Short-term Wind Speed and Output Power Forecasting Based on WT and LSSVM

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***Abstract*—Wind speed and output power forecasting is very important to the utilization of wind energy. In order to improve the forecast precision, a forecasting method based on wavelet transform (WT) and least square support vector machine (LSSVM) is proposed in this paper. The wind speed time series was decomposed into different frequency components. The different LSSVM models to forecast the high frequency and low frequency are built up. These forecasting results of the different frequency bands are combined to obtain the final forecasting results. According to the power characteristics, unit efficiency and the operate condition of the generators, the short-term output power forecasting on the wind farm can be obtained.**

Keywords-short-term forecasting; wavelet transform (WT); least square support vector machine (LSSVM); different frequency; wind power

I. INTRODUCTION

Wind energy is considered one of the most rapidly growing energy resources all over the world and become the rapid development of the new energy. It is expected that about 12% of the total world electricity demands to be supplied from wind energy resources by 2020[1]. Recently, the capacity of stand-alone generating units and the large-scale wind farm have been increased highly. As the development of technology, the cost of the new energy resources has already approached the conventional energy. The main method of exploitation and utilization the wind energy is the large-scale power generation connected with grid at present. Wind speed and power prediction is an essential issue for: wind farms maintenance, optimal power flow between power network and wind farms, electricity marketing bidding, power system scheduling, energy reserves, storages planning and scheduling [2].

Wind power as an intermittent energy has strong randomness and difficult to be controlled, usually, the fluctuation range of speed and the output power is very large. Because of these reasons, it is difficult to control the voltage, reactive power and peak adjusting. At present, a number of different approaches have been applied to forecast wind speed and the power produced by wind farms. Such as: Physical method[3], it uses physical considerations to predict the future speed and direction of wind, so the input variables will be the physical or meteorology information, such as description of orography, roughness, obstacles, meteo and so on. Statistical method [4], it has a high precision about short-term wind speed forecast. But, the precision of prediction for long term will be decreased obviously. Spatial correlation model [5], it takes the spatial relationship of different sites' wind speed into account. The wind speed time series of the predicted points and its neighboring sites are employed to predict the wind speed. This method is very difficult in using because the measurement of many spatial correlated sites' wind speed values and timely transmission are all needed. Kalman filter [3], this method needs to know the statistical features of the noise, in fact, estimate the statistical features of the noise is a difficulty in the method. Time series method [6], one of the advantages of this method is that the less information are needed in constructing model, and it is very convenient to computing. Artificial neural network (ANN) [7] is one of the most widely used models in the last decade. But it is difficult to determine the reasonable network frame. It also has some intrinsic defects such as, slow study speed, local the minimum point in some areas and so on. Fuzzy logic method [8], the ability of forecast about fuzzy logic method is so weak and the fuzzy theory is still imperfect. The forecast ability of wind speed above mentioned methods are not very excellent and the mean absolute percentage error (MAPE) usually located from 25% to 40%.

Considering the intrinsic characteristics of wind speed, a forecasting method based on wavelet transform (WT) and least square support vector machine (LSSVM) is proposed in this paper. Firstly, the wind speed signal was decomposed into several different frequency components. Secondly, LSSVM is used to construct the high frequency and low frequency forecasting models. The last, forecasting results of the different frequency bands are combined to obtain the final forecasting results. Considering the power characteristics, unit efficiency, operate condition of the device, the output power of the wind farm can be obtained.

II. THEORY OF THE MODEL

A. Wavelet Transform

Wavelet transform can be expressed as a basic wavelet or mother wavelet $\psi(t)$ through stretching factor a and translation factor b generating a function race $\{\psi_{a,b}(t)\}$ [9].

$$\psi_{a,b}(t) = a^{-1/2}\psi\left(\frac{t-b}{a}\right), \qquad a > 0, b \in R \tag{1}$$

The wavelet transform of the signal can be defined as:

$$WT_x(a,b) = a^{-1/2}\int_{+\infty}^{-\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)dt \tag{2}$$

In Eq. (2), $\psi^*(t)$ is the complex conjugate function of the $\psi(t)$. Because of the time series is an ordered set of discrete data, so discrete wavelet transform (DWT) can be used to decomposition and reconstruction of the time series. In practice,

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Mallat algorithm [10] is the best method, it can be applied to discrete dyadic wavelet transform algorithm. Figure 1 shows the decomposition process.

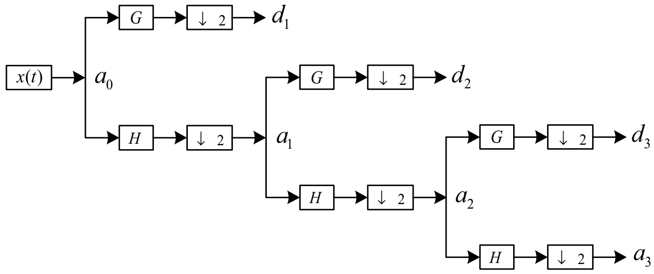

Fig. 1 Wavelet decomposition and reconstruction

If *x(t)*: *{x(1), x(2) …}* represents the wind speed time series, through wavelet multi-scale decomposition, approximation signal a_j and detail signal d_i $(i = 1,2\ldots, j)$ can be obtained, then:

$$x(t) = a_j + \sum_{i=1}^{j} d_i \tag{3}$$

B. Least Squares Support Vector Machines

Support vector machines (SVM) for classification and nonlinear function estimation, as introduced by Vapnik [11-12] and further investigated by many others, is an important methodology in the area of neural networks and nonlinear modeling. A modified version of SVM classifier, Least Squares SVM (LSSVM) classifier [13-14], was proposed by Suykens and Vandewalle (1999). A two-norm was taken with equality instead of inequality constraints so as to obtain a linear set of equations instead of a quadratic programming problem in the dual space. The formulation of LSSVM is introduced by reference [13-14].

III. MODELING PROCESS

Wind speed is a kind of non-stationary time series, in order to improve the forecast precision, the forecast method based on WT and LSSVM is proposed in this paper. Through wavelet decomposition, wind speed can be decomposed in to a stationary time series in different frequency bands. The different forecasting models are constructed using the LSSVM. The forecasting results of the different frequency bands models are combined to obtain the final forecasting results. Figure 2 shows the detail process of the modeling.

IV. SHORT-TERM WIND SPEED FORECASTING

A. Data

Hexi Corridor in northwest of China, stores a lot of wind energy. The Development and Reform Commission in China has been started to construct a typical base which would be produce 10 million kilowatts wind energy per year in Jiuquan. Until 2010, the installed capacity of the wind power base will be reach to 5 million kilowatts, and until 2015 the installed capacity will reach or beyond to 12 million kilowatts. So, it is very significant to forecast accurately the wind speed and power of Jiuquan wind farm. In short-term wind speed forecasting, the data used in the research were collected at a large wind farm in Jiuquan. The data contains totally 151 groups and each group stands for the daily average wind speed (1th January, 2006 to April 30th, 2006). The 120 groups are considered as the training samples, and the other 31 groups (1th May, 2006 to 31th May, 2006) are considered as the verification samples.

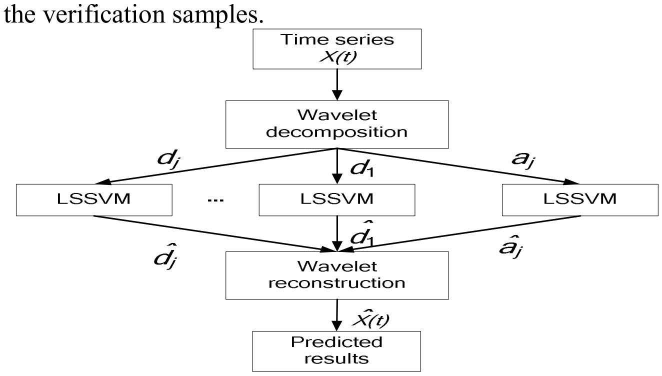

Fig. 2 Prediction modeling process based on WT and LSSVM

B. Decomposed the Time Series Based on WT

Use the *db3* wavelet function to decompose the original wind speed time series. The original wind speed time series can be decomposed into three classes' time series. The low frequency approximate signal $a_3(k)$ (trend term) and each high frequency detail signal $d_i(k)$ should be reconstructed. So, the new $a_3(k)$ and $d_i(k)$ $(i= 1,2, \ldots 3)$ can be obtained. Figure 3 shows the decomposition and reconstruction process by the wavelet.

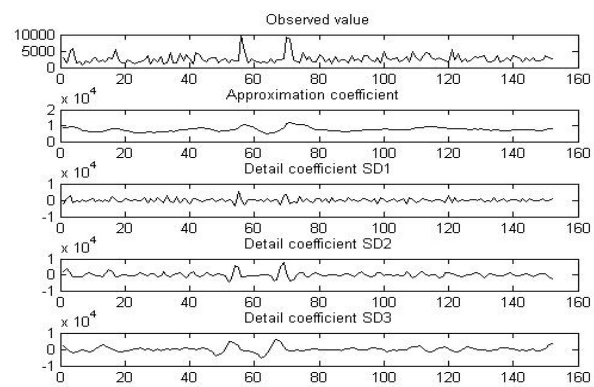

Fig. 3 Time series and its wavelet decomposing

C. Predicted Results of the Model

After wavelet decomposing, according to the characteristic of each frequency band, different LSSVM kernel functions and kernel parameters should be selected in order to construct the models. MATLAB7.0 software is used as a simulation tool to complete the simulation experiment. The high frequency bands are modeled by RBF kernel function. After grid search and cross validate, the parameters of the RBF kernel function can be obtained, where $\sigma=0.045$, $\gamma=125$. The low frequency band is modeled by polynomial kernel, where the parameter $d = 3$. The forecasted results of each frequency band can be displayed in Figure 4, 5, 6. Figure 7 shows the final forecasting results.

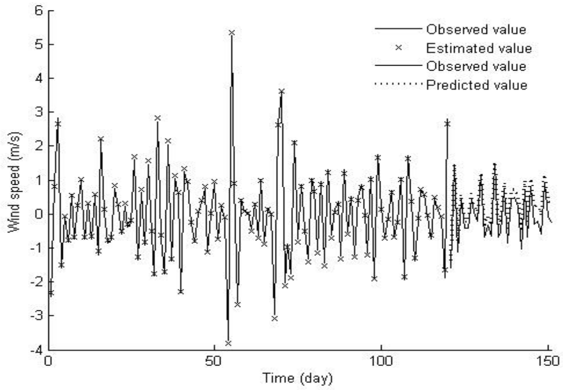

Fig. 4 WT-LSSVM modeling and forecasting results (Detail coefficient SD1)

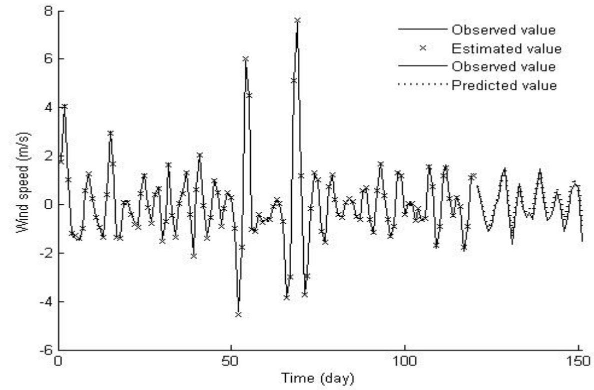

Fig. 5 WT-LSSVM modeling and forecasting results (Detail coefficient SD2)

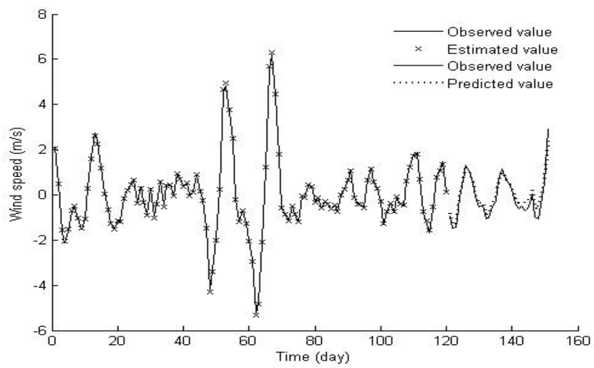

Fig. 6 WT-LSSVM modeling and forecasting results (Detail coefficient SD3)

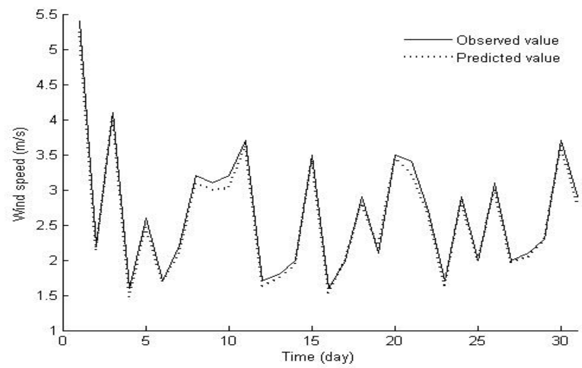

Fig. 7 Final forecasting results based on WT and LSSVM

D. Error Analysis

It is very significant to select the reasonable error analyze methods to judge the results. In this paper, the mean absolute percentage error (MAPE) and root-mean-squares of errors (RMSE) had been selected as the evaluation indicators.

In order to demonstrate the effectiveness of the model, another hybrid model using WT and recursive least square (RLS). And LSSVM model has been built to forecast the short-term wind speed.

Figure 8 shows the forecasting errors based on WT and LSSVM.

The comparisons of the MAPE and RMSE for the proposed three models (LSSVM model, WT-LSSVM model and WT- RLS model) are shown in Table I.

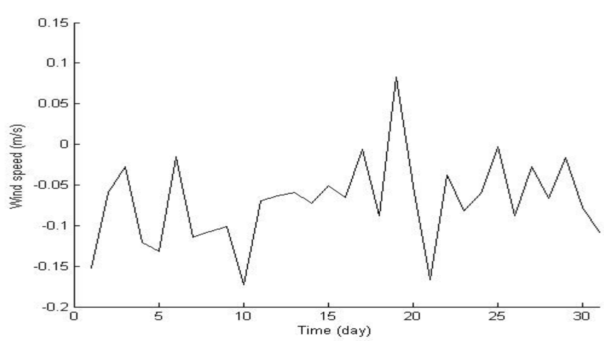

Fig. 8 Final forecasting errors based on WT and LSSVM

TABLE I. THE COMPARISON OF PREDICTION ERRORS

Model	*MAPE (%)*	*RMSE*
LSSVM	5.731	0.214
WT-LSSVM	2.933	0.096
WT-RLS	11.37	0.445

The scope of the MAPE for three models changes from 2.933% to 11.37% and the RMSE changes from 0.096 to 0.445. According to the forecasted errors, it is clearly see that WT-LSSVM model is the optimal model because of the lowest errors, not only the MAPE (2.933%) but also the RMSE (0.096), secondly, the LSSVM model, the WT-RLS model is not the ideal model in this paper, because of the poor forecasted errors. The simulation experiment demonstrates WT-LSSVM model has the ability in improving the predict precision towards the non-stationary time series.

V. OUTPUT POWER FORECASTING

Many factors can influence the output power of wind farm, the main factors, such as wind speed, wind direction, air pressure, temperature and humidity and so on. These factors can be described by data series, then, the data series and the forecasting wind speed can compose the basic input data space of the artificial neural network (ANN). Thus, the output of the ANN will be the output power of the every unit. Considering the unit efficiency, operate condition of the device and the wind farm losses, the forecast value of the output power of the wind farm can be obtained. Figure 9 shows the detail structure of the output power forecasting system.

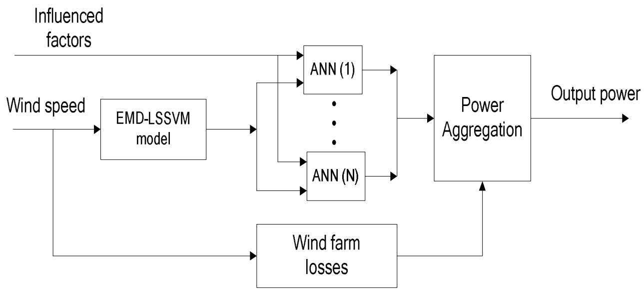

Fig. 9 Structure of the power forecasting system

In order to enhance the learning ability and the forecast precision of the ANN, the data should be normalized.

A. Wind Speed Normalization

$$v_n = \frac{v_t - v_{\min}}{v_{\max} - v_{\min}} \tag{4}$$

Where, v_n represents the normalized value of the wind speed. v_t represents the true value of the wind speed. v_{max} and v_{min} represent the maximum and minimum of the predicted wind speed.

B. Wind Direction Normalization

A circle can be divided into 360 degrees and the north direction is defined as the 0 degree. In order to distinguish all of the directions, one value of sine and cosine can be selected to represent the wind direction.

C. Air Pressure, Temperature, Humidity Normalization

The normalization of the air pressure, temperature and humidity is similar with the wind speed normalization. The maximum and minimum of these factors can be obtained from meteorological observation.

Figure 10 shows the basic structure of artificial neural network (ANN) in Figure 9.

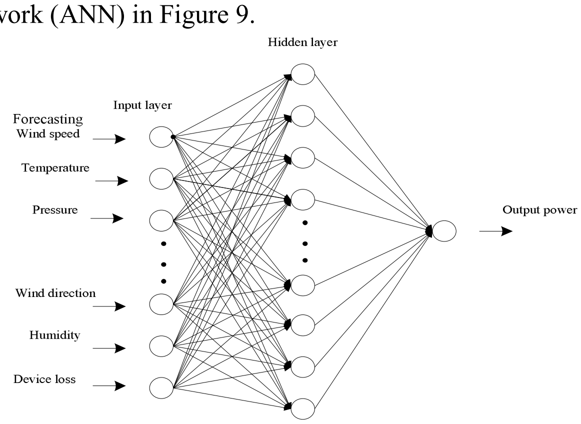

Fig. 10 Structure of the ANN

According to the forecasting models the wind speed forecasting values can be obtained. Considering the influencing factors, such as the local humidity, temperature, air pressure and the losses of the generator, the power characteristic models of the units can be constructed from first unit to *n*th unit using ANN. The short-term output power forecasting values of the wind farm can be obtained considering the losses of the wind farm.

VI. CONCLUSIONS

In this paper, The LSSVM model, WT-LSSVM model and WT-RLS models for forecasting wind power were built up. The short-term wind speed forecasting of the wind farm had been predicted by each of the models. The error analysis shows that WT-LSSVM model is the optimal model for short-term wind speed forecasting, due to the lowest MAPE (2.933%) and the RMSE (0.096). The simulation experiment shows that the hybrid model (WT-LSSVM) is an effective method towards the non-stationary time series forecasting. Utilizing the predicted values of the wind speed and considering the influencing factors of the wind farm the output power forecasting values of the wind farm can be obtained.

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