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Forecasting model of power generated by wind power plants

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Abstract. The power generated by wind power plants is unstable so forecasting is needed to maintain the power balance in interconnected system. The purpose of this research is to predict the power generated at the Sidrap and Jenepono wind power plants. The method used is an optimally pruned extreme learning machine (OPELM). The extreme learning machine (ELM) method is used as a comparison method. The mean absolute percentage error (MAPE) method is used to assess the level of forecasting accuracy. Forecasting power generation with Sidrap wind power plant data using the OPELM method is 0.8970% more accurate than the ELM which is 1.0853%. In general, the OPELM method is more accurate. Forecasting power generation with data from the Jenepono wind power plant using the OPELM method is 2.4887% more accurate than the ELM method is 2.9984%. These results indicate that linear, sigmoid, and Gaussian activation in the OPELM method can increase accuracy. The OPELM method can be tested in forecasting the power generation at the Sidrap and Jenepono wind power plants to maintain a power balance in the Sulsebar power grid system.

Keywords: OPELM, Forecasting model, Wind power plant.

1. Introduction

In the electric power system, there is a power balance theory where the generated power by generators is equal to the load power and losses [1], [2], [3], [4]. If the power generated is greater than the load power, then there is a waste of costs. On the other hand, if the load power is greater than the generating power, there will be an overload resulting in blackouts. The power generated by wind power plants can change at any time, so it must be predicted to avoid power imbalances in the system [5]. Estimated power generated by wind power generation can use various methods, including historical data recorded [6], tree-based learning algorithms [7], variational mode decomposition (VMD), convolutional long-short memory network (ConvLSTM) [8], convolution-based spatial-temporal wind power predictor (CSTWPP) [9], artificial neural network (ANN) [10], [11], heteroscedastic spline regression model (HSRM), and robust spline regression model (RSRM) [12]. The method used in this research is optimally pruned extreme learning machine (OPELM) [13]. The advantage of OPELM is that it can process data that has non-linear patterns quickly and precisely.

1.1. OPELM model

The OPELM method is based on the ELM algorithm using SLFN, [13]. The stages of compiling the OPELM algorithm can be seen in Figure 1 below.



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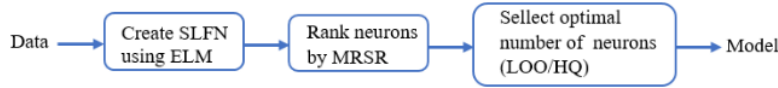


Figure 1. OPELM algorithm stages

1.2. ELM model

The speed of the feed-forward neural network method is enhanced by ELM [14], with the architectural design as shown in Figure 2 below.

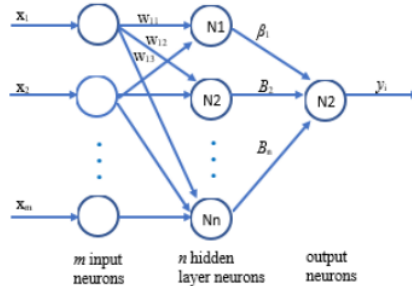


Figure 2. Extreme learning machine model design

1.3. ELM mathematical model

1.3.1. ELM Mathematical models for ELM training

The mathematical model for ELM [13] training can be seen as follows.

1. Initialize W_{jk} weight randomly.
2. Calculate the hidden layer output with the following formulation

$$H = \frac{1}{(1 + \exp(-H_{init}))} \tag{1}$$

$$H_{init} = X_{train} \times (W_{jk})^T \tag{2}$$

3. Weight is calculated by:

$$\beta = H^+ \times Y_{train} \tag{3}$$

$$H^+ = (H^t \times H)^{-1} \times H^t \tag{4}$$

1.3.2. Mathematical models for ELM testing

The mathematical model for ELM testing is as follows.

1. It is known the weight (W_{jk}) and final weight ($\hat{\beta}$) from the training results.
2. Calculate the hidden layer output using the following formula.

$$H = \frac{1}{(1 + \exp(-H_{init}))} \tag{5}$$

$$H_{init} = X_{train} \times (W_{jk})^T \tag{6}$$

3. Calculate the forecast using the following formula.

$$\hat{Y} = H \times \hat{\beta} \tag{7}$$

1.4. Calculating forecasting accuracy

Forecasting accuracy is calculated using MAPE with the following formula.

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{Y_{prediction} - Y_{target}}{Y_{target}} \right| \times 100\% \tag{8}$$

1.5. MAPE interpretation

The interpretation of MAPE values based on (Lewis, 1982 P.40) in [11], can be seen in Table 1 below.

Table 1. Interpretation of MAPE Value

MAPE Value	Interpretation Result
< 10	Highly accurate forecasting
10 - 20	Good forecasting
20 - 50	Reasonable forecasting
>50	Inaccurate forecasting

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2. Materials and Methods

2.1. Materials

2.1.1. Original data

The data used in this study is a power generated by the Sidrap and Jenepono wind power plants on Monday, March 2, 2020, as follows (Table 2).

Table 2. Power generated in PLTB Sidrap and Jenepono

Sidrap wind power plant				Jenepono wind power plant			
Time	Power	Time	Power	Time	Power	Time	Power
00.30 am	0.0	00.30 pm	4.4	00.30 am	0.2	00.30 pm	0.3
01.00 am	1.7	01.00 pm	7.9	01.00 am	0.2	01.00 pm	0.1
01.30 am	1.0	01.30 pm	4.3	01.30 am	0.2	01.30 pm	6.4
02.00 am	0.0	02.00 pm	10.5	02.00 am	16.1	02.00 pm	9.6
02.30 am	1.1	02.30 pm	15.5	02.30 am	46.6	02.30 pm	3.4
03.00 am	7.1	03.00 pm	24.6	03.00 am	21.9	03.00 pm	3.5
03.30 am	8.9	03.30 pm	30.8	03.30 am	26.7	03.30 pm	13.5
04.00 am	0.8	04.00 pm	29.5	04.00 am	13.6	04.00 pm	25.7
04.30 am	2.0	04.30 pm	34.8	04.30 am	18.2	04.30 pm	0.1
05.00 am	0.0	05.00 pm	30.1	05.00 am	18	05.00 pm	2.4
05.30 am	0.0	05.30 pm	29.2	05.30 am	19	05.30 pm	14.3
06.00 am	14.3	06.00 pm	21.6	06.00 am	12.1	06.00 pm	14.9
06.30 am	1.7	06.30 pm	22.0	06.30 am	21.2	06.30 pm	14.9
07.00 am	0.2	07.00 pm	26.4	07.00 am	16.4	07.00 pm	11.9
07.30 am	0.0	07.30 pm	24.5	07.30 am	9.6	07.30 pm	10
08.00 am	0.0	08.00 pm	24.8	08.00 am	3.4	08.00 pm	9.5
08.30 am	0.2	08.30 pm	23.9	08.30 am	0	08.30 pm	13.6
09.00 am	2.2	09.00 pm	22.0	09.00 am	0	09.00 pm	8.4
09.30 am	0.4	09.30 pm	27.8	09.30 am	0	09.30 pm	8.9
10.00 am	0.1	10.00 pm	24.4	10.00 am	0	10.00 pm	40.3
10.30 am	0.5	10.30 pm	27.5	10.30 am	0	10.30 pm	19.6
11.00 am	3.1	11.00 pm	20.1	11.00 am	0	11.00 pm	22.1
11.30 am	2.3	11.30 pm	20.7	11.30 am	0	11.30 pm	21.6
12.00 am	1.3	12.00 pm	25.1	12.00 am	0	12.00 pm	13.1

Source : PT PLN (Persero) Sulawesi Generation and Distribution Main Unit, UP2B Makassar System

2.1.2. Data of input on OPELM model

Wind power plant data that have been tabulated for input data in the OPELM model can be seen in the following example data (Table 3).

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Table 3. Tabulated data

AM	X1	X2	X3	X4	X5	X6	Y	PM	X1	X2	X3	X4	X5	X6	Y
0.3	1.0	1.7	1.1	1.0	1.1	7.1	8.9	0.3	4.4	7.9	7.3	11.5	15.5	24.6	31.8
1.0	1.7	1.1	1.0	1.1	7.1	8.9	1.8	1.0	7.9	7.3	11.5	15.5	24.6	31.8	29.5
1.3	1.1	1.0	1.1	7.1	8.9	1.8	2.0	1.3	7.3	11.5	15.5	24.6	31.8	29.5	34.8
2.0	1.0	1.1	7.1	8.9	1.8	2.0	1.0	2.0	11.5	15.5	24.6	31.8	29.5	34.8	31.1
2.3	1.1	7.1	8.9	1.8	2.0	1.0	1.0	2.3	15.5	24.6	31.8	29.5	34.8	31.1	29.2
3.0	7.1	8.9	1.8	2.0	1.0	1.0	14.3	3.0	24.6	31.8	29.5	34.8	31.1	29.2	21.6
3.3	8.9	1.8	2.0	1.0	1.0	14.3	1.7	3.3	31.8	29.5	34.8	31.1	29.2	21.6	22.1
4.0	1.8	2.0	1.0	1.0	14.3	1.7	1.2	4.0	29.5	34.8	31.1	29.2	21.6	22.1	26.4
4.3	2.0	1.0	1.0	14.3	1.7	1.2	1.0	4.3	34.8	31.1	29.2	21.6	22.1	26.4	24.5
5.0	1.0	1.0	14.3	1.7	1.2	1.0	1.0	5.0	31.1	29.2	21.6	22.1	26.4	24.5	24.8
5.3	1.0	14.3	1.7	1.2	1.0	1.0	1.2	5.3	29.2	21.6	22.1	26.4	24.5	24.8	23.9
6.0	14.3	1.7	1.2	1.0	1.0	1.2	2.2	6.0	21.6	22.1	26.4	24.5	24.8	23.9	22.0
6.3	1.7	1.2	1.0	1.0	1.2	2.2	1.4	6.3	22.1	26.4	24.5	24.8	23.9	22.0	27.8
7.0	1.2	1.0	1.0	1.2	2.2	1.4	1.2	7.0	26.4	24.5	24.8	23.9	22.0	27.8	24.4
7.3	1.0	1.0	1.2	2.2	1.4	1.2	1.5	7.3	24.5	24.8	23.9	22.0	27.8	24.4	27.5
8.0	1.0	1.2	2.2	1.4	1.2	1.5	3.1	8.0	24.8	23.9	22.0	27.8	24.4	27.5	21.2
8.3	1.2	2.2	1.4	1.2	1.5	3.1	2.3	8.3	23.9	22.0	27.8	24.4	27.5	21.2	21.7
9.0	2.2	1.4	1.2	1.5	3.1	2.3	1.3	9.0	22.0	27.8	24.4	27.5	21.2	21.7	25.1
9.3	1.4	1.2	1.5	3.1	2.3	1.3	4.4	9.3	22.1	26.4	24.5	24.8	23.9	22.0	27.8
10.0	1.2	1.5	3.1	2.3	1.3	4.4	7.9	10.0	26.4	24.5	24.8	23.9	22.0	27.8	24.4
10.3	1.5	3.1	2.3	1.3	4.4	7.9	7.3	10.3	24.5	24.8	23.9	22.0	27.8	24.4	27.5
11.0	3.1	2.3	1.3	4.4	7.9	7.3	11.5	11.0	24.8	23.9	22.0	27.8	24.4	27.5	21.2
11.3	2.3	1.3	4.4	7.9	7.3	11.5	15.5	11.3	23.9	22.0	27.8	24.4	27.5	21.2	21.7
12.0	1.3	4.4	7.9	7.3	11.5	15.5	24.6	12.0	22.0	27.8	24.4	27.5	21.2	21.7	25.1

2.2. Methods

The forecasting method using is OPELM, while the ELM method is used to comparison or validate. The research flowchart can be seen in Figure 3 below.

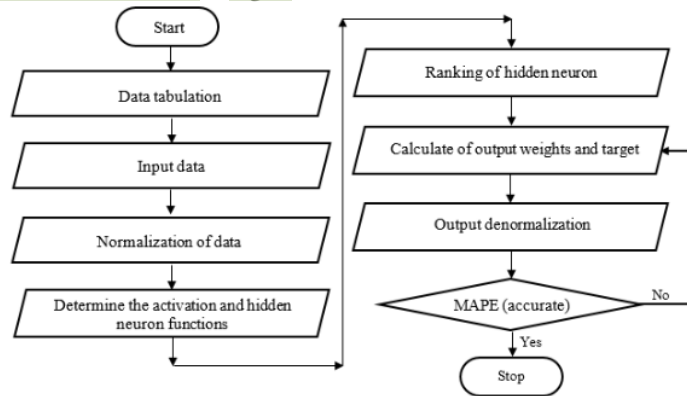


Figure 3. Research flowchart

3. Results and Discussion

Training is the first step in forecasting. The model obtained from the training results is used in the testing process to predict the power generated at the wind power plant. The data used in forecasting the power generation of PLTB is data dated March 2, 2020. The data are tabulated to avoid errors in the activation function, where the zero generation power is changed to 1.

3.1. Sidrap wind power plant

The graph of training and testing at forecasting power generated by the Sidrap wind power plant using OPELM and ELM can be seen in Figure 4 below.

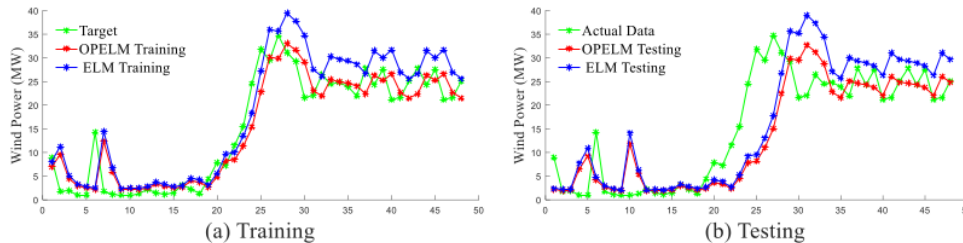


Figure 4. Results of power forecasting training and testing of Sidrap wind power plant

Figure 4 above shows the difference in the results of (a) training and (b) testing, where the training graph shows the target value close to the training value. While on the test graph, it can be seen that the actual value is not close to the testing value. The level of training accuracy can be seen in the MAPE value in Table 4 below.

Table 4. The level of accuracy power forecasting of Sidrap wind power plant

Hidden neuron	Activation function	Method	Training	Testing
			MAPE (%)	MAPE (%)
6	linear	ELM	0.8958	1.0853
	linear, sigmoid, gaussian	OPELM	0.7263	0.8970

The level of training accuracy shows that the OPELM method is 0.7263% more accurate than the ELM method is 0.8985. While the level of accuracy of OPELM testing is 0.8970%, and ELM is 1.0853%.

3.2. Jeneponto Wind Power Plant

The results of the training and testing of the Jeneponto PLTB power forecasting can be seen in Figure 5 below.

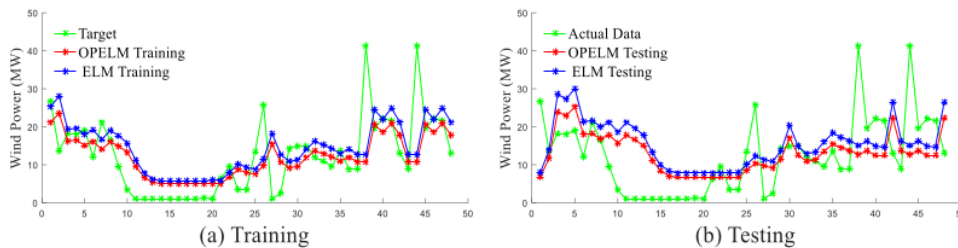


Figure 5. Results of power forecasting training and testing of Jeneponto wind power plant

Figure 5 shows several of power generated of the same value (linear). The linear value causes differences between the target and training graphs, as well as the testing graphs. Accuracy of training and testing can be seen in Table 5 below.

Table 5. The level of accuracy power forecasting of Jeneponto wind power plant

Hidden neuron	Activation function	Method	Training	Testing
			MAPE (%)	MAPE (%)
6	linear	ELM	1.9225	2.9984
	linear, sigmoid, gaussian	OPELM	1.5941	2.4887

The accuracy of training using the OPELM method is 1.5941%, which is more accurate than the ELM method of 2.9984%. The level of accuracy of OPELM testing is 1.5941% and ELM is 2.2887%.

4. Conclusion

The results of forecasting power generation at the Sidrap and Jeneponto wind power plants can be concluded as follows.

1. Forecasting power generation with Sidrap wind power plant data using the OPELM method is 0.8970% more accurate than the ELM which is 1.0853%. In general, the OPELM method is more accurate.
2. Forecasting power generation with data from the Jeneponto wind power plant using the OPELM method is 2.4887% more accurate than the ELM method is 2.9984%. These results indicate that linear, sigmoid, and Gaussian activation in the OPELM method can increase accuracy.
3. The OPELM method can be tested in forecasting the power generation at the Sidrap and Jeneponto wind power plants to maintain a power balance in the Sulsebar power grid system.

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