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# Optimization of Permanent Magnet Synchronous Generator Output Power in Wind Power Plants with ANN Back Propagation

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***Abstract* – The focus of this research is optimizing a wind power plant using a Permanent Magnet Synchronous Generator (PMSG). The backpropagation method of the artificial neural network system was chosen to optimize the output power of the wind power generator. Based on the simulation results, the backpropagation algorithm of the artificial neural network obtains the output power based on the input variable in the form of changing wind speed. The results show that the best value is learning rate = 0.5, error = 0.0001, max. epoch= 100000, neuron hidden layer = 5. The Mean Square Error (MSE) value obtained is 0.1026 reaching the goal at epoch 14845. The reverse training regretion reaches 0.99917. The optimization results are close to the specified error, which is 0.0001, while what is obtained is 0.0145. The power generated by the wind speed is 10.7 m/s before being optimized using the back propagation neural network method worth 321 watts, while the optimized power results are 409 watts. The difference in the average target power obtained is 88 watts compared to the power of the Artificial Neural Network (ANN).**

**Keywords: Wind power plant; optimal power; Permanent Magnet Synchronous Generator (PMSG); Back propagation; Artificial Neural Network (ANN).**



## I. INTRODUCTION

In the wind power generation system, the generator is one of the key technological elements. In order to achieve high efficiency, the use of synchronous generators with heavy rare earth permanent magnets is increasing. However, such heavy rare earth permanent magnets are expensive and unequal in supply and demand. Therefore, to overcome this problem, a type of permanent magnet that is cheaper and more stable in meeting the needs was developed [1].

The production of electrical energy from wind energy sources is a renewable resource that is abundant and environmentally friendly. Power production data from 2010-2019 was used and three different trend models (linear trend, s-curve and quadratic) were used to evaluate the trend analysis of power generation in Turkey. The results show that the trend model in a certain place is the most suitable model to predict the production of electrical energy from wind energy sources. This is important because the development of wind energy is an important aspect in the development of renewable energy so that growth in Indonesia ranges up to 20% - 30% per year. The wind energy industry is very important, especially in areas that have not yet been reached by PT. PLN globally [2].

The results of monitoring and evaluation of wind potential data in Indonesia, the wind potential varies depending on the season and the geographical conditions of the area. The average wind speed in Indonesia ranges from 2.5 – 6 m/s and is classified as low wind speed. The power generated at a balanced load in the dry season is 1919 W and in the rainy season is 1859 W. Meanwhile, at an unbalanced load, a power of 2207 W is obtained; 680 W; 1062 W [3].

A grid-connected wind power system, known as a Grid-Connected Wind Power System (GCWPS), which uses a Permanent Magnet Synchronous Generator (PMSG) and Artificial Intelligence (AI) controls. The proposed system uses two Voltage-based Source Converters (VSC) based on Insulated-Gate-Bipolar-Transistor (IGBT) technology, one connected to the generator side (rectifier) and the other to the network side (inverter). This study uses an artificial neural network to simulate the proposed technique and predict Maximum Power Point Tracking (MPPT) from wind turbine characteristics [4].

In designing an efficient Surface Permanent Magnet Synchronous Motor (SPMSM) or Generator (SPMSG) using a mathematical model as the basis for the SPMSM design, determining the size of the air gap and permanent magnets becomes very important. In our method, we found that the output torque of the motor is related to the torque angle chosen in the design, which has an impact on the size of the air gap and the permanent magnet. Selection of a low torque angle can improve the power delivery capability of the motor or generator. In addition, the stiffness value of a permanent magnet is also very important in designing a motor or generator because it affects the air gap flux density, cogging torque, and efficiency. To avoid the knee effect, the working point of the selected permanent magnet must be greater than 0.5[5]-[7].

The results of this study are to be able to contribute to optimizing PMSG power which is affected by variations in wind speed, so that it can be used as an additional reference for operating wind power plants according to the type of generator for people who need it.

## II. BASIC OF THEORY

Energy production contributes to the environment such as air pollution and other environmental problems. Until now, renewable energy sources have not been able to provide sufficient production, but have the advantage of being friendly to the environment [12].

One way to meet the demand for electricity in these remote areas is to utilize wind energy when this energy source is an alternative energy source that has considerable potential in Indonesia which is renewable and environmentally friendly. Therefore, for now the most feasible solution to be implemented in Indonesia is widespread wind power generation [13].

The excitation field of the Permanent Magnet Synchronous Generator (PMSG) is generated by a permanent magnet instead of a coil so that the magnetic flux is generated by a permanent magnetic field. A rotating permanent magnet synchronous generator with a classic 3-phase stator which is like an induction generator in general. Permanent magnets can be surface mounted or embedded in the rotor. Permanent magnet synchronous generators are used for small-scale electric generator systems, making it possible to generate wind power in a distributed manner [6].

Optimization is a systematic effort to select the best element from a set of existing elements. Optimization can also be expressed as a systematic effort to find the minimum or maximum value of a function. In other words, optimization is the process of finding the best value based on the objective function with a defined origin. Optimization can be expressed as min/max f(x). For example, by taking the quadratic function $f(x) = x^2$. with x as a member of the real numbers $(x \in R)$. In this example, $f(x) = x^2$is the objective function, while x is the domain defined as a member of the real numbers [7].

Artificial Neural Network is a system for processing information that is designed to mimic how the human brain works, so that it can solve problems by carrying out learning processes through activities based on past data, past data will be studied by artificial neural networks so that they have the ability to make decisions about data that has never been studied [8].

Back propagation is a gradient reduction method to minimize the squared output error. Back propagation trains the network to get a balance between the network's ability to recognize the pattern used during training and the network's ability to provide the pattern used during training.

Back propagation or feedforward network is a network consisting of many layers (multilayer neural network). In the backpropagation network, each input layer is connected to each hidden layer, as well as the hidden layer is connected to the output layer.

Back propagation method is carried out starting from the training stage to testing. Figure 1 is an image of the backpropagation architecture. At the input layer there is Figure 1 consisting of 1 input variable, namely $X_{0.1}$ which is the bias wind speed data at the input layer is $X_0$ . At the input layer, go to the hidden layer $Z_1$ with the formula ($Z_{net1}$ =($V_{01}$)+$X_1$ *$V_{11}$ ,....go to $Z_2$ and so on) .

The network consists of 1, 5, 10, and 15 units in the hidden layer. The hidden layer will issue its respective output ($Z_1$, $Z_2$, $Z_3$ ... and so on) with the formula (in this study using the binary sigmoid activation function). After completing output to the hidden layer, then the hidden layer will go to the output layer with a value of Zk (k=1, ∑=15) and initial weight Wk (k=1 ∑=15) and bias on the hidden layer ($W_{01}$) by using the $Y_{net}$ equation and so on until it's finished [14]-[15].

Once received at the output layer, the output layer will issue an output with the binary sigmoid activation formula. Y = forward propagation activation function. In the hidden layer there are hidden layer neurons 1 to 15, while in the output layer there is 1 neuron. Furthermore, in backward propagation the process that occurs is that each output unit receives a target which will be compared with the resulting output changing the weights calculating the new hidden layer weight with $x_o$, $x_1$ is the input, parameter $z_0$ and so on is the hidden layer and $Y_0$ is the output . Details are shown in Figure 1.

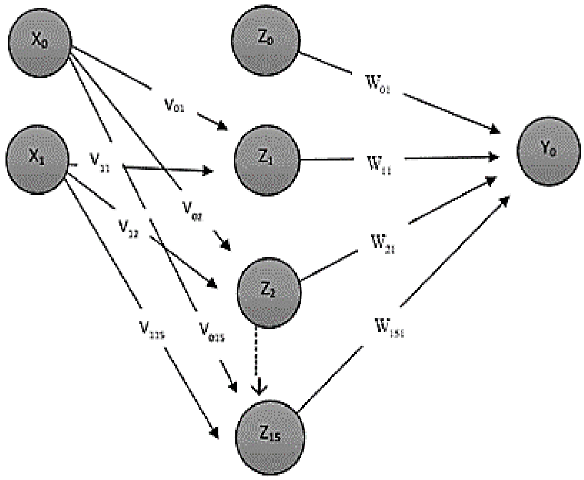


Figure 1 Back propagation ANN architecture

In Figure 1, the input unit (input) $x_i$ has a line weight, namely $v_{ji}$ , which connects the input unit $x_i$ with the $z_j$ unit , and the bias unit always has a value of 1, has a line weight, namely $v_{jo}$ , which connects the bias unit with the $z_j$ unit. The hidden layer unit $z_j$ has a line weight that is $w_{kj}$ which connects the hidden layer unit $z_j$ with the output unit $Y_k$ and the bias unit has a line weight $w_{k0}$ which connects the bias unit with the output unit $Y_k$.

## III. METHOD AND DESIGN

The back propagation neural network is used as a method for optimizing the output power of a Wind Power Plant which has a working mechanism shown in Figure 2 below:

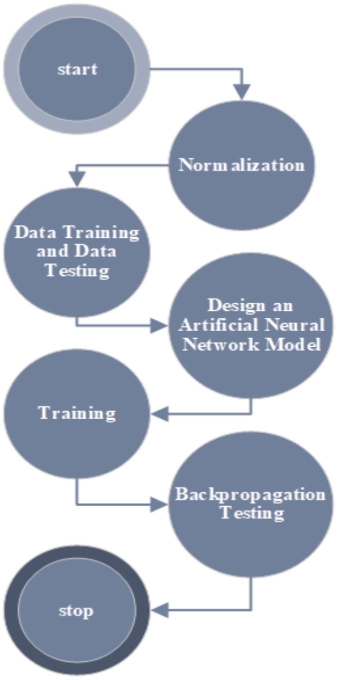


Figure 2 Back propagation neural network mechanism

To provide a clearer picture, below will be given an explanation of the author's research stages, including:

A. Data Preprocessing.

The data preprocessing is intended to determine the input and output parameters. The input of this research is the wind speed while the output is the output power. The amount of data on wind speed and output power is 30 data ;

B. Data Normalization

Data normalization is needed with a view to simplifying the calculation process, namely by transforming data values into a certain range or range of values. The data range is transformed between 0 and 1. This is adjusted to the needs or the binary sigmoid activation method;

C. Data Training and Data Testing

Dividing the data into 2 parts, for training purposes (data training) and testing (data testing). Determine data as input (vector input) or as targets (output) in accordance with the developed ANN model;

D. Design an Artificial Neural Network Model.

The design of the wind power generation optimization model is carried out by building an artificial neural network (ANN) with the back propagation learning method. Design the ANN model in the form of programming with MATLAB. Make changes to the learning rate and the number of neurons in the hidden layer by trial and error in order to get convergent results;

E. Training.

Training on ANN back propagation is carried out to determine the accuracy of the results or output of the optimization model built, compared to wind speed and real output power. During the training process, graphs of training performance, training state, and training regression will be displayed. Until the best training results can be known;

F. Back Propagation Testing.

This process is a test of the back propagation neural network. From the input values entered, it will display output values that refer to parameters, training, the number of hidden layers and iterations used. In the testing process Y will be displayed as ANN output in the form of normalization data and the target display as ANN prediction denormalization data in the form of output power in watts.

## IV. RESULTS AND DISCUSSION

Permanent magnet synchronous generator data model owned by PT. Lentera Bumi Nusantara is used as a reference in this study to calculate the output power generated by a permanent magnet synchronous generator. Solving the problem of optimizing the output power of a permanent magnet synchronous generator in a wind power plant using the back propagation method of artificial neural networks. Table 1. Wind speed data and generator power

Table 1 Wind Speed data and generator power

| Wind Velocity | Power (W) |
|---|---|
| 1,0 | 5,00 |
| 2,0 | 8,00 |
| 3,5 | 10,50 |
| 4,0 | 12,70 |
| 5,0 | 57,00 |
| 2,2 | 10,20 |
| 7,0 | 124,00 |
| 8,0 | 220,00 |
| 10,0 | 393,00 |
| 3,6 | 10,78 |
| 10,7 | 396,00 |
| 4,1 | 49,00 |
| 9,0 | 357,00 |
| 9,5 | 360,00 |

Manual calculations at the training stage consists of 3 phases, namely phase 1 of forward propagation, phase 2 of backward propagation and phase 3 of changing the weights in back propagation as the initial weight value initial bias with a small random number ranging from 0 to 1. The initial weight at the input to the hidden layer can be shown in:

$$V_1 = 0.2. \quad (1)$$

$$W_1 = 0.1 \quad (2)$$

$$W_0 = 0.2 \quad (3)$$

Equation (1), $V_1 = 0.2$. The initial weight of the hidden layer to the output layer can be shown in equation (2). $W_1 = 0.1$. Requirements at the training stage determine the maximum epoch, target error, and learning rate. Determination of learning rate, maximum epoch and error in this study refers to research by previous researchers which has high accuracy. Training learning rate 0.5 hidden layer 5 and data ratio 10:20 can be shown in Figure 3

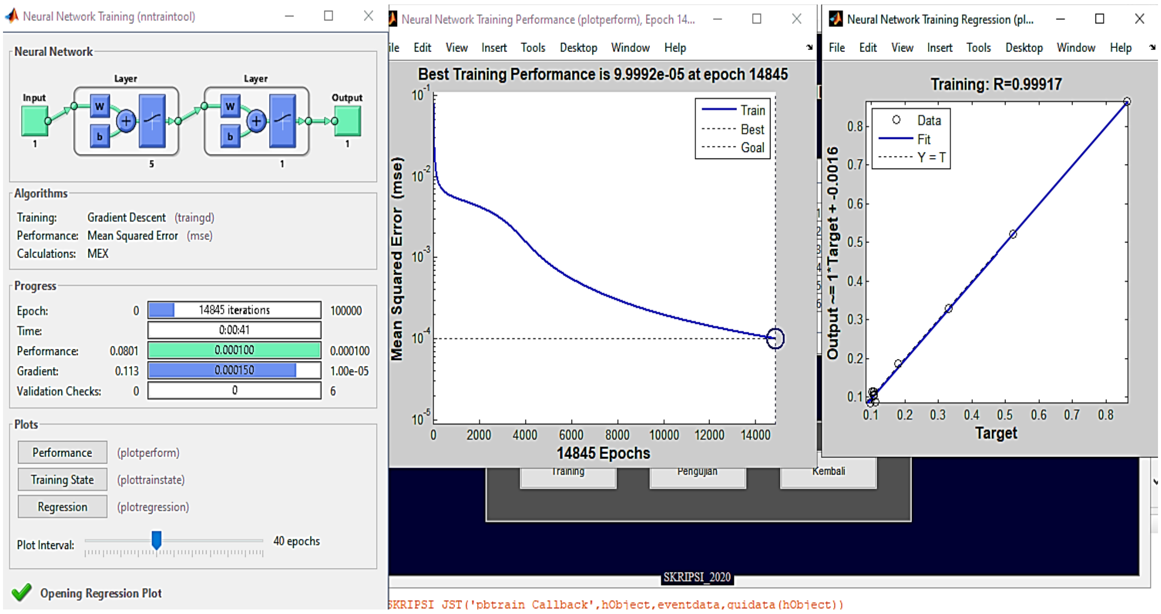


Figure 3 Training learning rate 0.5 hidden layer 5 and data comparison 10:20

Training using Learning Rate = 0.5 Error/Error = 0.0001 Max.Epoch = 100000 Neuron Hidden Layer = 15. The training results produce the best training performance with an MSE of 0.1014 when it reaches the goal at epoch 100000. The training reaches its maximum epoch so the expected MSE value has not achieved. ANN training regretion graph with Learning Rate = 0.5 Error/Error = 0.0001 Max.Epoch = 100000 Neuron Hidden Layer = 5 produces a fit line (matching) with the dotted line (target) reaching its best line.

The training regretion/reverse sequence training reaches 0.99917. The graph shows the circles (training data) which are not far from the targeted line which means good training is produced.

The testing phase of the ANN model is carried out by providing new data patterns that have never been used in the training process. The data for testing is separated from the start.

The back propagation test that was first carried out in this study was a test of the back propagation parameter with a learning rate of 0.5. Maximum epoch 100000. Error value 0.0001. The number of hidden layer neurons is 5, 10, and 15. Distribution of the first data (20 training data and 10 test data), the second (15 training data and 15 test data) and the third (20 training data and 10 test data).

Optimization of the model using MSE with the error value is the real data minus the predicted data squared from the normalized data, then added up and divided by the number of test data. The following are the results of testing the back propagation of artificial neural networks:

The test results at a learning rate of 0.5, hidden layer 10 neurons, a comparison of 10 training data and 20 test data can be shown in Table 2.

Table 2 Tests on a learning rate of 0.5, hidden layer neurons 10, comparison of 10 training data and 20 test data

| Normalization | | | Denormalization | | |
|---|---|---|---|---|---|
| ANN power targets (Y) | Output power | Error^2 | ANN power targets (Y) | Output power | Difference |
| 0.2699 | 0.27228 | 0.0000 | 73 | 94 | 19 |
| 0.6806 | 0.79426 | 0.0129 | 239 | 357.6 | 3 |
| 0.8649 | 0.89604 | 0.0010 | 314 | 409 | 2 |
| 0.3502 | 0.36337 | 0.0002 | 106 | 140 | 25 |
| 0.8686 | 0.86634 | 0.0000 | 315 | 394 | 9 |
| 0.8407 | 0.82475 | 0.0003 | 304 | 373 | 20 |
| 0.3256 | 0.31980 | 0.0000 | 96 | 118 | 18 |
| 0.446 | 0.47822 | 0.0010 | 144 | 198 | 5 |
| 0.5983 | 0.77921 | 0.0327 | 206 | 350 | 13 |
| 0.2312 | 0.28812 | 0.0032 | 58 | 102 | 25 |
| MSE | | 0.0051 | difference | | 9 |

The results of the three combinations of comparison of back propagation ANN test data that have been carried out, the best test is the seventh test using a learning rate of 0.5 neuron hidden layer 5, the comparison of training data = 10 and test data = 20. The optimization results are close to the specified error, namely 0.0001. The difference in the average power target is 10 compared to the ANN target.

Testing with hidden layer 5 neurons is the best test because the smallest error is obtained and the ANN target is very close to the original, which means that the network has found the optimal value for system testing based on the training that has been done. It is proven that back propagation neural networks can be used for power optimization in wind power plants.

## V. CONCLUSION

Back propagation method of the gradient descent training function used in this study can display the output power based on the input variable in the form of changing wind speed. The training results show that the best training is with learning rate = 0.5, error = 0.0001, max. epoch = 100000, neuron hidden layer = 5. The MSE value obtained was 0.1026 reaching the goal during the epoch 14845. The training regretion/reverse order training reached 0.99917. The best test results are using a learning rate of 0.5, hidden layer neurons of 15, comparison of training data = 10 and test data = 20. The optimization results are close to the specified error, which is 0.0001 while what is obtained is 0.0145. The power generated by the wind speed is 10.7 m/s before being optimized using the back propagation neural network method of 321 watts while the optimized power results using the back propagation neural network method with a wind speed of 10.7 m/s is 409 watts. The difference in the average target power obtained is 88 watts compared to the ANN power.

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