Short-Term Wind Speed Forecast Based on Wavelet Packet Transform and LS-SVM

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Abstract: It is well known that large-capacity wind power, as a type of strong fluctuations and random power, has an impact on grid safety. Due to this situation, accurate wind speed forecast plays an important role in reducing the impact of wind power on the grid. In this paper, we discuss the short-term wind speed forecast problem based on the wavelet packet transform and least squares support vector machine (LS-SVM). Firstly, high-frequency and low-frequency signals of wind speed are analyzed by the wavelet packet algorithm. Then, optimal wavelet packet transform is selected by minimum entropy principle. Based on these, short-term wind speed forecast model is established by LS-SVM. As an application of the proposed method, a case study with the actual data of a wind farm is presented to show the efficiency and accuracy compared with the previous results.

Key Words: Wind Speed Forecast; Wavelet Packet; LS-SVM

1 INTRODUCTION

Wind power in the grid is increasing in recent years[1], large-capacity wind power generation have impact on security and stability of the grid. Accurate forecast of the wind speed is necessary for safety of the grid dispatching department and wind farm in generation bidding.

Wind speed forecasts more than three hours should consider the nature of atmospheric[2], numerical weather prediction is necessary. Short-term wind speed forecast between 0 and 3 hours depends on atmospheric continuous conditions. The main algorithm[3-8] includes continuous prediction method, time series method, Kalman filter method, neural network algorithm, support vector machine and so on. Wavelet analysis[9] and EMD method can improve the prediction accuracy.

Wind speed time series is random fluctuations in the time domain. However, through analyzing different frequency components, it can be found that the same frequency components have similar characteristics. Hence, modeling of different frequency components can improve the wind speed forecast accuracy. Traditional wavelet analysis only focuses on the low frequency components. Differently, this paper analyzes both low-frequency and high-frequency signals of wind speed by wavelet packet transform and entropy criterion. Then, models of various components are established by LS-SVM. The final model is obtained base on the methods above. Simulation results show that the proposed algorithm is more accurate than the traditional algorithm.

This work was supported by the National Basic Research Program of China (“973” Program) (Grant No. 2012CB215203)

2 WAVELET PACKET ALGORITHM

Wavelet packet[10] do further decomposition of the signal details based on wavelet analysis. Wavelet packet method is more accurate and flexible.

2.1 Definition of the wavelet packet functions

For orthogonal scaling function ϕ and wavelet function ψ in multi-scale analysis, a double-scale equation:

$$\begin{cases} \phi(x) = \sqrt{2}\sum_k h_k \phi(2x-k) \\ \psi(x) = \sqrt{2}\sum_k g_k \phi(2x-k) \end{cases} \tag{1}$$

Make $\mu_0(x)=\phi(x), \mu_1(x)=\psi(x)$

$$\begin{cases} \mu_{2n}(x) = \sqrt{2}\sum_k h_k u_n(2x-k) \\ \mu_{2n+1}(x) = \sqrt{2}\sum_k g_k u_n(2x-k) \end{cases} \tag{2}$$

So $\{\mu_n(x)\}_{n\in N}$ is called wavelet packet functions derived from the scaling function ϕ.

2.2 Recursive Algorithm of Wavelet Packet Transform

Wavelet packet transform uses a new subspace U_j^n:

$$U_j^n = close\left\{2^{-j/2}\mu_n(2^{-j}x-k)\right\}_{k\in Z} \tag{3}$$

Wavelet packet make up for deficiencies wavelet cannot decompose high frequency component.

$$W_j = U^2_{j+1} \oplus U^3_{j+1} = U^4_{j+2} \oplus U^5_{j+2} \oplus U^6_{j+2} \oplus U^7_{j+2}$$
$$= \cdots = U^{2^{k_j}}_{j+k_j} \oplus \cdots U^{2^{k_j+1}-1}_{j+k_j} \tag{4}$$

$d_l^{2n,j+1}, d_l^{2n+1,j+1}$ derived from $d_l^{n,j}$ of wavelet packet is the following formula:

$$d_l^{2n,j+1} = \sum_{k \in Z} h^*_{k-2l} d_k^{n,j} \tag{5}$$

$$d_l^{2n+1,j+1} = \sum_{k \in Z} g^*_{k-2l} d_k^{n,j} \tag{6}$$

$d_l^{2n,j+1}$, $d_l^{2n+1,j+1}$ derived from $d_l^{n,j}$ of wavelet packet reconstruction algorithm is the following formula:

$$d_l^{n,j} = \sum_{k \in Z} (d_k^{2n,j+1} h_{l-2k} + d_k^{2n+1,j+1} g_{l-2k}) \tag{7}$$

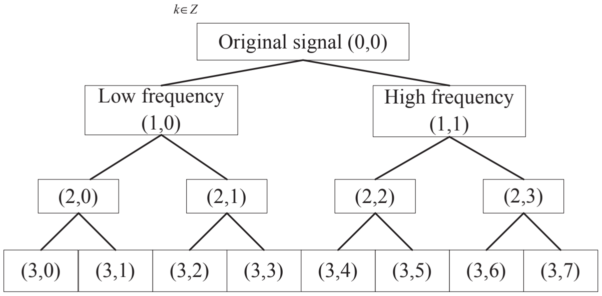

Fig 1. Three complete decomposition map of wavelet packet

2.3 Optimal Wavelet Packet Basis

To select the optimal wavelet packet basis, we must firstly define a sequence of cost function. The cost function selects Shannon entropy in this paper:

$$M(u) = -\sum_{k \in Z} |u_k|^2 \log |u_k|^2, \log 0 = 0 \tag{8}$$

3 LEAST SQUARES SUPPORT VECTOR MACHINE

Least squares support vector machine[11,12] uses the least squares linear system as a loss function, instead of the traditional quadratic programming in support vector machine. The optimization problem in structural risk principle becomes:

$$\min \frac{1}{2}\|w\|^2 + \frac{1}{2}\gamma \sum_{i=1}^{l} \xi_i^2 \tag{9}$$

$$\text{s.t. } y_i(w^T \psi(x_i) + b) + \xi_i = 1 \text{, i} = 1, \cdots, l \tag{10}$$

LS-SVM optimization problem is transformed into the following quadratic programming problem:

$$\min J_{LSSVM} = \frac{1}{2}\|w\|^2 + \frac{1}{2}\gamma \sum_{i=1}^{l} e_i^2 - \sum_{i=1}^{l} a_i [y_i (w^T \psi(x_i) + \text{b}) + e_i - 1] \tag{11}$$

a_i is the Lagrange operator.

Under optimal conditions:

$$\frac{\partial J}{\partial w} = 0, \frac{\partial J}{\partial b} = 0, \frac{\partial J}{\partial \xi} = 0, \frac{\partial J}{\partial a} = 0 \tag{12}$$

Get:

$$w = \sum_{i=1}^{l} a_i \psi(x_i), \sum_{i=1}^{l} a_i = 0, a_i = \gamma \xi_i,$$
$$w\psi(x_i) + b + \xi_i - y_i = 0 \tag{13}$$

Define the kernel function $K(x_i, x_j) = \psi(x_i)\psi(x_j)$, the optimization problem become into a linear problem:

$$\begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 & y_1 & \cdots & y_1 \\ y_1 & K(x_1, x_1) + \frac{1}{\gamma} & \cdots & K(x_l, x_l) \\ \vdots & \vdots & \ddots & \vdots \\ y_1 & K(x_l, x_l) & \cdots & K(x_l, x_l) + \frac{1}{\gamma} \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \tag{14}$$

Compare to SVM quadratic programming optimization problem, LS-SVM computational complexity is low and running speed is faster. But LS-SVM is easier to trap into local optimum, reduce the robustness of the model.

This paper uses both coupled simulated annealing[13] and grid search method to tune parameters. Firstly, we use coupled simulated annealing to determine the approximate range of optimal parameters. Then accurate parameters can be got by grid search in small range.

4 CASE STUDY

In this paper, a wind speed series in a wind farm over a month, mainly in the value of wind speed 3m/s to 5m/s region, is shown in Figure 2.

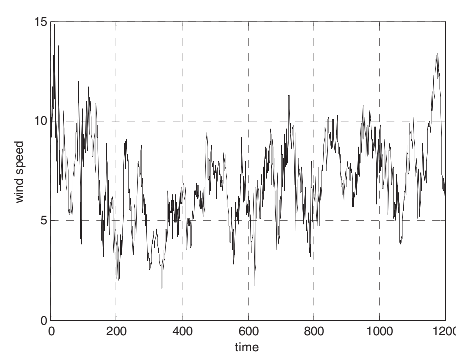

Fig 2. The original signal of the wind speed series

Firstly, the wind speed series decomposed into high frequency and low frequency of 4 layers by wavelet packet analysis. Then use Shannon entropy to select the best wavelet packet form of decomposition, as figure3.

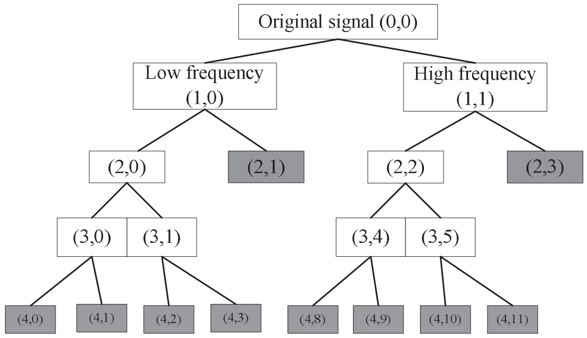

Fig 3. Best wavelet packet decomposition

Decomposition components (4,0), (4,1), (4,2), (4,3), (2,1), (4,8), (4,9), (4,10), (4,11), (2,3) as following figure4 and figure 5:

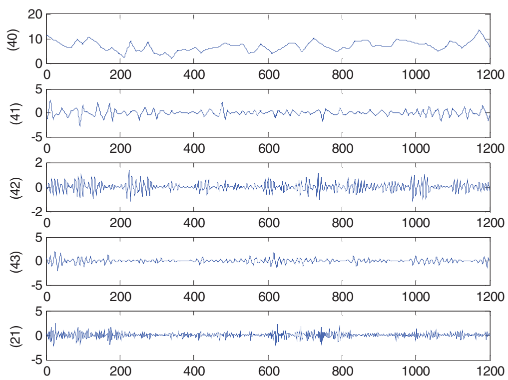

Fig 4. Decomposition components

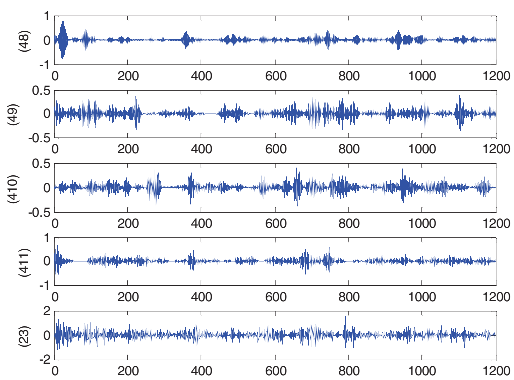

Fig 5. Decomposition components

Prediction model of each decomposition signal is established by LS-SVM. Inputs are the 7 values before. Output is the prediction value. The number of training samples is 800, the number of testing samples is 120. Parameter optimization method uses both coupled simulated annealing and grid search. Figure 6 shows cost value distribution near the optimal parameters (gamma and sigma^2).

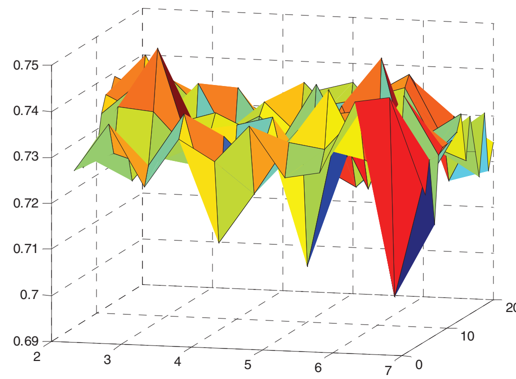

Fig 6. Parameters optimization of LS-SVM

The result of prediction model by only LS-SVM is shown as figure7 and wavelet packet and LS-SVM is shown as figure8. Table 1 shows 3 types of errors of 2 method. The wind speed forecast model of wavelet packet and LS-SVM shows better effect on accuracy.

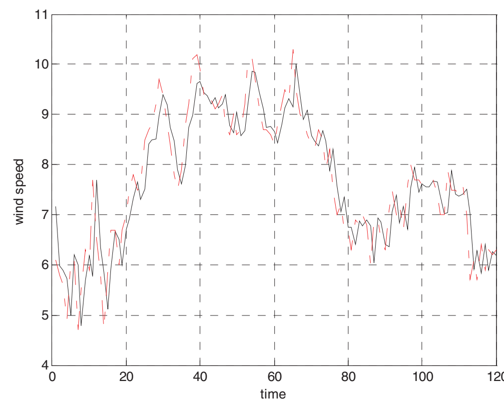

Fig 7. Prediction result by only LS-SVM

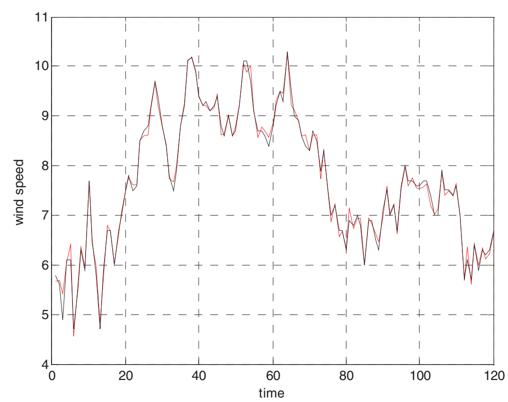

Fig 8. Prediction result by wavelet packet and LS-SVM

Table.1 Compare of the error

	LSSVM	WPT-LSSVM
Average error	0.4295m/s	0.0844m/s
Relative error	6.07%	1.18%
RMS error	0.5683	0.1156

5 CONCLUSION

This paper discussed the short-term wind speed forecast problem based on the wavelet packet transform and LS-SVM. Firstly, the wavelet packet algorithm is used to analyze the high-frequency and low-frequency signals of wind speed. Then entropy criteria are used to select the optimal decomposition form. Each decomposition component model is established by LS-SVM. Coupled simulated annealing and grid search method are used in modeling parameters tuning. The results show that the accuracy of the designed model is obviously improved compared with traditional model.

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