Comparison Accuracy W-NN and WD-SVM Method In Predicted Wind Power Model on Wind Farm Pandansimo

Conference Paper · November 2018

DOI: 10.1109/ICNERE.2018.8642585

Ane Prasetyowati
University of Indonesia

Dodi Sudiana
University of Indonesia

Comparison Accuracy W-NN and WD-SVM Method In Predicted Wind Power Model on Wind Farm Pandansimo

A.Prasetyowati, D.Sudiana and H.Sudibyo

Department of Electrical Engineering Indonesia University, Depok
Indonesia TEL. +62-21-7270078 FAX. +62-21-7270077
e-mail: ane.prasetyowati51@ui.ac.id, dodi.sudiana@ui.ac.id, harisudi@ui.ac.id

***Abstract*, Wind power is one of the environmentally friendly renewable energy systems. The biggest obstacle is the operation of wind energy at intermittent wind speeds. Unstable wind speed conditions tend to be very influential in the production of electricity produced. For this reason, this study aims to create and compare wind power prediction models using the WD-NN and WD-SVM methods in wind fields that have very high intermittent levels such as Pandansimo wind farms.**

Keywords—Wind Power, Prediction, Intermittent, WD-NN,WD-SVM

I. INTRODUCTION

Modeling a wind power prediction has obstacles that are not easy. Wind power patterns that are difficult to trace and have patterns that change for each second, making this prediction model very important to be made to prepare the network in generation for wind energy. The intermittent conditions of wind speed in wind land in the islands greatly complicate the process of predicting wind power. The approach to the value of accuracy in the process of predicting wind power was the main topic of this study. In this study an accuracy comparison of wind power prediction models will be carried out using a hybrid wavelet with Neural network method (WD-NN) and hybrid wavelet with Support Vector Machine (WD-SVM) method. Comparison is done by looking at the performance of the two models with predictive results that can follow the real pattern of wind power conditions on the observation field. The best assessment of wind power prediction models by comparing accuracy values using the RSME (Root Square Mean Error) value of each output of the prediction model. This is done with the aim of knowing the daily wind power estimates on the observation land so that it can be used as a reference for preparatory actions on the generating network. The estimated pattern of readable wind power before generation preparation can also reduce the maintenance costs of turbine equipment in the plant. So it is expected that with this wind power prediction model generated, the efficiency of generation of wind energy in wind fields on islands that have high intermittent can be achieved.

II. WAVELET DECOMPOSITION AS A FILTER

Wavelet is a local wave that is limited by functions that move up and down in time space [1]. Wavelets can be referred to as short waves. Decomposition of a frequency in a time space that gives a time base is a Wavelet Transform (WT) [2], Mother Wavelet is a function used in wavelet transforms. Through certain scaling the mother wavelet will determine the characteristics of the resulting wavelet transformation. The selection of the mother wavelet requires precision so that the transformation is more efficient. Wavelet transforms can identify and analyze moving signals. Analyze moving signals to obtain information and frequency spectrum at the same time. Discrete wavelet transform (DWT) works on two functions, namely the scale function and the wavelet function, each of which has a function as a low-pass filter and a high-pass filter. [3]. The decomposition structure of the wavelet transformation for level 3 can be seen in Figure 1

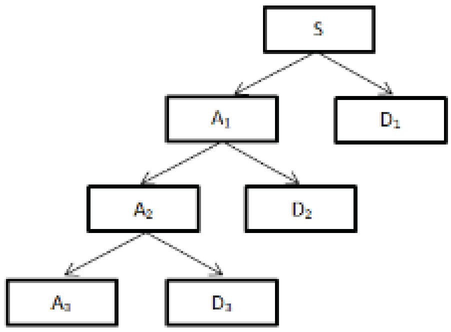

Figure 1. Decomposition structure of the wavelet transformation for level 3

In this study wavelets used Haar wavelets. This type of wavelet is perfect for detecting information with local time. The function of the Haar wavelet is to improve the performance of the prediction technique [2][3]. Haar wavelets have two functions called estimation and difference functions. The approximation function of the haar wavelet produces an average sequence between two consecutive data in the data input. While the difference function produces the current time approach. Both functions are executed recursively and the decomposition process will stop when elements in the order of difference produce a

978-1-5386-7553-3/18/$31.00 ©2018 IEEE

single sequence of functions. The i approximation sequence is shown in the equation

$$A_i = \frac{A_{i-1}(1)+A_{i-1}(2)}{2} + \frac{A_{i-1}(3)+A_{i-1}(4)}{2} + \cdots + \frac{A_{i-1}(n-1)+A_{i-1}(n)}{2} \quad (1)$$

where $A_{i-1}(j)$ is the $j-th$ element in the sequence (A_{i-1}) for $j = 1,2,\ldots,n$.

The decomposition process is carried out through level one or more. The discrete wavelet series contains a series that functions as an estimate of $(A_t)$and series detail detail (D_t). Dimensional signals can be divided into two parts, namely low frequency and high frequency. High frequencies are analyzed by a low-pass filter, while low frequencies are analyzed with a high-pass filter. Both filters are used to analyze various signal resolutions. The generated signal can be subsamped by removing the second sample. Decomposition for each layer can be represented by an equation

$$ylow(k) = \sum x(i)h(2k-i) \; and \; yhigh(k) = \sum x(i)g(2k-i) \quad (2)$$

Where ylow and yhigh are low-pass and high-pass filters. The notation k is a decomposition and the notation x shows as the original signal. The two functions above can be reused in the next decomposition. The DWT coefficient consists of high-pass and low-pass filter output. High and low filter functions are followed by a reverse sequence in signal reconstruction. Signal reconstruction using equations

$$x(i) = \sum_k yhigh(k)g'(-n+2k) + ylow(k)h'(-n+2k) \quad (3)$$

The reconstruction process aims to restore the original signal from the data. Reconstruction begins by combining the DWT coefficient which is at the end of the previous decomposition. The reconstruction process is the opposite of the decomposition process according to the desired decomposition level.

III. PREDICTEDING MODEL WITH HYBRID ALGORITHM WD-NN

Forecasting model built using decomposition wavelet decomposition process. The goal is to find trend data that occurs on a series of input data selected to be processed in this model experiment. Expected results can further minimize the error value in the model of wind power forecasting. Figure 2 is a chart of the model that has been done:

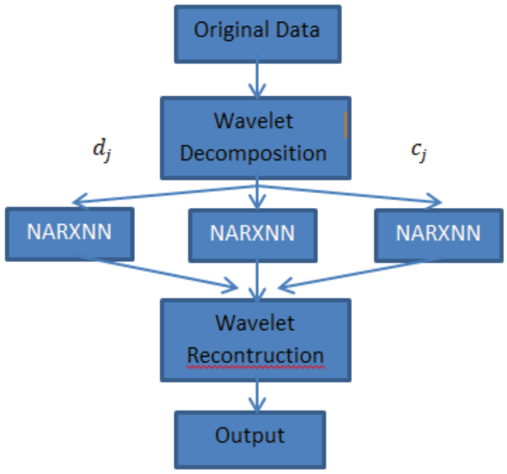

Figure 2. Wind Power Forecast Model with WD-NN

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.[4][5]

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 3.

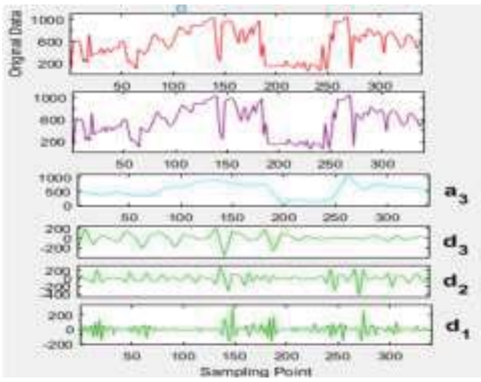

Figure 3. The result of wavelet decomposition

For decomposed time series, built a model with NARXNN predictions, then the predicted results can be improved. By comparing the above simulation results, figure 4 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.

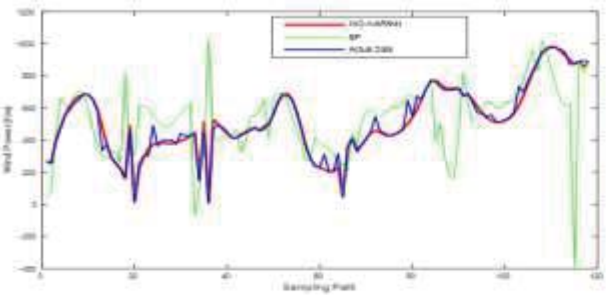

Figure 4. Forecasting mean error of BP and WD-NARXNN in Jan, 16-21, 2013

IV. PREDICTING MODEL WITH HYBRID ALGORITHM (WAVELET DECOMPOSITION-SUPPORT VECTOR MACHINE)

The use of Vector Machine support (SVM) in this study can classify the conditions of daily wind speed. This classification of wind velocity conditions can provide information on generating estimates of how much wind power will be generated. If these conditions can be properly classified, the cost of generation can be calculated more accurately. Here is a Characteristic of the Support Vector Machine:[6][7]

1. Support Vector Machine is a linear classifier (Support Vector Machine is a linear classifier)
2. Pattern Recognition is done by transforming data on the input space to a higher dimension space, and the optimization is done in the new vector space.
   3. Applying the strategy of Structural Risk Minimization (SRM)
   The working principle of Support Vector Machine is basically only able to handle the classification of two classes[8][9]

Real wind data using Pandansimo wind farm data with actual output data from 21 wind turbines, which has manufacturer specifications for 1 unit as follows: capacity 1 Kw / 240V, Cut-in speed: 3 m / s, Cut-off speed: 25 m / s Rpm: 300-500 rpm and has blade type: fins. Output data for the analysis of 168 data of wind power output in January 2013. Database used last 3 years data as historical data in the form of data wind speed, wind direction, temperature and humidity.

Clustering and regression algorithm for wind power prediction model using SVM method as in the picture 4 make the wind power data fluctuated so that the output of wind power generated per day does not have a fixed scale. This study aims to find the scale of wind power that often occurs in January, so the results can be used to predict the wind power output 1 day ahead with short-term forecast.

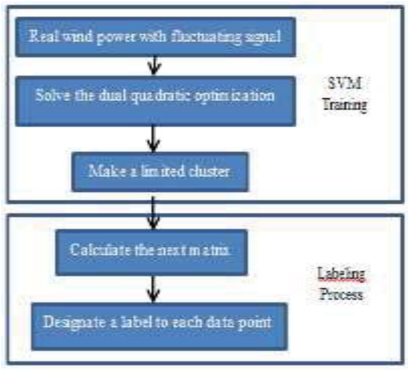

Figure 5. Clustering and regression processes on the SVM method

Stages of Training and Labeling process which conducted by SVM method to generate predictive data scale. These predictive data will know each of the wind power points resulting in a large-scale category of wind power generated. This model chart can be seen in Figure 6.

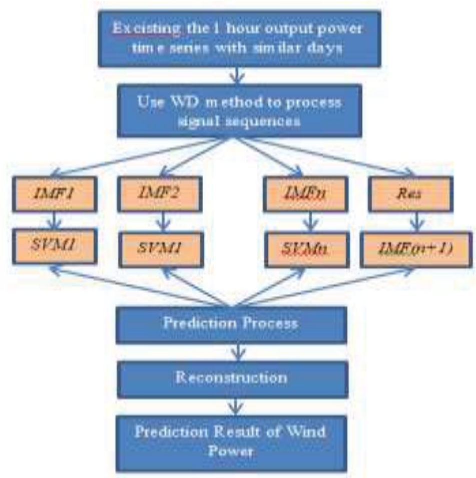

Figure 6. Predicting Model wind power with WD-SVM

The prediction results in this model are shown in Figure 7 below:

978-1-5386-7553-3/18/$31.00 ©2018 IEEE

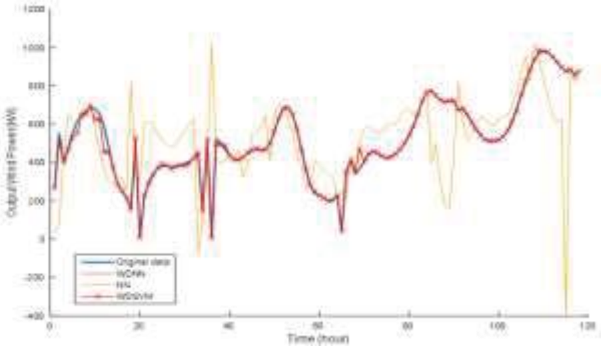

Figure 7. Predicted result curves for the different models.

The performance result of the predicting model WD-SVM show ratio on the prediction model using NN average is 0.14471, WD-NN model is 0.127 while WD-SVM model gives the smallest error rate of 0.0517. SVM classification model gives the performance of the model to be better when recognizing the original pattern of data that has a non-linear pattern. Wavelet decomposition helps SVM work that could not work on large data when not using a hybrid model.

V. CONCLUTIONS

The use of Wavelet on the wind power prediction model in this study helps to make the pattern of more wind speed wind speed data follow a real wind speed pattern, so that the resulting wind power prediction is closer to the actual wind power pattern. Both regression models used to execute data produce predictive data that has almost the same level of accuracy. But the hybrid WD-SVM model is better than the WD-NN. The NN learning process which results in processing is slower than the training process conducted by SVM.

References

[1] R. Maheswaran and R. Khosa, “Neurocomputing Wavelet Volterra Coupled Models for forecasting of nonlinear and non-stationary time series,” *Neurocomputing*, vol. 149, pp. 1074–1084, 2015.

[2] V. N. Lestari, J. Matematika, F. Matematika, and P. Alam, “Transformasi Wavelet Diskret Untuk Data Time Series,” pp. 163–170, 2015.

[3] P. Sugiartawan, R. Pulungan, and A. K. Sari, “Prediction by a Hybrid of Wavelet Transform and Long-Short-Term-Memory Neural Network,” vol. 8, no. 2, 2017.

[4] I. Pranata, H. M. Junaidi, and B. Lareno, “Penerapan Algoritma Wavelet Neural Network Untuk Prediksi Beban Penyulang Listrik Jangka Pendek,” pp. 9–10, 2015.

[5] X. Wang, Y. Zheng, L. Li, L. Zhou, and G. Yao, “Short-Term Wind Power Prediction Based on Wavelet,” pp. 645–653.

[6] Y. Ren, P. N. Suganthan, and N. Srikanth, “A Novel Empirical Mode Decomposition With Support Vector Regression for Wind Speed Forecasting,” vol. 27, no. 8, pp. 1793–1798, 2016.

[7] Y. Ren, X. Qiu, and P. N. Suganthan, “Empirical Mode Decomposition based AdaBoost-Backpropagation Neural Network Method for Wind Speed Forecasting,” pp. 1–6, 2014.

[8] C. Yu, Y. Li, Y. Bao, H. Tang, and G. Zhai, “A novel framework for wind speed prediction based on recurrent neural networks and support vector machine,” *Energy Convers. Manag.*, vol. 178, no. September, pp. 137–145, 2018.

[9] “No Title,” vol. 28, pp. 35–49, 2015.