VOL. 11, NO. 15, AUGUST 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

HYBRID PREDICTION MODEL FOR SHORT TERM WIND SPEED FORECASTING

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ABSTRACT

Due to notable depletion of fuel, non-conventional energy aids the present grid for Power management across the country. Wind energy indeed has major contribution next to solar. Prediction of wind power is essential to integrate wind farms into the grid. Due to intermittency and variability of wind power, forecasting of wind behavior becomes intricate. Wind speed forecasting tools can resolve this issue as prediction of wind power depends on the forecasting of Wind speed. A hybrid model is proposed and developed using both Auto Regressive integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) to achieve best forecast of Wind speed in a given region.

Keywords: artificial neural network, autoregressive integrated moving average, wind speed, autocorrelation, statistical measures.

INTRODUCTION

We know that fossil fuels are being depleted ata very fast rate which motivates to supplement the power generation from the renewable sources such as wind, solar, tidal and fuel cells etc. Among the several renewable power generating systems, the wind power generation dominates the other sources of renewable power. Integration of wind power system to the existing power system possess a number of problems in view of achieving good power quality, stability and power dispatching issues, due to the fact it is non-dispatch able and volatility.

These problems can be resolved if one could forecast the wind speed and wind power. It may be noted that as wind power is a function of wind speed, forecasting of wind power can be accomplished though wind speed forecast. But wind power generation depends on the availability of the wind. It is estimated that by 2020, about 12% of the world's electricity will be contributed from Wind Power.

The greatest problem in wind power penetration is due to the chaotic nature of wind speed. There are several methods to estimate wind speed. These methods are classified into the ARIMA method and ANN method of forecasting .In this project; Hourly wind speed forecasting can be done separately with ARIMA and ANN.

LITERATURE REVIEW

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Novel wavelet recurrent neural networks (WRNNs) helps at recovering a 2 day forecast [1].

Wind power forecasting strategy developed where feature selection component and a forecasting engine has taken under consideration [2].

A combining approach of wavelet transformation, particle swarm optimization process, and an adaptive-network-based fuzzy inference system is proposed for short-term wind power forecasting in Portugal [3].

ANN involves two steps: training or learning step and testing step. During training phase all free parameters get updated to model thegiven problem. After learning step, it may be tested with new unknown patterns of inputs and its accuracy can be tested during testing step. ANN has become a powerful computing technique because of its capability to map nonlinear relationships of input-outputpatterns [4].

AUTO REGRESSIVE INTEGRATED MOVING AVERAGE

ARIMA models offer another way to time series forecasting. Time series forecasting uses two widely known approaches namely Exponential smoothing and ARIMA models. It also provides complementary approaches to the problem. Whilst exponential smoothing models were based on a account of trend and seasonality in the data, ARIMA models aim to describe the autocorrelations in the data.

Before the introduction to the ARIMA models, the idea of stationarity and the method of differencing time series are discussed below:

VOL. 11, NO. 15, AUGUST 2016 ISSN 1819-6608
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Stationarity and differencing

A stationary time series is one whose properties do not depend on the time at which the series is experimental. A stationary time series will have no conventional patterns in the long-term. Time plots will illustrate the series to be roughly horizontal (although some cyclic behavior is possible) with constant variance. Differencing will stabilize the mean of the time series by removing the change in the level of the time series.

Backshift notation

Backshift notation is very useful when collaborating differences as the operator can be treated using common algebraic rules. In particular, terms involving B can be multiplied together.

Auto regressive models

In an auto regression model, we forecast the variable of interest using a linear combination of past values of the variable. The term auto regression denotes that it is a regression of the variable against itself. Autoregressive models are surprisingly flexible at handling a broad range of different time series patterns. Thus an autoregressive model of order p can be written as,

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + e_t$$

Where c is a constant and et is white noise. This is yet a multiple regression with *lagged values* of$\boldsymbol{y_t}$which are depicted as predictors. We refer to this as an AR model.

Moving average models

Instead of using past values of the forecasting variable in a regression, a moving average model takes up past forecast errors in a regression-like model.

$$y_t = c + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q}$$

Where $\boldsymbol{e_t}$ is white noise, we refer to this as an MA model. A moving average model is used for forecasting potential values while moving average smoothing is used for estimating a trend in the past values.

Non-seasonal ARIMA models

If we merge differencing with auto regression and a moving average model, we obtain a non-seasonal ARIMA model. 'Integration' in this context denotes the reverse of differencing. The full model can be expressed as

$$y'_t = c + \emptyset_1 y'_{t-1} + \cdots + \emptyset_p y'_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t$$

Where $\boldsymbol{y'_t}$ is the differenced series (it may have been differenced more than once). The predictors on the right hand side include both lagged values of $\boldsymbol{y_t}$and errors. We call thisas an ARIMA (p,d,q) model, where

p = order of the autoregressive part;
d = degree of first differencing involved;
q = order of the moving average part.

The similar stationarity and invertibility conditions that are used for moving average and autoregressive models relate to this ARIMA model.

ARTIFICIAL NEURAL NETWORK

A family of models analogous to the human neural network in cognitive science, which are used to approximate functions that have large number of inputs that are unknown. An ANN is typically defined by 3 types of parameters:

a) The interconnection pattern between the unlike layers of neurons

b) The learning procedure for updating the weights of the interconnections

c) The activation function that converts a neuron's subjective input to its output activation

Feed forward Architecture (MLP)

Also known as Multi layer Perceptron wherein More than one simple processing unit, namely artificial neurons or nodes are connected.

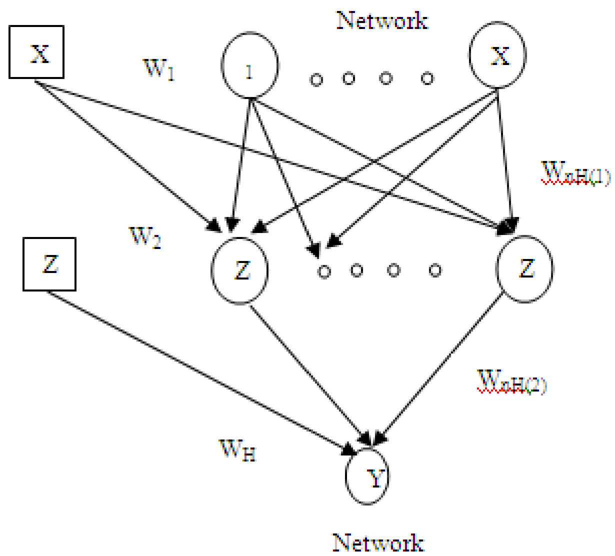

Figure-1. Feed forward Neural Network flow process.

Each node is connected to several other nodes by means of 'weights' but not with the nodes of the same layer. FNN comprises of both an input and an output layer, they also possess an additional node namely 'bias unit' in all the layers except the output layer. This node acts as an intercept in linear models.

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Backpropagation

The back propagation algorithm exploits the network structure in order to compute recursively the gradient.

Back propagation is an algorithm which, once the number of hidden nodes H is given, estimates the weights α_N=w(l),l=1,2on the basis of the training set Dn. It is a gradient-based algorithm which aims to minimize the cost function.

$$SSE(\alpha_N) = \sum_{i=1}^{N} (y_i - \bar{y}_i)^2 = \sum_{i=1}^{N} (y_i - h(x_i, \alpha_N))^2$$

where α_N=w(l),l=1,2 is the set of weights. The weights are initialized with random values and are changed in a way that will reduce the error. A convergence criterion is used to end the algorithm. This method is practically inefficient since a lot of steps are needed to reach a stationary point and monotone decrease of SSE is not required.

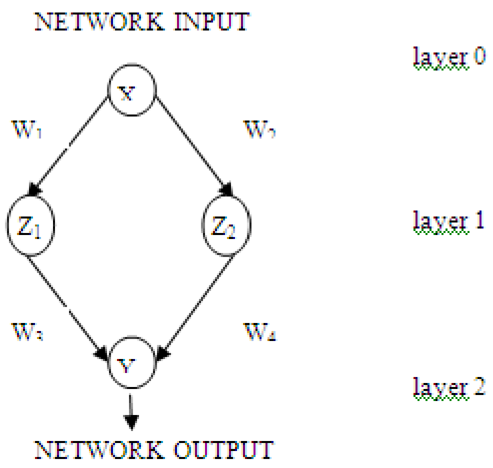

Figure-2. Backpropagation training algorithm.

HYBRID MODEL

Historical Data along with Numerical weather prediction model is fed into the hybrid model as an input. this data is further normalized into the required sample series (for e.g. 10-mins, hourly, monthly and yearly).The normalized data is fed equally, such that the degree of differencing is identified for further procedures according to ARIMA and another set of data is initialized for training. Once, degree of differencing is identified ACF and PACF plots are generated to identify lags and trends in the time series model.

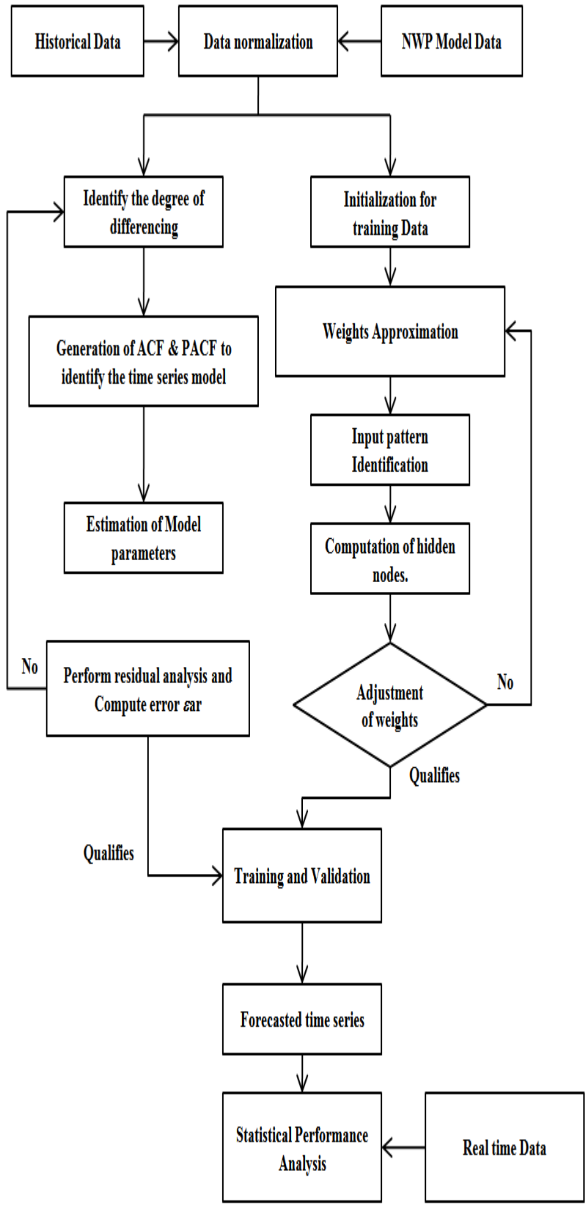

Figure-3. Flowchart of the hybrid model.

The time series model thus generated is produced for estimation of ARIMA Model parameters. After estimation, Residual analysis is performed and an error coefficient is obtained. On the other hand, the data set that is initialized for training is put forth for weights approximation, post which the pattern of series is identified and compared with the time series obtained from ARIMA estimation of Hybrid model.

Hence, the hidden nodes are computed, simultaneously the weights are adjusted at the time series dataset to obtain minimal error. The resulting time series output is trained and validated to obtain Forecasted time series which goes through further Statistical Performance Analysis.

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RESULTS

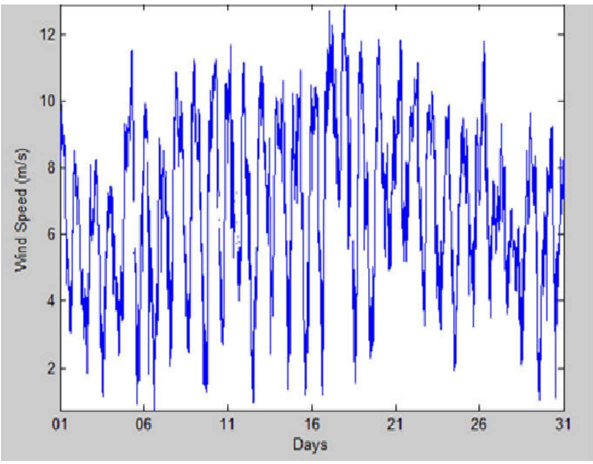

Figure-4. Time series analysis of wind speed data.

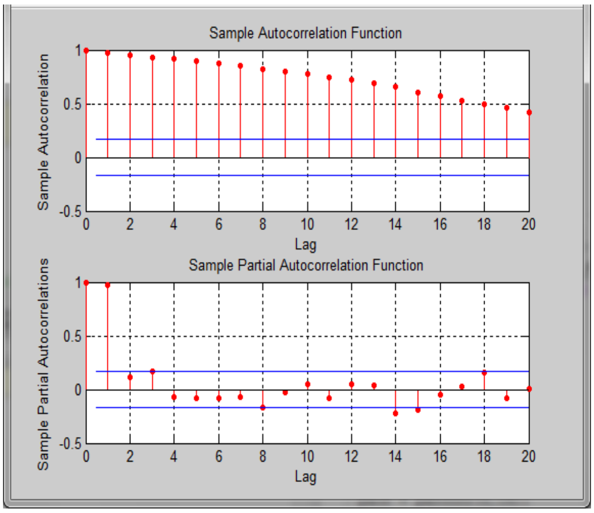

Figure-5. Generation of ACF and PACF to identify the time series model.

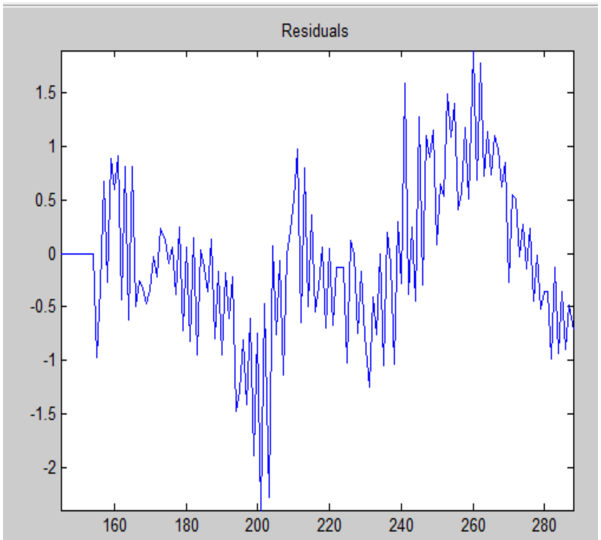

Figure-6. Residual analysis.

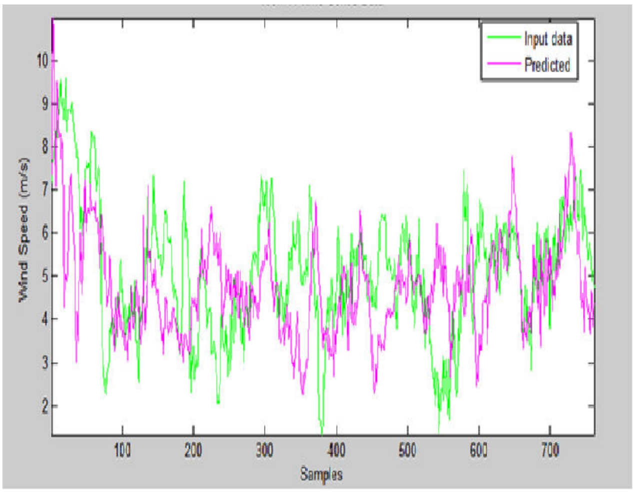

Figure-7. Comparison of actual and predicted time series response.

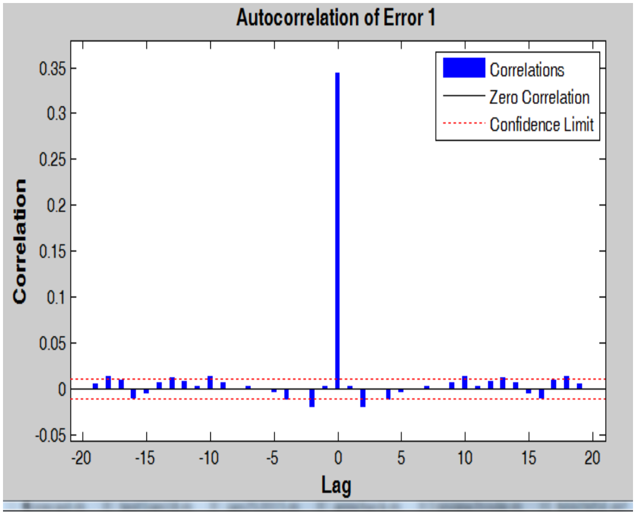

Figure-8. Auto correlation plot.

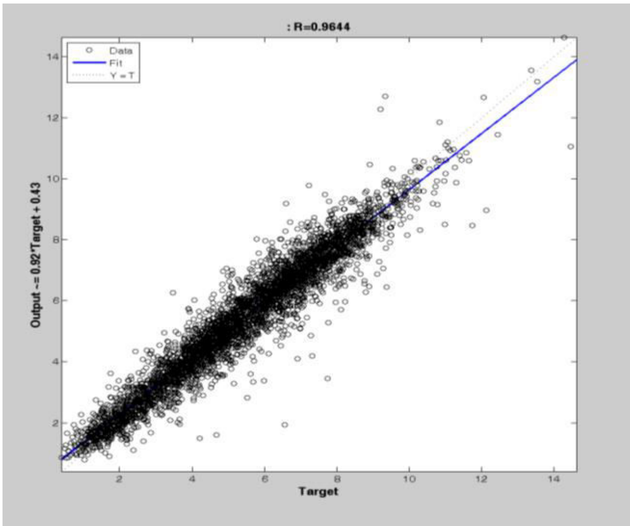

Figure-9. Regression Plot R^2 = 0. 9644.

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Table-1. Comparison of Statistical error measures in ANN and ARIMA.

Statistical parameters	ARIMA	ANN
MAE	1.2493	0.3798
MSE	2.4551	0.2662
RMSE	1.5669	0.5159
Correlation Co-efficient	0.7000	0.9644

CONCLUSIONS

The different terrains observed across the country remarks the variations in Wind speed. Also, on an annual note the wind speed is highly revamping. Due to this chaotic nature of Wind, forecasting tools such ARIMA and ANN are used to forecast the short term wind speed in any area. Both the forecasting tools are individually producing results with a small amount of error quotient. The model that infers a lesser error quotient is preferred. But, for any suitable terrain and seasonal conditions a hybrid model comprising both ARIMA and ANN is developed that infers a very lower error quotient. Thus, potential Wind speed in a particular region can be forecasted for prediction of Wind Power.

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