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Improving Forecast Accuracy of Wind Speed Using Wavelet Transform and Neural Networks

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Abstract – In this paper a new hybrid forecast method composed of wavelet transform and neural network is proposed to forecast the wind speed more accurately. In the field of wind energy research, accurate forecast of wind speed is a challenging task. This will influence the power system scheduling and the dynamic control of wind turbine. The wind data used here is measured at 15 minute time intervals. The performance is evaluated based on the metrics, namely, mean square error, mean absolute error, sum squared error of the proposed model and compared with the back propagation model. Simulation studies are carried out and it is reported that the proposed model outperforms the compared model based on the metrics used and conclusions were drawn appropriately.

Keywords: Wind speed, Forecast, Wavelet transform, Neural networks, Back propagation

1. Introduction

In the recent years, wind energy is gaining more importance among the researchers worldwide. Wind energy is intermittent in nature and hence the power system scheduling and dynamic control of wind turbine requires an estimate of wind energy. Wind speed is basically a time series data measured at regular intervals of time. Based on the time duration of wind speed forecast, it has been classified into short-term, medium-term and long-term forecasting. Short-term forecasting is an extremely important research field in the energy sector as its time-step varies from few seconds to hours [1], where the system operators have to handle the varying wind speed and the corresponding power generated in an optimal way.

In the thorough literature made, several methods to forecast the wind speed [2] have been reported which are broadly grouped as physical and statistical methods. The physical methods such as Numerical Weather Forecast (NWF) and mesoscale models provide satisfactory results for long-term forecasts [3]. Statistical methods such as autoregressive (AR) models, autoregressive integrated moving average (ARIMA) which makes good relation with the observed data and used for short-term and medium-term forecasting.

Recently, some new methods based on neural networks have been reported by various researchers in this field. Moreover, hybrid algorithms like neuro-fuzzy, statistical-neural based approaches are also developed by various researchers [4-8]. Neural networks (NN) can learn from past time based data, recognize the relationships in it through hidden patterns and utilize that to forecast the future data values. Hence, NN will suit best for wind speed forecast [9]. Among the various neural networks proposed for this application back propagation network has been widely used.

Different network structures, learning models, inputs leads to different forecast accuracies. To the best of author's knowledge, there is no such benchmarked problem on this domain. Hence, we conclude that the results can be compared on various metrics for the same input data with different methodologies.

This paper presents a hybrid method combining wavelet transform (WT) and NN for the wind speed forecast. The proposed method is compared with back propagation network (BPN) with metrics and demonstrated the improvement achieved along with the computational time. The rest of the paper is organized as follows. Section 2 describes the proposed approach of wind speed forecast. Performance metrics are discussed in Section 3. Section 4 presents the results and validation. The conclusions were drawn in the last section.

2. Proposed Methodology

The proposed method Wavelet transform followed by neural network (WTNN) to forecast wind speed is based on the combination of WT and NN. The WT is used to decompose the time series data into different consecutive data series. Then these data's are given to the NN to forecast the future values.

2.1 Wavelet transform

Wavelet transform can be mainly classified into continuous wavelet transform (CWT) and discrete wavelet transforms (DWT) types. The CWT is obtained by

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continuous scaling and translating the wavelet [10], which is usually referred as mother wavelet in a substantial passion. The CWT *W(a,b)* of a given signal *f(x)* is achieved using the following relation:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(x) \phi\left(\frac{x-b}{a}\right) dx \tag{1}$$

where, the *a* is the scale parameter controls the wavelet spread, *b* determines the central position and *φ(x)* is the mother wavelet. Since the translation of mother wavelet leads to redundant information, one can replace CWT by DWT where scaling and translation can be done by restricted scales and positions on mother wavelets. This scheme is more efficient and accurate and it is defined as:

$$W(m,n) = 2^{-(m/2)} \sum_{t=0}^{T-1} f(t) \phi\left(\frac{t - n.2^m}{2^m}\right) \tag{2}$$

where, T is the length of the signal, t is the discrete time index. m and n are scaling and translation parameters. This DWT drastically reduces the computation time and implementation is easier.

To analyze a signal at different frequencies with different resolutions concept of multiresolution analysis (MRA) can be applied. MRA on a DWT can be achieved through Mallat's algorithm. In this algorithm the given signal is decomposed into *approximations* (low frequency component) and *details* (high frequency component). The approximations hold the general trend of the signal. And the decomposition can be made for multiple levels by successive decompositions of approximations. The decomposition levels will be stopped for which the standard deviation (S.D) of the approximation component is substantially less than the original signal [11]. This is achieved through the empirical relation shown below:

$$\frac{S.D(A_j)}{S.D(x)} < 0.1 \tag{3}$$

Here A_j represents the approximation component at the j^{th} decomposition level and *x* is the input signal.

The wavelet family can be selected based on following parameters [12]

1. Speed of convergence to zero, when time or frequency reaches infinity.
2. Symmetry
3. Number of vanishing moments of the mother wavelet
4. Regularities for smoothness and reconstruction.

Based on the parameters commonly used wavelet families are Daubechies (dbN), Symlet and Coiflet. For our application dbN with order 3 and the level of decomposition of order 3 is chosen which will be appropriate for short-term wind speed forecast. Similar wavelets have been considered by various researchers in the literature for load forecasting, power quality analysis and temperature forecast. The Fig. 1 represents the 3-level decomposition of a signal and its reconstruction [13].

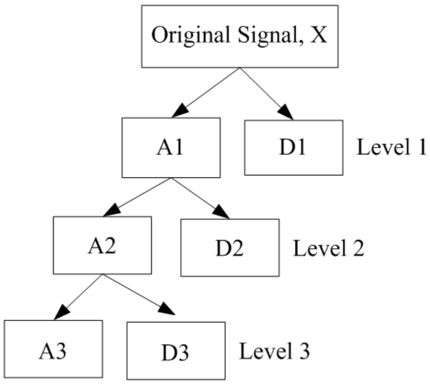

Fig. 1. Multilevel decomposition, A and D represents approximate and detail components respectively (X=A3+D1+D2+D3)

2.2 Multi-layer neural network

Artificial neural network is widely used in time forecasting models due to its characteristics of extreme computational power, massive parallelism, and fault tolerance and it is more efficient through learning without enormous programming [14]. Neural networks not only learn the smooth prediction function but also are trained to enumerate unexpected short term regularities in a time series data. Feed forward back-propagation is one of the most popular techniques in NN. The common topology of the BP network is shown in Fig. 2. The input layer receives the input and propagates to the hidden layer. The hidden layer output signals are used as input signals to the output layer. The output layer gives the overall response of the network.

For a network with *n* input neurons, *m* hidden neurons and one output neuron, the training is described as below:

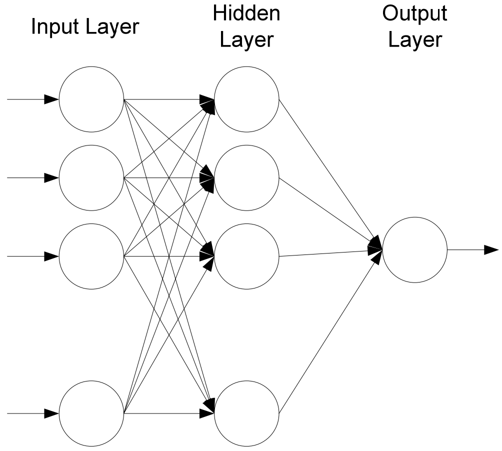

Fig. 2. Topology of back propagation neural network

1. Calculate outputs of all hidden layer nodes
2. Calculate the outputs of all output layer neurons
3. Minimize the error through the iterative training algorithm

The output of the BPN network can be expressed as:

$$Y_j = f\left(\sum_i w_{ij} X_{ij}\right) \tag{4}$$

where, Y_j is the output of node j, $f(.)$ is the transfer function, w_{ij} is the network connection between node j and node i and X_{ij} is the input signal from node i to node j. The determination of number of nodes of the architecture is not completely identified. Different architectures use different nodes and hidden layers. For optimal solution we can choose the number of nodes in trial and error combinations. The combinations include different number of hidden layers, different number of neurons in each layer and different types of transfer functions.

From various evaluations it has been decided to choose the configuration with tangent sigmoid transfer function in the hidden layer and pure linear transfer function at the output layer. On the chosen model, if there are few neurons, the network is not able to model the data well. At the same time, if there were too many neurons, the network may over fit the data. The best results were produced by choosing twelve neurons in the hidden layer.

The NN based forecasting involves two steps, training and learning. During training the historical time instant based data which contains both the inputs and corresponding desired output, is presented to the network. In the learning process, the network maps the input with output by adjusting the weights and biases iteratively until acceptable output is met. This results in slow convergence. To the increase the convergence speed, various methodologies, like Levenberg-Marquardt (LM), gradient descent momentum, scaled conjucate gradient and re-silient back propagation have been identified and it has been concluded that the LM algorithm provides good results [15].

2.3 Formulation of the proposed model

The BP network based on LM algorithm, which is faster in convergence, has its own limitation. There is more possibility of convergence occurs in local minima [16]. This can be avoided if the inputs to the network is pre-processed using the wavelet transform. During WT based decomposition the noises are reduced in the measured time series data. The decomposed data is fed to the NN to forecast the future values which is shown in Fig. 3. The optimal parameter values and the chosen model of the proposed method are listed in Table 1.

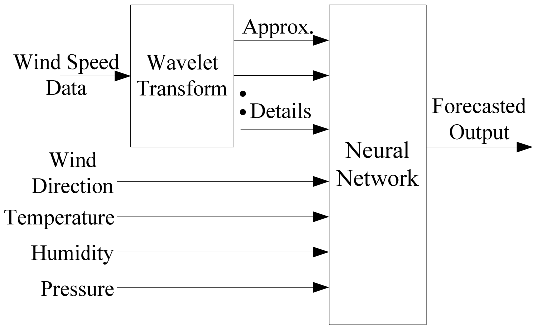

Fig. 3. Proposed Wind Speed Forecast model

Table 1. Optimal configuration chosen for wind speed forecasting

Parameter	Optimal Value/Method
Wavelet function	Daubechies(db)
Wavelet order	3
Wavelet decomposition level	3
Neural network model	Back propagation(BP)
NN input neurons	7
NN hidden neurons	12
NN output neurons	1
NN Training algorithm	Levenberg – Marquart(LM)
NN learning rate	0.9
NN momentum factor	0.95

3 Evaluation Criteria

The proposed WTNN (wavelet transform followed by neural network) approach to forecast the wind speed is evaluated using various criterions. The accuracy is evaluated in comparison with the actual wind speed data. The metrics used are correlation coefficient (R), coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE), mean average error (MAE), mean average percentage error (MAPE) and sum of squared error (SSE) and they are defined as follows:

The R criterion is given by,

$$R = \frac{R_{yt}}{std(y)std(t)} \tag{5}$$

where y and t are forecasted and actual wind speed, R_{yt} is the covariance between y and t, $std(y)$ and $std(t)$ represents the standard deviation of y and t respectively.

The R^2 criterion is given by,

$$R^2 = \left(\frac{R_{yt}}{std(y)std(t)}\right)^2 \tag{6}$$

The MSE criterion is given by,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2 \quad (7)$$

where N is the number of forecasted samples.

The RMSE criterion is given by,

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2} \quad (8)$$

The MAE criterion is given by,

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|t_i - y_i| \quad (9)$$

The MAPE criterion is given by,

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}|t_i - y_i| * 100 \quad (10)$$

The SSE criterion is given by,

$$SSE = \sum_{i=1}^{N}(t_i - y_i)^2 \quad (11)$$

4. Implementation and Testing

The proposed method is tested for the sample data, measured at 15 minute intervals obtained from weather station at University of Waterloo. In addition to the wind speed, the other contributing parameters such as wind direction, humidity, temperature and pressure are aggregated and considered as inputs for the model. The performance of the proposed model based on the various metrics is compared with the BP network without WT for the same parameters. Table 2 presents the values for the criterions used for the BP network with variation in number of hidden neurons and it has been concluded that for 12 hidden neurons network model is able to produce good accuracy as the error criterions are less comparatively. Also for this model learning rate of 0.9 and momentum factor of 0.95 were chosen. The above said methodology is implemented using Matlab R2011b.

Table 2. Performance metrics comparative results for BPN model

N	R^2	RMSE	MAPE	SSE
10	0.8953	0.3806	23.11	43.314
11	0.8405	0.4628	35.52	64.055
12	0.9071	0.3539	26.62	37.461
13	0.8930	0.3795	28.72	43.064
14	0.8798	0.4015	29.92	48.212
15	0.8689	0.4062	30.14	49.456
20	0.8921	0.3816	27.92	43.526

The actual and forecasted results for the BP model are shown in Fig. 4. The figure shows actual wind speed in dashed line and forecasted wind speed in solid line.

The results of the proposed model are shown in Fig. 5 for the selected parameter in BP model and it is processed by db3 wavelet of level 3 decomposition. The same inputs of the BP model are passed to the proposed along with the approximate and detailed coefficients obtained from WT.

Table 3 presents the values of the performance criterions for the proposed network and compared with the 12 hidden neuron based BP model. It is clear from the results that the performance of the proposed model is better than the BP model in terms of accuracy as the error criterions reduces comparatively. The comparison of the results of proposed

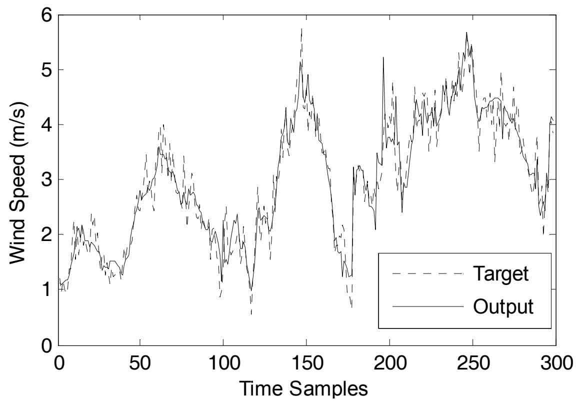

Fig. 4. BPN output

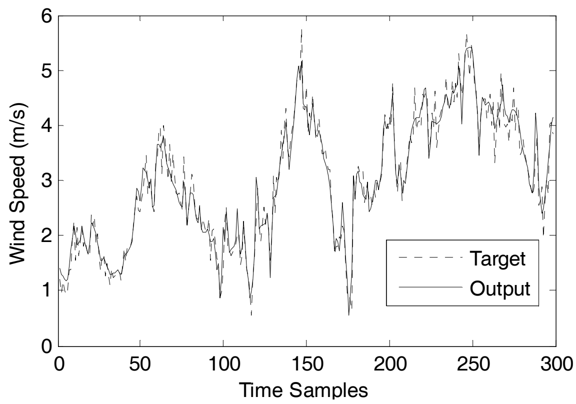

Fig. 5. WTNN output

Table 3. Comparison between proposed WTNN and BPN model based on performance

Metrics	Proposed WTNN	BPN model
R	0.9808	0.9524
R^2	0.9619	0.9071
MSE	0.0515	0.1253
RMSE	0.2269	0.3539
MAE	0.1771	0.2662
MAPE	17.71	26.62
SSE	15.3932	37.4612

model and BP model with the actual wind speed data is shown in Fig. 6.

The performance comparison of both the proposed (WTNN) and BPN model is shown in Fig. 7. The proposed model shows the improvement of 2.84 % and 5.48 % in terms of regression coefficient and coefficient of determination respectively. Also the error criterions measured for the proposed model shows, better reduction when compared with BPN model. The mean square error reduces by 7.38%, RMSE reduces by 12.7% and mean average error reduces by 8.91%. These values prove the effectiveness of the proposed model.

Moreover, the computation time required by the proposed WTNN approach is less than the NN approach with the added advantage of filtering effect in WT. Hence, the proposed WTNN model is easy to implement for short term forecasting of wind speed with improved accuracy.

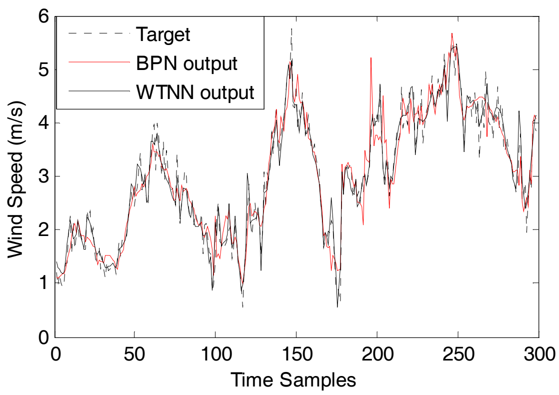

Fig. 6. Comparison output of BPN and WTNN

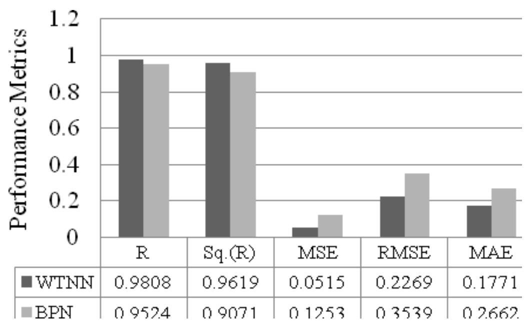

Fig. 7. Performance Comparison of BPN and WTNN

5. Conclusion

A WTNN approach is proposed in combination with wavelet transform and neural network for the wind speed forecasting. The application of WTNN model to the sample data taken outperforms the NN model in all the performance metrics chosen in this paper with less computation time. Hence, the proposed approach improves the forecast accuracy of wind speed and validates the proficiency of the application towards short term wind speed forecasting.

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