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Very-Short Term Wind Power Forecasting through Wavelet Based ANFIS

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ABSTRACT

This paper proposes a Wavelet based Adaptive Neuro-Fuzzy Inference System (WANFIS) applied to forecast the wind power and enhance the accuracy of one step ahead with a 10 minutes resolution of real time data collected from a wind farm in North India. The proposed method consists two cases. In the first case all the inputs of wind series and output of wind power decomposition coefficients are carried out to predict the wind power. In the second case all the inputs of wind series decomposition coefficients are carried out to get wind power prediction. The performance of proposed WANFIS is compared to Wavelet Neural Network (WNN) and the results of the proposed model are shown superior to compared methods.

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1. INTRODUCTION

Solving the wind power forecasting problem is the most significant to integrate the power grid. Wind power forecasting also helps towards the voltage stability for transmission and distribution of system, quality of power, reliability and maintenance schedule for optimal operating cost, real time dispatch decision for electric market, unit commitment, load scheduling, power reserves, etc. When the wind energy is highly stochastic nonlinear in nature then the wind power producers need to give very accurate information in order to mitigate uncertainty. Many advanced studies have been committed to improvements of wind power forecasting techniques. A good number of methods are developed on these forecasting techniques mainly Naïve Method, Physical Approach, Statistical Approaches, New Techniques, and Hybrid Approaches explained by Soman S.S *et al.* [1]. Naïve forecasting method is also known as 'Persistence Method'. It is the most cost effective method and a benchmark which is more sophisticated and it is assumed to have the wind speed at time 't+Δt'.

Physical-approach forecasting technology consist of several sub-methods which altogether and deliver the translation from the wind prediction at a certain point and model level, to predict power at the site considered. Statistical approach forecasting methods are based on historical data of meteorological variables, generated power and wind power measurements. These are frequently updated during online process for accounting recently available information. The statistical models consist of nonlinear and linear. Auto-Regressive Moving Average (ARMA) are more popular in the time series approach, Auto regressive integrated moving average (ARIMA), seasonal- and fractional-ARIMA, ARMA with exogenous input (ARMAX or ARX) are several variations to predict wind speed and power[2-4]. Hybrid method is the combination of physical and statistical approaches for short term and medium-term forecasting models, which is considered as hybrid forecasting approach. For example, artificial neural network techniques with NWP models to get wind speed and power forecasting [5-7].

Forecasting of the wind power generation can be classified into four different time scales, depending upon application. From milliseconds to few minutes, for very short term forecasting system, it can be used for the turbine active power control, Electricity Market, and Regulation procedures. For hours to days, forecast may be considered medium term forecasting system. It may be used for Generator On/Offline Decisions, Operational Security. For longer time scales from days to week more forecasts may be considered as long term forecasting system, for planning the maintenance of wind farms, power reserve decisions, maintenance scheduling to Obtain Optimal Operating Cost [8]. M. Nandana Jyothi *et al*. explained artificial neural network, adaptive neuro fuzzy inference system (ANFIS) and Wavelet Neural Network for the very short term and short term wind power prediction of real time wind power generated data [19-20]. The present article work focuses on very-short term wind power forecasting performance evaluation and accuracy enhancement through Wavelet based Adaptive Neuro-Fuzzy Inference System (WANFIS). The hybrid wind power forecasting model is used to predict the wind power from real time SCADA wind farm system.

2. WIND FARM CHARACTERISTICS STUDY

The proposed work aim is based on measured data from wind power turbine in a wind farm at a specific location in North India. The time-series of 10 minutes data of wind speed, ambient temparature, wind direction, wind density and wind power. These are normalized to improve the performance of forecasting model. Figure 1 shows the typical power variations of a day. Figure 2 and 3 shows the normalized wind power vs normalized wind speed and normalized wind power vs normalized ambient temperature. Wind power curve is cubic and nonlinear nature. The total number of individual time series data of wind speed, wind density, ambient temperature and wind direction are 2143. In this 2000 data samples were taken into training purpose and 143 time series data samples are taken for testing of wind power forecasting model.

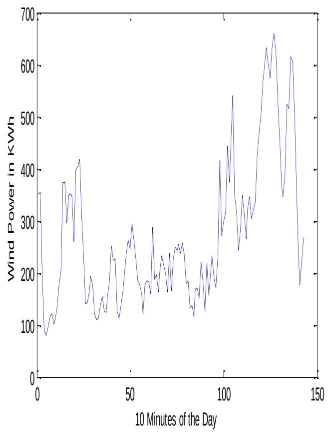

Figure 1. Typical Wind Power Variation of a Day

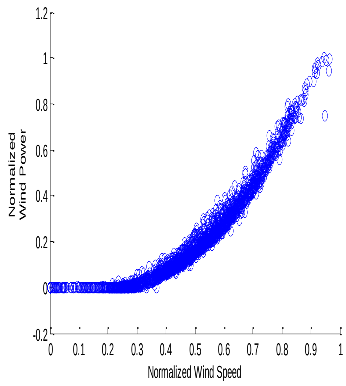

Figure 2. Normalized Wind Power Vs Normalized Wind Speed

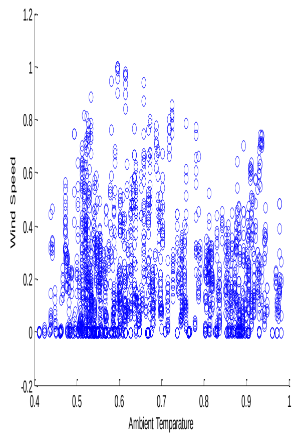

Figure.3. Normalized Wind Power Vs Normalized Ambient Temperature

3. WAVELET BASED ANFIS

3.1 Modelling of Wavelet based ANFIS

The Wavelet Based ANFIS structure is similar to ANFIS model but neural weights are, based on wavelet function value as well as dilation and translation parameters. Translation and dilation parameters are updated at every iteration so that network convergence is faster and accurate [13]. Wavelet Adaptive Neuro-Fuzzy Inference System (ANFIS) model is shown in Figure 4, which consist six layers. The first layer is input layer, second layer is fuzzification layer, third layer is inference layer and fourth layer is defuzzification layer, fifth layer is wavelet function layer and last layer is outut layer.First step of this model is identification of significant number of inputs. The second step is identification of appropriate number and shape of fuzzy partitioning that is modeling of fuzzy rules of TS model. Then the structure of the network is known. Every neuron in the fuzzification layer signifies the membership function [14].

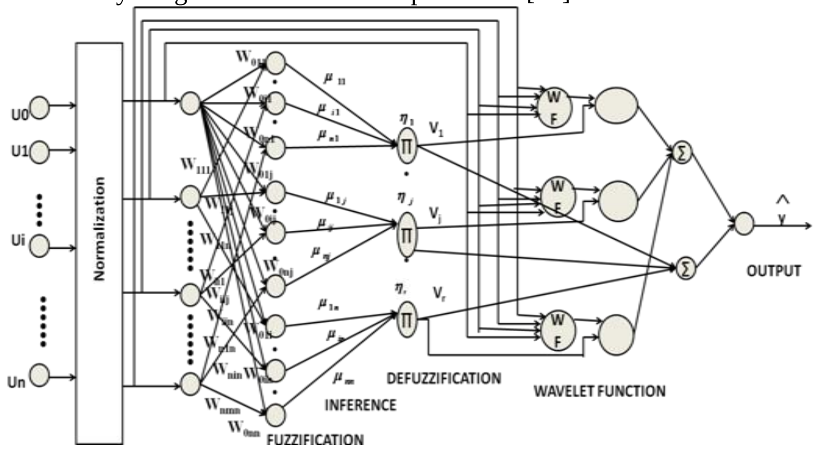

Figure 4. Structure of Wavelet Based ANFIS

The fuzzification output layer is expressed as

$$\mu_{ik}(u_i) = \exp(-|w_{ik}u_i + w_{0ik}u_0|)^{l_{ik}} \tag{1}$$

Where μ_{ik} is fuzzy membership function of the ith variable of input, which corresponds to the kth rule and l_{ik}

The output of Inference is

$$\eta_k(u_1, u_2, ..u_n) = \eta_k(u) = \prod_{i=1}^{n} \mu_{ik}(u_i) \tag{2}$$

The combination of input and the fuzzification layer is neural network weight, which is expressed as

$W = \{w_{ik}, w_{\sigma ik}\}$; Where i=1,2..n and k=1,2..r.

Here the weights connected in between third and fouth layers which central value is { v_k }. These are labeled by $V = (v_k : k = 1,2,..r)$.

The output of defuzzified layer is weighted sum

$$y = \sum_{k=1}^{r} v_k \eta_k(u) \tag{3}$$

The fifth layer each node is labelled with w_l . So the each node function is

$$W_l = (\sum_{i=1}^{n} \phi_{il}) w_l$$

$$W_l = (\sum_{i=1}^{n} - v_{il} \exp(\frac{-v_{il}}{2})^2) w_l \tag{4}$$

Where ϕ_{il} is Gaussian function as a mother wavelet function which represents $v_{il} = \dfrac{(u_i - b_{il})}{a_{il}}$

Where the a_{il} and b_{il} being the dilation and translation parameters of wavelet and also w_l is node parameter
The 5th layer output is in the form of

$$O_l = w_l v_l \tag{5}$$

The final output layer of WANFIS model labeled with summation of all incoming signal from layer five is

$$\hat{Y} = \sum_{l=1}^{n} w_l v_l \tag{6}$$

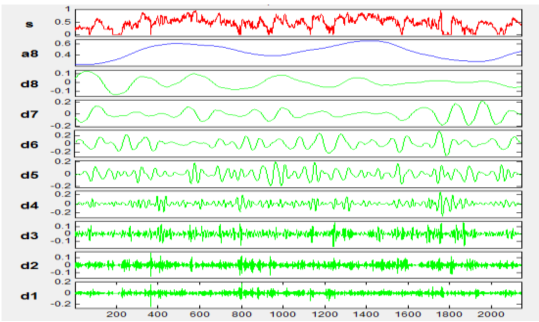

Figure 5. Normalized Wind Speed Decomposition

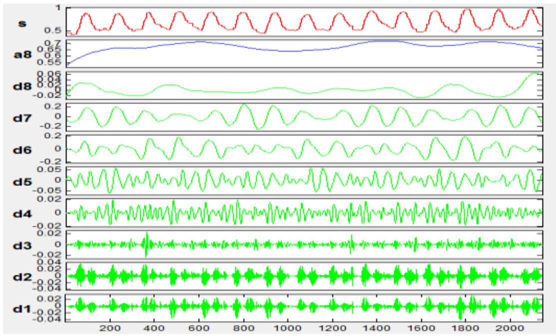

Figure 6. Normalized Ambient Temperature Decomposition

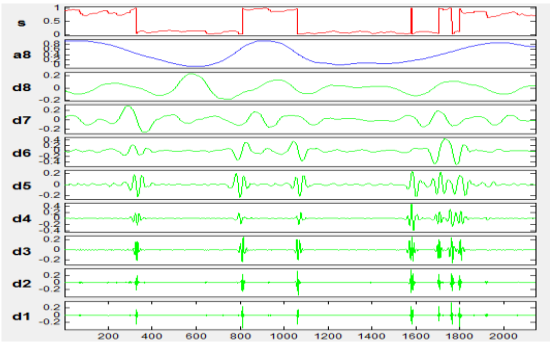

Figure 7. Normalized Wind Direction Decomposition

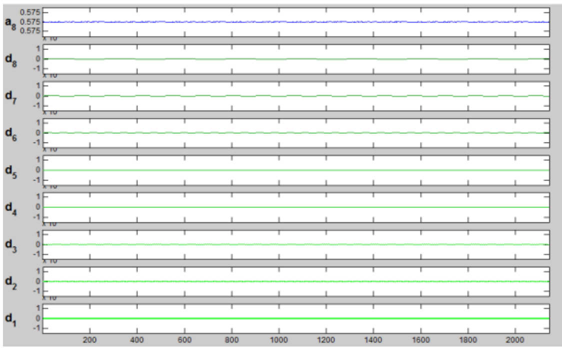

Figure 8. Normalized Wind Density Decomposition

Here the proposed problem is considered in two cases. In the first case all the input and output signals detailed and approximated coefficients were given to the network, finally all predicted coefficients are combined together to get actual forecasted wind power. In the second only the input signal coefficients were given to the network from the wavelet transformations. Finally found the forecasted wind power. The training of Wavelet based ANFIS network is having four inputs, for each input three sets of membership functions were used to get fuzzy rules. A gradient descent method with a back propagation algorithm is used to minimize cost of function. These are differentiable with respect to translation, dilation unknown variable weights and bias of the network [15-16]. Wavelet has two properties. The first is localization of time-frequency energy signal represented by a few expansion and compression coefficients. The second is Multi Resolution Analysis (MRA) of energy signal. The selection of wavelet transform depends on the type of application. Daubechies wavelet is used to decompose the signals, because it's having higher number of vanishing points. In this wavelet multi resolution analysis technique was used to decompose the wind speed, wind density, ambient temperature, wind direction and also found the approximated and detailed coefficients. These two coefficients combination is used to evaluate the signal at all levels and eliminate noise from signal which improves predicted accuracy. Figure 5-8 shows the wind speed, wind density, ambient temperature and wind direction decomposition at 8 level. These are found from wavelet tool box in the Matlab 2012a version [10- 13].

4. WAVELET NEAURAL NETWORK (WNN)

A. Modelling of Wavelet Neural Network

In this model inputs are u1, u2….. un , hidden layer nodes are z1, z2….. zn and weights (Wm) are v1, v2….. vn . The weights are connected in between hidden layer and output function of wavelet. Daubechies wavelet allows to picking up the overlapped approximated and detailed coefficients easier than other wavelet families for describing discrete wavelet transforms in forecasting problem. Figure 9. shows the wavelet neural network model [17]. A feed-forward neural network is used as nonlinear auto-regressive with exogenous wind series inputs and wind power outputs (NARX) for sigmoid activation in hidden layer. To train the network a back propagation algorithm is employed in WNN.

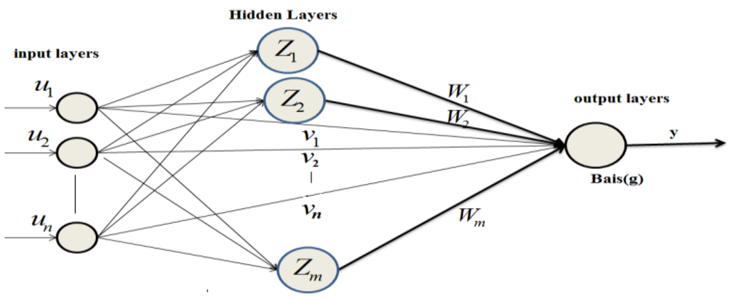

Figure 9. Wavelet Neural Network

Hidden layer output is given by

$$Z_m = \prod_{i=1}^{n} \Psi \frac{(u_i - b_{im})}{a_{im}} \qquad j \in n \tag{8}$$

Where a, b are translation and dilation parameters.
The wavelet neural network output representation is given below

$$y = \sum_{m=1}^{n} W_m Z_m + \sum_{i=1}^{n} v_i u_i + g \tag{9}$$

The Wavelet Neural Network is consisting of four inputs (i.e. wind speed, ambient temparature, wind direction, wind density) and one output (i.e. wind power).to train the network a back propagation algorithm is used to mitigate cost function. These are differentiable with respect to translation, dilation unknown variable weights and bias of the network, which are taken from decomposition coefficients of signals (i.e. wind speed, ambient temparature, wind direction, wind density and wind power).

5. RESULTS AND DISCUSSION

As already discussed each forecasting model has been applied in the following two cases:

a. Application of input and output wavelet coefficients are given in to WANFIS, WNN forecasted models on a training of 2000 samples and on a testing of 143 samples with the combined forecasted wind power.

b. Application of input wavelet coefficients are given in to two models on a training period of 2000 samples and on a testing period of 143 samples for WANFIS, WNN forecasted models.

The time series wind data like wind speed, wind density, ambient temperature, wind direction are taken as inputs and wind power is output, which are collected from North India. In this every 10 minutes data sets are taken for analysis. Data sets were normalized in the range [-1, 1] to improves performance of forecasting models. After normalization input and output signals are decomposed with Daubechie wavelet at a least asymmetry-8 (LA-8) applied to proposed wind forecasting models [18]. Daubechie wavelet gives smooth multi resolution signal with least phase shifting in order to get more accurate forecasting results. Here, the decomposed signals at level 8 is taken so that smooth and least phase shift signal can be predicted accurately Figure 5 to 8 illustrated D1 to D8 and A8 detailed and approximate coefficients of input and output signals Figure 10 shows wind power decomposition [19-20].

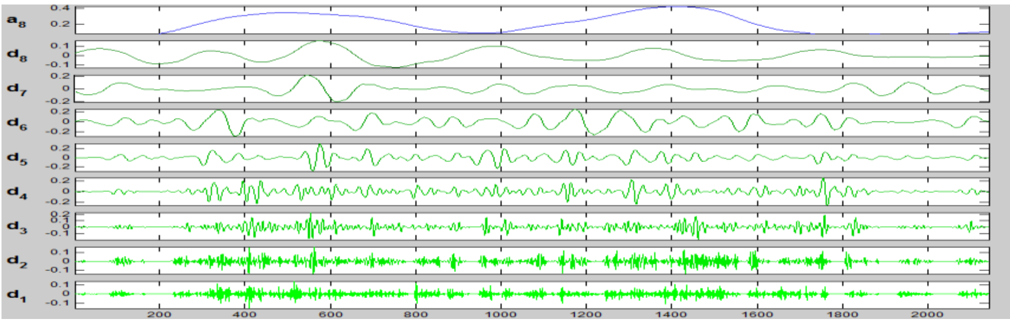

Figure 10. Wind Power Decomposition

In case 1 and case 2 WANFIS models the number of nodes are taken as 193. The number of linear and nonlinear parameters is taken as 81 and 48. The fuzzy inference model is Sugeno and the number of fuzzy rules is 81. For 'and'Method, 'or'Method and defuzzification were chosen as prod, probabilistic, wtaver (weighted average) custom operation. To train the network a back propagation algorithm used. The minimum testing error 0.0256 occurs in case 1 of WANFIS input and output decomposition with combined forecasted outputs, which is more accurate than the other methods. The Mean Square Error, Root Mean Square Error and Normalized Root Mean Square Errors of case 1 WANFIS model are 0.00065, 0.00928 and 0.00919. The second case of WANFIS model testing error is 0.07427 Figure 11. Shows the actual wind power vs forecasted wind power through WANFIS with input and output decomposition. Figure 12. shows the real wind power vs forecasted wind power through WANFIS input decompositions.

The minimum testing error is 0.0391 in the method of Wavelet Neural Networks with an input and output decomposition with combined forecasted output occurs at first hidden layer, two input delays and two Fedback delays are taken into the network. In Case 1 of WANFIS and WNN method accuracy is increased than the case 2 WANFIS and WNN methods. So that the input and output decomposition with recombined predicted outputs case is preferred to get more accurate wind power forecasting results.

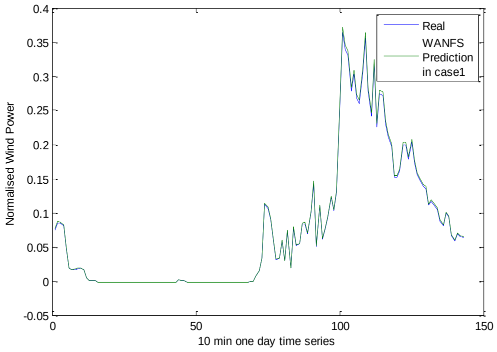

Figure 11. WANFIS Forecasted Wind Power for Case 1

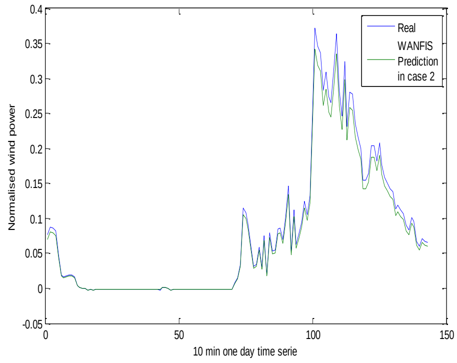

Figure 12. WANFIS Forecasted Wind Power for Case 2

And second case of Wavelet Neural Network testing error is 0.14 obtained at 1-8-8 and 3-8-8 of hidden layers, input delays and feedback delay. Figure13. and 14 shows real wind power vs forecasted wind power through WNN for both cases. Hence, the proposed Wavelet Based ANFIS case 1 method gets more accurate values than the other compared methods. The performance and regression analysis of wavelet neural network is shown in Figure 15, 16.

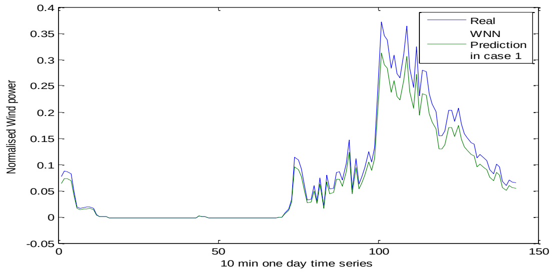

Figure 13. WNN Forecasted Wind Power for Case 1

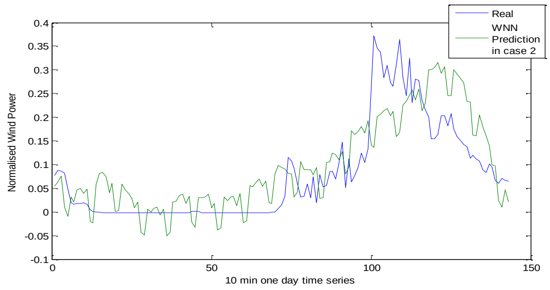

Figure 14. WNN Forecasted Wind Power for Case 2

6. ERROR ANALYSIS

The performance index provides results analysis which depends on error calculations of ME, AME, MSE, RMSE, and NRMSE. The errors can be calculated by using the given below formulas.

a. Mean Error (ME):

$$ME = \frac{1}{n}\sum_{j=1}^{n}(A_j - P_j) \tag{10}$$

b. Absolute Mean Error (AME):

$$AME = \frac{1}{n}\sum_{j=1}^{n}\left(\frac{A_j - P_j}{A_j}\right) \tag{11}$$

c. Mean Square Error (MSE):

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left(\frac{A_j - P_j}{A_j}\right)^2 \tag{12}$$

d. Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(\frac{A_j - P_j}{A_j}\right)^2} \tag{13}$$

e. Normalized Root Mean Square Error (NRMSE):

$$NRMSE = \left(\frac{1}{\max.value - \min.value}\right)\sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(\frac{A_j - P_j}{A_j}\right)^2} \tag{14}$$

Where N - No. of samples, A – Actual Output, P - Predicted Output

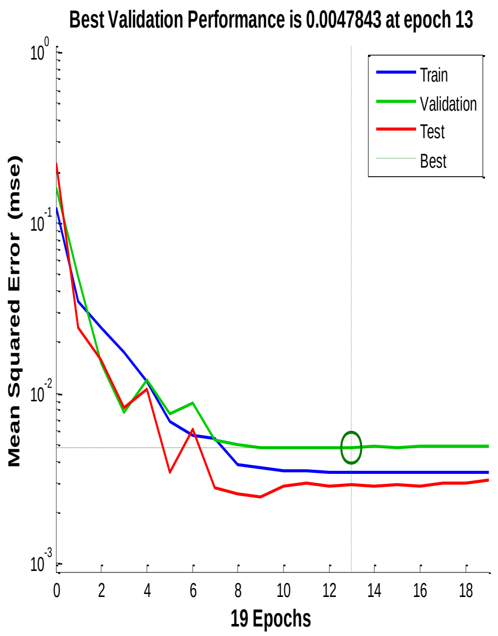

Figure 15. Performance Analysis of WNN

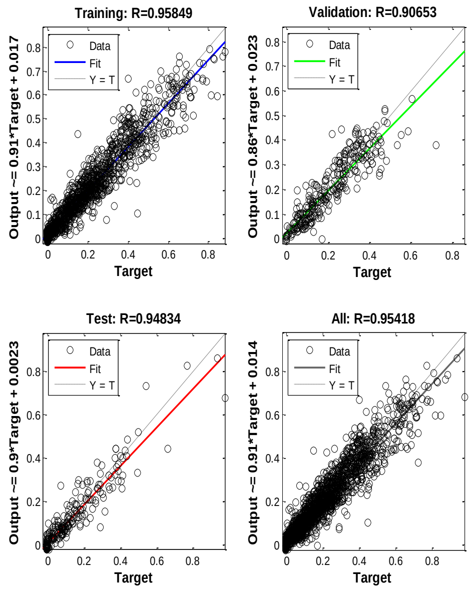

Figure 16. Regression Analysis of WNN

7. CONCLUSION

The solution of integration problem for the very short term wind power forecasting has been carried out between Wavelet Based ANFIS and Wavelet Neural Network at different cases. This comparison looks at a deeper performance analysis focused on ME, AME, MSE, RMSE, NRMSE at different hidden layers, input delays and feedback delays of networks. The best results were obtained in the case 1 of Wavelet Based ANFIS compared to other methods.

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