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Prediction of Wind Power Model Using Hybrid Method Based on WD-SVM Algorithm: Case Study Pandansimo Wind Farm

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Abstract. Wind power prediction with original data that has a nonstationary pattern and randomness becomes a major problem when the data is used for the preparation of the generation. Especially the wind power directly connected to the network. In this research, we proposed wavelet decomposition model and support vector machine (WD-SVM) to predict the power scale of wind power in Pandansimo wind farm. Time series data that is built in interval of 1 hour mean in 24 formed day data. The data is parsed using WD that generates the IMF component. The output of the WD model is reprocessed using the SVM model to do the clustering process which the outputs are the scale of selected wind power strength in 1 month approaching the historical data of measurement. Finally after going through the experiment, obtained the data prediction scale of wind power strength that has a high accuracy near the actual conditions. The WD-SVM hybrid model provides a smaller error than the predicted model of NN and WD-NN.

1. Introduction

Wind energy is a very environmentally friendly renewable energy. But the use of wind energy has its own constraints. The power of wind speed is the most important thing in wind energy generation [1]. Along with the increasing demand of wind energy that is marked by the construction of wind farms in Indonesia is also increasing the scale of wind energy systems connected to the network, because the side effects of intermittent characteristics that result in wind energy system have a constraint on predicting how much wind energy generated [2, 3]. If changes in wind power can be accurately predicted, scheduling network usage can be accurately planned and a balanced power load configuration can be achieved to protect the safety and stability of generation in this wind power system.This paper uses station measurement data around the wind farms. The measurement data is possible to predict the wind power of the connected network on wind farms. Data used for wind power prediction systems use different dates in the same month. This is done because the influence of weather in Indonesia which has different contour conditions resulted in wind velocity, humidity and temperature conditions experienced a very significant change. Predictive methods are made to estimate wind power that will occur in the future. The power of wind power is calculated using mathematical theories and statistics [4, 5]. In the preceding writing, wind power prediction uses wavelet decomposition method combined with neural network method and can predict nonlinear time stochastic circuit. This method can parse several timing sets into different frequency circuits, reduce white noise and reconstruct predicted results to get predicted values from the original series time series [6, 7]. In this paper, introduces wind power prediction models by combining decomposition wavelet methods with a support vector machine applied to wind farms in the tropics with significant rates of

data changes. This model is better compared to the incorporation of the decomposition wavelet method with the neural network method. Predictions for generation scheduling are more accurate and result in a more stable system of generation. This is advantageous for wind power systems connected to the network [6, 8].

2. Parameter clustering in the same week in power wind power output

In the measurement data found several factors that affect the power of wind power. The power of wind power has a tendency to change in different weather conditions. Figure 1 shows the output power changes within 1 week of the system. Figure 1 shows the behavior of the wind power output that fluctuates so that the signal strength trends are difficult to represent. This is very reasonable considering the size of the wind speed is sensitive to the influence of the monsoon climate occurring in archipelagic countries such as in Indonesia.[6] To facilitate the wind power prediction process, the wavelet decomposition method is used. Trend signals from wind power will be generated after using this method.
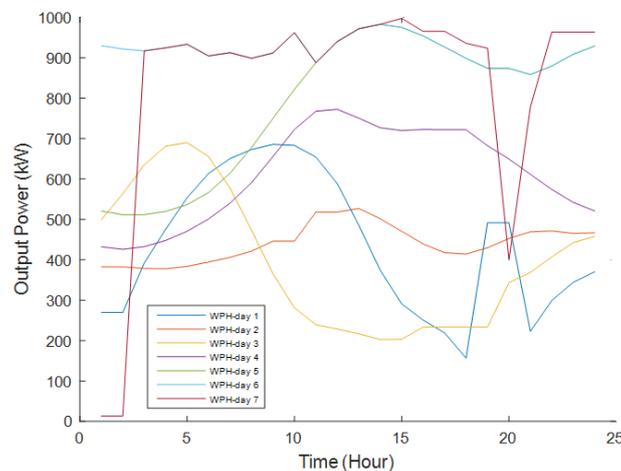

Figure 1. Average changes in wind power output per day (24 hours) in 1 week

After that the model in the clustering is classified using SVM method, clustering that will be subjected to the amount of potential wind velocity to generate wind power in 1 month. Classification is divided into 4 parts, wind speed <3 m / s with less potential category, 3 - 4 m / s small-scale wind power category, 4 - 5 m / s medium-scale wind power category and> large scale category. The SVM method is used to predict in 1 month the category of wind power scale obtained on one of the scales established in this study. If we already know the prediction in 1 month is on the scale set by the output with SVM method, it can help the generation process in its operation.

3. Reduce wind power process from turbine system wind connection grid with wavelet decomposition

Decomposition of Wavelet Decomposition (WD) aims to create a series of time series data from the output of Wind speed becomes more smooth because the signal is nonlinear and non-stationary based on the original characteristics. WD parses data that experience fluctuations or trends. Each data one by one from a complex signal creates an intrinsic mode (IMF) circuit [3, 9]. Wavelet decomposition is able to represent the signal of wind power output. The wavelet decomposition function is not seamless so that when there is a spike or high volatility the wavelet may to infinitive the narrow support.The wavelet decomposition of $x(t)$ and the time series of wind power are carried out as follows: The wavelet decomposition of $x(t)$ and the time series of wind power are carried out as follows:
1) Identification of $x(t)$ wind velocity data that has been processed to eliminate outlier data from the measurement results.

2) Determine the wavelet transform used in this paper using Discrete Wavelet Transform (DWT), with equation shows below:

$$x(t) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} d(k,l) 2^{-k/2} \Psi(2^{-k} t - l) \tag{1}$$

3) k is connected to a with $a = 2^k$ and b is connected to l with $b = 2^k l$, $d(k,l)$ is the result of the excerpt from $W(a,b)$,, at the discrete points k and l.

4) The signal x(t) with the original signal length is selected 1024, then the decomposition level uses $S = 5$, after decomposing the signal length becomes 32, then the signal is reconstructed by

$$x_p{}^{n.j} = \sum_{k \epsilon Z} \left[\Box(p - 2k) x_k{}^{2n.j+1} + \overline{g(p - 2k)} x_k{}^{2n.j+1} \right] \tag{2}$$

5) The reconstruction used using the downsampling method, to compute $x_p{}^{n.j}$ in the sequence $x_k{}^{2n.j+1}$, the value 0 is inserted between the sequences. With this reconstruction process, the original signal length becomes the same again. So that the result of smoothing signal can be produced in this decomposition process.

4. Construction of wind-power prediction model based on WD And SVM

The use of Vector Machine support (SVM) in this study can classify the condition of daily wind speed. This classification of wind velocity conditions can provide information to 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 [10, 11]. Here is a Characteristic of the Support Vector Machine:

1. Support Vector Machine is a 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)
4. The working principle of Support Vector Machine is basically only able to handle the classification of two classes.[4, 10]

Available data is denoted as $x \in R^d$ whereas on the label is notated $y_i \in \{-1 + 1\}$ for $i = 1,2,\ldots\ldots,n$ where n is the number of data. Class -1 dan $+1$ can be separated by a dimension of the hyperplane das the following equation:

$$\vec{w}.\vec{x} + b = 0 \tag{3}$$

Class -1 with the equation

$$\vec{w}.\vec{x} + b = -1 \tag{4}$$

Class $+1$ with the equation

$$\vec{w}.\vec{x} + b = +1 \tag{5}$$

The difference between class produces margin, the largest margin can be found by maximizing the distance value between the hyperplane and its nearest point, ie$1/\|W\|$. The smallest margin use quadratic programming method (QP) with the equation:

$$\vec{w} \, \tau(W) = \frac{1}{2}\|\vec{w}\|2 \tag{6}$$

$$yi(x \to w + b) - 1 \geq 0, \forall i \tag{7}$$

These positive margin points will produce support vectors. 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. The 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 figure 2 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 a short-term forecast.
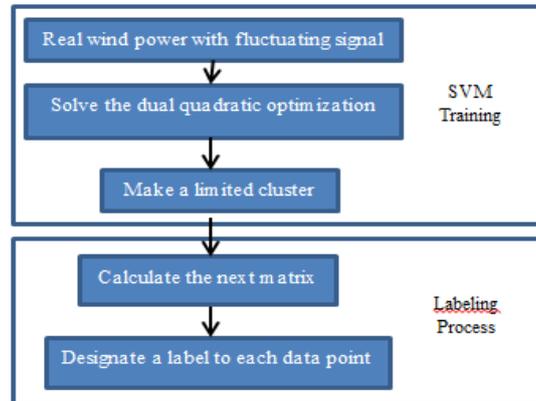

Figure 2. Clustering and regression processes on the SVM method

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. The following stages of wind power output process in SVM method as follows:

1) Identification of $x(t)$ and analyzing the output per day, the result of varied signal output, no clear scale pattern as shown in figure 1. It is difficult to determine the wind power output on which scale of the four categories set at the beginning of the study.
2) Create solution 1) with Quadratic Optimation formula to know the maximum value of wind power output and minimum wind power output that happens per day.
3) Creating cluster boundaries as shown in the above scale classification in the form of limitations of wind speed scale generated per day. This may reflect the wind power of the day.
4) After creating a cluster, the signal points are converted to a matrix and the result can know at which scale the wind power output during that week. Later is to prepare the process of generation. If the scale obtained on that day is not appropriate, it can give warning to the generation process.
5) The last step marks the label at each data points, within 1 week can be known the scale of data of wind power output per day.

5. Simulation result in case study

Building a prediction model of wind power with an output of 24 hours in 7 days, daily measurements performed hourly. The model builds on the historical concept of measurement data on wind farms. Then the time series output power is decomposed by the empirical method to obtain IMFn intrinsic component. From this process obtained data that has been free from outliers. To obtain trend data we used SVM method to know the scale of wind power that occurs per day ahead in 1 week. According to the method that has described above, clustering of similar day analyzes is conducted for weather conditions in 2013. The wind power per day is divided into 4 scales. In this study, 705 samples were sampled (actually 720, but 15 data were bad data on measurement). This study focused on 500 data that have the same trend pattern. The prediction model applies like as figure 3.
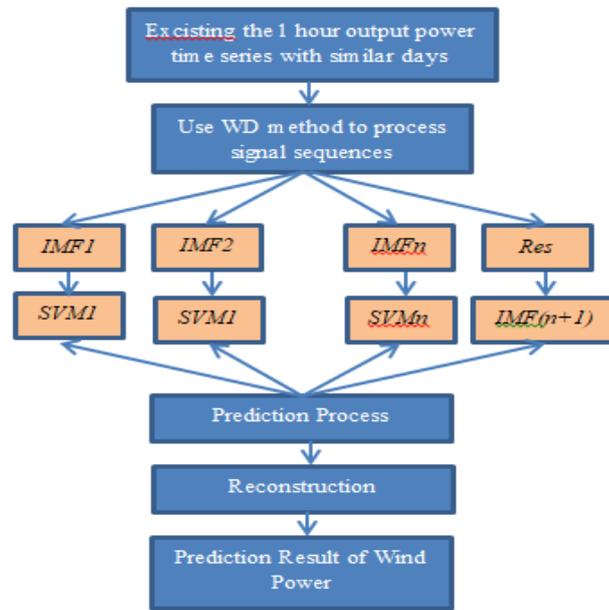
Figure 3. Wind power output predicting model construction based on WD-SVM

The model in this study works to predict power by the WD-SVM method. To analyze the model used 180 data with the condition has wind speed that does not change significantly, then time series data in decomposition with wavelet on the same scale to get 4 component IMF and 1 component Res, as seen in picture, IMF1 and IMF2 have high frequency and nonlinear signal behavior is very strong but when extreme weather changes are followed by changes in wind velocity, IMF4 and IMF5 frequencies will become very low with the use of decomposition to make the signal periodicities become formed. The Res component shows a smooth change of signals that have small amplitude and minor components of the wind power output. After a smooth signal is established and a trend model of the signal is known can be seen in figure 4.
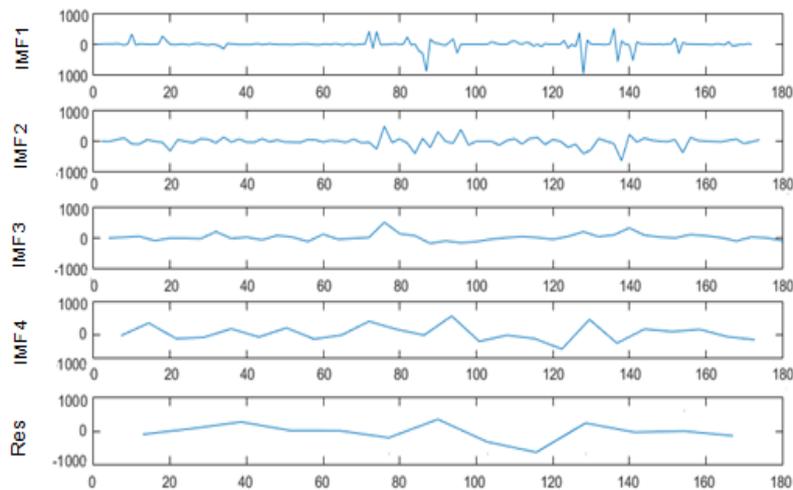

Figure 4. Decomposition graph of the output power sequence of 180 hours of the similar days with the WD.
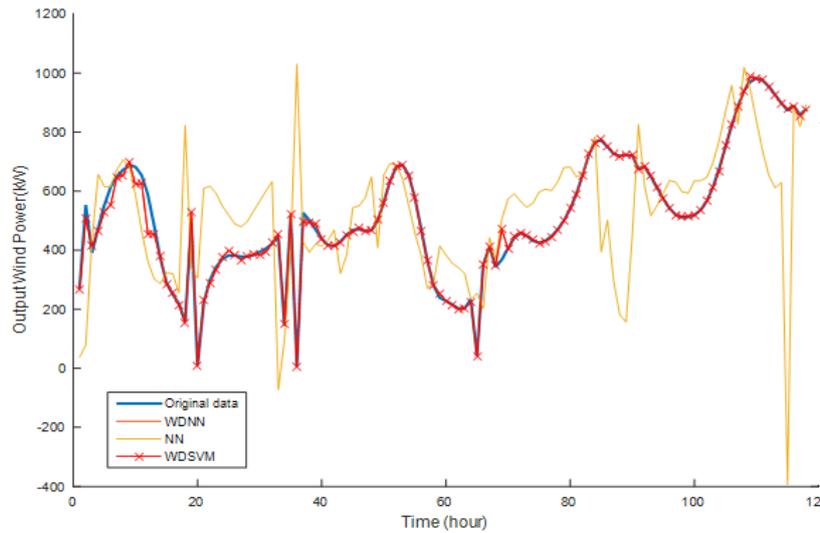
Figure 5. Predicted result curves for the different models.

The WDSVM model provides predictable results close to the original data from wind power output, a prediction constructed by first classifying wind speed scales in wind farms using the SVM model. Previously, wind speed data is processed through wavelet decomposition so that it can smoothing data. Comparison of predicted results with other models that ever built makes the WDSVM prediction model seen to follow the pattern of the original data, this can be seen in figure 5.

While the prediction results of each point in this study can be seen in **Table 1**. It is seen that there is the prediction of wind power for each model that is produced but cannot yet follow the value of wind power on the original data.

Table 1. Comparisons of predicted results using three models about output wind power

Number	Original Data(kW)	NN (kW)	WD-NN (kW)	WD-SVM (kW)	Number	Original Data(kW)	NN (kW)	WD-NN (kW)	WD-SVM (kW)
1	269.494859	37.89016619	253.9	269.494859	21	222.7470755	609.5025605	247.68	250.7470755
2	253.8952128	78.57874985	507.88	253.8952128	22	299.308072	617.2520089	253.9	300.308072
3	391.7827249	435.8732397	654.52	400.1500048	23	344.1325037	592.440514	599.988	300.1325037
4	475.3666023	657.1852333	626.74	475.3666023	24	370.3561323	549.7845077	623.72	493.8283303
5	553.6782774	615.7699627	530	553.6782774	25	382.273099	519.3858904	626.74	362.273099
6	613.6739971	615.1467122	353.9	589.1837821	21	222.7470755	609.5025605	247.68	250.7470755
7	650.3550632	673.0262326	247.68	626.7393572	22	299.308072	617.2520089	253.9	300.308072
8	672.796268	706.7300656	253.9	651.0430808	23	344.1325037	592.440514	599.988	300.1325037
9	685.44552	686.087086	599.988	685.44552	24	370.3561323	549.7845077	623.72	493.8283303
10	683.1528746	590.0247201	623.72	683.1528746	25	382.273099	519.3858904	626.74	362.273099
11	654.1009358	464.9611499	626.74	654.1009358	21	222.7470755	609.5025605	247.68	250.7470755
12	588.3931386	362.9255439	456.62	588.3931386	22	299.308072	617.2520089	253.9	300.308072
13	485.4371008	303.5763327	453.9	333.9266417	23	344.1325037	592.440514	599.988	300.1325037
14	374.3049273	287.1992032	348.98	374.3049273	24	370.3561323	549.7845077	623.72	493.8283303
15	290.877338	323.9542057	253.9	290.877338	25	382.273099	519.3858904	626.74	362.273099
16	250.8007872	321.4813163	507.88	255.8007872	21	222.7470755	609.5025605	247.68	250.7470755
17	219.0919509	255.5080952	654.52	220.0919509	22	299.308072	617.2520089	253.9	300.308072
18	156.722921	822.6672895	626.74	166.722921	23	344.1325037	592.440514	599.988	300.1325037
19	491.7327378	337.6247622	530	461.8016489	24	370.3561323	549.7845077	623.72	493.8283303

Table 2: Prediction error comparison between different models

NN (%)	WD-NN (%)	WD-SVM (%)	NN (%)	WD-NN (%)	WD-SVM (%)
0.11253818	0.602783679	0.012783841	0.435008912	0.239732083	0.086792453
0.002399833	0.422296002	0.069200947	0.481799354	0.086352266	0.056513139
0.03485968	0.598305153	0.09534765	0.502257363	0.274232517	0.040374677
0.050436959	0.592724561	0.0856762	1.162852222	2.644813267	0.003938558
0.374633022	0.103885242	0.333797002	0.21770637	0.261379439	0.108645108
0.281819407	0.799670773	0.009844845	0.1875579	0.16426601	0.12026107
0.166213976	1.704165376	0.001527837	0.216893848	0.121794626	0.024128156
4.24918298	0.571333132	0.01595558	0.103266115	0.287631538	0.027934576
0.313397835	0.113342582	0.056473753	0.05735853	0.447728509	0.042589268
28.2876525	1.125270657	0.005651314	0.03982924	0.208209202	0.006559733
1.736298823	0.040907005	0.113049096	0.131665143	0.512604892	0.001415058
1.062263155	0.073564883	0.003938558	0.251920979	0.612926516	0.014357742
0.721547682	0.431866981	0.0733348	0.152865514	0.202320921	0.018244407
0.484475238	0.460842138	0.197960941	0.161321312	0.211724772	0.031058222
0.358677584	0.470684525	0.031911159	0.167290923	0.406610609	0.035236921
0.279314172	0.26315784	0.059078377	0.243759649	0.365252289	0.045605316
0.266901003	0.269882284	0.035441443	0.39097407	0.205168818	0.03515919
0.316748661	0.556235397	0.033612418	0.181891325	0.305481964	0.004641437
0.387471223	0.456340986	0.01595558	0.162471356	0.096446898	0.010861281

Error models calculated using RSME (%) can be seen in **Table 2**, RSME ratio on the prediction model using NN average is 1.177%, WD-NN model is 0.455% 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.

6. Conclusions

In this paper, the SVM algorithm and the decomposition wavelet method are combined and successfully applied to short-term predictions on wind farms in Pandansimo. The wind power output can be securely connected to the grid when it is known for a more accurate prediction. The WD method is used to perform an empirical model that decomposes wind power output data, resulting in IMF components of different scales and 1 component which is the trend of the data being processed. The prediction results using selected data from the scale of wind power that has been filtered in clustering process with SVM. Finally, it is concluded that WD-SVM method can produce prediction data which has a small error rate compared toother prediction models ever done in this research.

Acknowledgments

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