Wind Power Prediction by Using Wavelet Decomposition Mode Based NARX-Neural Network

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ABSTRACT
Wind energy predictions have been widely developed with a variety of methods, this is due to the stochastic character and uncertainty in the wind. The need for wind energy generation is so great that it must be prepared for operational prediction on its network. This study is very important that aims to design an algorithm to predict wind power for grid operators that are useful to accelerate the management planning of the generation so that the resulting wind power is more optimal. In this paper, we propose a model of wind power prediction by attaching highly intermittent wind speed behavior that makes wind power change rapidly. To overcome this, Wavelet Decomposition method is proposed, then this model is hybridized using Nonlinear autoregressive using Nonlinear autoregressive modeling machine with exogenous input model Nonlinear Autoregressive with External-Neural Network (NARX-NN). The simulation results show that this model can improve the accuracy performance of previous models using BP-Neural Network.

CCS Concepts
Mathematics of computing→Computations in finite fields

Keywords
Wind Power Prediction; Wavelet decomposition; NARX-NN; Bp-Neural Network

1. INTRODUCTION
Wind power energy is one of the renewable energy that will quickly develop because it has the slightest excess of pollution generated in the wind energy generation process. But the source conditions of this wind energy which have varied and intermittent properties especially in the tropics, thus causing many problems of reliability and stability of the operation of this power system.[1] Wind power forecasting models have been widely developed using computer technology by developing hybrid algorithms. Accurate prediction of wind power can improve the optimization of the generation so that it can generate greater wind power and reduce the cost of integration of wind power generation operations. [2]

Usually the input of wind power is highly dependent on different meteorological parameters, in this study using two parameters of angina and wind angle velocities that are very influential on optimizing the output of wind turbines in wind farms. Therefor, the purpose of this study will see the effect of these two parameters on the predicted wind power that will be compared with the real condition of wind power generated in the observation field.

The related studies of this paper mostly use the same learning engine as auto-regressive integrated moving average (ARIMA), Regression Trees (RT), Support Vector Machines (SVM) and Neural Network. But power forecasting using ARIMA has limited ability to forecast time series with abrupt change.[3][4][5], While Gauss-Newton and nonlinear methods are widely developed for use in data mining. The disadvantages of ARMA and NARMA methods require a complete time series observation that limits the application of its computing process to short-term forecasting. [6][7]

Due to the above problems, this study will develop a hybrid methodology between wavelet decomposition and Nonlinear Autoregressive with External Input (NARX) model of Neural Network (NN). This hybrid methodology was chosen to look at the effect of 2 meteorological parameters on the power prediction generated in this method. This study would like to see the optimization of wind power prediction with the proposed model of real power in the field of observation.

2. WAVELET DECOMPOSITION
Wavelet Decomposition used in this study to analyze the response behavior of time series data from 2 parameters. Wavelet transform offers the ability of localized multi-resolution compositions.[8] The wavelet sequence approach of the y (t) circuit is defined by

$$y(t) = \sum_k C_{j,k} \emptyset_{j,k}(t) + \sum_{j=0}^{J} \sum_{k=0} W_{j,k} \psi_{j,k}(t) \qquad [1]$$

Wavelet analysis was also used to analyze the 3 most influential meteorological parameters on power prediction[9]. Signals can be analyzed by dilation and translation of mother Wavelet φ (t). Continuous wavelet transform (CWT) is defined as

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(x) \phi\left(\frac{x-b}{a}\right) dx \qquad [2]$$

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Where,

$\emptyset_{a,b}(x) = \frac{1}{\sqrt{a}}\phi\left(\frac{x-b}{a}\right)$ is base wavelet, a is scale factor and b is shift factor. In actual use, scale factor and shift factor should be discrete. Let $= a_0^j, b = ka_0^j b_0$, so the discrete wavelet transform (DWT) of signal $f(x)$ is

$W(j,k) = \int_{-\infty}^{+\infty} f(x)\phi_{j,k}(t)dt, j,k \in Z$……........[3]

As can be shown on Figure 1

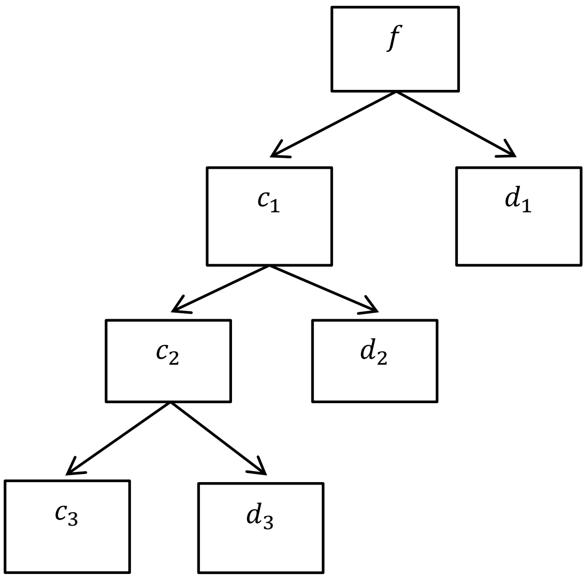

Figure 1. Wavelet decomposition tree.

3. ESTABLISHMENT NARX NEURAL NETWORK

In the NARX NN learning machine model, there are 3 neurons in the input layer, one neuron in the output layer, 2 neurons in the hidden layer, and the sigmoid function is used as an activation function. As can be shown on Figure 2

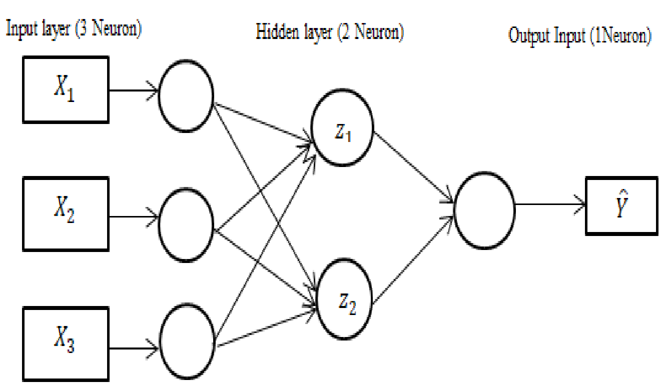

Figure 2. Neural Network Architecture for NARXNN.

3.1 Wind Power Prediction Model

In this study, time series data from 2 parameters, wind speed (Ws) and wind angle (Wa) are used as inputs and Wind power data (WP) is used as output, the three parameters are analyzed correlation using NARXNN. then the resulting signal is decomposed using wavelet transform, the pre-processing model of the study is shown in the figure 3.

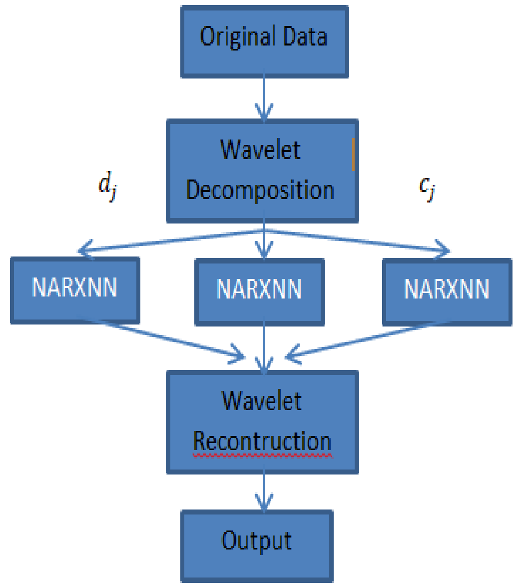

Figure 3. The Modeling Prediction of The WD-NARXNN.

4. RESULTS AND DISCUSSION

This study uses historical data from Wind Speed, Wind angle and Wind Power from Pandansimo wind farm, Bantul Yogyakarta. Simulation data using year 2013 data, with data sampling time span every hour. During this study experiment selected wind turbine data from January 1-15, 2013 to be used as a training sample, January 16-21,2013 data is used for forecasting models.

Using wavelet db3 to decode the original time series into four layers, the result of the wavelet decomposition is shown in Figure 4. Where C3 is the low frequency part whereas d1, d2, d3 are high frequency parts.[10]

The signal is decomposed separately using wavelet decomposition into several sequences in the same layer $(c_d(k), d_i(i = 1,2,3)$ and then reconstructed y(t) using the reconstruction wavelet as the output of wind power prediction on figure 4

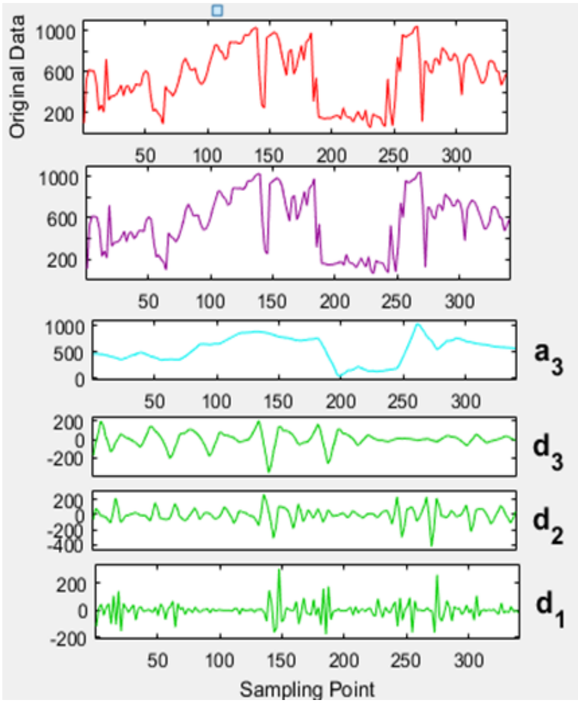

Figure 4. The result of wavelet decomposition.

For decomposed time series, built a model with NARXNN predictions, then the predicted results can be improved. By comparing the above simulation results, figure 5 shows actual wind power prediction of actual wind power and average tracking error of 12,73% for the WD-NARXNN method, this condition is better than BP prediction of 26,37%. It is known that the WD-NARXNN prediction effect in this study is superior to predictions using BP.

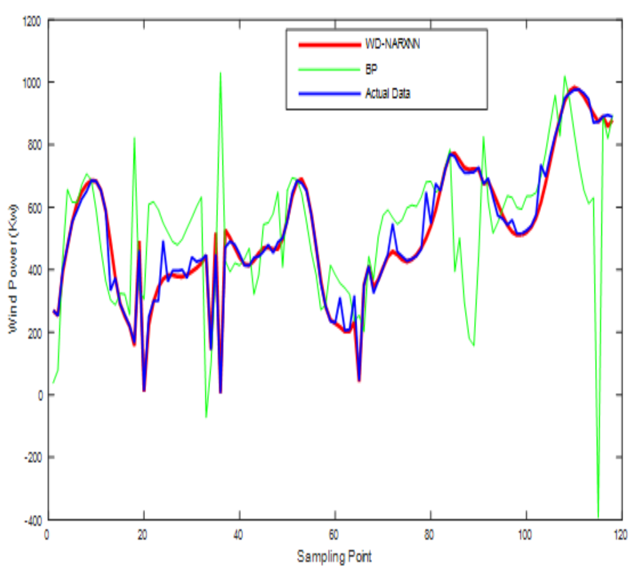

Figure 5. Forecasting mean error of BP and WD-NARXNN in Jan, 16-21, 2013.

Table 1. Predicting mean error of BP and WD-NARXNN in Jan, 16-21, 2013

	BP	WD-NARXNN
Mean Error (%)	26,37 %	12,73 %

Table 1 shows the percentage of mean wind power prediction error with back propagation (BP) method that has 26,37% error that is greater than WD-NARXNN method that has 12.37% error against actual wind power data.

5. CONCLUSION

In this study, Wavelet and NARX-Neural Network decomposition (WD_NARXNN) is proposed to obtain wind power prediction feature. The first thing is done by decomposition of 2 parameters that affect the wind power, by conducting a correlation test using NARX-Neural Network regression. Then the results are analyzed and compared with the predicted model of wind power that has been done before. It turns out the BP method still generates a very big error compared to the improvement using Wavelet Decomposition. While the prediction model of WD-NARXNN can improve the accuracy level better than the BP model, for future projects this prediction model should be tested for other wind farms around the current observation area.

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