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A Hybrid Method based on Discrete Wavelets and Least Squares Support Vector Machines for Short-Term Wind Speed Forecasting

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Abstract

Exponential increase in power consumption leads to the global attention towards pollution free and renewable energy resources. For instance, wind turbines to produce electrical energy thru wind energy. For wind energy domain, wind speed forecasting is of great significance for wind farms design and planning, its operational control, and wind power prediction etc. Due to the impact of several environmental factors, time series of wind speed exhibits high fluctuations, less correlation and stochastic volatility. In this paper, to enhance the wind speed forecasting, a two stage method that relies on discrete wavelet (a trou's wavelet transform) and least squares support vector machines (LS-SVM) is developed. In the first stage of the method, the time series of wind speed is decomposed into wavelet components by employing a trou's wavelet. In the later stage, an LS-SVM is trained with the obtained wavelet components as inputs and h-samples ahead data as the target data (output). To identify the optimal initialization for LS-SVM, a grid search is conducted for a wide range of values. The nonlinear mapping obtained with the training data set and optimal initialization is employed to perform forecasting. The forecasting results obtained with the proposed method show better performance as compared to the existing methods.

Keywords: Wind speed forecasting, atrous Wavelet, LSSVM

Introduction.

Exponential increase in energy consumption is leading towards rapid depletion of fossil fuel resources globally [1]. Due to this imminent shortage of fossil fuel resources, the power industry is exploring towards the renewable energy resources such as wind, tidal and solar energy etc. as a prime source for generation of energy [1, 9]. Owing to their capability of pollution free energy generation, renewable energy resources got more attention in recent past. For instance, wind turbines can generate electricity (green energy) with wind as the source. In China alone, the wind farms growth rate was reported as 114% in 2009 with the total wind generation capacity of 25805. 3 MW [9]. However, stable production of electricity with wind turbines is an arduous task due to the uncertainty and intermittency of wind speed. Further, the irregularities in wind speed cause damage to the cabin and pitch system of wind turbines. Thus, accurate forecasting of wind speed is required to know prior about the irregularities in wind speed and leads to better wind farms planning and design.

In the recent past, considerable research has been focused on wind speed forecasting. The forecasting models proposed till date can be categorized as three kinds: physical models, statistical models, and knowledge based models. Each model has its own merits and demerits. Of these three models, statistical models like Autoregressive integrated moving average (ARIMA) [2, 8] and knowledge based methods like artificial neural networks (ANN) [3, 6] are successful up to an extent. Further, hybrid methods rely on empirical mode of decomposition (EMD) to decompose the signal into intrinsic mode functions (IMFs) then aggregate the forecasting of each IMF to get final forecast result are developed [4, 8-10]. Nevertheless, due to the irregularity and non-stationary characteristics of wind speed data, an accurate forecasting method is still elusive.

From the literature [1-12], it is evident that wind speed forecasting is effective in two scenarios 1) Improving the forecasting performance of principal method with aid of other method (s)/technique (s), for example particle swarm optimization for best initialization of SVM and 2) Divide and conquer rule i. e. decompose the signal into independent components and then perform forecasting, for example EMD. In this study, we would like to explore the second scenario with discrete wavelets. In time series decomposing fields, discrete wavelets are generally recognized. In this paper, to build a hybrid method, we chose discrete wavelet i. e. a trous wavelet [5] to decompose the time series into wavelet components and a machine learning technique i. e. least squares support vector machines (LS-SVM) to forecast the wavelet components independently. Finally, the forecasted components are aggregated to attain the final forecast of wind speed. The proposed method is assessed by performing hourly forecasting on the wind speed time series acquired for every ten minutes from a wind farm at Laurel.

This paper is organized as follows: Section 2 states the methods in brief and framework of this study; Section 3 demonstrates the wind speed data used for forecasting and obtained performance analysis. Section IV concludes the paper.

Methods and Materials.

In this section, first a brief description of all methods is provided followed by the frame work of the proposed hybrid method.

Haar a Tours Wavelet.

A trous wavelet is computed in a sequential way to decompose the signal into individual wavelet components. Thereby, online processing of time series decomposition is also possible with the wavelet [5].

The decomposition with a trous wavelet can be given as:

$$c_{0,n} = y_n$$
$$c_{j+1,n} = \frac{1}{2}\left(c_{j,n-2^j} + c_{j,n}\right)$$
$$W_{j+1,n} = c_{j,n} - c_{j+1,n}$$

Computing the decomposition up level J, we get J+1 components representing the signal: W_1 ... W_j, the wavelet components, and c_j the smoothed signal and y_n is the signal at *n* th sample.

Least Squares Support Vector Machines.

LS-SVM address the regression problem by transforming the data with non-linear relationship to a high-dimensional space [6]. The function will be estimated based on the training data provided:

$$\{\boldsymbol{s}_i, y_i\}_{i=1}^{N}$$

where

$\boldsymbol{s}_i$ is the n-dimensional input vector and y_i is the corresponding target. Provided is the brief formulation for LS-SVM, for more information see [6]

The regression model for LS-SVM can be given as:

$$y = \omega^T \psi(\boldsymbol{s}) + b$$

where ω represents the weight vector and b represents bias.

The function estimation optimization problem can be defined as:

$$\min_{\omega,b} J(\omega,\psi) = \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{N} e_i^2$$

subject to the constraints $y_i = \omega^T\psi(\boldsymbol{s}_i) + b + e_i; i = 1,2,\dots N$ with C as regularization constant and e as estimation error.

The regression model with Radial bias function (RBF) as kernel can be obtained as:

$$\hat{y}_{t+T} = \sum_{i=1}^{N} \alpha_i K(\boldsymbol{s}_i, \boldsymbol{s}_t) + b; t = N+1,\dots,l$$

where K (.,.) represents the RBF Kernel and α represents the Lagrangian multipliers

Framework of Proposed Hybrid Method.

The hybrid method is designed to exploit the relative advantage by combining both the above explained methods. The procedure proposed in this paper for forecasting the wind speed consists of three phases, as shown in Fig. 1. In the first phase, named as decomposition, time series of wind speed will decompose into several wavelet components to separate the highly non-stationary nature from the time series [5]. In the second phase, named as individual wavelet components forecasting. LS-SVM will be employed individually to all wavelet components and attain the individual multistep forecasting. In the final phase, named as aggregation, all individual wavelet components forecasting will be aggregated to attain the final forecasting for wind speed.

Results and Discussions

In this section, first wind speed data used for prediction is described, followed by the performance indices employed and performance analysis are discussed.

Wind Speed data.

Wind speed data collected from the farms at Laurel, Nebraska, USA from a 20-meter anemometer is used for forecasting analysis in this paper. This data consists of average wind speed and the direction of the wind for the period 04/01/2005-05/01/2005. The data was originally made available by Wind Powering America, a DOE Office of Energy Efficiency & Renewable Energy (EERE) program. The data was acquired for every 10 mins in this data set, named as *Mins data* throughout this paper. For illustration, the Laurel wind speed profile (*Mins data*) is shown in Fig. 2.

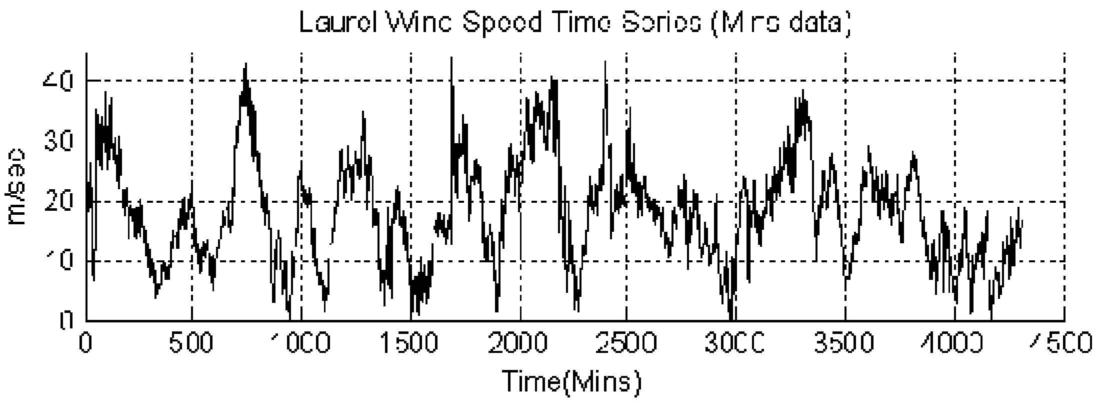


Figure 1 Laurel Wind Speed Time Series

Performance Indices.

In this paper, six-step ahead prediction was performed on *Mins data* to attain one hour ahead prediction. To highlight the advantages of the proposed hybrid approach, comparative analysis was performed with the other existing methods.

To evaluate the forecasting performance of all methods, the indices mean absolute error (MAE) and mean absolute percent error (MAPE) are employed. The indices are defined as follows:

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |s(t) - \hat{s}\ (t)|$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T} \frac{|s(t) - \hat{s}\ (t)|}{s\ (t)}\ X\ 100\ \%$$

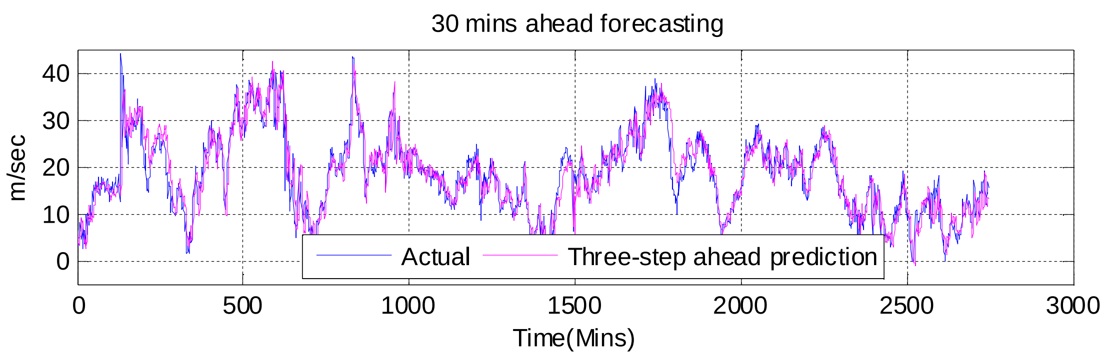
where *s (t)* represents the observation value at instant *t* and $\hat{s}\ (t)$ is the forecasted value at *t*.

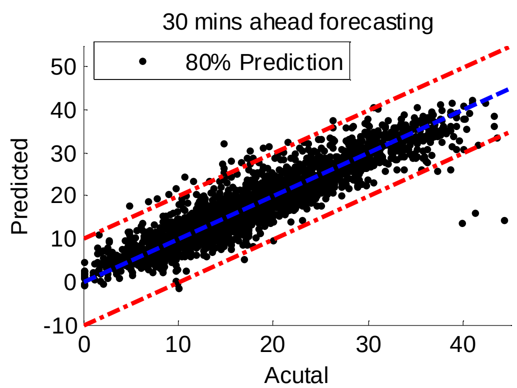
Parameter selection.

Wind speed time series was decomposed into seven individual components by a trous wavelet. By trail-and-error method, the parameters of LS-SVM are identified as C = 100, $\sigma^2 = 50$, and N = 1000.

Performance Analysis.

To analyze the performance of all methods for hourly forecasting of wind speed data, three-step, six-step and twelve-step ahead prediction of *Mins data* are considered. The horizon of six and twelve samples were selected to perform one and two hour ahead prediction respectively with *Mins data*. In this analysis results of the proposed hybrid method was compared with other methods 1) standard LS-SVM and 2) EMD-LS-SVM. For illustration, the performance of proposed hybrid method is shown in Fig. 4.





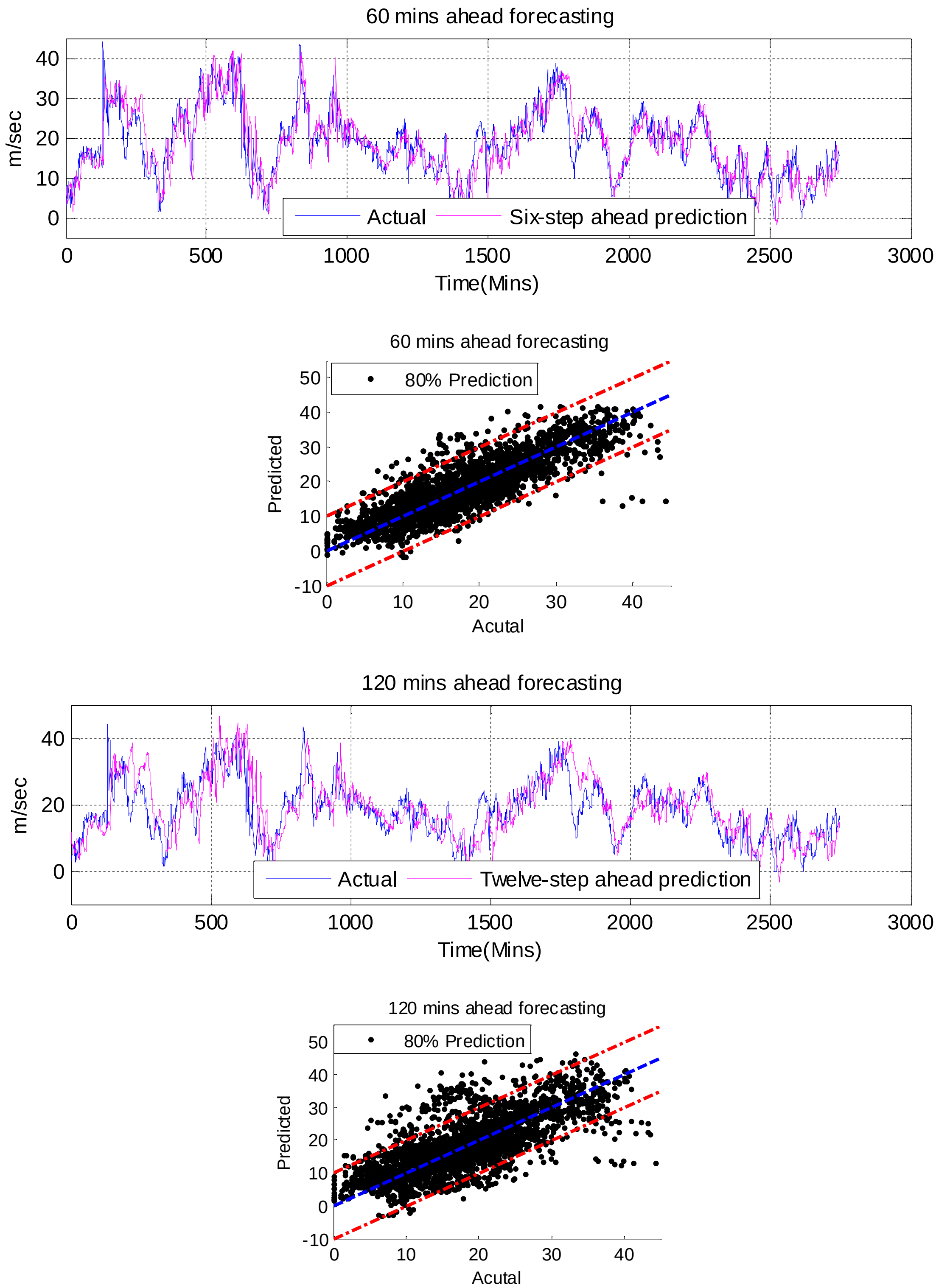


Figure 4 Performance analysis of proposed hybrid method (left column prediction traces around actual trace and in right column scatter plots with 80% accuracy lines (red dotted lines))

The statistical results obtained for other approaches and the proposed hybrid method are tabulated in Table. 1. With the proposed hybrid method MAE of 0. 46 is obtained for six-step ahead forecasting of *Mins data*, whereas with standard LS-SVM and EMD-LSSVM 0. 45 and 0. 51 MAE was obtained respectively. Furthermore, single-step prediction was performed with the similar procedure as multi-step prediction. For single-step prediction, the proposed hybrid method yields MAE of 0. 018 whereas standard LS-SVM and EMD-LSSVM yield MAE of 0. 026 and 0. 032 respectively.

Table 1 Statistical Analysis

Methods	**MAE**			**MAPE**		
	Three-step	Six-step	Twelve-step	Three-step	Six-step	Twelve step
LS-SVM [6]	0. 032	0. 51	0. 68	7. 9	35. 24	52. 45
EMD-LSSVM [4]	0. 026	0. 45	0. 58	7. 4	32. 64	42. 35
Proposed Hybrid Method	0. 018	0. 41	0. 51	5. 1	26. 65	35. 24

Conclusions.

In this paper, a hybrid approach for wind speed prediction is proposed. The developed methods is a combination of discrete wavelets and LS-SVM. In the first stage, the wind speed data is decomposed into independent wavelet components with a trous wavelet. In the second stage, individual wavelet components are forecasted with LS-SVM independently. With the proposed hybrid method, six-step ahead prediction was performed on *Mins data* from Laurel wind farm. The proposed hybrid approach yields MAE of 0. 51 for twelve samples ahead forecasting whereas the existing methods LS-SVM and EMD-LSSVM yield 0. 68 and 0. 58 respectively. This show that, the proposed hybrid method provides better forecasting performance as compared to the existing methods.

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