2020 1st International Conference on Information Technology, Advanced Mechanical and Electrical Engineering (ICITAMEE) | 978-1-7281-8309-1/20/$31.00 ©2020 IEEE | DOI: 10.1109/ICITAMEE50454.2020.9398419

Wind Speed Prediction in the area of PLTB Tolo Jeneponto South Sulawesi using Artificial Neural Network

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***Abstract*—Forecasting the output power of a wind turbine is very much determined by the ability to predict wind speed at the location of the wind turbine placement. The results of this forecast are highly correlated with the operating patterns that will be applied to the electric power system and also with the system operating costs. Wind speed forecasting at PLTB Tolo Jeneponto, South Sulawesi, Indonesia is done by taking wind speed data for the last 20 years. The method used in forecasting is an Artificial Neural Network. From the simulation results, it can be seen that the forecast error is 0.17883 percent. This shows that the ANN method can be accepted as a method in predicting wind speed.**

***Keywords*— forecasting, wind turbine, operating cost, artificial neural network, error**

I. Introduction

The integration of wind turbine power in the electric power system continues to increase in the future. Global warming factor which is predicted that in 2050 there will be an increase in global temperature around 1.5 ℃ to 2 ℃ due to increasing CO2 levels on earth. The increase in the earth's temperature will have an effect on climate change, rising sea levels, drought and other natural problems. This fact encourages every country in the world to reduce the level of global warming one of them by developing clean technology. Wind turbine is one of the most environmentally friendly energy management technologies [1].

Another problem that drives the rapid development of the use of wind turbines in power systems is the fact that energy sources derived from fossils will eventually run out. This requires each country to develop their renewable energy sector [2].

The national energy policy of the Indonesian government will increase the portion of Renewable Energy in the national energy mix by 23% by 2025. This condition makes the development of the Electric Energy sector from Renewable Energy such as Wind Turbine experience an increase.

In 2018, the Sidrap Wind Turbine project (PLTB Sidrap) was officially operated and integrated into the southern Sulawesi (Sulbagsel) electricity system with a power capacity of 75 MW, as shown in Fig. 1. This is a large-scale wind turbine project in Indonesia. Furthermore, the second project is the Tolo I PLTB which was also inaugurated and integrated into the system with a total power capacity of 72 MW, as shown in Fig. 2. The integration of these two Wind Turbines, has increased the portion of electrical energy derived from renewable energy by 2% of the total use of electricity [3].

Fig. 1. Tolo Jeneponto Wind Turbine with a capacity of 72 MW

Seen in Fig. 3, the composition of the use of electrical energy in the electricity system of South Sulawesi. The integration of Wind Turbine in an electric power system will have an impact in terms of system stability. The influence of intermittency of wind turbine will make the power balance in the generation and the power at the load will be disturbed. This imbalance will cause oscillations in the system frequency, so it is needed [4].

Fig. 2. Sidrap Wind Turbine with a capacity of 75 MW

The change in the output power of the wind turbine is greatly influenced by wind speed, while the wind speed is always changing which is influenced by natural conditions. Forecasting wind turbine output power is needed in the operation of the power system because it is closely related to the economical scheduling of existing plants. Accurate wind turbine output power forecasting will help reduce system operating costs and improve power system quality and reliability.

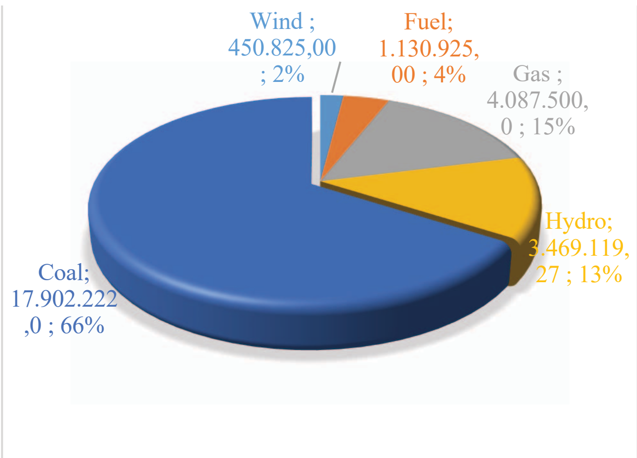

Fig. 3. Composition of Electric Energy Mix in Electrical Systems South Sulawesi

The application of artificial intelligence in forecasting security is very often done. There are several methods applied in recent years to predict wind speed, such as the regression method. temporary spatial models, Artificial Neural Network (ANN) and other artificial intelligence models [5].

In this study the forecasting model uses Artificial Neural Network with 6 input data taken from satellite data readings. The wind speed data used as a test case in this study is in the Jeneponto area as the location of the Jeneponto Wind Turbine.

The 6 data used as training data are: Wind Direction, Temperature at the base, Temperature at a height of 100 meters, Temperature of Water, Soil Temperature 0-10 cm, Humidity and Wind Speed at a height of 150 m as output data.

II. South Sulawesi Interconnection System

A. *Location and Data of Tolo Jeneponto Wind Turbine*

In this study, data will be taken from satellite readings in the North Empoang area which is the location of the placement of Wind Turbine, as shown in Fig. 4. The location coordinates of the location used as test samples in this study are Latitude: -5.62 and Longitude: 119.784

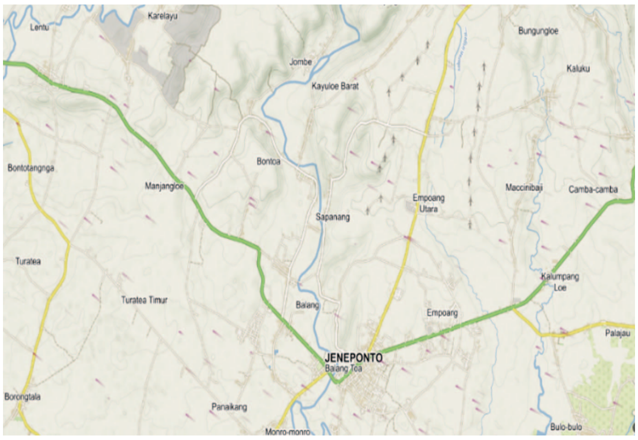

Fig. 4. Location of Tolo Wind Turbine placement

In this study, the system studied is the interconnection system of southern Sulawesi. According to data from PLN South Sulawesi interconnection system in 2019, the night peak load capacity in the South Sulawesi electricity system is 1411.20 MW while the afternoon peak load is 1212.20 MW. The South Sulawesi interconnection system partly operates at 275 kV and most uses a transmission voltage of 150 kV, as shown in Fig. 5 [6].

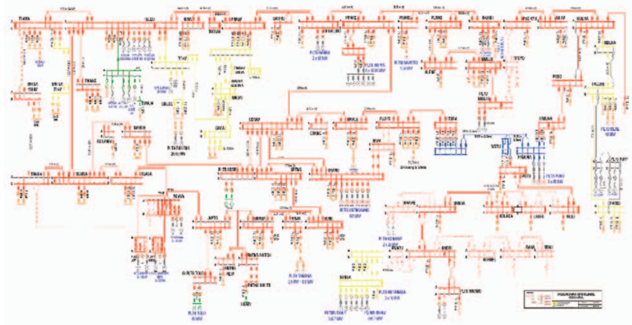

Fig. 5. Single Line Diagram of South Sulawesi Interconnection [2]

There are 2 locations of wind turbines in the South Sulawesi interconnection system namely Sidrap and Tolo (Jeneponto). For Sidrap Wind Turbine has a tower height of 80 m, with a blade length of 56 m. There are 30 towers, with installed power capacity of each unit of 2.5 MW. While Tolo Wind Turbine has an installed capacity of 72 MW [7].

III. Artificial Neural Network Backpropagation

Artificial Neural Network is a method of Artificial Intelligence whose concept mimics the neural network system that exists in the human brain, where nodes are built that are interconnected to one another. These nodes are connected through a link which is commonly referred to as weight. The basic idea is to adopt the workings of the human brain that has the characteristics of parallel processing, processing elements in large numbers and fault tolerance.

Artificial Neural Network Backpropagation, is a learning technique or supervised learning training that is most widely used for ANN. This method is an excellent method to solve relatively complex pattern recognition problems. In a backpropagation network, each unit that is in the input layer corresponds to every unit that is in the hidden layer. Every unit in the hidden layer is connected to every unit in the output layer. [8].

When this network is given an input pattern as a training pattern, then the pattern goes to the hidden layer units which are then passed on to the output layer units. Then the output layer units will respond as the output of the artificial neural network. When the output is not as expected, the output will be propagated backward on the hidden layer and then from the hidden layer to the input layer. This training stage is a step to train an artificial neural network, namely by changing the weight, while problem solving will be carried out if the training process has been completed, this phase is called the testing phase [9],[10].

A. Backpropagation Network Architecture.

Each unit from the input layer in the backpropagation network is always connected to every unit that is in the hidden layer, likewise every hidden layer unit is always connected to the unit in the output layer. Backpropagation Network Architecture in this study can be seen in the Fig. 6. The backpropagation network consists of many layers (multilayer network), namely:

1. Input layer (1 piece), which consists of 1 to n input units.
2. Hidden layer (minimum 1 piece), consisting of 1 to p hidden units.
3. Output layer (1 piece), consisting of 1 to m of output units

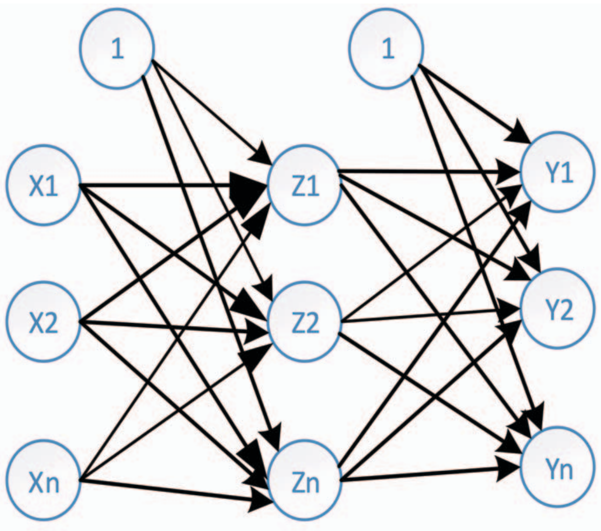

Fig. 6. Backpropagation Network Architecture

A. Forecasting Wind Speed Using Artificial Neural Network

The data used in this study was taken from the website http://indonesia.windprospecting.com/ which is data derived from satellite readings. Data collected from 2004 to 2015. There are a total of 8785 data for each data parameter used in this study. Then this data is shared, around 6588 or or about 75% of the total data is used as training data and the rest 2197 or 25% of the total data is used as testing data. The forecasting ANN model in this study can be seen in the Fig. 7.

The Forecasting Model created in this study uses 6 input data variables, namely:

1. Wind Direction at an altitude of 150m
2. Temperature at a height of 2 m
3. Temperature at a height of 10 m
4. Water Temperature
5. Soil Temperature 0-10 cm
6. Humidity at an altitude of 2 m

And the output data variable is Wind Speed.

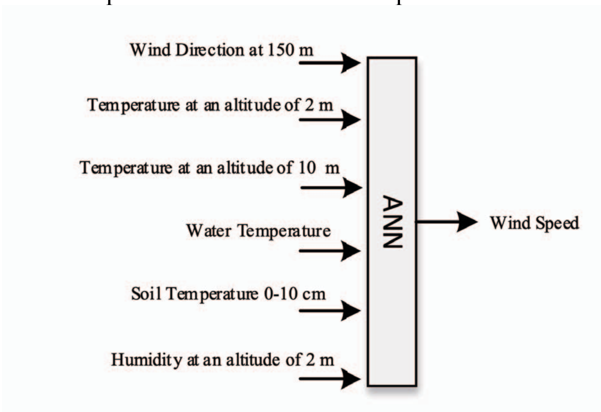

Fig. 7. Forecasting ANN models

The ANN model used uses 6 input layers, 2 hidden layers and 1 output layer. The activation functions used sequentially are: 'logsig', 'tansig', 'logsig', 'purelin'. Fig. 8. shows the ANN architecture model in Matlab.

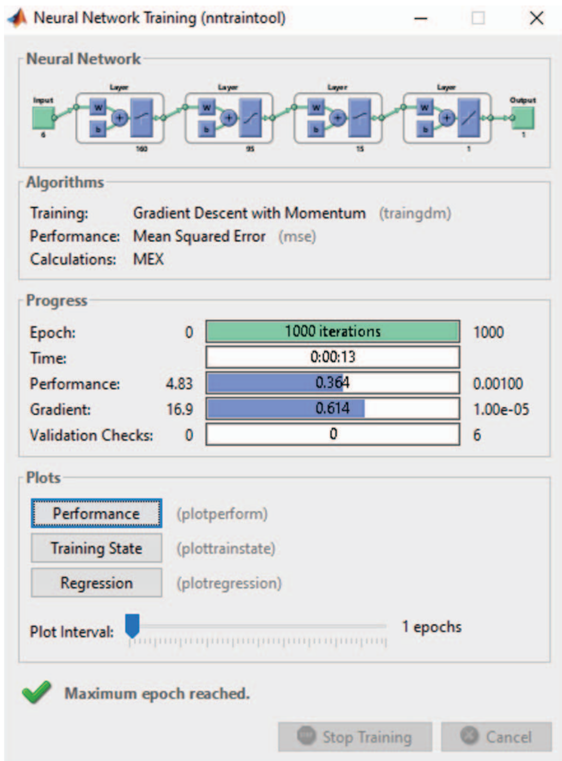

Fig. 8. ANN Architecture

After the training and testing data process is carried out, the next step is to perform a performance analysis of the forecasting results using the mean absolute percentage error (MAPE) method. As shown in the equation (1):

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (1)$$

Where A_t is the actual value at time point t

F_t is the Forecast Value at time point t

n is the size of the sample

TABLE I. INTERPRETATION OF TYPICAL MAPE VALUES

MAPE Value	Interpretation Result
< 10	Highly Accurate Forecasting
10 – 20	Good Forecasting
20 – 50	Reasonable Forecasting
> 50	Inaccurate Forecasting

Source: Lewis (1982, p.40)

The examples of data used in this study can be seen in the Table II. There are 6 input data variables and 1 output data variable.

TABLE II. EXAMPLE OF INPUT DATA VARIABLES USED IN WIND SPEED FORECASTING ON THE TOLO WIND TURBINE

wind Dir. 150	Temp. 2 m	Temp. 100 m	water Temp	soil Temp 0-10cm	real Humidity at 2m	Wind Speed at 150 m
279.2	28	26.1	30.4	25.4	74.83	9.7
280.7	29.4	27.1	32.7	26.1	66.99	10.53
277.4	30.3	27.5	35.5	26.9	62.53	10.69
274	30.8	27.7	36.4	27.9	61.2	11.19
271.7	31.4	28.1	37.8	28.9	59.18	11.64
270	31.4	28.1	37.8	29.8	59.12	12.47
269.9	31.2	27.9	37.2	30.5	60.81	12.91
270.6	30.6	27.5	35.6	31	64.09	13
271.5	29.7	27.3	33.2	31.2	66.45	12.46
271.1	28.6	26.7	30.4	31	74.04	11.88
270.8	27	26	26.9	30.6	80.52	11.51
270	25.8	25.3	25.4	29.8	88.84	11.09
272.8	25.9	25.5	25.5	29.2	87.2	11.26
276.5	25.8	25.4	25.3	28.6	88.43	10.89
278.5	25.7	25.4	25.1	28.1	86.78	10.5
282.2	25.4	25.3	24.7	27.7	87.32	10.18
284.6	25.1	25.4	24.4	27.2	89.17	9.67
279.1	25.2	25.6	24.5	26.8	86.64	10.07
279.1	25	25.5	24.3	26.5	87.64	9.28
276.9	25	25.4	24.3	26.2	88.57	9.84
284.5	25.2	25.4	24.5	25.9	89.86	11.12
287.8	25.4	25.5	24.6	25.7	84.63	11.44
292.1	25.2	25.4	24.5	25.6	83.35	10.98
295.9	27.5	26	29.1	25.7	71.82	9.6
294.4	29.6	27.4	32.7	26.3	60.87	10.4
289.9	30.9	28.2	35.4	27.1	56.6	11.43
286	31.7	28.7	37.5	28.1	53.43	11.7
281.3	32.1	28.7	38.7	29.2	54.34	12.24
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IV. RESULT AND DISCUSSION

From the simulation results, it is found that the MAPE value obtained is 15.007. This value is compared with the existing standards, as in Table I, it is found that the forecasting for the wind speed in the Tolo Wind Turbine is included in the good forecasting category.

The non-linearity factor of existing data makes the process of forecasting wind speed data still in the level of good forecasting.

TABLE III. THE MEAN ABSOLUTE PERCENTAGE ERROR (MAPE) RESULTS FOR WIND FORECASTING ON TOLO WIND TURBINE

Actual Wind Speed (m/s)	Forecasting Result (m/s)	Error (%)
10.31	8.1959	0.20505
9.69	8.4634	0.12659
9.75	10.189	0.044984
8.41	8.6464	0.028112
8.44	8.7279	0.03411
9.25	8.6289	0.067142
9.61	10.3	0.071754
10.03	10.979	0.094585
10.23	10.235	0.000537
9.07	8.7122	0.039453
7.58	7.3312	0.03282
6.16	6.3532	0.031358
4.62	6.8107	0.47417
5.1	5.5836	0.094828
5.1	5.4064	0.060083
5.06	5.2436	0.036285
5.04	4.92	0.023812
5.99	4.5555	0.23948
4.95	4.4657	0.097848
5.22	3.9698	0.2395
9.83	3.9086	0.60238
11.42	6.2872	0.44945
10.56	5.8434	0.44665
7.43	6.9781	0.06082

There are 6 input variable data that are used as training data. Data retrieved comes from hourly readings. So there are 24 data every day and there are 8785 data in a year.

This research is focused on predicting wind speed data in January-December 2020. The results of the wind speed graph for the ANN training results can be seen in Fig. 9. The average error generated from this training process is 0.05%, so it can be said that the accuracy of the training is already very good.

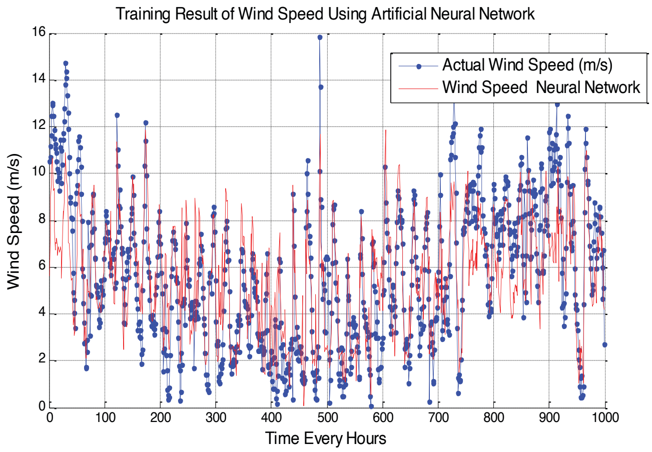

Fig. 9. Wind Speed Training Results at the Tolo Wind Turbine Location

Furthermore, the remaining data is tested and validated. The results of the ANN testing process in this study can be seen in Fig. 10. The performance of the test results for the wind speed of the Tolo Wind Turbine obtained a MAPE value of 15.007. This forecasting result is considered to be a good forecasting result. From the simulation result it can be seen that the forecasting error is 0.17883 percent.

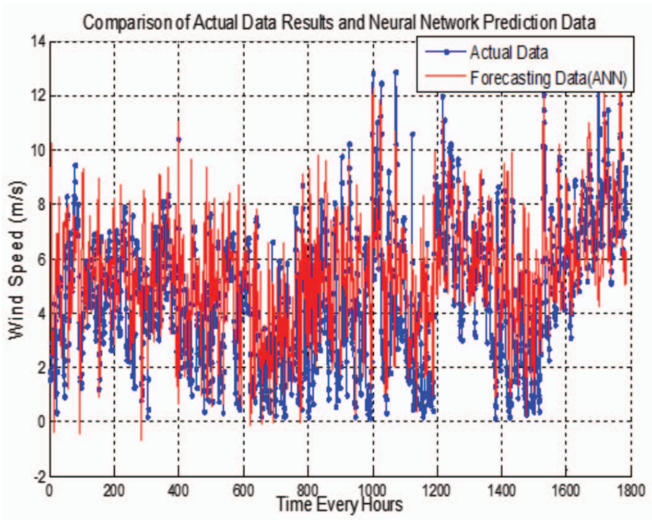

Fig. 10. Wind Speed Testing Results at the Tolo Wind Turbine Location

V. Conclusion

Forecasting wind speed in this study using 6 data which is used as input variables, namely: Wind Direction, Temperature at the base, Temperature at 100 meters, Temperature of Water, Soil Temperature 0-10 cm, Humidity. From the simulation, it can be seen that the wind speed forecasting method offered in this study using ANN Backpropagation has been able to produce good forecasts, with a mean absolute percentage error (MAPE) of 15.007 and forecasting error is 0.17883 percent.

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