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Research paper

Bayesian Hierarchy Non-stationary Neural Network on Short Term Prediction Wind Power Model for Measuring Work Capacity of Wind Turbine

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Abstract

Wind energy is environmentally friendly energy, intermittent problems often occur in the generation of this energy in tropical wind lands. Due to this problem the working capacity of wind turbines does not have an average work size. So that it is difficult for operators to calculate the capacity produced by the wind turbines which are located on the observation land. In this study wind speed identification using Peaks Over Threshold (POT) method with extreme data distribution pattern of wind speed generated by pareto distribution (GPD). Estimation of GPD parameters is carried out using the Bayesian Hierarchy Model (BHM) to overcome the problem of data limitations and uncertainty of parameters in determining the capacity of the wind turbine. Regression model to get a prediction of wind turbine working capacity using Neural Network (NN). The Bayes Neural Network model provides the smallest error in wind power prediction compared to the Neural Network (NN) prediction model and the Wavelet Decomposition Neural Network (WDNN) model.

***Keyword** : Wind Power,POT,GDP,BHM,NN,WDNN*

1. Introduction

Wind farms in islands such as Indonesia are very difficult to predict the stability in the generation process. This is influenced by geography which causes wind speed parameters to be influenced by many factors. The wind speed that comes to the wind land is uncertain. Factors like this cause the generation of wind energy to experience very high intermittent problems. As a result the operator cannot estimate how much the working capacity of the wind turbine is installed in the wind field. uncertainty of the working capacity of this wind turbine which results in unpredictable generation planning. In the study, a wind power prediction model will be presented to determine the working capacity of wind turbines.[1] The first identification was carried out using the Peak Over Threshold (POT) method at wind speed as an energy source for wind turbines that followed the Pareto distribution. [2][3]Extreme value identification of wind speed can be done with extreme value theory (EVT) with two approach methods, namely Block Maxima (BM) and Peak Over Threshold (POT).[3][4] The POT approach is more efficient because it can use extreme data. It is said to be extreme data because observation data for wind turbine work capacity is rarely done, so the data is very limited. Research on wind speed prediction by classifying data at different levels is very rare. Wind speed data measured every hour is data with a two- tier hierarchical structure, the first level of wind power generated on the day during observation and

the second level is wind power generated from wind speed data recorded at the observation station. Thus the wind power prediction can be modeled. The results of the prediction model are used as a reference to calculate the working capacity of the wind turbine. Grouping of hierarchical structured data can be done because of the similarity of data in two ways of observing wind speed. Non-stationary EVT with limited data that was applied using Bayesian Hierarchy model (BHM) using the POT approach was also done to predict rainfall. GPD parameter estimation in pareto distribution does not consider nonstationary factors in the observation area. But other studies have taken a nonstationary approach to Bayesian hierarchy models that produce EVT better than using independent prediction methods. Based on this description, this study examines the characteristics of wind speed in Pandansimo wind land. Furthermore, extreme value identification with the POT method was carried out. The BHM method is carried out to obtain the estimated calculation of the wind power produced. Regression method as part of the smooting process of prediction is done using NN. With input data from the results of the BHM method. From the NN prediction data output, get reference data on the working capacity of wind turbines in wind fields.

2. Peaks Over Threshold

The EVT method used in this study is the Peak Over Threshold (POT) method. This method identifies the extreme value of wind speed. The POT method uses

a reference value called the threshold. The distribution used in the POT method with pareto distribution (GPD). The higher the threshold value, the distribution will follow the GPD. Figure 1 shows the extreme data collection using POT[3][5]

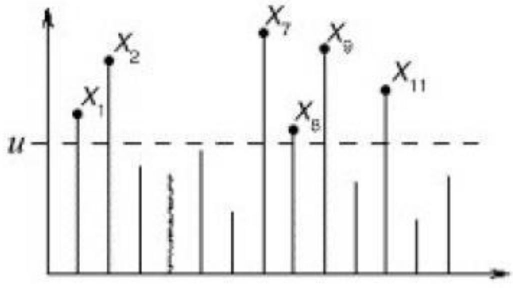

Figure 1: Extreme Data Collection Using POT

Where and are values that are above the threshold (u), so that the value is extreme. The higher the threshold value the extreme data will follow the Pareto distribution. Here is the probability of using a Pareto distribution GPD)
The greater the value of , the distribution will have a tail that gets fatter. So that the chance of the occurrence of extreme values is greater. Then the distribution of pareto will be formed.[6]

3. Bayesian Method

The Bayesian method works as an estimator of the same two parameters by combining information from a measurement sample in a wind field with measurements at an observation station or historical data. The data size in the population contains the random variable x which is used in the form of opportunity rules, as follows:

Where (|) is the density constant for the prior distribution. The Bayesian method illustrates that in situations where different wind speeds can be represented in modeling. With the formation of modeling, wind speed conditions can be predicted as inputs for wind turbines, so the wind power capacity is predicted.
Prior distribution is very difficult to apply to bayesian methods. This distribution does not have a standard reference to determine the prior distribution for an unknown parameter. But according to the existing physical conditions bayesian method is used with the distribution of markov chain monte carlo (MCMC) and Gibbs Sampling. MCMC is used to generate parameter data in accordance with the Markov Chain process by using an Monte Carlo simulation iteratively to obtain a stationary posterior distribution (steady state). Gibbs Sampling is a technique for generating random variables from a marginal distribution directly without having to calculate the distribution density function. [3][5][6]

4. Model Linier Hierarchy

The hierarchical linear model (LHM) is used as a regression model with hierarchical data. This research uses two levels starting with as the parameter set of GPD in month j where dimana_
( ) and ( ) are the mean and variance of the Gaussian distribution with the parameter . In this model formation is influenced by which is a covariate in each month , causing to vary every month, so that the regression model is formed as follows

5. Hierarchical Bayesian Neural Network (HBNN)

The Bayesian neural network hierarchy model will be a large model to predict wind power as a reference for the working capacity of wind turbines. The weight that connects the neuron in layer 1 to the neuron at layer 2 in the category Placement of the prior fix value is assumed that each weight comes from the overall distribution group (as the estimated key and simultaneous from the data. Here is figure 2 structure of the HBNN:[7][8]

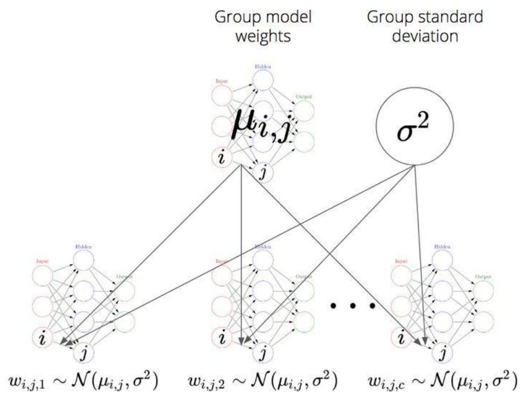

Figure 2: Sturcture of The HBNN

Each individual weight has its own hierarchical structure with single group mean parameters and 16 weights per category distributed around the group mean. Although this creates a large number of group distributions (as many as flat NNs have weight). This model is quite complex but has the right degree of freedom.[2][9]

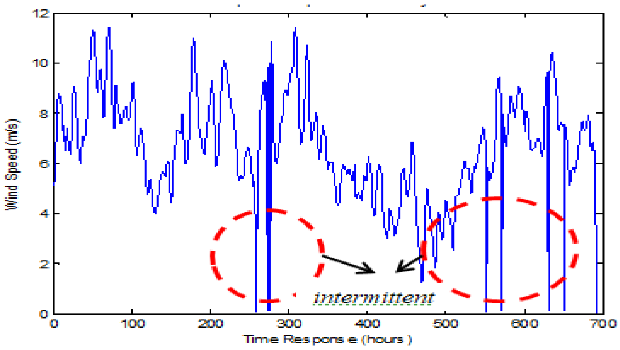

Figure 3: Wind Speed Response

6. Wind Speed and Wind Speed Extreme

Wind speed on the observation wind land in Indonesia looks like figure 3. In the measurement of 700 hours of time series data, the response at 274 seconds wind speed changes suddenly from the speed of 6.67 m / s to 0 m/ s, as well as at 667 hours, the wind speed is 7.78 m / s to 0 m / s and the hour to 643, the wind speed is 6.54 m / s to 0 m/ s. On the contrary, when the wind speed is at 0 m / s, it immediately moves to 6.80 at 603 hours. This condition indicates the existence of extreme wind speeds resulting in intermittent patterns in the observation of the wind speed behavior of the observation land.[10][11]

7. Research Methodology

- Data Source
  In this study using secondary data is data on wind speed, temperature and air pressure with measurements made per hour. Data processed from January to June 2013 conducted by the National Institute of Aviation and Space (LAPAN). Measurements were made using an anemometer with a measurement height of 80 meters on the Pandansimo wind field, Yogyakarta, Indonesia.
- Research Variable
  Research variable that been using can be seen in the table below:

Table 1:Research Variable

Variable	Variable Name	Operation Definision
	Wind Power ( )	The amount of mechanical energy that can be generated by wind turbine rotors due to the obtaining power from wind gusts
	Wind Speed ( )	Air velocity that moves horizontally at a height of two meters above the ground

8. Analysis Step:

1. Determine the sample data using the Peak Over Threshold method
2. Identifying Data Wind Speed with measurements every hour from January to May in 2013

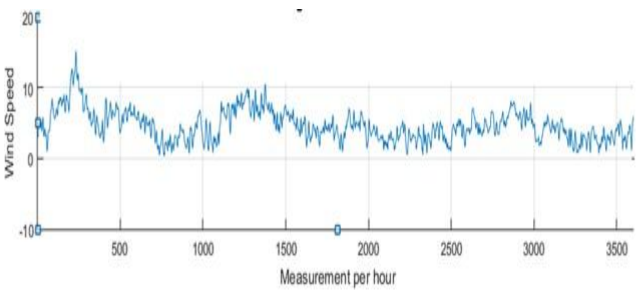

Figure 4: Saturation Peak

In Figure 4 shows the saturation peak to find the highest peak output of wind speed. This step is done to find out the findpeaks limit. This saturation is done to determine the threshold wind speed value on wind land. The vertical axis shows the number of measurements taken when testing wind speed saturation of 3500 hours. While the horizontal axis is the threshold value (u) which tends to be linear[12][13]

3. Distribution Testing uses Generate Extreme,Pareto Distribution and Extreme Value

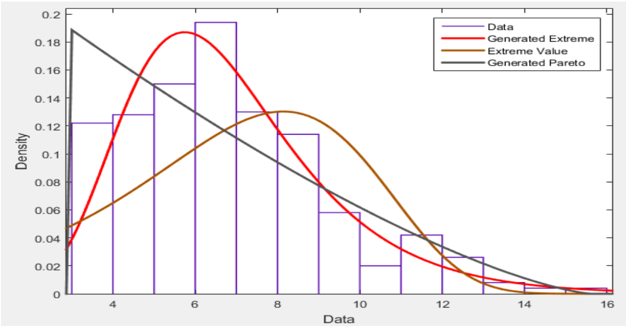

Figure 5: Testing of 3 Distribution

Figure 5 shows the testing of 3 distribution methods to determine the distribution of data. By using the Generalized Pareto distribution log likelihood is at the point -1013.05 with the data mean of 3.30447 and variance 4.55152, the estimation parameter with the value of k = 0.699546, std. -0.00857436. To test the normalization of the data, Generalized Extreme Value distribution is used with values k = -0.0182153 and std. Err = 0.0445851 with mean wind speed 3.44079 and variance 3.31422 and tested with Extreme Value distribution with a mean value of 3.29984 and variance 5.91528. The three distribution tests selected using a generalized pareto distribution because it has the smallest corrected k value

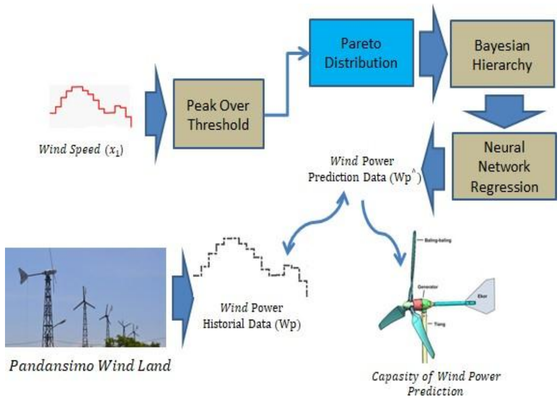

Figure 6: Model Proposed of The Research

9. The Proposed of Research

In Figure 6 shows the model that will be proposed in this study input the system in the form of wind speed. Peak over threshold is used to determine the threshold point of the measurement data function to determine the limit of wind speed generated in the measurement of the sample data to be analyzed. The selected distribution uses a pareto distribution with a theta value of 3 m / s. The method used for the classification process uses Bayesian hierarchy with a regression model using a neural network. The output of the regression is the prediction of wind power. Prediction accuracy is shown by the error value between the prediction results and historical wind power data in Pandansimo wind fields.

10. Analisys and Result

Analysis and research results show that the average Wind Speed prediction of the results of the model developed shows that it is close to the average value of historical data in the wind field the average wind speed of the developed model is 6.545117 while the real data in the wind field is 6.529819, the comparison between the two is only 0.015299. For comparison with other models it looks not too big with the Neural Network model with an average wind speed of 6.701484 greater than 0.171666 from the average wind speed real on wind land and the Wavelet model of Neural Network Decomposition has an average wind speed of 6.458071, more small 0.071747 of wind speed from the average wind speed from the land of the wind. From the data in table 2 it can be seen that wind power predictions will show the same symptoms that the proposed model is able to predict better than other models with the same processed data.

Table 2: Wind Speed Prediction for 3 model

Ws-NN	Ws-WDNN	Ws-BayesNN	Ws-Plant
0.603827	4.143426295	4.294738789	4.294738789
1.252251	4.06374502	4.046138849	4.046138849
5.719095	6.358565737	6.376892507	6.376892507
Ws-NN	Ws-WDNN	Ws-BayesNN	Ws-Plant
8.879446	7.490039841	7.575563383	7.575563383
9.813067	8.764940239	8.796812749	8.796812749
9.803135	9.561752988	9.243027888	9.243027888
10.72552	9.960159363	9.880478088	9.880478088
11.26263	10.35856574	10.35856574	10.35856574
10.93366	10.51792829	10.91633466	10.91633466
9.402784	10.91633466	10.8868984	10.83665339
7.409739	10.35856574	10.4239193	10.51792829

5.783674	7.96812749	9.290836653	9.290836653
4.83787	4.780876494	5.258964143	5.258964143
4.57688	5.896414343	5.960159363	5.960159363
5.162617	4.621513944	4.635495426	4.541832669
5.123208	4.076506569	4.076506569	3.984063745
4.071842	3.507441449	3.507441449	3.474103586
13.11024	2.65693898	2.549800797	2.549800797
5.380474	7.359388827	7.362549801	7.362549801
0.398406	0.197962498	0.207171315	0.207171315
4.780876	3.995969331	3.995969331	3.90438247
7.266932	4.785786008	4.785786008	4.940239044
6.413395	4.782988107	4.782988107	4.589641434
8.124056	7.869774188	7.869774188	7.80876494

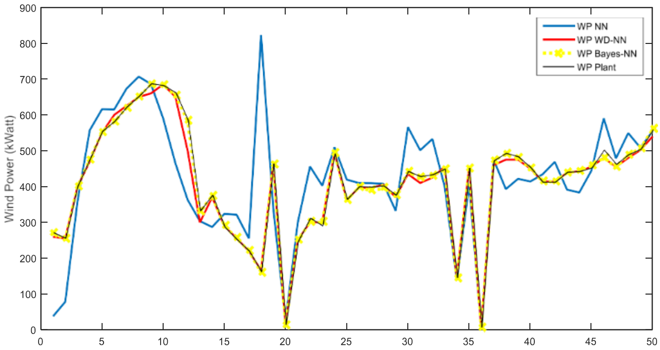

Figure 7: Result Wind Power Prediction for 3 Model Using Neural Network

In Figure 7 using 50 sample data measurements obtained prediction patterns with analysis on the wind power prediction model using the Neural Network model shows an average error of 1.1001253. using the WD-NN model shows an average error of 0.1053783 and using the Bayes-NN model shows the average error is smaller than the other models that is equal to 0.022592439. Table 2 shows 25 hours of measurement samples from Wind Power in the 3 prediction models previously carried out. While figure 8 shows the magnitude of the error in each measurement hour. Seen with the Bayes- Neural Network model, it has the smallest error value in every hour of measurement. The output of this model follows the pattern of real measurements in wind fields.

Table 3: Error Prediction for 3 Model

Err-NN	Err-WDNN	Err-BayesNN
2.3160469	0.0949486	0
1.7531646	0.0110479	0
0.4127677	0.0115	0
0.8181863	0.053666	0
0.6376996	0.02	0
0.3514671	0.2	0
0.5302623	0.05	0
0.5673007	0	0
0.0108709	0.25	0
0.8997528	0.05	0.031528746
1.9503885	0.1	0.058990642
2.2007446	0.83	0
0.2642367	0.3	0
0.868008	0.04	0
0.3895421	0.05	0.05877338
0.7148132	0.0580079	0.058007872
0.375081	0.0209195	0.020919509
6.6266729	0.0672292	0
1.2437524	0.0019835	0
0.12	0.0057785	0
0.55	0.0574708	0.057470755
1.46	0.0969193	0.09691928
1.1444051	0.121325	0.121325037
0.1978451	0.0382833	0.038283303
1.1001253	**0.1053783**	**0.022592439**

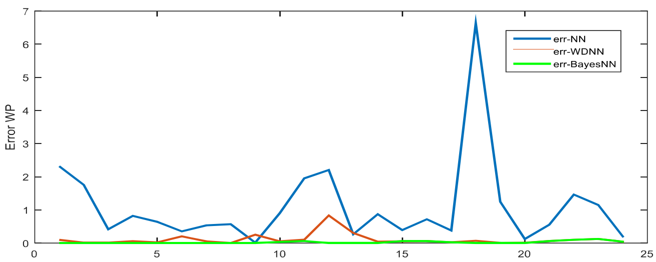

Figure 8: The magnitude of error

11. Discussion & Conclusion

Finally, the prediction model uses the Bayesian hierarchy method to solve data problems that have a non-stationary pattern by determining the threshold value limit of time series data in wind fields using POT resulting in a threshold of u = 8 m / s able to follow the wind power pattern in real data in the field of wind observation . Distribution to test data normalization using generalized pareto because it has a lower standard error compared to other distributions. By comparing the disadvantages and advantages of Generalized Extreme Value and Extreme Value distributions. After testing the distribution. Continued by doing regression with linear hierarchical method by accommodating hierarchical data by using the mean and variance values of the pareto distribution results. Training at the regression stage to get predictive values using the Neural Network method. From the results of the processing it is found that the proposed model can produce predictions describing the Wind Power pattern with a lower error value compared to the previous model. This model has not been tested for the location of wind speed measurements in wind fields in other locations. The magnitude of the extreme value of wind speed on wind land in Indonesia is due to the influence of monsoon on the islands which results in not having a model applied to each wind land with different locations. In the next study this model will be tested for wind land with different locations. Will be tested with the approach of mean and variance in the distribution test. [1][14][15]The importance of this study is to find out how much wind power can be produced on wind land without building infrastructure on site. Using this prediction model will cut the cost of wind farm development planning by using only wind speed measurement data at the observation site.

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