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Wind speed prediction using extreme learning machine and neural network for resolving uncertainty in microgrids

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Abstract. Wind energy is one of the several types of renewable energy that exist today. however, wind energy has a high degree of uncertainty due to weather effects. Wind speed prediction is needed to determine the energy that wind turbines can produce at each unit. For optimizing wind speed scheduling, the accuracy of wind speed prediction is considered. Extreme learning machine (ELM) and neural network (NN) is implemented to predict hourly wind speed for 24 hour and power generation from wind turbines can produce. Wind speed probability data is taken from sidrap wind farms in indonesia. To determine the performance of wind predictions based on the error value between actual and predicted, mean absolute percentage error (MAPE) is applied.

1. Introduction

Indonesia as the archipelagic country, International Renewable Energy Agency (IRENA) has an estimated total potential energy in Indonesia for onshore wind energy around of 9,3 MW. Java-Bali, Sulawesi and Nusa Tenggara regions has dominated total potential wind energy in Indonesia with an estimated that nearly of 85 percent.

Wind speed has unstable character [1-9] and causes the result of its generation from wind turbines (WTs) to be unstable. Probability data of wind speed in a wind farm [2] is very important information to know the character of wind speed and power can be generated by WTs based on times series[3-7].

Based on the probability data, wind speed prediction can be done by studying the character. Some prediction methods like NN[9-11], IPSO-BP[9], Markov[7] and hybrid[10] have been carried out and shown promising results. Promising results and accuracy of the prediction method are important to help the optimizing process of WTs scheduling.

In this paper, extreme learning machine (ELM) and neural network (NN) are implemented as a prediction function of wind speed hourly for 24 hours. ELM and NN are artificial intelligence methods that consist of 3 layers (input layer, hidden layer, output layer) but both methods have different construction.

2. Typical of Wind Turbines (WTs)

Typical generator of WTs and probability data of wind speed are the part of WTs system in this paper



2.1. Typical Generator of WTs

Generally, WTs convert kinetic energy to electricity using the equation as shown in eq.1, but based on the typical data of the WTs, the equation to convert energy is shown in eq.2. In this paper WTs with 140 kW capacity is used. Typical data specification of this WTs as shown in Table 1. 4 WTs installed and can generate 560 kW of the maximum capacity.

$$P = 0.5\rho AC_p V^3 \quad (1)$$

With: P is power generation (Watt), ρ is air density (kg/m^3), C_p is coefficient power, V is wind speed (m/s)

Table 1. Typical data of WTs

Power rate (P_r)	140 kW
Wind speed cut in (V_{ci})	3 m/s
Rating speed (V_r)	15.01 m/s
Wind speed cut off (V_{co})	17 m/s
a	-0,015
b	0,033
c	-0,9
d	-2,1
e	7,1

$$P_{out} = aVw^4 + bVw^3 + cVw^2 + dVw + e \quad (2)$$

With: P_{out} is power generation (Watt), V_w is wind speed (m/s)

2.2. Probability of Wind Speed Data

In fig.1 is shown the pattern of the probability of wind speed data at the geographical location in sidrap wind farms during december 2015[12]. Wind probability data is time series data in hourly for 24 hours and in a month. The pattern data as shown in Fig.1 shows the character of the wind speed increase towards morning, decrease toward night and forming the same repetition.

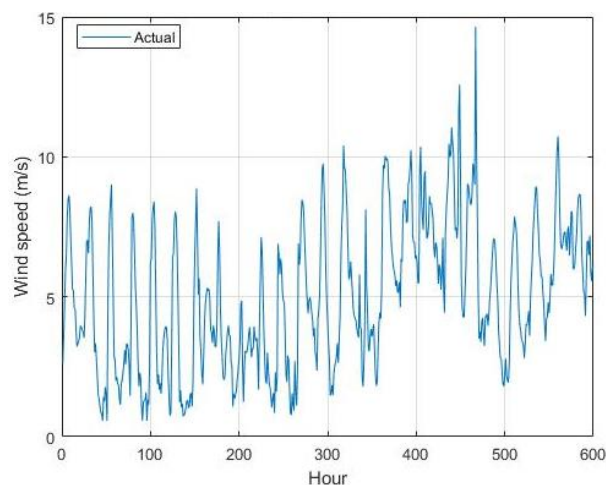


Figure 1. A month probability of wind speed data

3. Methodology

ELM and NN in this paper are constructed by 6 inputs, they are current air temperature (CAT), current air humidity (CAH), current wind speed (CWS), 2 until 4 hours previous wind speed (PWS) and single output as representation of the wind speed prediction as shown in Figure 2.

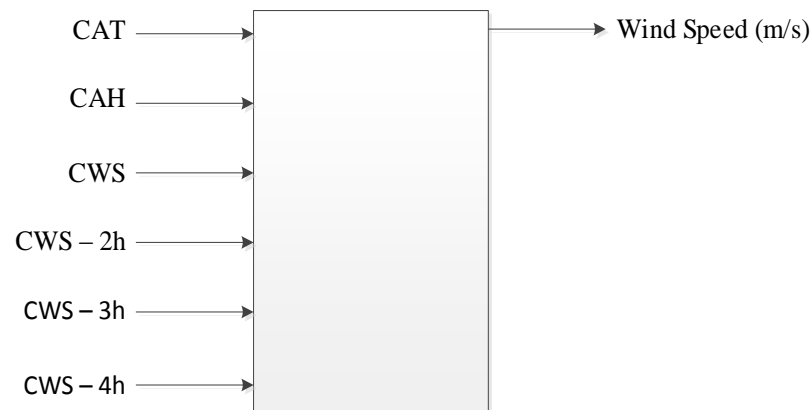


Figure 2. ELM and NN architecture

Input and output training data for the both method using same format. There are 600 columns data in this paper, contains data probability wind speed from first day in december until day 25, so the table display (as show in Table 2 and Table 3) format is taken as an outline.

Tabel 2. Input data train format for ELM and NN

Hour	00.00	01.00	02.00	04.00	>>	22.00	23.00
CAT	24.10	27.80	29.10	29.50	>>	23.50	22.90
CAH	88.78	61.58	53.88	51.20	>>	96.43	92.42
CWS	3.35	2.40	3.33	4.46	>>	3.01	2.65
CWS - 2h	2.95	3.35	2.40	3.33	>>	1.69	3.01
CWS - 3	2.89	2.95	3.35	2.40	>>	1.39	1.69
CWS - 4	2.70	2.89	2.95	3.35	>>	2.10	1.39

Tabel 3. Output data train format for ELM and NN

Hour	00.00	01.00	02.00	04.00	>>	22.00	23.00
Target	2.4	3.33	4.46	5.67	>>	2.65	1.54

3.1. Extreme Learning Machine (ELM)

3.1.1. Design the ELM Structure

The ELM has a different mathematical equation with NN because ELM in this paper consists of 1 hidden layer called matrix H, Beta matrix and single output (as shown in Fig. 3) to predict the hourly wind speed for 24 hours. ELM is constructed by single layer with 600 neurons, because the input data are 600 and the H matrix will be 600 x 600.

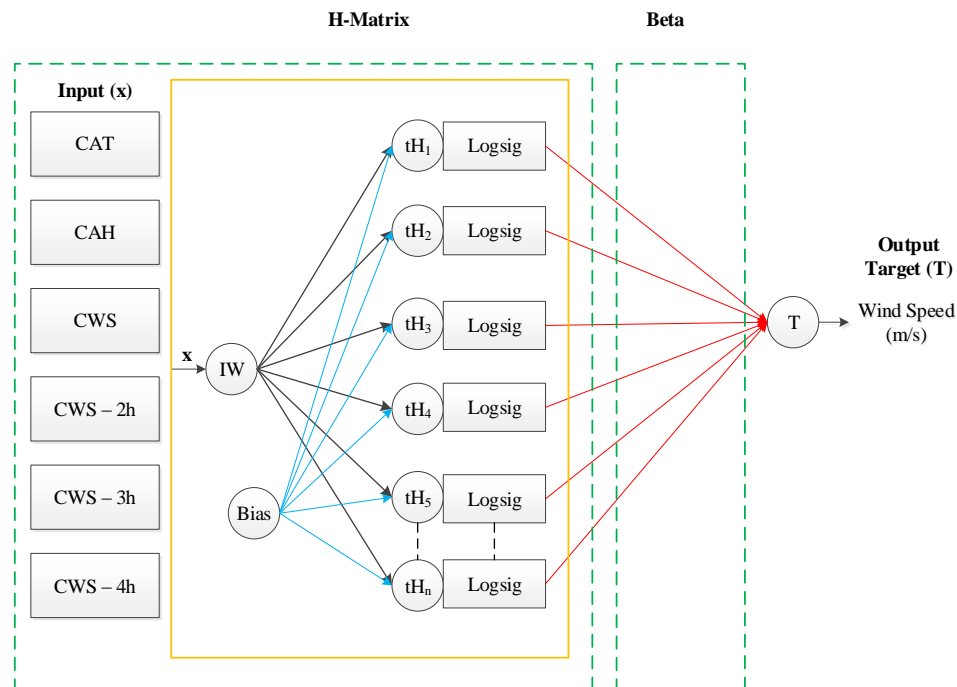


Figure 3. ELM structure

3.1.2. Determining ELM Weight Value

Final goal to finish ELM procedure is to find beta (β) and the input weights (IW) are determined by random value as shown in table 4 and likewise the bias input weight (BIW) as shown in table 5.

Table 4. Weight data of ELM from input layer to hidden layer

Neuron	IW 1	IW 2	IW 3	IW 4	IW 5	IW 6
	to Neuron					
1	0.6232	0.4867	0.9641	0.7356	0.2313	0.6496
2	0.1616	0.0285	0.8676	0.1617	0.7891	0.0848
3	0.2404	0.1791	0.8624	0.3878	0.5765	0.6823
4	0.3351	0.9201	0.7363	0.3633	0.1681	0.5237
5	0.2100	0.4473	0.6638	0.9678	0.0123	0.8361
>>	>>	>>	>>	>>	>>	>>
598	0.7580	0.8613	0.8190	0.3904	0.2196	0.6230
599	0.9003	0.4094	0.6128	0.9880	0.6854	0.1143
600	0.4492	0.8106	0.0533	0.6224	0.9132	0.0429

Table 5. Bias data of ELM from input layer to hidden layer

Neuron	BIW
1	0.211249
2	0.840057
3	0.641954
4	0.008514
>>	>>
598	0.589435
599	0.344251
600	0.445729

3.1.3. Find beta (β) Value

To find beta (β) value, it can be determined by using formula as shown in eq.3[13] below :

$$H \times \beta = T \quad (3)$$

With, H is H Matrix, β is Beta and T is Target

By multiplying value inverse H matrix and T matrix, β can be determined as shown in eq.4. After calculaing β value using eq.4, the value of β as shown in table 6.

$$\beta = H^{-1} \times T \quad (4)$$

Table 6. β value

Neuron	beta (β)
1	1797764484.99
2	-6043934929.45
3	-8147597789.76
4	47078160254.40
5	2901319991.93
>>	>>
588	-110572679878.06
589	-5994258175.21
600	16960226705.63

3.2. Neural Network (NN)

3.2.1. Design The NN Structure

NN structure in this paper construct by 100 neurons to predict the hourly wind speed for 24 hours, with the construction of NN as shown in fig.4.

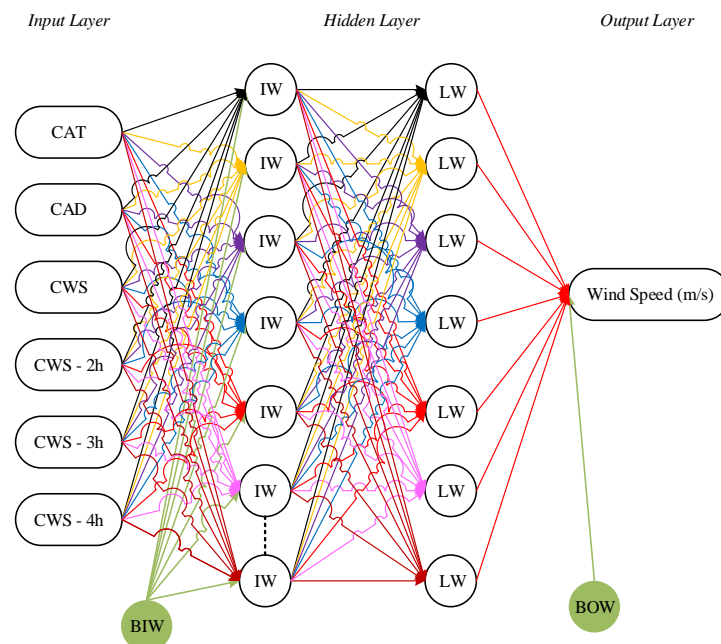


Figure 4. NN structure

3.2.2. Find NN Weight Value

Training process is required to find the weight value of NN. There are 4 types weight value of NN, they are input weight (IW), bias input weight (BIW), bias output weight (BOW) and layer weight (LW). In this paper training process using matlab. The training process has been completed and successful with an indication of the performance section showing green as shown in Fig.5.

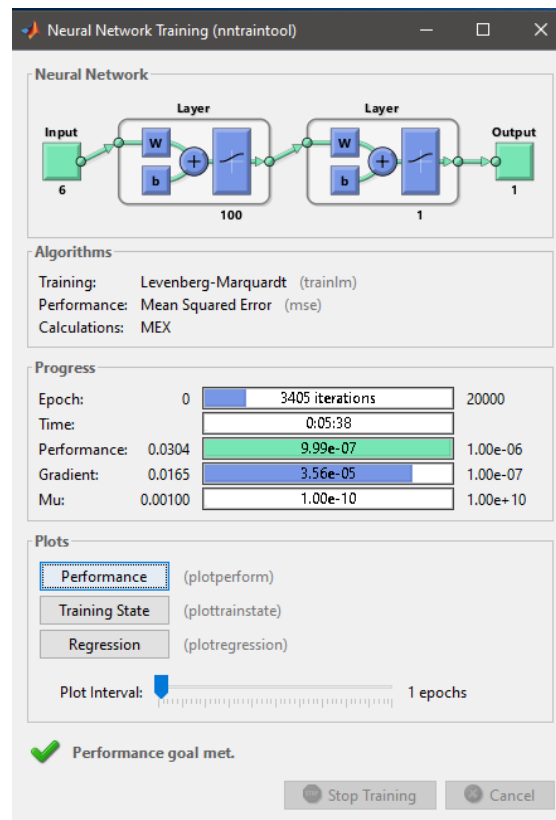


Figure 5. NN training process

To determine the output of NN after all weights is known, it can be determined by using formula as shown in eq.5[13] below :

$$\text{Wind Speed} = \text{Logsig} (\text{LW} \times \text{Logsig} (\text{IW} \times \text{Input} + \text{BIW}) + \text{BOW}) \quad (5)$$

4. Simulation and Data Analysis

Both methods are tested to predict hourly wind speed for 24 hours and compares with the actuals data. As the first-day test on December 26th, in fig.6 there are 2 sides color line, blue and orange, to illustrate the comparison of actuals data and predictions data from both methods for 24 hours. On December 26 for 24 hours, ELM produces a maximum error for each hour of prediction of 0.0381% while NN produces a maximum error of 0.1923%. The next-day until the last day in december ELM produces maximum errors of 0.0463%, 0.0328%, 0.0512%, 0.0410% and 0.0525% and NN produces maximum errors of 0.1993%, 0.0132%, 0.0322%, 0.0973% and 0.0663%. To know the accuracy of hourly wind speed prediction for 24 hours from both methods mean absolute percentage error (MAPE) is applied.

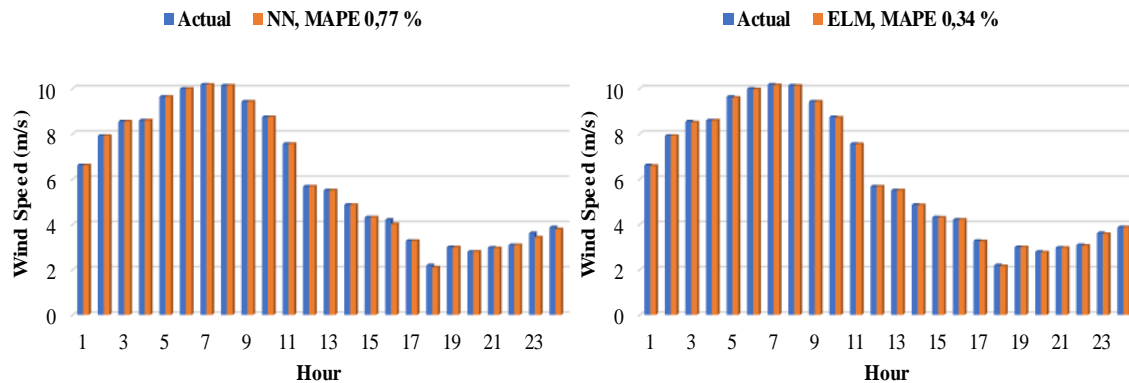


Figure 6. Results prediction from both method, ELM and NN, on December 26th

In table 7, On the first and second day of testing, ELM shown minimum MAPE values of 0.3470% and 0.5392 compared to NN with MAPE values of 0.7707% and 0.9422. But in the last 4 days of testing, NN shown minimum MAPE values of 0.0673, 0.1672, 0.8521 and 0.6489 compared to ELM with MAPE values of 0.2609, 0.2676, 0.9063 and 0.7242. To illustrate the difference of the MAPE results between NN and ELM for 6 times of testing as shown in fig.7. The average of MAPE results in 6 days test from both methods shown under 1%. ELM shown minimum result of 0.5075% in average and NN shown little bit higher of 0.5747% in average.

Table 7. Comparison error forecasting between ELM and NN

Numb.	Date	MAPE (%)	
		ELM	NN
1	December 26, 2015	0.3470	0.7707
2	December 27, 2015	0.5392	0.9422
3	December 28, 2015	0.2609	0.0673
4	December 29, 2015	0.2676	0.1672
5	December 30, 2015	0.9063	0.8521
6	December 31, 2015	0.7242	0.6489
Average MAPE (%)		0.5075	0.5747

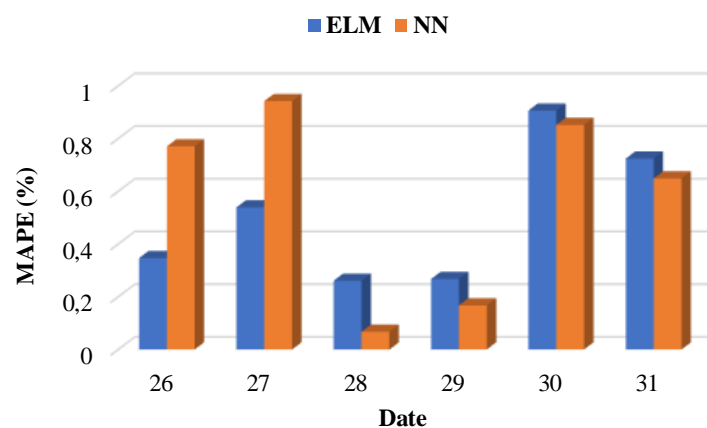


Figure 7. Comparison chart of error prediction results between NN and ELM.

5. Conclusions

Both methods, NN and ELM shown promising result as prediction function in 6 days test with 6 inputs and single output as the construction's. All MAPE results shown under 1% error from both methods. ELM performs the best results than NN on the first-two-days test with minimum MAPE values of 0.3470% and 0.5392. Otherwise, on the last-four-days test NN performs the best results than ELM with minimum MAPE values of 0.2609, 0.2676, 0.9063 and 0.7242. From all of the testing results data, NN performs better performance on day-ahead wind speeds prediction than ELM with the same architecture.

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