

*Research article*

## Wind Speed Forecasting Using Hybrid Wavelet Transform—ARMA Techniques

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**Abstract:** The objective of this paper is to develop a novel wind speed forecasting technique, which produces more accurate prediction. The Wavelet Transform (WT) along with the Auto Regressive Moving Average (ARMA) is chosen to form a hybrid whose combination is expected to give minimum Mean Absolute Prediction Error (MAPE). A simulation study has been conducted by comparing the forecasting results using the Wavelet-ARMA with the ARMA and Artificial Neural Network (ANN)-Ensemble Kalman Filter (EnKF) hybrid technique to verify the effectiveness of the proposed hybrid method. Results of the proposed hybrid show significant improvements in the forecasting error.

**Keywords:** Wind Speed Forecasting; Wavelet Transform; ARMA; MATLAB

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### 1. Introduction

Environmental considerations have led to a strong interest and an increase in the use of various renewable resources for electricity generation. Wind is a clean, renewable resource that may be converted into wind power and has become very popular in recent years. With the increasing popularity and utilization of wind power technology, the cost of the new energy resources has already approached the conventional energy and thus, it has the potential ability to compete with traditional power plants [1].

The main problem with wind is its intermittent nature, which makes the output power of wind farms difficult to control. An effective solution is to predict the future values of wind power

production, for which the most important factor responsible is the local wind speed. If a reliable forecasting of local wind speed/power is performed from a few minutes to several hours ahead, the effective utilization of wind power for generation of electricity can be realized thereby relieving the electric network from stress associated with uncertainty. With increasing wind penetration more robust and innovative approaches are required to decrease the forecasting error and improve the generation output estimation model.

This paper focuses on the improvement of the existing forecasting methods and reduction of the forecasting error. The Wavelet Transform (WT) along with ARMA model is proposed to form a hybrid method for better forecasting. Reference [18] shows that this combination has been successful for predicting water demand of Dalian City. It combines WT, ARMA and Least Squares method and comes out with the most accurate prediction of that area. This hybrid however, has not been tried much in the field of wind forecasting yet. Reference [19] shows the potential of this hybrid but this paper fails to justify it for a long duration of time and is very limited on experimental observations. Reference [17] shows the capability of the hybrid method by evaluating few case studies and proposing recommendation for further research. It demonstrates how pre filtering can enhance the performance and efficiency of computation. This paper has investigated how a hybrid method using WT and ARMA can be used towards wind speed forecasting.

The Wavelet analysis is a well-established technique used in various application areas for forecasting. It analyses the signal capturing both time and frequency resolutions. It also overcomes the drawbacks of Short-Time Fourier Transform (STFT) as it is a windowing technique that uses variable sized regions [17]. The second techniques used for the proposed hybrid is the ARMA model, which is a time series model. ARMA models are widely used because of their simplicity, cost-effectiveness and accuracy for timely forecasting. It can be used to solve the problems in the fields of mathematics, finance and engineering industry that deal with a large amount of observed data from history.

The proposed hybrid model (WT-ARMA) is designed to work as follows. The WT decomposes highly nonlinear wind speed time series into several approximate stationary time series. The decomposed time series is fed to different ARMA models established respectively, and then the outputs of each ARMA models are combined to get the forecasting results. In order to see the effectiveness of the proposed approach, actual wind speed data from a weather station is used to test the forecasting model. The results confirm that wavelet analysis is a useful tool for wind speed forecasting and when combined along with the ARMA model brings significant improvement to reduce forecasting errors.

## 2. Literature Review

Wind speed forecasting is a very involved task and generally the forecast method developed for one site or wind farm does not suit the other due to variety of reasons like change in terrain, and different wind speed patterns just to name a few. A lot of research is being done in order to decrease the forecasting error but there is still scope to develop methods for short term forecasting.

The Ensemble Kalman Filter (EnKF) method is explained in [2]. Reference [3] uses EnKF to predict 10 min ahead wind speed that gives an error of about 5.06%. Linear prediction model of the ARMA is shown in [4] where results from 1s to 5s only are reported. A hybrid between the ARMA model and the ARCH (Auto Regressive Conditional Heteroscedasticity) is used in [5] where

comparisons are drawn with the classic Persistence model. The results however show high MAE (Mean Absolute Error), up to 29.37%. The mean absolute error (MAE) is a quantity used to measure how close the forecasts or predictions are to the eventual outcomes. When the Wavelet Theory is combined with the neural network it shows satisfactory results [3]. Reference [1] shows a similar result when the WT is combined with an empirical mode decomposition (EMD) showing 4.53% Mean Absolute Prediction Error (MAPE). The MAPE is a measure of accuracy used for methods using time series value. The absolute values of all errors are summed up and the average is computed to arrive at MAPE, which has been chosen in this paper to measure the accuracy of the forecast wind speed.

Grey Model is a time series model and is used in [6] to predict the next 3 hours. There is very little research done in this area and the paper only shows a pilot study which gives significant forecast errors. Developing a generalized, portable and easy-to-operate model is therefore a big challenge. Such a method is presented in [7] that has strong robustness giving 40% better results than the Persistence model.

Reference [8] shows that over fitting is a result of excessive complexity and lack of clear guidelines for the number of parameters to be chosen while modeling for a given sample size. A case study from Tasmania, Australia is shown in [9] for very-short term forecasting in which more importance is given to wind direction rather than wind speed. Numeric Weather Prediction (NWP) models are used for up to 6 hours ahead forecasts and show better results when weather conditions are stable. NWPs include global forecasting systems [10] or High Resolution Limited Area Model (HIRLAM) [11] for instance. The method in [12] uses a new statistical approach that combines artificial intelligence and fuzzy logic techniques.

Reference [21] shows different approaches of ARMA for short term forecasting of wind speed. The effectiveness of ARMA-GARCH is reported in [22]. It also demonstrates different GARCH approaches consistently improving the modeling sufficiency of the mean wind speed. However, the output prediction decreases with increase in the height, which is a drawback.

Reference [23] shows the impact of wind speed forecasting on the dynamic response of wind turbine. It calculates rotor speed and aerodynamic torque to estimate the effectiveness of wind speed by an inversion of a static aerodynamic model and hence shows that this may also be helpful for wind turbine response. Wind speed prediction is not only a problem for wind power prediction but also for aqueducts in China that still withstand wind loads constantly [24]. These wind loads shorten aqueducts fatigue life along with large amplitude sloshing of water and further leading to structural resonance. Another application can be seen in [25] where variable-speed wind turbine generators (WTGs) employ anemometers to measure wind speed so that the desired optimal shaft speed can be derived. Results show that the wind speed was accurately estimated and hence proved useful.

A lot of research has been done to forecast wind speed but still work needs to be done to develop methods to realized robust and more accurate predictions. Some hybrid methods have got satisfactory results and smaller MAPE but they have not been tested for more than one-hour prediction. The ARMA model on the other hand has shown good results for long term forecasting. In this paper, ARMA is combined with the WT, given the complementary strengths of both techniques, to assess their forecasting accuracy.

### 3. Methodologies

As discussed in the previous section, in this paper the Wavelet Transform (WT) together with the ARMA is chosen as a hybrid technique. These methods have been chosen since the proposed hybrid has a high potential for producing more accurate forecasting results. The Wavelet analysis is a novel technique that is being adapted in various fields for forecasting purposes. The second method used is the ARMA model, a time series model.

#### 3.1. Wavelet Analysis

Wavelet means a small wave or a pulse of short duration with finite energy that integrates to zero. The WT breaks the original signal into projections of translated and scaled versions of the original mother wavelet. The basis function of the Wavelet Analysis is the mother wavelet function ( $\psi$ ) [13,14].

##### 3.1.1. Continuous Wavelet Transform (CWT)

The continuous time wavelet transform of  $f(t)$  with respect to a wavelet ( $t$ ) is given by

$$W(m, n) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|m|}} \Psi^* \left[ \frac{t-m}{n} \right] dt \quad (1)$$

where,  $m$  is the scale variable,  $n$  is the translation variable and  $*$  denotes complex conjugate. The CWT maps the one dimensional function  $f(t)$  to a function  $W(m, n)$  having continuous real variables  $m$  and  $n$ . The coefficients of  $W(m, n)$  at a particular scale and translation, measure how well the original function or signal  $f(t)$  matches with the scaled or translated mother wavelet. However, to recover the function, all the coefficients of  $W(m, n)$  are not required. As a result CWT gives a redundant way to represent the signal [13,17].

##### 3.1.2. Discrete Wavelet Transform (DWT)

DWT is used to decompose a signal into different resolution levels. Compared with CWT, DWT is sufficient in decomposing and reconstructing most wind speed disturbances. It provides enough information and offers high reduction in the computational time. Multi-resolution analysis is to break a continuous real valued finite energy function into a hierarchy of approximations. It is a technique that represents a function on many different scales, which are formed by scaled and translated mother wavelet.

In order to obtain a matrix  $W$  of wavelet coefficients for Discrete Wavelet Transform,  $x$  being a time series is defined as  $x = [x_1, x_2, \dots, x_N]^T$  with  $N$  an integer multiple of  $2^j$  where  $j$  is the level of resolution. It is possible to define  $w$ , in order to obtain a matrix  $W$  of wavelet coefficients, which results in the Discrete Wavelet Transform.

$$W = w.x \quad (2)$$

This matrix  $w$  in (2) can be represented as  $w = [w_1, w_2, w_2, \dots, w_j, v_j]^T$ . Similarly,  $W$  can be

defined as  $W = [W_1, W_2, \dots, W_J, V_J]^T$ . For the DWT the first  $J$  sub vectors contain all the wavelet coefficients for scale  $J$ . Each  $W_j$  column vector has  $N/2\tau_j$  coefficients associated with changes on a scale of length  $\tau_j = 2^{j-1}$ , for  $j = 1, 2, 3, \dots, J$ . The final sub-vector  $v_j$  contains just the scaling coefficients associated with averages on a scale of length  $2^J$ .

The Multi Resolution Analysis (MRA) equation resulting from the reconstruction of the wavelet coefficients is

$$x = w^T \cdot W = \sum_{j=1}^J (w_j^T \cdot W_j) + v_j^T \cdot V_J = \sum_{j=1}^J (D_j) + A_J \quad (3)$$

In (3), the time series  $x$  is stated as the sum of a constant vector  $A_J$  and  $J$  other vectors,  $D_j$  ( $j=1, 2, 3, \dots, J$ ), each of which contains a time series related to variations in  $x$  at a certain scale. The  $D_j$  refers to the  $j^{\text{th}}$  wavelet detail and the  $A_J$  as the approximation. MRA is intended to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This methodology has proved to give good results especially when the signal has high frequency components for short durations and low frequency components for long durations [13,17].

### 3.2. ARMA

Auto Regressive (AR) model describes a time series as a linear function of its past values. The order of the AR model signifies the number of lagged past values included. A Moving Average (MA) model is a form of the ARMA model in which the time series is regarded as a moving average (unevenly weighted) of a random shock series  $a_t$ . This shows that the AR model includes lagged terms on the time series itself, and that the MA model includes lagged terms on the noise or residuals. So, by taking both types of lagged terms, an autoregressive-moving-average, or ARMA, model is established. The order of the ARMA model is included in parentheses as ARMA ( $p, q$ ), where  $p$  is the autoregressive order and  $q$  the moving-average order. It is convenient for weighted moving average time series.

An ARMA ( $p, q$ ) model of order  $p$  and  $q$ , with  $\varphi_j$  and  $\theta_j$  the autocorrelation and the moving average coefficients respectively, is represented [14] by

$$y_t = \sum_{j=1}^p \varphi_j y_{t-j} + a_t - \sum_{j=1}^q \theta_j a_{t-j} \quad (4)$$

The process of the ARMA( $p, q$ ) is combined by the processes of AR ( $p$ ) and MA ( $q$ ). If  $q = 0$ , then equation becomes an AR model of order  $p$ . When  $p = 0$ , the process becomes an MA model of order  $q$ . In the ARMA ( $p, q$ ) model,  $\{y_t\}$  is the return series of original time series and  $\{a_t\}$  is the innovations noise process. In the process of constructing an ARMA model, it is imperative to confirm the order  $p$  and  $q$ . These orders have been calculated with the values from AIC (Akaike Criterion Method) method. It is generally a good practice to find the smallest values of  $p$  and  $q$  that provide an acceptable fit to the data. The following steps are considered.

First, fix the range of the ARMA model orders to be considered ( $1 \leq p \leq p_{max}$  and  $1 \leq q \leq q_{max}$ ).

Then, estimation of the model parameters by an appropriate algorithm such as ANN is done. Compute the predicted signal and keeping the error variance equal to one mimicking what has been done in [20]. Evaluate AIC over  $1 \leq p \leq p_{max}$ , and choose the value of  $d$  that minimizes AIC to find the true order of ARMA. The order (2,2) was found to be the best according to AIC. However, the results have been tested for few more combinations of  $p$  and  $q$ .

Equation (4) is substituted into (3) to get the proposed hybrid formula that is

$$x = \sum_{j=1}^J D_j + A_j = \sum_{j=1}^J D_j + \{y_t - \sum_{j=1}^p \varphi_j y_{t-j} + \sum_{j=1}^q \theta_j a_{t-j}\} \quad (5)$$

A forecast error is the difference between the actual (or real) and the predicted (or forecast) value of a time series or any other phenomenon of interest. The MAPE is a measure of accuracy in fitted time series value. This paper uses MAPE to forecast wind speed due to its accuracy.

$$MAPE = 1/n \sum_{t=1}^n |A_t - F_t / A_t| \quad (6)$$

where,  $A_t$  is the actual value and  $F_t$  is the forecast value.

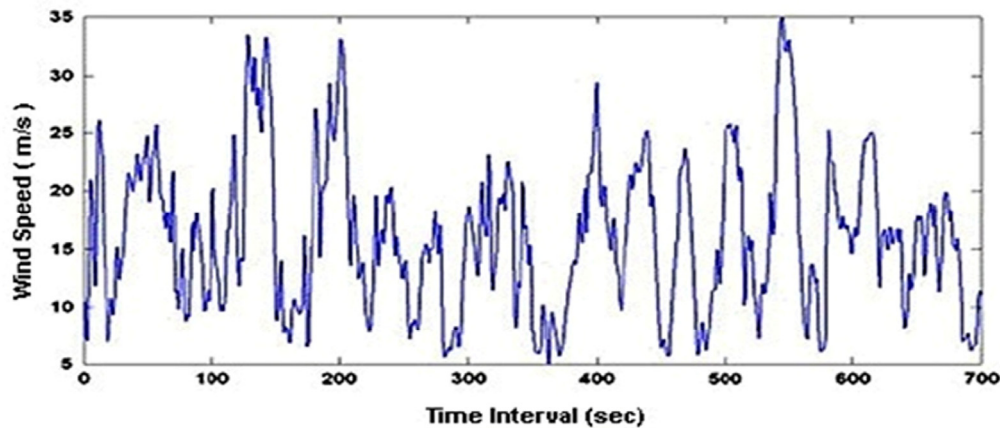
#### 4. Results

In the present study, actual wind data and the input-output patterns for training of a network are taken from Auckland City, New Zealand, for the year 2011 on hourly basis. This dataset was provided by National Institute of Water and Atmospheric Research Ltd (NIWA), which is the only producer of wind speed datasets in New Zealand. Only wind speed and direction were provided therefore no other factors such as temperature are considered here. The platform chosen to test the available set of data is MATLAB. The forecasting errors are also computed using MATLAB. The six hourly wind fields are extracted from the data for the period of January 2011 to July 2011.

A hybrid model is established on the basis of consecutive hourly mean wind speed samples, thus allowing the prediction of wind speeds at future time-steps.

First, the original wind speed time series is decomposed into detailed time series at different resolutions (scales),  $d_1, d_2, \dots, d_J$  and a coarse approximation time series  $a_j$ , then we obtain  $D_j$  ( $1 \leq j \leq J$ ) and  $A_j$  by reconstruction. From this, the data is being filtered. If direct data is put into the ARMA model then the results will not be very accurate [14]. As a result, for different time series ( $D_j$  and  $A_j$ ) of Wavelet Transform, the ARMA models are established to forecast respectively. Last, the hybrid approach is utilized to obtain the forecasting result.

In the experiments, 250 input/output data values are used for the simulation. The first 215 data values form the training data set, whereas the others are used as checking data for validating the wavelet-ARMA model. Since it is a comparison between the individual and the hybrid of the two methodologies, different graphs have been plotted. The six hourly data was selected for the execution of wind speed model graph. The original wind data is shown in Figure 1. It shows the graph between position and the time index for 700 datasets and the general pattern of wind speed in that location. The larger variances show large-scale patterns with slow changing amplitudes representing stability whereas the smaller variances show small-scale patterns with fast changing amplitudes representing instability.



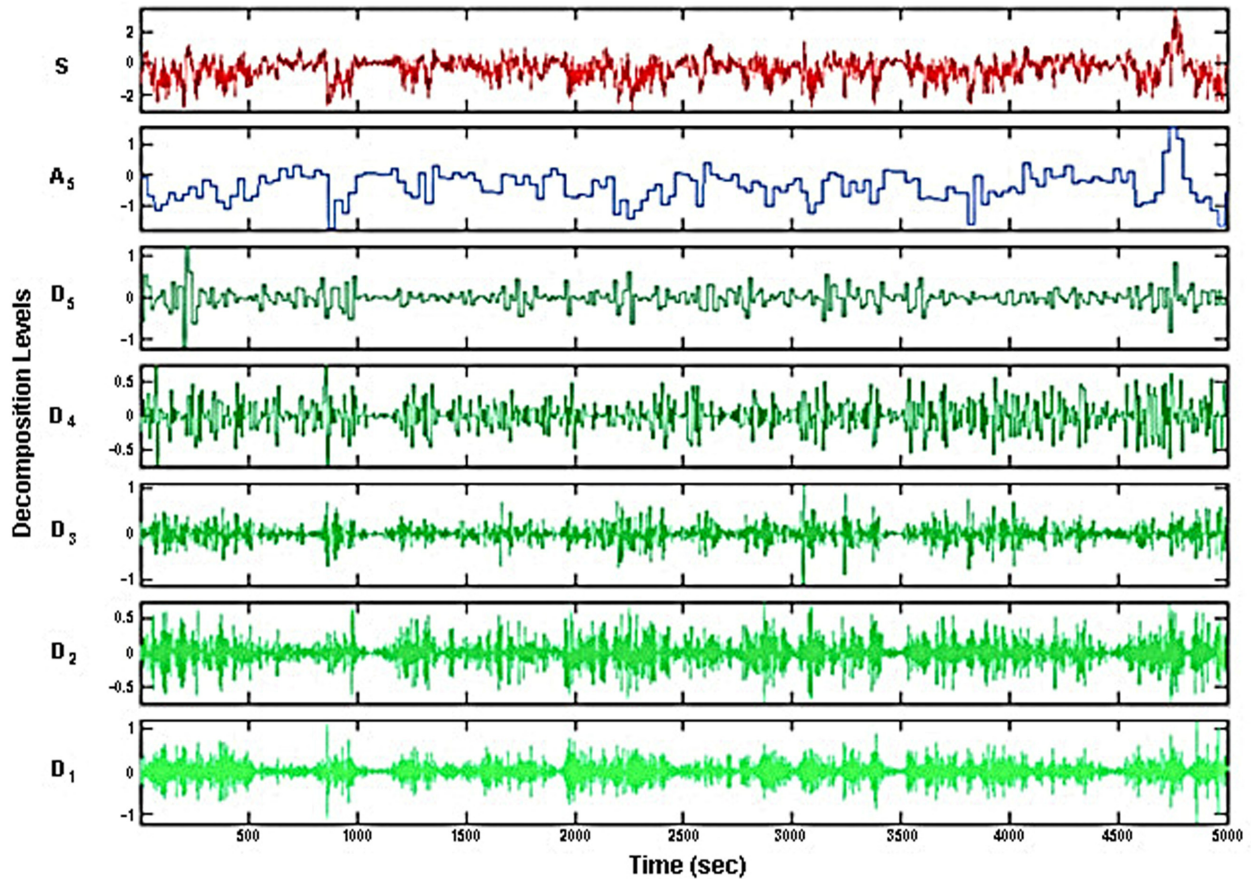
**Figure 1. Original Wind Data.**

Figure 2 is plotted for WT, which is the sum of the decomposition at level 5 and reconstruction of the wavelets. The approximations for the low frequency and details for high frequency are added and the summation of both is shown in this figure. It shows the decomposed coefficients of every scale.  $D_1, D_2, \dots, D_5$  are details, they reflect the detail information of every scale.  $A_5$  is the approximation; it reflects the development trend of wind speed. The relation between  $A_5$  and  $D_j$  ( $1 \leq j \leq 5$ ) meets  $S = A_5 + D_5 + D_4 + D_3 + D_2 + D_1$ .

The characteristic of wavelet decomposition is that the more scales the original signal can be decomposed into, the better signals are, but great errors will be brought about at the same time. As a compromise the decomposed number of scales is always less than 6 and we have chosen the number of scales  $j = 5$  in this paper. The data was tested for  $j = 1-6$  levels for the hybrid and  $j = 5$  was seen to be giving the best results therefore  $j = 5$  has been chosen in this paper. Table 1 shows the different errors (MAPE) obtained for different values of  $j$  and hence  $j = 5$  has been chosen for testing this particular dataset in this paper.

**Table 1. Different Error for Different values of  $1 \leq j \leq 6$ .**

$j$	WT-ARMA MAPE
1	3.4
2	3.2
3	3.0
4	3.0
5	2.7
6	2.9



**Figure 2. Output of Wavelet Analysis shows approximations for the low frequency ( $A_5$ ) and details for high frequency  $D_j$  ( $1 \leq j \leq 5$ ) that are added as (S).**

Now the ARMA model is fed with the wavelet transform output and the results analyzed for different  $p$  and  $q$ . The results of ARMA(1,1), ARMA(1,2), ARMA(2,1), and ARMA(2,2) are compared. However, no significant discrepancies between the results are observed. As an example, the results for ARMA(1,1) are displayed in Figure 3. One of the possible reasons for not observing any difference could be due to the use of synthetic data.

After the parameters are learned from the training set, the forecasting algorithm is applied as described in Section 3 to make 35 points' predictions (1-hour-ahead prediction). Figure 4 compares the forecasted results of WT-ARMA hybrid to the original wind. Figure 5 shows the Wavelet ARMA hybrid with the original wind data and gives a very good minimum error.



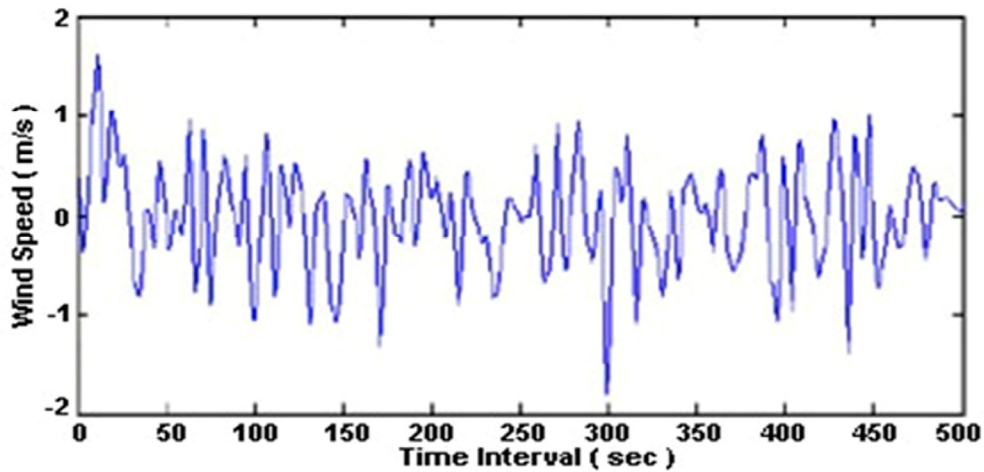


Figure 3. Output of ARMA fed with Wavelet.

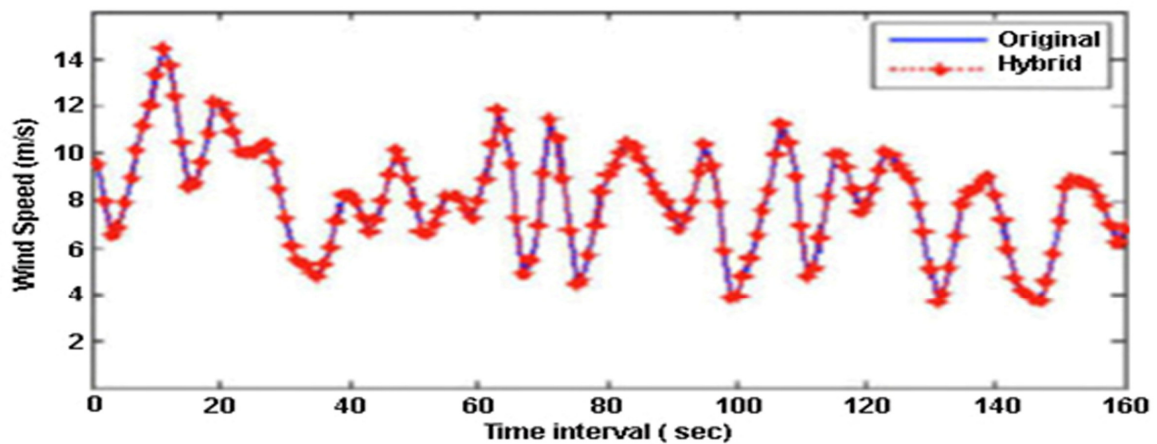
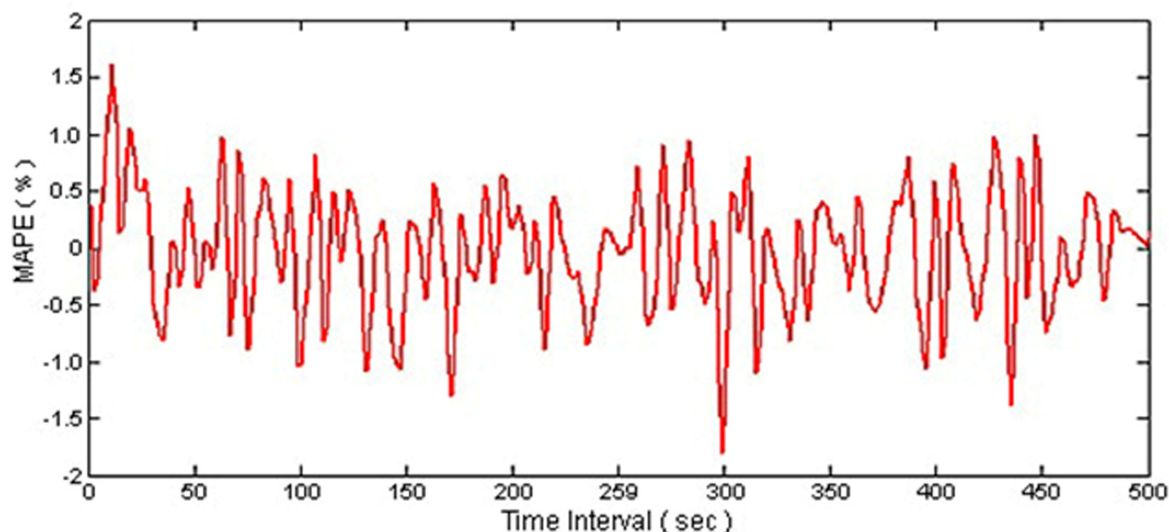


Figure 4. Actual Wind Speed versus Forecasted using Hybrid Model.

These results have been compared with the Artificial Neural Networks (ANN)—the Ensemble Kalman Filter (EnKF) hybrid [15]. The MAPE of the ARMA has been shown to be between 7% for 1-hour up to 18% for the next six hours [16] as shown in Table 2. Table 2 shows the MAPE and the computational time for ARMA, ANN-EnKF and Wavelet-ARMA techniques. It clearly shows the MAPE for the Wavelet- ARMA hybrid is the smallest and thus proving it to be an output correction scheme.



**Figure 5. Error graph (MAPE) for WT-ARMA hybrid.**

**Table 2. Result Analysis.**

<b>Comparison between Wavelet ARMA hybrid and ANN-KF in Wind Speed Forecasting</b>			
Method	ARMA	ANN-KF	Wavelet -ARMA
MAPE%	7.98%	6.57%	2.7%
Computational Time	100 sec	180 sec	160 sec

## 5. Conclusion

The demand for using various renewable resources arose from environmental changes. This research uses wind as a renewable resource for better integration of wind power into the electric grid. Intermittency of wind is the greatest challenge and managing it becomes crucial. The effective solution is to predict the future values of wind power production, which is totally dependent on wind speed. Changing the prediction model to decrease the forecast error is one way and has been chosen in this paper. The need arises for a hybrid method that can accurately predict wind speed from a few minutes to several hours. The ARMA model has been chosen due to its high accuracy for long term forecasting in load forecasting and price forecasting. Simple input data can be fed into the ARMA but if pre-processed data are fed into it then better results can be obtained. The Wavelet Transform has been chosen for this task since it decomposes the data and then reconstructs it. The proposed hybrid is tested with synthetic data for one hour ahead prediction on MATLAB. Results are presented for the WT and the ARMA model. The error graph for WT-ARMA hybrid when compared with the original wind speed shows a very good match. Comparisons have been done with another ANN-EnKF hybrid. The simulation study results show that the WT-ARMA hybrid has comparatively less errors and less computational time than the ANN-EnKF hybrid. The forecasts of the ARMA

model are unreliable with data series having less than 50 data points.

The future scope lies in combining this method with some other techniques, which are able to remedy this problem. Upcoming new methods like Support Vector Machine (SVM), that has been tested for few hours forecasts, can be combined with these methods to predict day ahead forecast to reduce the forecasting error even further. This research can also be extended to predict several hours ahead wind speed and can be improved for medium or long term forecast. This work may not only benefit forecasting of wind but also several other applications as well such as load forecasting or flood forecasting. This research finds its application in the economics part as well since better scheduling and dispatch can be done. If wind is forecasted properly then wind power production due to wind energy will increase. Optimization errors can also be decreased when this research is taken onto another level.

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