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A method of Wind Speed Estimation by a non stastical approach using ANN

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Abstract

short-term forecasting problems as it is capable to learn non-linear relationship between inputs and outputs by a non-statistical approach and dont require any predefined mathematical model. Investigates the effectiveness of recurrent wavelet neural network (RWNN) and artificial wavelet neural network (AWNN) dynamics for wind speed forecasting. We evaluate the RWNN and AWNN against multilayer feed-forward neural network. The RWNN and AWNN are trained using back propagation gradient descent algorithm. The experimental results show that the performance of RWNN and AWNN approaches outperforms the multilayer feed-forward neural network. The three models use Hourly averaged time series data (2982 numbers of samples) for wind speed. Simulation is done in MATLAB SIMULINK environment. From the entire three neural networks, RWNN gives better results (in terms of mean absolute error as a performance index) as compared to other two methods (AWNN and multi-layer feed forward neural network).

***Key Words*:**artificial wavelet neural network ,RWNN,AWNN multilayer feed-forward neural network, maximum overlap discrete wavelet techniques,discrete wavelet techniques

1 INTRODUCTION

Among the several renewable power generating systems, the wind power generation dominates the other sources of renewable power. However, 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 worlds electricity will be available through wind generation [3].

There are several existing models for wind speed/wind power prediction. NWT (numerical weather prediction) models predict the weather not just the wind [5]. Persistence model for prediction problem is better than NWP model. Basically forecasting model divided into two approaches that is physical and statistical approaches. NWP model comes under the physical approaches of wind speed/wind power estimation where meteorological conditions are taken into account. In case of statistical approach amount of data taken for consideration should be more, where meteorological information does not require. Autoregressive (AR), moving average (MA), autoregressive moving average model (ARMA) and autoregressive integrated moving average model (ARIMA), all these models comes under statistical approach for forecasting problem. Learning approaches like neural network (NN), fuzzy logic, support vector machine (SVM), all these approaches learn from the relationship between predicted values and the historical time series. Neural network has been shown as better approximation capability than other models [6], [7], and [8]. In control application like in wind turbines control, wind forecast is carried out up to few seconds [9] and [10]. The wavelet technique for wind speed forecasting has been first introduced by Hunt and Nason. Short term wind data has been collected from a site and long term data from a reference site using Measure correlate predict technique, wind speed and power has been predicted. Accurate predictions of wind speed and power at 10-min intervals up to 1h into the future by the support vector machine regression algorithm provided in [11]. Integration of wind power system to existing one, an advanced statistical method has been developed where forecasting horizon will be 48h ahead [12]. An advanced model, based on recurrent high order neural networks, with forecast of the WECS power output profile for the next 2 or 3 hours with a time step in the order of 10-min [13].

ANN involves two steps: training or learning step and testing step. During training phase all free parameters get updated to model the given 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-output patterns. Complex valued pipelined recurrent neural network (CPRNN) architecture is proposed where the network is trained by the complex valued real-time recurrent learning (CRTRL) algorithm with a complex activation function which is suitable for forecasting wind signal in its complex form (speed and direction)[14]. A 2-day forecast is obtained by using novel wavelet recurrent neural networks (WRNNs) [16]. Three different forecast scenarios are simulated based on the persistence approach where a linear approximation has been developed to describe the relationship between the persistence forecast and the related mean measured power [17].An advanced model, based on recurrent high order neural networks, is developed for the prediction of the power output profile of a wind park [18]. A case study from Tasmania, Australia has been done with a short term wind prediction model for power generation where the approach model is the application of an adaptive neuro-fuzzy inference system to forecasting a wind time series [19].Some example of statistical model for wind power forecast, takes the NWP forecast as a inputs which has been proposed, involves forecasting models as the wind power prediction tool (WPPT), a time series-based statistical model, wind power management system (WPMS), and advanced wind power prediction system (AWPPS) are artificial intelligence and fuzzy-based models [20],[21].Wind power forecasting strategy developed where feature selection component and a forecasting engine has taken under consideration [22].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 [23].

2 Methodology

2.1 Wavelet analysis

Wavelet decomposition can be utilized to analysis the non-linearity present in the historic wind power signal. The wavelet-based Neural Network (WNN) approach. First, the wind power data is decomposed into an approximate part (associated with the general trend of original signal with low frequency) and several detail parts (associated with high frequencies) through the multi-level wavelet decomposition. In the second stage, each decomposed part is fed into respective NN as input for the respective training and prediction. The outputs from the NNs, in the third and last stage, are recombined to obtain the final predicted output [14].

2.2 CONTINUOUS WAVELET TRANSFORMS (CWT)

From the Continuous Wavelet Transform (CWT), one can obtain the surface of the wavelet coefficients, for different values of scaling and translation factors which maps a function of a continuous variable into a function of two continuous variables.

In wavelet analysis, the input signal is compared with the wavelet function to obtain a set of coefficients that represent how these two signals match. The computation of these coefficients is performed using the continuous WT (CWT).

The definition of CWT for a given signal x (t) with respect to a mother waveletΨ(t) is given by

$$CWT(a,b) = \frac{1}{a}\int x(t)\varphi\frac{(t-b)}{a}dt$$

where b is the translation factor and defines the decomposition filters at different frequency levels and a is the scaling parameter and scales decomposition filters for each levels.

2.3 MAXIMUM OVERLAP DISCRETE WAVELET TRANSFORMS (MODWT)

Multi-resolution analysis (MRA) of the given wind speed sample can be performed using maximum overlap discrete wavelet transformation (MODWT) which is based on filtering operations (Fig.2.3.1) known as Pyramid Algorithm

2.3.1 PYRAMID ALGORITHM:

The original signal passing through high pass filter and low pass filters results in detail and approximation coefficients. The approximation coefficients which are obtained in the 1st level of decomposition, further allowed to pass through the next level wavelet (high pass filter)and scaling filters (low pass filter) which gives the next level detail and approximation coefficients. This process is repeated up to the required level of decomposition [4].

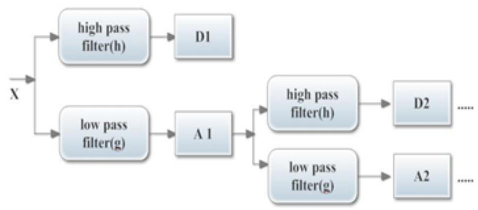


Fig.2.3.1 Decomposition of a signal(x) by MODWT

In Fig.2.3.1, X defines the input data samples (here wind speed), D1 and A1 are detail &smooth coefficients at 1st level of decomposition, D2 and A2 are details &smooth coefficients at 2ndlevel, etc.

In discrete domain, a signal defined as

X=$[X, X_1 \cdots X_n]$

where the length of the time series is N ($=2^j$), then the DWT of X is given by [27],

W=OX

where W is a column vector of length N whose n^{th} element is the n^{th} DWT coefficient W_n , and O is a N $\times$ N real valued matrix representing the DWT and satisfying orthonormal condition

$$X = O_J^T W = \sum_{j=1}^{J} O_J^T W_{J+} V_J^T . V_{j-1}^T = \sum P_j + S_j$$

where the j^{th} detail signal is defined by D_j and the last vector is referred as smooth signal S_J which leads to the multi-resolution analysis.

2.4 Neural Network

Wind speed estimation using BPA in multilayer feed-forward neural network

A back propagation networks consists of at least three layers that input layer, hidden layer and the output layer [29, 30]. The need of forecasting of wind speed is for errorless wind speed forecast results in accurate prediction on wind power which gives estimation of the expected production of wind turbines. Existing problem like operational, planning and economic problems which are created due to penetration of wind power system with the existing power system can be reduced. ANN consists of interconnected parallel distributed processor which have natural tendency for storing experimental data and making it available for use. BPA can be used to train this artificial neural network (ANN).Training has to begin with arbitrary weights.

Error= $[T-Y]^2$, T =Target output, Y =Actual output

This neural network consists of three layers that are input layer, hidden layer and outputlayer. Here sigmoid function is chosen for activation function in hidden layer. Sigmoid function is define as

$\phi x = \dfrac{1}{1+e^{-x}}$

Where $[X_1, X_2, \cdots, X_i]$are the patterns given as input to the forecasting model, $[Z_1, Z_2, \cdots, Z-J]$are the output of the hidden layer,$W_1, W_2, \cdots, W_J$ are the weights connecting to output layer from hidden layer, $V_1, V_2, \cdots, V_i$ are the weights connecting to output layer from input layer. i Is the total number of input nodes and j as the number of hidden nodes, and finally Y as the total output of the forecasting model. For this model output can be computed as

$$Y = \sum_{n-1}^{i} X_n V_n + \sum_{m-1}^{i} Z_m W_m$$

Algorithm for Multilayer Feed forward Neural network for wind speed estimation

Step1. Normalized wind speed samples have been selected as input to the model. And normalization of the samples has been done by MODWT wavelet transforms with db4 mother wavelet. Decomposition of the wind speed samples (500) has been made up to 5th levels.

Step2. Each decomposed signal is allowed to pass through the forecasting model. And each level forecast has been done. Random weights are selected for initialization between hidden to output layer and input to output layer.

Step3. For training step, first 10 wind speed samples (one pattern) are selected.30 patterns have been considered for training.

Step4. There will be no weights connecting from input to hidden layer, output of the input node is directly given to the hidden layer, output of hidden layer and output of output layers are evaluated by using sigmoid activation function.

Step5. First 1-10 wind speed samples (one pattern) are selected and target is 11thwind speed sample and error has been evaluated. This error has been used to update weights.

Step6. Next 2-11 wind speed sample have been given as inputs to the networkand 12thwind sample is the target.

Step7. Similarly train the network for next 30 patterns.

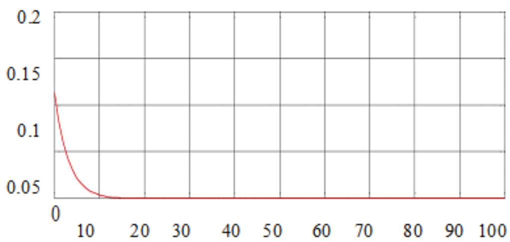
Step8. This process has been continued till convergence occurs.

Step9. Final weights are stored after convergence.

Step10. For testing the network model 41-50 wind samples are given as input and 51st is the output sample. The output is used recursively for forecast the wind speed.

Series	Inputs	Architecture
S5	1-10	10-3-1
D5	1-10	10-3-1
D4	1-10	10-3-1
D3	1-10	10-3-1
D2	1-10	10-3-1
D1	1-10	10-3-1

2.4.1..Input variables selected for the forecasting model



2.4.1.mean square error for detail coefficients

2.4.1 WIND SPEED ESTIMATION BY ARTIFICIAL WAVELET NEURAL NETWORK

Quick estimation can be possible by the WNN forecasting model with total five free parameters as input-to-output layer weights, hidden-to-output layer weights, bias, translation, and dilation. The AWNN offers better adaptivity as it uses wavelet coefficients instead of radial distances used in the RBFNN. As wavelets are localized functions, a fast initialization approach is employed in the proposed work to initialize the wavelet parameters that not only reduces the training time but also improves the accuracy. A linear relationship between input and output is mapped directly. A simple back propagation (BP) algorithm with adaptive learning rate is used for network parameter training.

Step1. Wavelet decomposition: The hourly wind speed data consisting of 1000 samples is decomposed to the 5th level using la8.

Step2. Input pattern fed to the Wavelet Neural Network. The elements of each pattern represent the values of continuous lag hours of available decomposed signal. Step3.The function whose net area is zero can be the mother wavelet function. A Mexican hat is chosen as mother wavelet in wavelet layer (hidden layer).

Mother wavelet function ψ (.) for the wavelet layer is defined as

$$\varphi a.b(ui) = (1 - (i^{u-b})1^2) * e^{-0.5(\frac{u-b}{a})^2}, i \in n; a, b \in R, a$$

where a is the dilation parameter and b is the translation parameter, input nodes. Dilating and translating the mother wavelet over discretized information instead of continuous one. Input pattern for this neural network is defined as

$$i = \begin{bmatrix} x & x_1 & x_n \\ 1 & 2 & n \end{bmatrix}$$

where n denotes the number of input nodes. The input data in the input layer is directly passed to the wavelet layer.

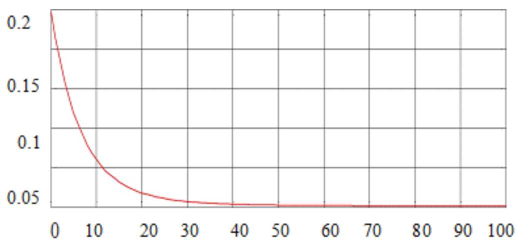
$$Z_J = \Pi\psi a_{ij}, b_{ij}U_i, J \in m$$

where Z_j is the output of wavelet layer (hidden layer), j is a integer value of hidden

node units.In order to map the linear input-output relation, it is customary to have additional direct connection from input layer to output layer, as there is no point in using wavelets for reconstructing linear term. The output of the AWNN, representing the hour-ahead forecast of the decomposed signal, can be computed as

$$y = \sum w_i Z_i + \sum V_i U_i + g$$

Step4. Wavelet Reconstruction: The signal is reconstructed using original and new predicted approximation & detail coefficients. The reconstructed signal contains the original samples plus 30 hours predicted wind speed data.



2.4.2.1..Input variables selected for the forecasting model

Series	Inputs	Architecture
S5	1-10	10-5-1
D5	1-10	10-5-1
D4	1-10	10-5-1
D3	1-10	10-5-1
D2	1-10	10-5-1
D1	1-10	10-5-1

2.4.2.1.Mean square error for detail coefficients

2.4.2 WIND SPEED ESTIMATION BY RECURRENT WAVELET NEURAL NETWORK

Here the use of the wavelet RNN (WRNN) architecture to find a forecasting model for the prediction of wind speed is investigated. The main objective of this paper is to investigate the WRNN architecture for modeling and prediction of the wind speed. First we decompose the wind sample data sequence into several components (levels) of various time-frequency domains according to wavelet analysis. Next we use WRNN to make forecasts for all decomposed levels individually. Finally, the algebraic sum of all forecasts levels gives rise to final forecast.

WRNN algorithm:

This is achieved by feeding the network with a delayed version of the past observations. This network consists of three layers as the input layer, the hidden layer (input and context layers) and the output layer. The input layer units at time k receive as input not only the input vectors for time k but also hidden layer output of time k-1. The new inputs that are the feedback hidden layer outputs are called context vectors.

$$\psi^k = F(X(1))K + \sum \psi i(K-1)$$

where ψ i (k) is the output of wind speed forecasting. And context layer.

Then the output functions y(.)hidden node j at time k , f (.) is the hidden neuron function for the xd(1) is the output of input layer at time k , (k-1) is output of the of the WRNN can be presented as follows:

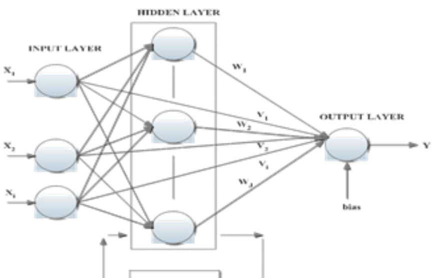
$$y = \sum_{n-1}^{i} X_n V_n + \sum_{m-1}^{i} Z_m W_m$$

i (k) is the output of wind speed forecasting. And context layer.

Then the output functions y(.)hidden node j at time k , f (.) is the hidden neuron function for the x d(1) is the output of input layer at time k ,(k-1) is output of the of the WRNN can be presented as follows:

$$e(k) = y^d(k) - y(k)$$

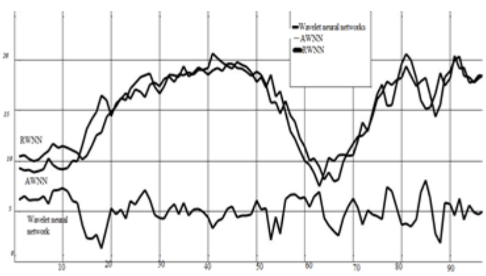
where y (k) is the forecasted output and y^d(k) is the desired output for a given k th input pattern.



General Structure of WRNN

Series	Inputs	Architecture
S5	1-10	10-5-1
D5	1-10	10-5-1
D4	1-10	10-5-1
D3	1-10	10-5-1
D2	1-10	10-5-1
D1	1-10	10-5-1

Input variables selected for the forecasting model



Wind speed forecasting comparison using wavelet, AWNN, RWNN

3 Result and Discussion:

Wind speed forecasting with artificial neural network shows better results than neural network having activation function of sigmoidal type. The error is reduced compared to multilayer feed forward neural network, AWNN and WRNN. wind speed estimation can be calculated through mean absolute error MAE%1.53% . %MAE %1.14% %MAE %10.1 The wind speed data has been studied with the two wavelet techniques (DWT and MODWT) and then with the MODWT technique the available wind speed data is decomposed up to 5th level. Each level decomposition coefficients (detail coefficients of all the level and smooth coefficients of last 5th level) are allowed to pass through three different neural networks for estimation of wind speed.Each level signal has been forecasted individually and then with the inverse processes the signal reconstruction is carried out to get the original forecasted wind speed sample up to 100 consecutive hours ahead. Among the entire three forecast model, RWNN model performs better results (in terms of mean absolute error as the performance index) than other two models.

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