Frontiers in Power and Energy Systems (2022)
Clausius Scientific Press, Canada
DOI: 10.23977/fpes.2022.010101
ISSN 2516-2926 Vol. 1 Num. 1

New Design of Short-Term Wind Power Forecasting Algorithm Based on VMD-Grid-SVM

Feng Huang*, Renyuan Jia, Shixiong Bai, Hong You

School of Electrical and Information Engineering, Hunan Institute of Engineering, Xiangtan, 411101, China
**Corresponding author*

Keywords: Grid Search, SVM, VMD, Wind Power

Abstract: In this paper, a short-term power forecasting model is established by using non-linear fitting characteristics of Support Vector Machine (SVM). A grid method based on Variational Mode Decomposition (VMD) is designed to optimize the short-term power forecasting algorithm. First, the wind power data is pre-processed and decomposed to 6 stable power components using VMD algorithm, thus reducing the impact of excessive forecasting errors of oscillatory points at peaks and valleys. Then, the grid search method is used to optimize the kernel function and penalty factor of the SVM to establish a short-term power forecasting model. Finally, each stable component data is processed using the Grid-SVM power forecasting model, and then the results are combined to get the final power forecasting value. Analysis of test results show that the forecasting accuracy is about three times that of the traditional SVM power forecasting model, is two times that of the Grid-SVM power forecasting model. The forecasting accuracy and speed meet the requirements for safe operation of wind farms.

1. Introduction

Nowadays, with gradual depletion of fossil energy provided by the main energy, green, environmentally friendly, and renewable wind energy has aroused people’s concern [1,2]. Wind energy represents the most valuable renewable energy for large-scale development and utilization in the near future, which carries great significance to environmental protection and sustainable social development [3]. Generation power of wind farms is unstable and is restricted by factors like wind speed, climate, which affects the safety of grid connection. To facilitate reasonable dispatch of wind power by the grid, power forecasting of wind farms is necessary [4-6].

Researchers proposed some statistical forecasting methods for wind power forecasting. Landberg designed Prediktor forecasting system to draw a wind-power curve by wind speed and output power [7]. But statistical method has low accuracy. In general, the prediction efficiency of the mixed prediction model is obviously better than that of the single prediction model [8].The School of Modeling and Mathematics of Technical University of Denmark developed a short-term wind power forecasting system Zephry by using a combination of physical methods and statistical methods [9].

Traditional statistical methods have simple principles and wide application ranges, but wind power forecasting accuracy is not ideal, especially for oscillatory points such as wind power peaks and valleys. Nowadays, some methods using artificial intelligence has been proposed. Reference that published by Peng T and Zhou J designed a hybrid RT algorithm with extreme learning machine (RT-ELM) model embedded with complementary ensemble empirical mode decomposition with adaptive noise (CEEMDAN), VMD and AdaBoost.RT algorithm [10]. The model could capture the nonlinear characteristics of wind speed. Document that published by Yu M and Wang B proposed a wind speed forecasting model based on ensemble empirical mode decomposition (EEMD) [11]. Gang Z and Liu H proposes a multi-frequency combination prediction model based on VMD which use a back propagation neural network (BPNN) [12], autoregressive moving average (ARMA) and least square support vector machine (LS-SVM) to predict high, intermediate, and low frequency components. Ru D and Wang X proposed a short-term wind speed forecasting method based on hybrid particle swarm algorithm [13]. For high-precision wind speed predictions, Zhang W and Qu Z proposed a wind speed forecasting method based on CEEMDAN, flower pollination algorithm with chaotic local search (CLSFPA) and no negative constraint theory (NNCT) [14].The CEEMDAN-combined model had advantages of individual models. Wang Y and Zhu Y also established particle swarm optimization-based SVM for power forecasting [15]. But these methods have the problems of low forecasting accuracy and difficult model parameter selection. VMD can expose important parts of the original signal while filtering out noise, and its end effect can be effectively handled by mirror extension, that was proposed by reference [16]. The grid search algorithm can optimize the kernel function and penalty factor of SVM, thus solve the problem of difficult parameter selection in SVM, that was proposed by reference [17]. Many researchers mentioned introduce serval methods for decomposing data, like reference [18-20].

This paper proposes a grid search method based on variational modal classification to optimize the SVM forecasting model, which can solve the problem of low forecasting accuracy and difficult model parameter selection. Case analysis shows that the mixed forecasting model can effectively improve short-term wind power forecasting accuracy.

2. VMD

VMD is a new type of complex signal decomposition method based on EMD. When accuracy is not so good for some oscillatory points, its purpose is to decompose the original complex and singular signal into several finite bandwidths with different center frequencies, then use alternate direction multiplier method to continuously update each mode and its center frequency. Each mode is gradually demodulated to the corresponding base band, and finally components with different center frequencies were obtained [16,21]. VMD is essentially a variational issue, mainly involving structure and solution of variational issue. The VMD algorithm process is as follows:

(1) Calculate the analytical signal of each modal function $u_k(t)$ using Hibbert transform to obtain the unilateral spectrum;

(2) For the decomposed signal of each mode, modulate the frequency spectrum of each mode to the base band by adjusting the exponential term e^{-jwkt};

(3) Adjust the signal according to Gaussian smoothness and gradient square criterion, calculate the square L_2 norm of the gradient to obtain the bandwidth of each decomposition mode.

3. Object Analysis

Take the No.23 wind turbine of Big Board-Beam Wind Farm as the object for simulation analysis. The wind turbine is XE105-2000 with diameter 105 meters and rated power 2 MW. The sampling time interval is 10min, with a total of 200 sampling points. The first 160 sampling points are selected as the forecasting model training set, and the latter 40 sampling points are used as the test set for rolling forecasting. The forecasting time is 20 minutes. The wind power curve after preprocessing of the historical power data is shown in Figure 1.

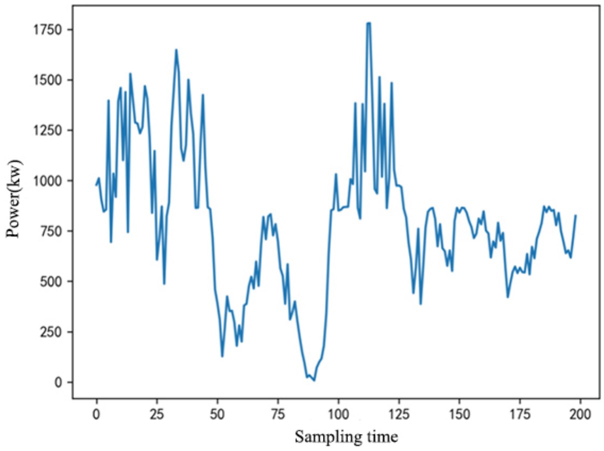


Figure 1: Original power curve

Use VMD for decomposition, and the decomposition result is shown in the Figure 2.

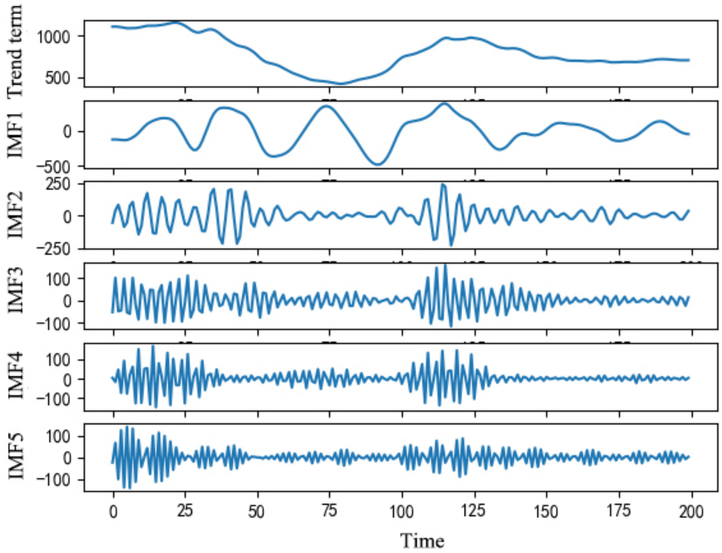


Figure 2: VMD decomposition of original power data

In the figure, the first graph is a trend item, which reflects the variation trend of the original power curve; IMF1 is a detail component, which reflects the variation trend of the original power curve in different details, and IMF2-IMF5 is a random component, which reflects randomness in the original power generation.

4. Grid-SVM Forecasting Model

During the SVM training [22,23], the collected samples are often non-linear data and it is impossible to find a hyperplane to classify non-linear data. Classification requires that it must be converted to linear data. By kernel function, SVM can easily map the nonlinear sample space to the high-dimensional linear space. Then, different types of sample segmentation are possible by finding the best segmentation hyperplane in the linear space. There are linear and non-linear SVMs. For linear classifiable training sample sets, the classification equation is:

$$w^T(x)+b=0 \tag{1}$$

Where w is an n-dimensional vector and b is a bias term.

For non-linear classifiable training sample set, the decision function is:

$$f(x)=w^T(x)+b \tag{2}$$

In the decision function, let all xi meet the absolute value of f(xi)≥1, so that the distance between the sample and the optimal classification plane is minimal. The minimum distance d between the two is expressed as follows:

$$d=\frac{|f(x_i)|}{\|w\|}=\frac{1}{\|w\|} \tag{3}$$

To let the samples correspond correctly on the optimal classification plane, the constraint function is limited as follows:

$$y_i\left[w^T x_i+b\right]\geq 1,\ \ i=1,2,\cdots,t \tag{4}$$

Support vector sample meets:

$$y_i\left[w^T x_i+b\right]=1 \tag{5}$$

Introduce the Lagrangian function to solve the optimization problem [21]:

$$L(w,a,b)=\frac{1}{2}w^T w-\sum_{i=1}^{i}a_i\left[y_i\left(w^T x_i+b\right)-1\right] \tag{6}$$

In the formula, ai represents the Lagrangian coefficient and the maximum value is usually greater than 0; Respectively take the derivative of w and b in the above formula, when the partial derivative is 0, there is:

$$\frac{\partial L}{\partial w}=0,\frac{\partial L}{\partial b}=0 \tag{7}$$

Substitute formulas (8) and (11) into formula (9) to transform the optimization problem into a dual problem. Its maximization function is:

$$w(a)=\frac{1}{2}\sum_{i,j=1}^{t}a_i,a_j y_i y_j(x_i{}^T x_j)+\sum_{i=1}^{t}a_i \tag{8}$$

The constraint is:

$$\sum_{i=1}^{t}a_i y_i=0,0\leq a_i\leq C,\ \ i=1,2,\cdots,t \tag{9}$$

In the formula, sample with non-zero ai is support vector. Thus, there is discriminant function f(x):

$$f(x)=sign(w^T x+b) \tag{10}$$

When solving nonlinear problems, the essential solution idea is similar to that of linear problems. The best way to deal with such problem is to establish a high-dimensional mapping. By mapping to the high-dimensional space for classification, classification of the original samples can be obtained [24]. The regression function f(x) is:

$$f(x,w) = w\psi(x) + b = (w, \psi(x)) + b \tag{11}$$

Where w is the weight vector, b is a constant, and minimization of w and b is estimated by the following formula:

$$\min_Q \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{m}(\xi_i + \xi_i^*) \tag{12}$$

The constraints are:

$$\begin{cases} wx_i + b - y_i \le \varepsilon + \xi_i \\ y_i - w_i - b \le \varepsilon + \xi_i^* \\ \varepsilon, \xi_i^* \ge 0; i = 1, 2, \cdots, m \end{cases} \tag{13}$$

Where C is the penalty factor, ξ_i , ξ_i^* are relaxation factors, and ε is the loss function.

Due to high dimensionality of the feature space, Langrangian multiplier method is generally adopted to solve the high-dimensional quadratic programming problem in practical applications:

$$W(a_i, b_i) = \sum_{i=1}^{m} y_i (a_i - b_i) - \varepsilon \sum_{i=1}^{m} (a_i + a_i^*) - \frac{1}{2}\sum_{i=1}^{m} (a_i - a_i^*)(a_j - a_i^*) x_i x_j^* \tag{14}$$

The constraints are:

$$\begin{cases} \sum_{i=1}^{n} (a_i - a_i^*) = 0 \\ a_i \ge 0, a_i^* \le C \end{cases} \qquad i = 1, 2, \cdots m \tag{15}$$

Where $x_{i,j}$ is the input variable, y_i is the output variable, a_i and b_i are Lagrangian multipliers.

Grid Search algorithm is a method with a particularly high usage rate for optimizing the two parameters of SVM [25-27]. Its basic principle is to divide the parameters to be searched into grids within a certain spatial range and traverse all points in the grid to find the optimal parameters. In the process of classification modeling, if σ is too small or C is too large, over-fitting will occur; If σ is too large or C is too small, classification accuracy will be reduced [28]. This paper uses grid search algorithm to optimize the SVM parameters, and integrates K-fold cross-validation to reduce the forecasting error.

The principle of grid search algorithm is to continuously search the intersection of C and g, compare the errors of each intersection, and select the optimal parameter combination for optimization. It sets the value range and search step length of C and $g=1/2\sigma^2$, then establishes a two-dimensional grid with C and g as coordinates, traverses each grid, uses the corresponding parameter values to train SVM, and finally selects C and g with the highest classification accuracy as the optimal parameter value. Different from heuristic or approximation algorithm, grid search algorithm uses exhaustive search to find the optimal solution from all possible solutions, and basically only involves two parameters. Its optimization time is not much longer compared to advanced algorithms such as PSO algorithm and GA algorithm. In addition, the various groups of parameters in the algorithm process are decoupled from each other, thus facilitating parallel calculations. The optimization process is as follows [29]:

- Determine the value range of parameters C and g.
- Select the parameters within the given range and appropriate step size to construct a two-dimensional grid plane (C, g).
- Input each parameter pair (C, g) to the node for training, use samples for learning, and input cross-validation error. Take the parameter with the smallest error as the optimal parameter combination.

The SVM forecasting effect is subject to influence of its own kernel function parameters and penalty coefficient parameters. Traditional SVM has big forecasting error, while wind power is also affected by other objective factors such as wind speed, so uncertainty is high. Compared with heuristic algorithms such as GA optimization and PSO optimization, grid search algorithm is simple to operate, which can traverse all possible solutions within a certain parameter range, thus has high classification accuracy and high operating efficiency.

5. VMD-Grid-SVM Forecasting Model

It can be seen from the 6 sets of decomposed signals that, compared with the original wind power input signal, the decomposed intrinsic mode function IMF is relatively stable. In stable signals forecasting, the forecasting results are often superior compared to the original signals. Owing to great fluctuations and instability of wind power, if the original input-output power is directly forecasted, the forecasting error will often be high, and the power forecasting requirements for accuracy will not be met. If the wind power is decomposed by VMD, the decomposed data is respectively forecasted by Grid-SVM, and then each group of forecasted values is combined to establish a VMD-Grid-SVM combined forecasting model, it will further improve the forecasting accuracy and achieve better results. The model flowchart is shown in Figure 3.

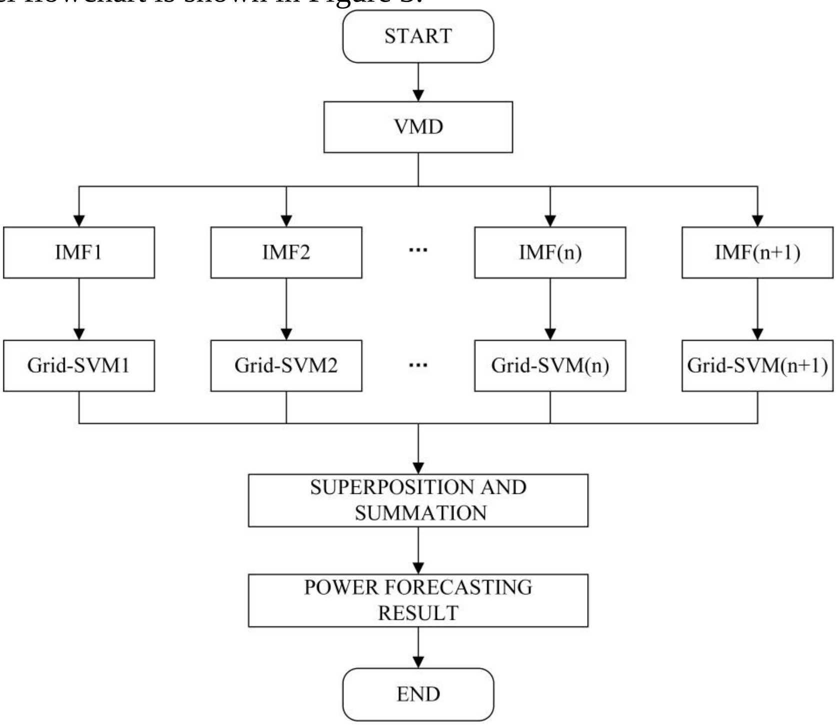


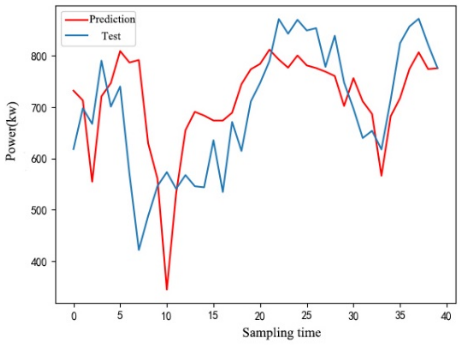
Figure 3: VMD-Grid-SVM forecasting flowchart

The forecasting model steps are as follows:

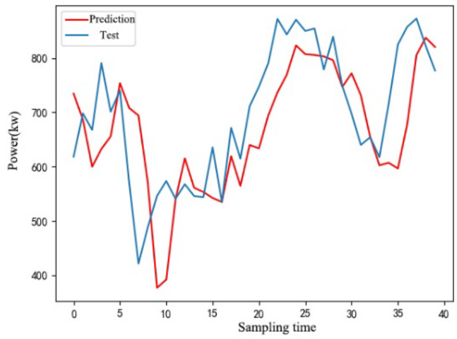
- First, perform VMD decomposition on the original wind power input signal, and decompose the original signal into multiple stationary intrinsic mode functions IMF and trend terms. Here the wind power data is decomposed to 6 power components using VMD decomposition. The first component is a trend item. IMF1 is a detail component. IMF2-IMF5 are random components.

- Then perform Grid-SVM forecasting for each IMF and trend item separately to obtain more accurate forecasting results. Here it determine the value range of parameters C and g.
- Then reorganize the Grid-SVM forecasting results of each component to obtain a forecasting result closer to the original data. Take the parameter with the smallest error as the last parameter combination.
- Finally, the forecasting results of VMD-Grid-SVM and traditional Grid-SVM are evaluated for error. MAE(Mean Absolute Error) and RMSE (Root Mean Squared Error) are taken to calculate the deviation between the forecasted output and the actual output.

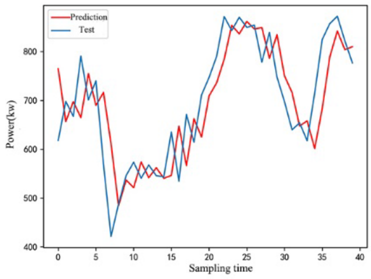
6. Experimental Analysis



(a) SVM model



(b) Grid-SVM model



(c) VMD-Grid-SVM model

Figure 4: Comparison of forecasted value and actual value of each model.

The sampling time interval is 10 min, with a total of 200 sampling points. The first 160 sampling points are selected as the forecasting model training set, and the latter 40 sampling points are used as the test set for rolling forecasting. The forecasting time is 20 minutes. With the pre-processed wind power sequence as input, SVM, Grid-SVM, VMD-Grid-SVM forecasting models are established respectively for error analysis. Forecasting results of each model are compared with the actual values, as shown in Figure 4. The running time of VMD-Grid-SVM algorithm is 27.3s (the CPU of computer was Intel's core i5 1.6 GHz with 4GB RAM, and Windows 10 operating system).

The average percentage error and root mean square error of the above three models are compared and analyzed to obtain the following error analysis in Table 1. By comparing the difference between the actual value and forecasted value of the above models, it can be known that the forecasting result of VMD-Grid-SVM has a forecasting curve more consistent with the actual value compared to SVM model, Grid-SVM model, and Grid-SVM model has a forecasted value closer to the true value than SVM model.

Table 1: Error comparison and analysis of each model

Model	E_{RMSE}	$E_{MAPE\%}$
SVM	118.97	12.33%
Grid-SVM	90.78	8.89%
VMD-Grid-SVM	40.56	5.07%

7. Conclusions

It designed a new short-term wind power forecasting algorithm based on VMD-Grid-SVM mode. The new algorithm had stable component reducing the impact of excessive prediction errors of oscillatory points at peaks and valleys. The forecasting accuracy is about three times that of the traditional SVM power forecasting model, two times that of the Grid-SVM power forecasting model. The new algorithm was of great significance to deal with the wind power forecasting with fluctuation and unsteadiness.

Acknowledgment

This work was supported by Hunan Provincial Natural Science Foundation of China (Grant Number 2022JJ50014 and 2022JJ50116), Postgraduate Scientific Research Innovation Project of Hunan Province (Grant Number CX20211261), Special project for construction of Changzhutan National Independent Innovation Demonstration Zone (Grant Number CG-YB 20211030 and CG-YB 20211025).

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