaluating the complexity of time series, fuzzy entropy can measure the probability of generating new patterns when the dimension of time series changes. The size of fuzzy entropy can reflect the complexity of newly generated sequences. The larger the value, the higher the complexity [13]. When the VMD decomposition effect is good, the waveform of each IMF component is regular and the fuzzy entropy is small. When the fuzzy entropy is selected as the fitness function, the local minimum entropy is taken as the final optimization goal.

The fuzzy entropy algorithm is described as follows: for a given time series: [u (1), u (2),..., u (n)], firstly, the non negative integer m is introduced to reconstruct the time series and generate a set of m-dimensional vectors:

$$X(i) = \{u(i), u(i+1), \cdots, u(i+n-1)\} - u_0(i) \tag{5}$$

U_0 (i) is the mean value of m-dimensional vector, and the representation range of i is [1, N-M + 1], See formula (6) for details:

$$u_0(i) = \frac{1}{m}\sum_{j=0}^{m-1} u(i+j) \tag{6}$$

Define the distance d between two vectors x (I) and X (J) as the one with the largest difference between their corresponding elements

$$d_{ij}^m = d[X(i), X(j)] = \max_{p=1,2,\ldots,m} (|u(i+p-1) - u_0(i)| - |u(j+p-1) - u_0(j)|) \tag{7}$$

The fuzzy membership function is introduced to define the similarity of two vectors Dmij:

$$D_{ij}^m = \mu(d_{ij}^m, n, r) = exp(\,(-d_{ij}^m)^N / r) \tag{8}$$

Where R is the similarity tolerance, and the function is defined:

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$$\Phi^m(r) = \frac{1}{N-m}\sum_{j=1}^{N-m+1} D_{ij}^m \tag{9}$$

Finally, the fuzzy entropy of the original time series is defined:

$$F(m,r) = ln\Phi^m(r) - ln\Phi^{m+1}(r) \tag{10}$$

To sum up, according to the principle of particle swarm optimization algorithm and combined with longicorn search optimization algorithm, the specific process of bas-pso optimizing VMD parameter seeking is as follows:

1) Initialize the particle population parameters, set the population size to m, and combine the parameters{ α,K} As the particle position, m parameters are randomly generated, which are combined into the initial position X_i (i∈ [1, M]) of each particle, the moving speed VI of each particle is randomly initialized, and the inertia weight is initialized ω, Number of iterations N and acceleration factors C_1, C_2, C_3.

2) According to the fuzzy entropy theory, the fitness function f (x) is defined to initialize the search parameters of longicorn beetles. Set the left-right distance of each particle to d0 and set the step size δ. The calculation formula of two-day ox whisker coordinates in the iteration process is:

$$\begin{cases} X_{iL} = X_i + d_0 \cdot dir/2 \\ X_{iR} = X_i - d_0 \cdot dir/2 \end{cases} \tag{11}$$

Where dir is the random number between (0, 1).

3) Before calculating the moving speed and position of the centroid of longicorn beetle, first calculate the odor intensity of its two-day beetle whisker, that is, perform variational modal decomposition on the original time series at the left and right whisker positions of each longicorn particle to obtain the current optimal two-day beetle whisker fitness values f (Xil) and F (xir).

4) According to the fitness value of two longicorn whiskers in step 3, generate the position update rule of longicorn particles and adjust the position of longicorn centroid. The formula is as follows:

$$X_i' = X_i + \delta\vec{b}sign[f(X_{iL}) - f(X_{iR})] \tag{12}$$

Where b is the unit direction vector.

5) Carry out step 3 and step 4 for each longicorn particle iteration until the specified number of longicorn particle iterations is reached to obtain the current optimal centroid position of longicorn example.

6) Calculate the fitness f (Xi ') for the adjusted centroid, and update the individual optimal solution PI and the global optimal solution g as follows:

$$\begin{cases} p_i = min(f(X_i)) \\ g = min(p_1, p_2, \cdots, p_M) \end{cases} \tag{13}$$

7) The bull particle updates its speed and position to the global optimal solution by updating the individual local extreme Pi and the global extreme g of the population. The formula of update speed and position in PSO-VMD algorithm is:

$$\begin{cases} v_i^{k+1} = \omega v_i^k + c_1 r_1 (p_i - X_i^{k'}) + c_2 r_2 (g - X_i^{k'}) \\ \qquad + c_3 r_3 v_0 \\ X_i^{k+1} = X_i^{k'} + v_i^{k+1} \end{cases} \tag{14}$$

8) In the formula, I is the ith particle, and K is the number of iterations.ωC1, C2 and C3 are accelerators, r1, R2 and R3 are random numbers distributed between [0,1], and V0 is the particle renewal rate.

9) Return to step (3) using the updated particle velocity and position to iterate until the maximum number of iterations is reached.

The Taurus search optimization particle swarm algorithm effectively avoids the possible local convergence of single particle swarm algorithm in VMD optimization and ensures the validity of the parameters required for VMD. The flow chart of BAS-PSO-VMD model is shown in Figure 2.

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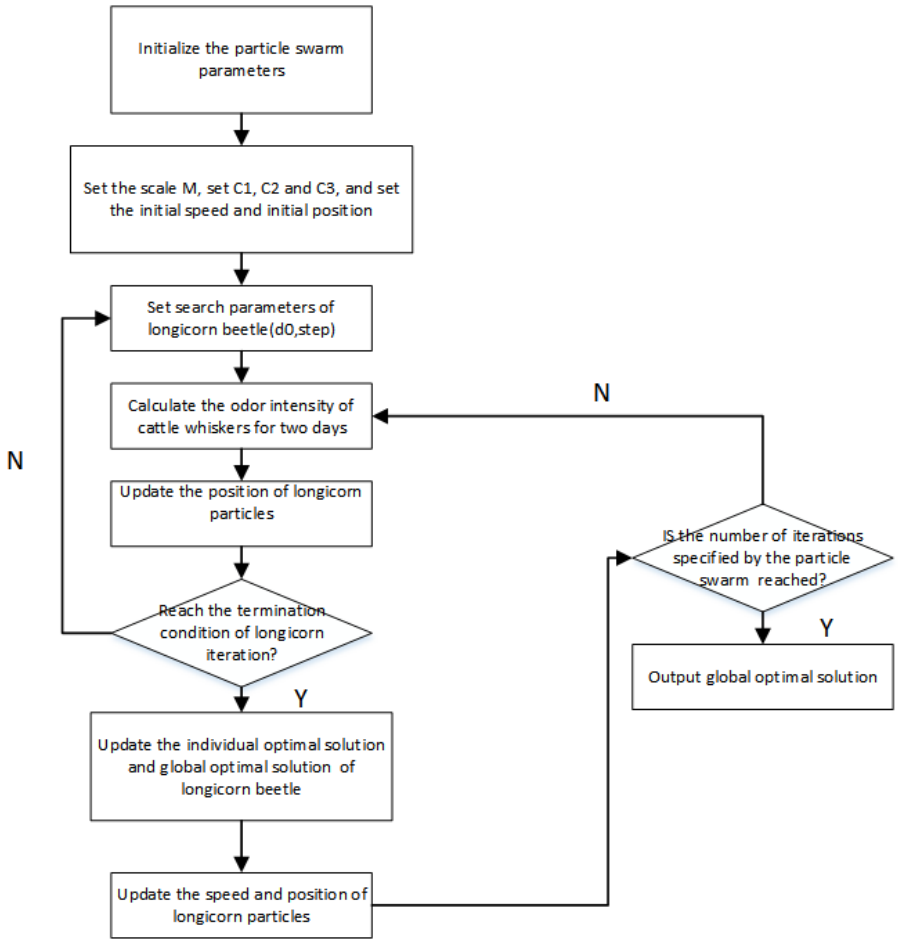

Fig. 2 BAS-PSO-VMD algorithm

3. Support Vector Regression Machine

Support Vector Machine (SVM) is a kind of machine learning algorithm based on the idea of minimizing structural risk. It was first used to deal with linear binary classification problems. After introducing a nonlinear kernel function, support vector machine can map the nonlinear data samples into a high-dimensional feature space, convert them into linear problems and complete the classification [14]. Support Vector Regression Machine (SVR) is a kind of support vector machine that can be used to solve regression problems.

For a given sample $D=\{(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)\}$, when a support vector regression machine establishes a regression model, it first maps through $\varphi(x)$ map the input x to a high-dimensional feature space and construct a linear regression function. Use the ε- insensitive loss function expresses the regression constraint problem as:

$$min\frac{1}{2}\left||w||^2+C\sum_{i=1}^{n}(\xi_i+\hat{\xi}_i\right),(i=1,2,\ldots n)$$

$$s.t.$$

$$\begin{cases} y_i-w\cdot\Phi(x)-b\le\varepsilon+\hat{\xi}_i \\ w\cdot\Phi(x)+b-y_i\le\varepsilon+\xi_i \\ \xi_i,\hat{\xi}_i\ge 0 \end{cases} \tag{15}$$

The solution of SVR can be obtained by introducing Lagrange multiplier solution:

$$f(x)=\sum_{i=1}^{m}(\hat{\alpha}_i-\alpha_i)\,K(x_i^T x)+b \tag{16}$$

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$K(x_i^T x)$ is the kernel function in the formula. Common kernel functions are Linear, Polynomial, Gaussian Radial Basis Function (RBF), sigmoid kernel function. The Gaussian Radial Basis Function can achieve nonlinear mapping and has good interpolation ability for local range data [15]. It is used as the kernel function in SVR model in this paper.

4. Modeling

Based on the above BAS-PSO optimization algorithm, VMD method and SVR model, this paper establishes a combined model to predict short-term wind farm fan power, as shown in Figure 3.

1) The wind power time series X(t) of the fan is introduced as the iteration original data of BAS-PSO optimization algorithm, and the optimal VMD parameter pair is found by the iteration curve. α,K}.

2) Importing parameters, the original wind power data X(t) of the fan is decomposed by VMD to get different intrinsic mode IMFn, which combines with the original meteorological data such as wind speed, ambient temperature and wind direction angle to form n input and output sample sets.

3) The SVR prediction model is applied to the prediction of each subsequence, and the final prediction value is accumulated.

4) Error analysis is performed on the predicted results.

5. Experimental analysis

In order to verify the accuracy of this model in short-term wind power prediction, this paper selects power data of a wind farm and a fan in a geoelectric field for a week in August 2016. The wind farm system collects data every 10 minutes, 24 hours a day, 144 statistical records a day. A total of 1140 data from August 24 to 31 are selected as the experimental data set. The input data dimension of the dataset is 4-dimensional, and the output data is the active power of the fan. In the modeling, the data in the week of 24-29 days is selected as the training set. In order to ensure the prediction accuracy, 72 data from 0-12 hours on 30 days are selected as the prediction test set. The power time series curve of the original data of the training set is shown in Figure 3. Some power data are sh own in Table 1.

Table 1. Partial power and meteorological data of draught fan

time	*wind speed*	*temperature*	*angle of direction wind*	...	*active power (Kw)*
8/24 0:00	6.04	39.24	32.26	...	236.39
8/24 0:10	5.75	41.29	32.31	...	219.13
8/24 0:20	5.99	39.58	32.34	...	240.89
8/24 0:30	5.82	38.49	32.37	...	215.25

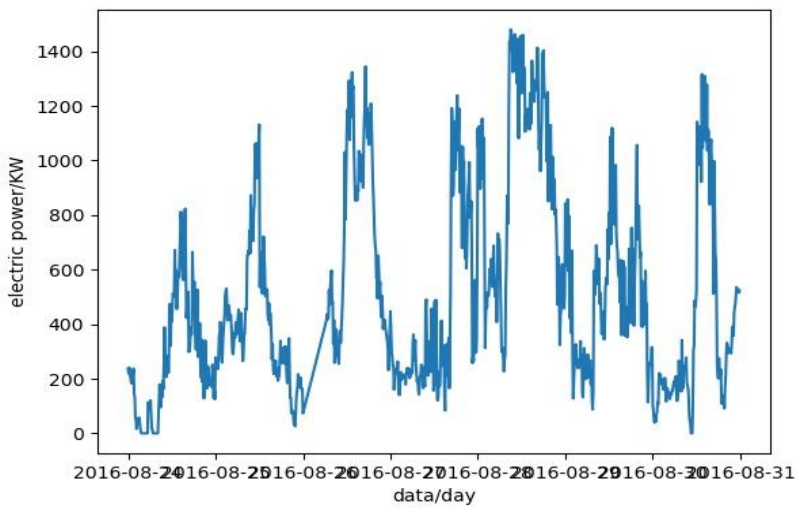

Fig. 3 Original power timing curve

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Using BAS-PSO optimization algorithm to optimize the VMD parameter selection, the original wind power series is used as the iteration dataset, the fuzzy entropy value is changed as the fitness value during the iteration process, and the optimal {K,a} parameter pair for variational mode decomposition is obtained in hours of fuzzy entropy value. As shown in Fig. 4, the fuzzy entropy value tends to be stable and the minimum fuzzy entropy value is obtained during the eighth iteration, and then the K value is 5 for the optimization.The a value is 1692.

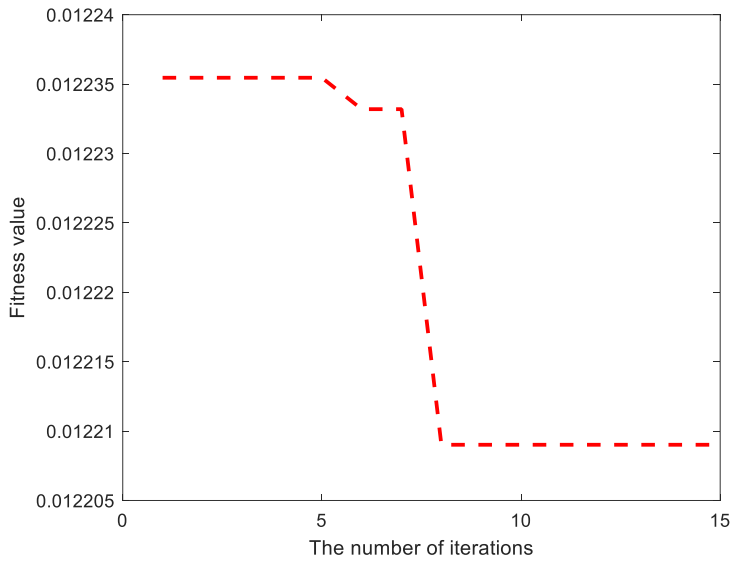

Fig. 4 Variation of minimum fuzzy entropy with iteration times

Set the VMD parameter K value to 5 and a value to 1692, decompose the original wind power, and get the power decomposition sequence as shown in Figure 5.

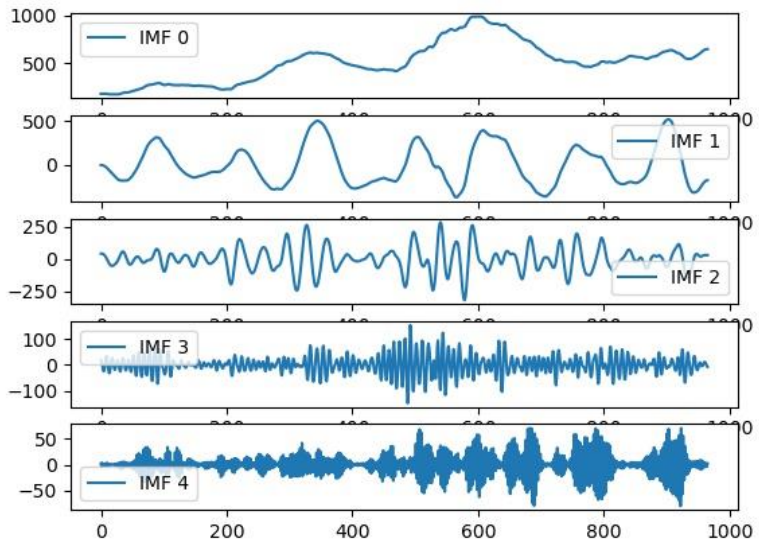

Fig. 5 VMD decomposition of wind power series

In order to validate the validity of the PSO-BAS-VMD-SVR combination model, this paper establishes the SVR, EMD-SVR models for comparison, and the model prediction curve is shown in Figure 6.

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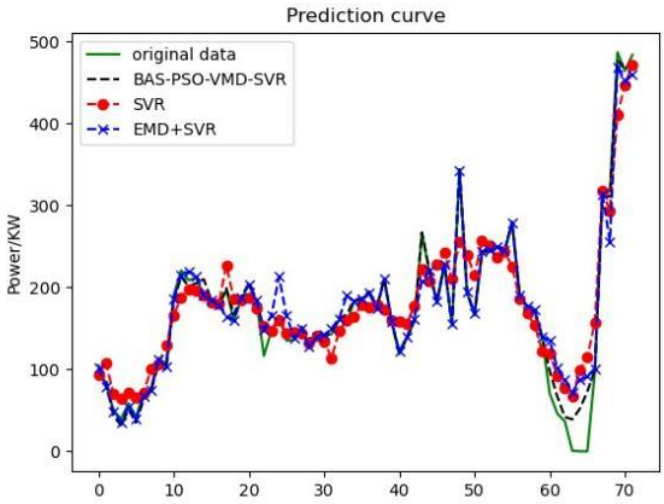

Fig. 6 One-step-ahead Prediction curve of each model

For the qualitative description of the prediction curve, the root mean square error RMSE, mean absolute error MAE are used as the error evaluation index, and the goodness of fit R2 is used. The prediction experimental error indicators are shown in Table 2.

Table 2. Comparision of three types of operation mode

Model	*MAE(KW)*	*RMSE(KW)*	R^2
SVR	20.115	33.801	0.814
EMD-SVR	13.772	25.427	0.910
BAS-PSO-VMD-SVR	7.952	13.647	0.967

Table 2 shows that compared with the single SVR prediction model, the EMD-SVM prediction model reduces the MAE and RMSE indices by 6.343Kw and 8.372Kw, respectively, with a relative improvement of 31% and 24%.Based on the combination model, an optimization algorithm is used to optimize the model to obtain higher prediction accuracy.

In summary, the VMD with optimized parameters improves the prediction results better than EMD technology. It is validated that the VMD with optimized parameters can effectively solve the mode overlap problem in EMD and reduce the influence of noise error of each mode component on the prediction. At the same time, Figure 7 shows the prediction results visually. The prediction curve of BAS-PSO-VMD-SVR combined model almost coincides with the actual curve.The prediction results are verified.

6. Conclusion

This paper presents a combined power prediction method based on Improved Particle Swarm Optimization variational mode parameters and support vector regression machine. The following conclusions are obtained through simulation experiments:

(1) Particle swarm optimization algorithm based on the modified Teneberry search optimization algorithm has better parameter optimization ability, which can effectively solve the problem that parameters are difficult to determine in the VMD decomposition method, and then effectively reduce the non-stationarity of the decomposition sequence.

(2) Combining the variational mode decomposition based on parameter optimization with the support vector regression machine can greatly improve the accuracy of the single prediction model, which is also better than the typical EMD-SVR combination prediction model.

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