Short-Term Wind-Power Prediction Based on Wavelet Transform–Support Vector Machine and Statistic-Characteristics Analysis

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***Abstract*—The prediction algorithm is one of the most important factors in the quality of wind-power prediction. In this paper, based on the principles of wavelet transform and support vector machines (SVMs), as well as the characteristics of wind-turbine generation systems, two prediction methods are presented and discussed. In method 1, the time series of model input are decomposed into different frequency modes, and the models are set up separately based on the SVM theory. The results are combined together to forecast the final wind-power output. For comparison purposes, the wavelet kernel function is applied in place of the radial basis function (RBF) kernel function during SVM training in method 2. The operation data of one wind farm from Texas are used. Mean relative error and relative mean square error are used to evaluate the forecasting errors of the two proposed methods and the RBF SVM model. The means of evaluating the prediction-algorithm precision is also proposed.**

***Index Terms*—Prediction methods, support vector machines (SVMs), uncertainty analysis, wavelet transforms (WTs), wind-power generation.**

I. INTRODUCTION

THE DEVELOPMENT of renewable energy, particularly wind energy, is among top national policies by countries all over the world. Due to the intermittent nature of wind generation, the increasing wind-power penetration level will affect the operation of the grid. A reliable and accurate wind-power prediction is one of the most effective solutions to deal with this problem. In general, the wind-capacity forecasting methods include multiple linear regression, autoregressive moving average, artificial neural networks, fuzzy logic, etc. [4], [5], [8], [10], [18]. Although researchers have devoted significant efforts in developing algorithms on wind-capacity forecasting, there is room for improvement. Fig. 1 shows the difference between forecasting and actual output of wind generation on May 16, 2009, in the Electric Reliability Council of Texas (ERCOT) [1]. The forecasting error was due to a cold front that passed through the region. The 5000-MW difference between the observed value and the forecasted value at 2:30 A.M. presents challenges to the system operators.

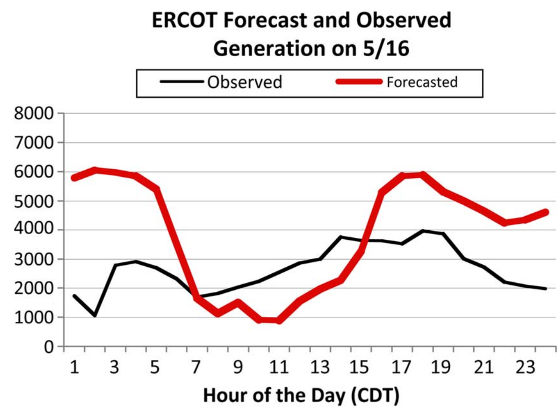

Fig. 1. ERCOT forecasted and observed wind generation on May 16, 2009.

To enhance the prediction model and improve the prediction accuracy and calculation speed, this paper compares two wavelet transform (WT)–support vector machine (SVM) models for wind-capacity forecasting. The effectiveness of the models is verified with the actual output of the wind farm in Texas. The study shows that the mean relative error (MRE) and relative mean square error (RMSE) on the proposed method 1 are better than those on the traditional approaches. In addition, the prediction scope can be obtained with a degree of confidence to support the wind-farm operation by making use of statistical characteristics of prediction errors.

II. SVMs

An SVM is a general learning method developed from statistical learning theory with a better performance than many other routine methods. Statistical learning theory is based on a set of harder theory foundations, which provides a united frame in order to solve the problem of limited sample learning. The basic idea of SVM applied to regression prediction is described as follows [14], [17].

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Given the observation sample set $P(x,y)$, (x_1,y_1), $(x_2,y_2),\ldots,(x_n,y_n) \in R^n \times R$, suppose that the regression function is

$$F = \left\{ f | f(x) = \omega^T \cdot x + b,\ w \in R^n \right\}. \tag{1}$$

Introduce the structure risk function

$$R_{\text{reg}} = \frac{1}{2}\|\omega\|^2 + C \cdot R_{\text{emp}}[f] \tag{2}$$

where $\|\omega\|^2$ is the describing function, $f(\cdot)$ is the complexity term, and C is a constant which determines the tradeoff between the empirical risk and the model complexity.

The main idea of nonlinear support vector regression is to map the input vector x into a high-dimensional feature space by using a nonlinear mapping function $\phi(x)$ and then perform linear regression on the feature space. In this higher space, there is a greater possibility that the data can be linearly separated. Then, the problem can be described as

$$\min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}\xi_i \tag{3}$$

subject to

$$y_i\left(\omega \cdot \phi(x_i) + b\right) \geq 1 - \xi_i, \qquad \xi_i \geq 0; \quad i = 1,\ldots,l; \quad C > 0.$$

The inner products $\phi(x_i)$ in the high-dimensional space can be replaced by some special kernel functions $K(x_i,x_j)$, which can be calculated. All the necessary computations can be performed directly in input space by calculation kernels. The popular kernels are shown as follows:

1) radial basis function (RBF) kernel

$$K(x,x_i) = \exp\left(-\gamma\|x - x_i\|^2\right) \tag{4}$$

2) polynomial kernel

$$K(x,x_i) = (1 + x \cdot x_i)^d \tag{5}$$

where γ and d are parameters. Different learning machines with arbitrary types of decision surfaces can be constructed by using various kinds of kernel functions $K(x_i,x_j)$.

In actual application, the kernel function has an influence on the realized effect. It is important to select a proper kernel function to optimize the kernel-function solution. As mentioned earlier, polynomial kernel function, RBF kernel functions, and sigmoid functions are the three routine methods for kernel functions [9], [19].

III. WT

A. Definition of WT

Assume that the expression $\psi(t)$ is a square integral function, $\psi(t) \in L^2(R)$, and its Fourier transform $\hat{\psi}(t)$ satisfies the condition [13]

$$\int_R \frac{\left|\hat{\psi}(w)\right|^2}{|w|} dw < +\infty. \tag{6}$$

Take $\psi(t)$ as a wavelet base or mother wavelet function. The mother wavelet function $\psi(t)$ can be extended and translated into

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right), \qquad a,b \in R; \quad a \neq 0. \tag{7}$$

Just consider the aforementioned equation as a wavelet series, where a is the scale factor and b is the translation factor. Consider any function like $f(t) \in L^2(R)$; the definition of continuous WT can be expressed as

$$W_f(a,b) = \langle f, \psi_{a,b}\rangle = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty} f(t)\bar{\psi}\left(\frac{t-b}{a}\right)dt. \tag{8}$$

Its reconstruction formula is

$$f(t) = C_\psi^{-1}\iint_\infty W_f(a,b)\psi\left(\frac{t-b}{a}\right)\frac{dadb}{a^2}. \tag{9}$$

Because the wavelet $\psi_{a,b}(t)$ is generated by the mother wavelet function, where $\psi(t)$ plays the role as an observation window on the analyzed signals, $\psi(t)$ must satisfy the ordinary function constraint condition; also

$$\int_{-\infty}^{\infty}\psi(t)dt < \infty. \tag{10}$$

Therefore, $\hat{\psi}(w)$ is a continuous function which is shown as follows:

$$\hat{\psi}(0)\int_{-\infty}^{\infty}\psi(t)dt = 0. \tag{11}$$

In order to be numerically stable, except the complete reconstruction condition, assure $\psi(t)$ Fourier transform to satisfy the following stability condition:

$$A \leq \sum_{-\infty}^{\infty}\left|\hat{\psi}(2^{-j}w)\right| \leq B \tag{12}$$

where $0 \leq A \leq B \prec \infty$.

B. Mother Wavelet Function

By replacing the mother wavelet function by certain forms, the kernel function can be obtained. The space $L^2(R)$ multiresolution means that $L^2(R)$ satisfies the monotonicity, flexibility, translation invariance, and a series space $\{V_j\}_{j\in z}$ that assure the Riesz base to exist [7].

According to the theory of WT–SVM kernel-function constructed condition, the 1-D WT kernel function can be constructed [1], [15]

$$K(s,t) = \sum_{j,k} \psi_{j,k}(s)\psi_{j,k}(t). \quad (13)$$

The multidimensional situation can be obtained according to 1-D spreading for tensor theory

$$K^d(s,t) = \prod_{i=1}^{d} K(s_i,t_i) = \prod_{i=1}^{d} \sum_{j,k} \psi_{j,k}(s_i)\psi_{j,k}(t). \quad (14)$$

IV. WT–SVM Model for Short-Term Wind-Power Prediction

A. Data

As mentioned earlier, SVM has advantages in predicting certain samples. All the data in this paper come from a wind farm located in Texas with the time period of 30 days (April 2008). Because nearly all the wind conditions are included in this season, the data samples in April are selected to prove the wide application of the proposed model. The measurement wind-power-output data are the hourly average of 1-min data. The influence of climate, temperature, and pressure is not considered in this paper; only the cosine and sine of wind speed and the hour average of wind-power outputs are taken as input values. Although the kinds of variables are reduced and the error will be larger than before, the predicting errors are below 20% which is allowed. Additionally, the scale of input sample is simpler, and it is easier and faster to adjust the parameters. MATLAB Version 7.5 is used as the experiment platform in this paper [16]. A toolbox named SVM_SteveGunn is used to perform training and testing on the sample data after the decomposed process of WT [2].

B. WT–SVM Modeling Process

Two methods which are illustrated as follows are introduced in this paper to establish the WT–SVM model.

Method 1: The time series of wind speed and wind-power outputs are decomposed into different frequency components according to the WT. The different SVM models to predict the components from high frequency to low frequency are established. After the model training and testing, these predicting results of the different frequency bounds are combined to obtain the final results.

Method 2: The structure of this model is nearly the same as that of the RBF SVM one. Replace the RBF kernel function with a wavelet kernel one when mapping the input vector x into high-dimensional feature space and perform linear regression in the feature space [3]. The regression function is shown as follows:

$$f(t) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(t_i,t) + b = \sum_{i=1}^{l} K_j(t_i,t) + b \quad (15)$$

where $K_j(t_i,t) = \sum_k y_{j,k}(s) y_{j,k}(t)$ is the multiresolution wavelet kernel function.

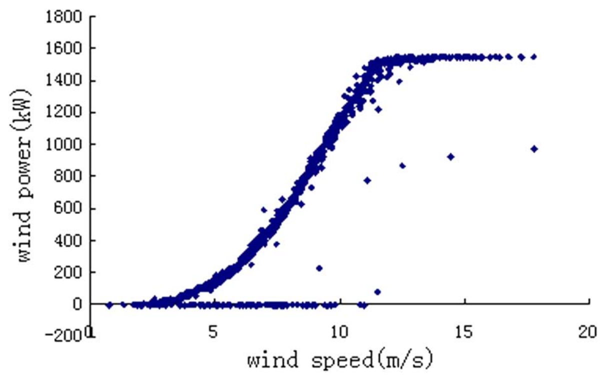

Fig. 2. Relationship between wind power and wind speed.

V. Case Study

A. Model Data Conformation

The WT–SVM model is established by the use of the historical data from the wind farm. Take the series of 1-h-ahead, 2-h-ahead, and 3-h-ahead historical data before testing, including the wind-power output, wind speed, and cosine and sine of wind direction as model input. Take 1-h-ahead wind-power output as model output.

B. Modeling Process

1) Characteristic Analysis on Wind-Turbine Power Curve: The wind-turbine output is defined as follows [6], [16]:

$$P_s = \frac{1}{2}\rho v^3 f C_p \quad (16)$$

where P_s is the output of the wind turbine in kilowatts, ρ is the air density in kilograms per cubic meter, v is the wind speed in meters per second, f is area in square meters, and C_p is the utilization coefficient of wind energy. For a level-axis wind turbine, the maximum is 0.593.

The output data of the relationship between wind power and wind speed from one wind-turbine generator in a wind farm in Texas are shown in Fig. 2.

From Fig. 2, it can be seen that, as the wind speed increases, the wind power gets larger as a whole. There are two forms taking the point of 12 m/s as the dividing point. That means that there is an inflexion at the point of 12 m/s. When wind speed is below 12 m/s, wind power increases as shown in Fig. 2, whereas when wind speed is higher than 12 m/s, the wind power stays steady. As a result, the proposed model is divided into two parts for training. After judging whether the moment-ahead wind-speed values are below or above 12 m/s, the related predicting model is chosen to obtain a more accurate output value. This piecewise SVM (PSVM) model [11] is utilized before both method 1 and method 2 in this paper.

2) Modeling Steps: The process of predicting wind-power output are as follows.

Method 1:

a) The wind-power-related data are treated as nonstationary time series to be used as training sample to minimize the forecasting error. The training sample is composed by wind speed, wind-power output, and

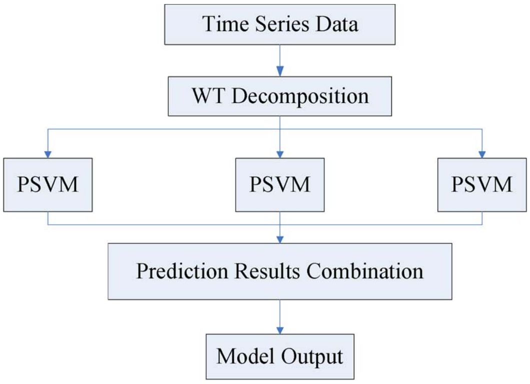

Fig. 3. Flowchart of the predicting process using method 1.

cosine and sine of the wind direction; the training object is to forecast wind-power output in the studied time horizon.

b) The time series are decomposed into a stationary series in different frequency bands through wavelet decomposition.

c) The decomposition results are calculated using smoothing processing and normalization processing, which means that the historical data are changed between [−1, 1].

d) Different piecewise models are constructed using the PSVM model.

e) The predicting results of different-frequency-band models are combined to obtain the final predicting results.

f) Antinormalization processing is chosen after the prediction result is obtained, and then, the MRE and RMSE are calculated.

Fig. 3 shows the process of method 1 for predicting 1-h-ahead wind-power output.

Method 2:

a) According to the method mentioned in the last section, the training sample, training object, testing sample, and testing object are separately developed in MATLAB.

b) Historical data are calculated using smoothing processing and normalization processing, which causes the historical data to be between [−1, 1].

c) Global variables are defined as $P1$ and C, among which $P1$ is the width of kernel function, while C is a coefficient. Both of them are given idiographic data according to different models [12], [20], [21].

d) A kernel-function wavelet and insensitive coefficient are chosen in this process for model training and testing through MATLAB Version 7.5.

e) Antinormalization processing is chosen after obtaining the predicting result. The MRE and RMSE are then calculated.

C. Prediction Results and Uncertainty Analysis

1) Prediction Results and Discussion: The historical data including wind power and wind speed as well as wind direction from the wind farm are utilized in this paper to predict 1-h-ahead wind-power output. The prediction results are compared with the true value, and the errors are illustrated as follows:

$$MRE = \frac{1}{N}\sum_{t=1}^{N}\frac{W_{\text{prediction}} - W_{\text{measurement}}}{W_{\text{sum}}}\times 100\% \quad (17)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(W_{\text{prediction}} - W_{\text{measurement}})^2}{N}} \quad (18)$$

where $W_{\text{prediction}}$ is the prediction value; $W_{\text{measurement}}$ is the measurement value; W_{sum} is the capability of the wind farm which is the rated wind-power summation of each wind-turbine generator, 120 600 kW for the case study; and N is the sample scope.

Fig. 4 shows the time series and wavelet decomposing, and Fig. 5 shows the effect of method 1 applied on the wind farm.

Use the biorthogonal wavelet function to decompose the original wind-power-output series. The wind-power output can be decomposed into a four-class time series. The low-frequency approximate signal a4(k) (trend term) and each high-frequency detail signal di(k) $(i = 1, 2, \ldots, 4)$ should be reconstructed to obtain the new a4(k) and di(k) $(i = 1, 2, \ldots, 4)$. Fig. 4 shows the decomposition and reconstruction process by the wavelet. After PSVM training in every decomposition, the prediction results are combined together to obtain the final prediction results using method 1.

It can be seen from Fig. 5 that the prediction results of the WT–SVM model have better precision than that with the RBF model. The reason why the model setting in this paper is better than the traditional one is that the wavelet has multiresolution characteristics to observe data from a large scope to a small scope. Therefore, it is useful and meaningful to make use of wavelet transformation before setting the SVM model.

For the comparison of different time scales using two forecasting methods, the historical data in three time scales are utilized separately in the forecasting models. Table I presents the forecasting MRE and RMSE which are between historical value and forecasting value using two proposed models as well as the RBF SVM comparison model in the wind farm in Texas. The training data samples are during the time scales which are 1, 2, and 3 h before the forecasting time moment.

Comparing methods using values in Table I, it can be seen that method 1 has more accuracy than method 2 and the RBF SVM model in all testing time scales. Prediction method 2 does not produce satisfactory results. Method 1 has a better accuracy and faster calculating speed. This is because, after the WT transformation, the original unsteady and nonlinear data are changed into certain components which have fixed frequency and periodicity. For the SVM algorithm, if all the units are linear, it cannot easily become computationally infeasible for both polynomial features of higher order and higher dimensionality.

Among the WT–SVM models with two methods and traditional RBF SVM models, the model in method 1 is the best option.

2) Uncertainty Analysis: To analyze market risk related to wind-power prediction, the probability prediction based on the

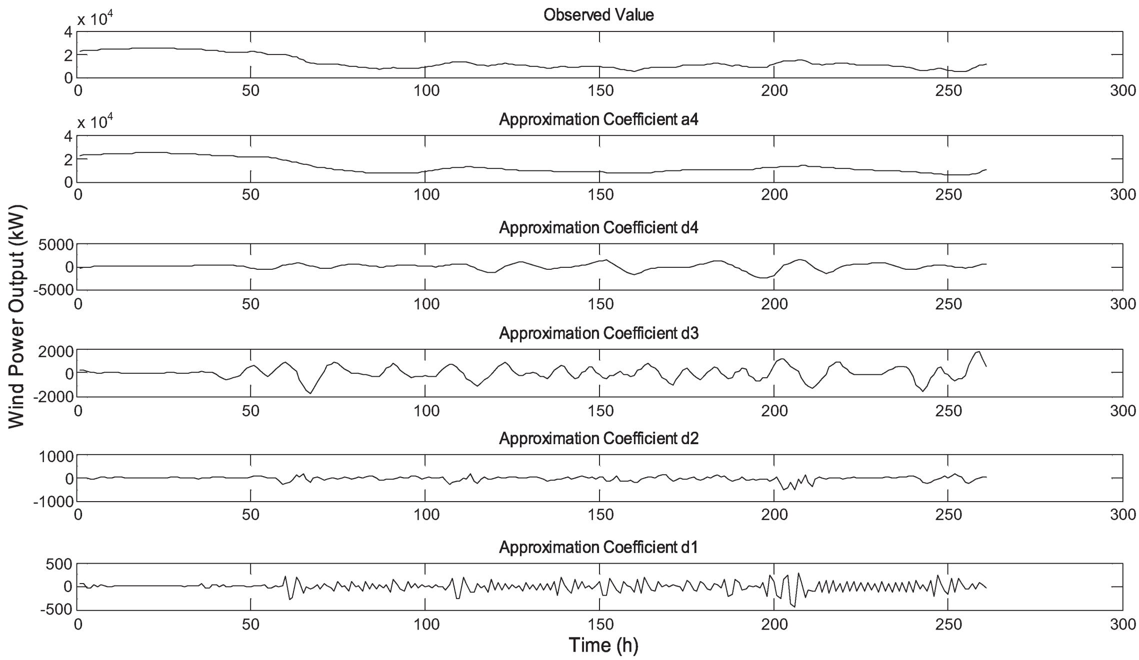

Fig. 4. Time series and wavelet-decomposing result.

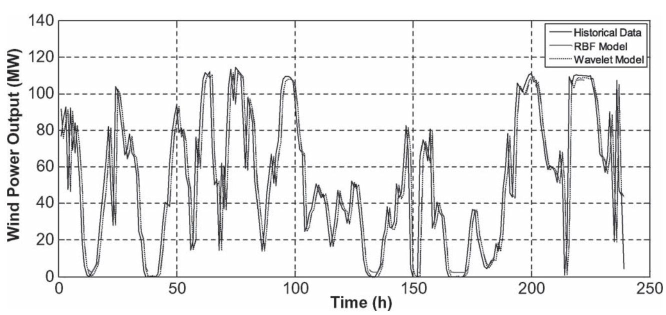

Fig. 5. One-hour-ahead prediction results of method 1.

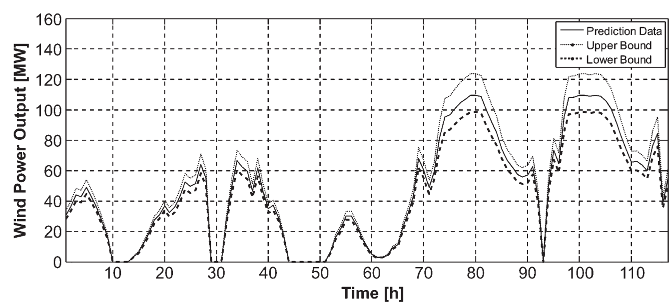

Fig. 6. Uncertainty-analysis results (90% confidence degree).

TABLE I
PREDICTION ERRORS IN THREE TIME SCALES USING METHOD 1, METHOD 2, AND THE RBF SVM MODEL

Time Scale	1 hour		2 hours		3 hours	
	MRE	RMSE	MRE	RMSE	MRE	RMSE
Method 1	7.97	11.52	4.08	6.22	4.76	7.02
Method 2	10.55	16.38	10.44	16.48	10.57	16.63
RBF SVM	10.50	16.19	10.42	16.28	10.56	16.46

statistical characteristics of prediction errors to estimate the uncertainties of wind power is introduced in this paper. It can help the wind-farm owner in the decision-making process in marketing participation. The steps are described as follows.

1) The distribution between wind-power output and prediction error is obtained based upon the difference between the hour-ahead prediction value and historical data. According to the wind-power output, the data samples are divided into four groups between the maximum value (115.76 MW) and the minimum value (0 MW) to set up the prediction-error distribution in each interval. The four data sets are (0, 30), (30, 60), (60, 90), and (90, 120).
2) The prediction-error distribution of wind power is analyzed in each wind-power interval. The data from April 1–20, 2008, are taken as the sample period. After model analysis, the data between April 26 and April 30, 2011, are used to illustrate the proposed approach. Using the confidence-interval errors of the group which the data belong to, the prediction data can be transferred to an upper value and a lower value. After all the prediction data are generated, the upper bound and lower bound have been formed to predict possible boundaries of wind-generation output. After uncertainty analysis, the confidence intervals of prediction wind power with 90% confidence degree are shown in Fig. 6.

VI. CONCLUSION

An algorithm for short-term wind-power prediction has been proposed in this paper. Its merits have been evaluated by historical data. The main content and conclusions are shown as follows.

1) The WT–SVM model has been set up according to the characteristics of wind turbines and the principles of WT (method 1). The method 2 model has been based on the characteristics of wind turbines and the replacement of RBF kernel function for wind-power prediction.

2) The case studies have shown that the WT–SVM models (method 1) outperform the RBF SVM (method 2).
3) The errors of prediction results have been evaluated based upon the output levels of the wind farm. The concept of confidence interval in this paper reflects a potential risk factor in prediction, which supplies the precondition for the reliability study.

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