

Development and Testing of Artificial Neural Network with Backpropagation Algorithm to Predict the Power Ratio of Savonius Wind Turbine

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ABSTRACT

A power ratio of Savonius as a vertical wind type has been predicted using an artificial neural network (ANN) with a backpropagation algorithm. The ANN is a method for processing information that is adapted from a biological neuron. This method is developed from the principle of a human being's brain which is consist of input and output neurons. The procedure in this method is conducted using the initial input as the power ratio target to predict the next value as the output target. This prediction is employed to know the blade characteristic and its effect on the power. The ANN architecture is multi-layers with a backpropagation algorithm. The layers are input, hidden, and output. The learning rule is consisting of the forward-propagation, backward-propagation, and weight-update with the number of neurons being 2-5-1, respectively. The result of this development and testing shows that the optimum values for momentum and learning rate are 0.90 and 0.01, respectively. The result has been tested by comparing the output and input with an error of approximately 0.65%. This result indicates that the ANN method with backpropagation algorithm is prospective to predict the power ratio of various blades of Savonius wind turbine.

Keywords: ANN, rotor, Savonius, wind.

1. INTRODUCTION

The use of new and renewable energies of natural resources is indispensable for supplying electric power especially in remote areas [1-3]. In the last decade, the use of alternative energy has increased significantly, such as hydropower, solar, biomass, wind, geothermal, ocean waves, and tidal. [4-8]. The alternative energy that has not been explored intensively is wind energy. As an abundant source of energy, wind energy will remain as long as the earth still gets energy from the sun. By applying the right energy conversion technology, wind energy is expected to be an environmentally friendly energy source that will never run out [9-11].

A problem with wind energy exploration is the low wind speed under the normal condition, at approximately 2.5 – 6.0 m/s [12-14]. This potential is on average quite low, but actually, quite a lot of areas have wind energy potential that is feasible to be utilized, especially as electrical energy. The situation certainly

has an impact on the low electrical energy produced, so the installation price becomes very expensive [13, 14]. For example, if a wind turbine can produce power of 10 kW at a wind speed of 10 m/s, then if the wind speed is only 5 m/s the power produced by the wind turbine is only about 1.25 kW. For this reason, to produce 10 kW of power, 8 units of wind turbines are needed [14, 15]. This condition causes the cost of producing electricity from wind turbines to be very expensive, even economically unfeasible.

For wind energy to be used intensively, it is necessary to engineer wind turbines that can work at low wind speeds and can also produce large amounts of energy. Several modifications have been produced and applied, such as variations in rotor surface area, low-speed generators, a reduced moment of inertia, and higher pile applications [12-15]. Besides, the engineering that has been carried out related to the effectiveness of the rotor in wind turbines is the use of the vertical axis. A form of vertical turbine that is considered effective in the conversion process of

potential energy from the wind into mechanical energy in the form of rotor rotation is Savonius turbine. The effectiveness value is known after being compared with the two vertical turbine types, namely Darrieus and H-rotor [13, 15, 18, 19]. Furthermore, the geometric shape of the Savonius turbine has also been analyzed by considering the number of blades where the performance coefficient for the two blades shows an increase of about 27.3% [20-22].

In this study, simulation and performance analysis of a two-blade Savonius turbine were carried out using the artificial neural network (ANN) method. This algorithm was developed based on the ANN method for the same case with different approximations. Prediction of power and torque performance with the ANN method has been successfully used for a three-bucket Savonius [23, 24]. In addition, this method was developed based on the analysis of power and torque for the case of the multi-blade effect [23-25]. The results of this simulation are expected to be used as a basis for the manufacture of the Savonius wind turbine. The power ratio of the Savonius wind turbine is expected to be predicted by using an artificial neural network method with a backpropagation algorithm.

2. METHOD

2.1 Power ratio formula for Savonius turbine

The Savonius wind turbine is a type of vertical axis wind turbine. The rotation of the axis is perpendicular to the direction of the wind. The Savonius rotor includes two semicircular axes (diameter and height are D and H , respectively) and there is a gap spacing (S) as shown in Figure 1 parts (a) and (b). The Savonius rotor is varied with six different axes in a wind tunnel. In rotors I to VI, each axis is semicircular with the same diameter but the distance gap varies as shown in Figure 1 part (c) [19-21].

The power ratio is assumed as the comparison of the power in the turbine axis (P_g) and the power from wind force (P_a). The ratio is written in the form:

$$C_p = P_g / P_a \tag{1}$$

The product of the power equation in the shaft shows that only the ratio of the power of the force equal to the direction of effective rotation can generate electricity. Therefore, the blade model on a vertical axis turbine is very important [21]. Furthermore, the variable of the tip speed ratio (λ) is represented as

$$\lambda = \frac{u}{v} = \frac{\omega D}{2v} \tag{2}$$

Here, the power ratio (C_p) can be determined using

$$C_p = \frac{2Fu}{\rho v^3 DH} \tag{3}$$

By substituting equation (2) into equation (3), the general form of the power ratio can be simplified in the form

$$C_p = \frac{2F}{\rho v^2 DH} \tag{4}$$

The Reynold number (Re) for this case is

$$Re = \frac{uD}{\nu} \tag{5}$$

The symbols of D , u , ν , and F in equations (4) and (5) are the rotor diameter, blade tip speed, kinematic viscosity, and thrust force, respectively [23,25].

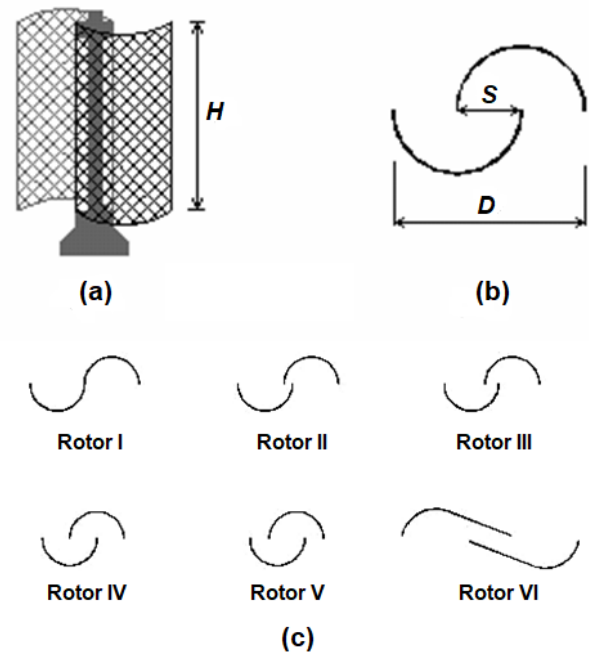


Figure 1 Rotor and blade schemes of Savonius turbine (a) front look, (b) looks like a semi-circle, (c) rotor axis experiment [24, 25].

2.2 The ANN method

The ANN imitates a biological neural network made up of neurons. The development of the idea of a biological neural network is the existence of processing elements in an artificial neural network that are interconnected and operate in parallel. The main components of a neuron can be grouped into three parts, namely dendrites which are responsible for receiving information. Soma serves for a place of processing information. Axons transmit impulses to other nerve cells [26]. A neuron with dendrites and an axon can be seen in Figure 2.

A neuron is an information processing unit that is the basis for the operation of the ANN. Neurons consist of three constituent elements including a set of several units that are connected by connection pathways. First, the summing unit will add up the signal inputs that have

been multiplied by their weight. Second, the activation function will determine whether the signal from the input neuron will be forwarded to other neurons or not. Each neuron in the network receives and sends signals to and from other neurons. Signal transmission is conveyed through the connector. The strength of the relationship that occurs between each neuron is known as the weight [26].

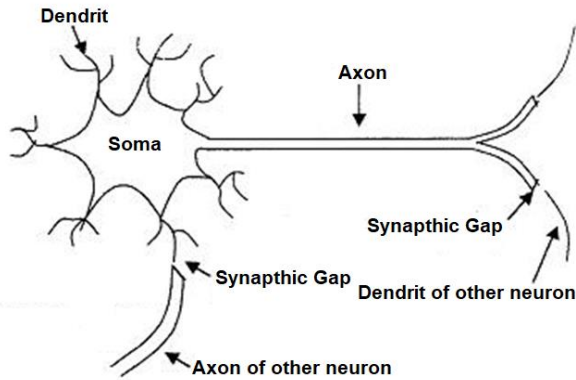


Figure 2 Scheme of neuron, axon, and dendrite.

The ANN method is developed based on architecture and algorithms. The architecture usually describes the direction the signal travels in the network whereas the algorithm describes how the weights are governed. Both aim to direct input and output following the target of the learning rule. The changes in connection weight values can be done in various ways, depending on the type of training algorithm. By adjusting the value of this weight, network performance can be improved in learning various patterns expressed by input and output pairs [26]. The ANN model used in this study is the multi-layer network. Here, the ANN has the input and output units, accompanied by the hidden unit. In Figure 3 the multi-layer network consists of n , h , and m of input, hidden, and output units, respectively [26,27].

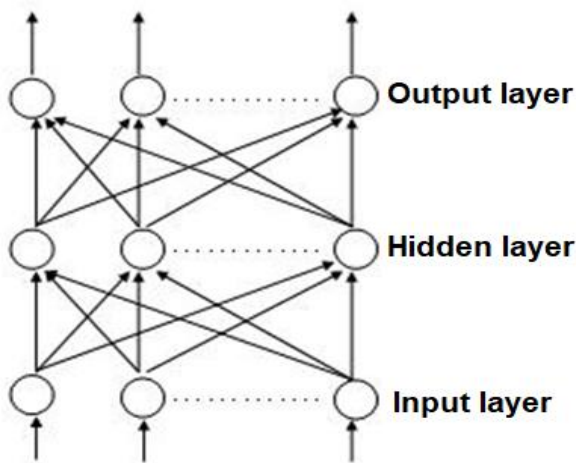


Figure 3 Scheme of multi-layers ANN.

The backpropagation algorithm is an ANN training method. The hallmark of this method is to minimize errors at the output which is produced from the learning process. The backpropagation algorithm that uses a multilayer network, not only has the input, hidden, and output, but also the bias [27]. The ANN architecture of the backpropagation algorithm can be seen in Figure 4.

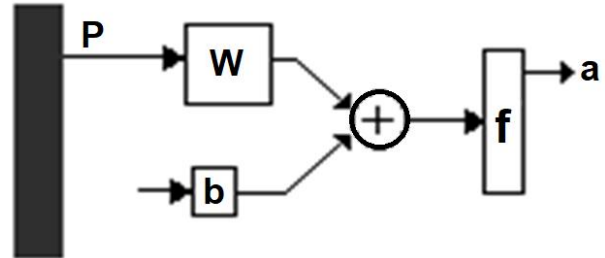


Figure 4 Architecture of ANN.

The optimization of the backpropagation method is affected by several parameters, i.e.: selection of initial weights, number of training patterns, number of hidden layers, learning rate, and iteration time (epoch). The backpropagation method tends to provide reasonable answers when compared with the target. The standard backpropagation method is a network weight differential gradient which is modified based on the equation [25,27]:

$$w_{ij}(n+1) = w_{ij}(n) + \eta \delta_i(n) x_j(n) \tag{6}$$

Where the weight of $w_{ij}(n+1)$ from i to j in the order of $(n+1)$ and $w_{ij}(n)$ is similar in the n -order. The symbol $\delta_i(n)$ is the local error which is evaluated at the $e_i(n)$ - and n - orders. The local error is represented as

$$e_i = d_i(n) - y_i(n) \tag{7}$$

The special function used for the ANN training feed is the average number of squares of errors between the output network and the output target. In batch activation, the gradient corresponding to the momentum of the algorithm is used as a training function. Momentum is a gradient-forming algorithm obtained from the relationship

$$w_{ij}(n+1) = w_{ij}(n) + \eta \delta_i(n) x_j(n) + \alpha (w_{ij}(n) - w_{ij}(n-1)) \tag{8}$$

Here, α is the momentum coefficient with the range values between 0.1 and 0.9. Neurons in ANN are also known as units. Each neuron consists of a switching function that expresses its internal level of activation. The output of the neuron is determined through input transformation using the appropriate transfer functions, namely: sigmoid function, tangent hyperbolic function, and linear function. The sigmoid function is most widely used for non-linear relationships. The general form of this function is shown in the equation:

$$y_i = f(x_j) = \frac{1}{1 + e^{-x_j}} \tag{9}$$

Furthermore, the performance of the ANN was evaluated utilizing the root mean square error (RMSE). The relationship between the output model and the size of the data set is stated as

$$RMSE = \sqrt{\frac{\sum (X_{obs} - X_{est})^2}{N}} \quad (10)$$

Both x_{obs} and x_{est} are the results of model calculations and target estimates, respectively, while N is the amount of data in the testing process [25-27].

2.3 Algorithm of power ratio calculation

A backpropagation propagation algorithm in references [22-25] is developed to predict the power ratio of Rotors I – VI in Figure 1 (c). The data used to predict the power ratio value is the data of the previous power ratio value (the last two power ratio values) for each rotor. The following is an ANN algorithm with a backpropagation learning method:

- (0) Input target: C_p (power ratio)
- (1) Weight in the input layer: $Z_{-in_j} = v_0 + \sum_{i=1}^n x_i v_{ij}$
- (2) Activation function:

$$Z_j = f(Z_{-in_j}) = \frac{1}{1 + \exp(-Z_{-in_j})}$$
- (3) Weight in the output layer:

$$Y_{-in_k} = w_{0k} + \sum_{j=1}^k z_j w_{jk}$$
- (4) Output layer: $Y_k = f(Y_{-in_k}) = \frac{1}{1 + \exp(-Y_{-in_k})}$
- (5) In the input: C_p (power ratio) \approx output Y_k (point 5), the target is appropriate with the output, the learning process is finished, if NO, the procedure is continued to point (6)
- (6) Compatibility between input and output target using:

$$\delta_k = (C_p - T_k) f'(Y_{-in_k})$$

$$\Delta w_{jk} = \alpha \delta_k z_j$$

$$\delta_j = \delta w_{jk} f'(Z_{-in_j})$$

$$\Delta v_{jk} = \alpha \delta_j z_k$$
- (7) New weight for input layer:

$$w_{jk}^* = w_{jk} + \Delta w_{jk}$$

$$v_{jk}^* = v_{jk} + \Delta v_{jk}$$
- (8) Back to the point (1) as a new target

From this procedure, an effective model for predicting the entire rotor is known based on the error value. The value is determined based on the output close to the target set for each rotor.

3. RESULT AND DISCUSSION

3.1 Backpropagation algorithm testing

The ANN architecture with the backpropagation algorithm used in this study consists of three layers, namely the input, hidden and output layers which can be seen in Figure 5. The training accuracy for the backpropagation algorithm is RMSE (root mean square error). The smaller the RMSE value, the better the model will be. In Figure 6, the smallest RMSE value can be seen at formation: 2,5,1 of input, hidden, output units, respectively. The result of this development and testing shows that the optimum values for momentum and learning rate are 0.90 and 0.01, respectively. The most optimal formation corresponds to the values and methods in references [23, 24].

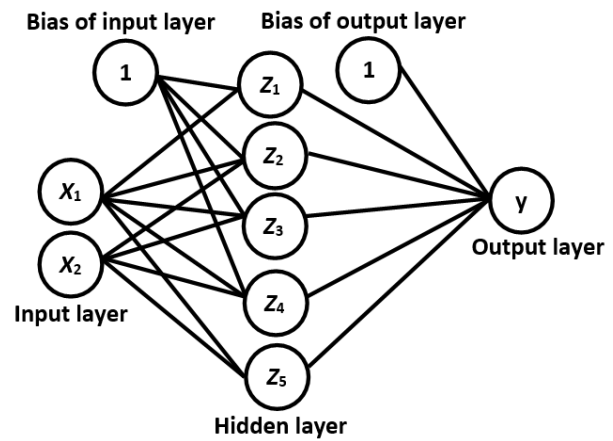


Figure 5 Architecture backpropagation algorithm.

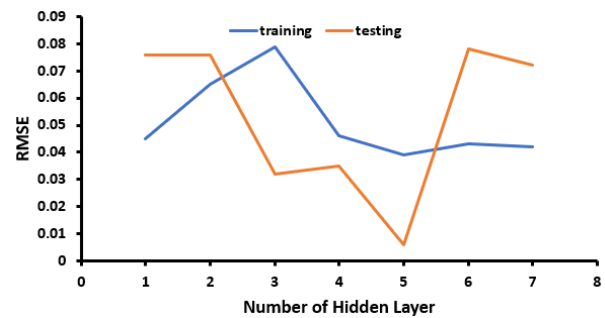


Figure 6 Comparison between the RMSE and number of hidden layers for both training and testing.

3.2 Power ratio prediction

Figure 7 shows the power ratio characteristic based on the tip speed ratio. The values for the target (data) and prediction (predictive) are almost similar for all rotors. The power ratio values for the next three values are predicted from the previous values of the I – VI rotors. From the figure, the predictions process for the fifth, sixth, and seventh values based on the training

which are performed on the four previous values (two training patterns) are close to the target for all rotors. The results indicate that the pattern is almost similar to the prediction process of the power and torque performance with the ANN method has been successfully used for a three-bucket Savonius [23, 24]. The condition confirms that the prediction method to find the next power ratio value based on the previous power ratio value shows a small error and the output value is close to the target.

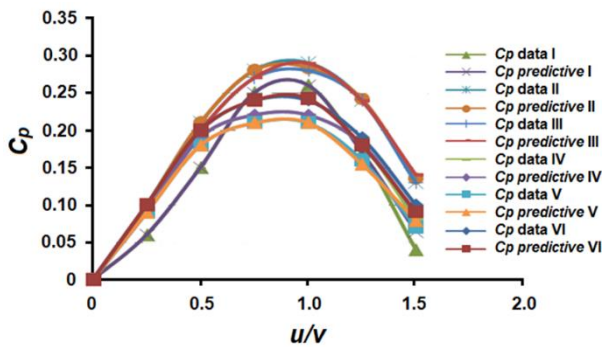


Figure 7 Comparison of the power ratio between the target and predictive derived from the tip speed ratio for rotors I-IV.

Figure 8 is a form of testing the ANN method with the backpropagation algorithm in predicting the power ratio at different Reynolds numbers. The power ratio value used in the training process consists of four values (two data patterns) to predict the fifth, sixth, and seventh values (third, fourth and fifth patterns). This condition indicates that the target and output values have a very small difference. The type of gap tested in this procedure is rotor I with an RMSE value of about 0.65%. The same method has also been tried on the II-VI rotor with small error results and the output value is close to the target. These results show that the developed ANN in this study can minimize error after comparing with the methods in references [24, 25]. Therefore, the ways in developing and testing the ANN method with the backpropagation algorithm are recommended for several types of Savonius wind.

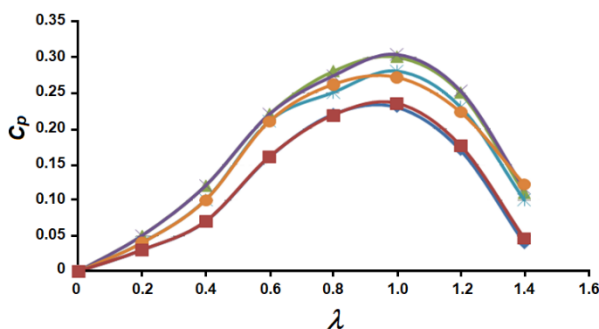


Figure 8 The predictive power ratio based on various Reynold numbers in learning process.

4. CONCLUSION

The ANN method with a backpropagation algorithm has been applied to predict the power ratio of the Savonius turbine. The procedure started from testing the backpropagation algorithm and then continued by predicting the value of the power ratio to the six-rotor models. The training accuracy used in the backpropagation algorithm is RMSE. The most optimal RMSE value is obtained in conditions of 5 hidden, 2 input, and 1 output. Furthermore, the prediction of the power ratio value carried out in this study is to find the next power ratio value based on the previous power ratio value. The prediction results of the power ratio value show a small error and the output value is close to the target. These results show that the ANN method with the backpropagation algorithm can be used for various forms of the Savonius turbine blade model.

AUTHORS' CONTRIBUTIONS

Both authors, J.A and B.B, have contributions about CONCEPT, METHOD, and ANALYSIS. The contribution in EDITING is J.A. Both authors (J.A and B.B) provided feedback, discussed result and contributed to the final manuscript.

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REFERENCES

- [1] Tumiwa, H. Imelda, The energy-poor: the facts in civil society. Institute for Essential Services Reform (IESR), 2011, pp. 70-85.
- [2] M. Fathi, A. Mehrabipour, A. Mahmoudi, A.A.S.B.M. Zin, M.A.M. Ramli, Optimum hybrid renewable energy systems suitable for remote area, Journal Smart Science, vol. 7, issue 2, 2019, pp. 147-159.
- [3] Z. Arthouros, Global status report. Paris: REN21 Secretariat, 2019, p. 336.
- [4] W. Beabpimai, T. Chitsomboon, Numerical study of effect of blade twist modifications on the aerodynamic performance of wind turbine, Int. Journal of Renewable Energy Development, vol 8, no. 3, 2019, pp. 285-292.

- [5] J. Aminuddin, R.F. Abdullatif, Wihantoro, A mapping of the potential area for developing wave power energy generation in Cilacap coast area and surroundings, *SIMETRI, Journal of Indonesian Physics Science*, vol. 2, no. 2, 2016, pp.68-73.
- [6] S.K. Singal, R.P. Saini, C.S. Raghuvanshi, Analysis for cost estimation of low head run-of-river small hydropower schemes”, *Energy for Sustainable Development*, vol. 14, issue 2, 2010, pp. 117–126.
- [7] A. Santoni, G. Cavazzini, G. Pavesi, G. Ardizzon, A. Rossetti, Techno-economical method for the capacity sizing of a small hydropower plant, *Energy Conversion and Management*, vol. 52, no. 7, 2011, pp. 2533-2541.
- [8] M. Berkun, Hydroelectric potential and environmental effects of multi-dam hydropower projects in Turkey, *Energy for Sustainable Development*, vol. 14, issue 4, 2010, pp. 320-329.
- [9] N. Sinaga, Flow analysis of wind turbine rotor with horizontal axis using computational approximation, *Exergy: Journal of Energy Technique*, vol. 13, no. 3, 2017, pp: 84-91.
- [10] J. Aminuddin, A. Widiyani, P. Razi, A. N. Aziz, R. F. Abdullatif, A. Arifin, Estimation of ideal configuration and dimension of pico hydropower using Euler-Lagrange equation and Runge-Kutta method. *Int. Journal of Physics: Conference Series*, vol. 1494, no. 1, 2020, p. 012039. DOI:10.1088/1742-6596/1494/1/012039.
- [11] J. Aminuddin, M. Effendi, Nurhayati, A. Widiyani, P. Razi, Wihantoro, A.N. Aziz, R.F. Abdullatif, Sunardi, Bilalodin, A. Arifian, Numerical analysis of energy converter for wave energy power generation-pendulum system, *Int. J. of Renewable Energy Development*, vol. 9, no. 2, 2020. pp.255-261. DOI:10.14710/ijred.9.2.255-261.
- [12] R.K. Singh, M.R. Ahmed, Blade design and performance testing of a small wind turbine rotor for low wind speed applications, *Renewable Energy*, vol. 50, 2013, pp 812-819.
- [13] R.H. Barnes, E. V. Morozov, K. Shankar, Improved Methodology for Design of Low Wind Speed Specific Wind Turbine Blades, *Composite Structure*, vol. 119, 2015, pp 677-684.
- [14] H. Erich, *Wind turbines: fundamentals, technologies, application, economics*, 2nd Edition, Springer, Germany, 2005.
- [15] E.N. Jacobs, A. Sherman, Airfoil section characteristics as affected by variations of the Reynolds number, Report No. 586, National Advisory Committee for Aeronautics, 2009.
- [16] S. Mathew, C.M. Lim, M. I., Petra, G. S. Philip, M. Noorfathin, M.S. Mathew, V. Raj, Matching the characteristics of low wind speed turbines with candidate wind regimes, *Energy Procedia*, vol. 95, 2016, pp 286-293.
- [17] A. Ramadan, K. Yousef, M. Said, M.H. Mohamed, Shape optimization and experimental validation of a drag vertical axis wind turbine, *Energy*, vol 15, no. 151, 2018, pp. 839-853.
- [18] K.H. Wong, W.T. Chong, N.L. Sukiman, S.C. Poh, Y.C. Shiah, C.T. Wang, Performance enhancements on vertical axis wind turbines using flow augmentation systems: *a review*, *Renewable and Sustainable Energy Reviews*, vol. 73, 2017, pp.904-921.
- [19] M. Zemamou, M. Aggour, A. Toumi, Review of Savonius wind turbine design and performance, *Energy Procedia*, vol. 141, 2017, pp. 383-388.
- [20] W. Tian, Z. Mao, B. Zhang, Y. Li Y, Shape optimization of a Savonius wind rotor with different convex and concave sides, *Renewable Energy.*, vol. 117, 2018, pp. 287-299.
- [21] N. Alom, U.K. Saha. Influence of blade profiles on Savonius rotor performance: *numerical simulation and experimental validation*. *Energy conversion and management*, vol. 186, 2019, pp. 267-277.
- [22] J. Sargolzaei, A. Kianifar, Modeling and simulation of wind turbine Savonius rotors using artificial neural networks for estimation of the power ratio and torque, *Simulation Modelling Practice and Theory*, vol. 17, no. 7, 2009, pp. 1290-1298. DOI: 10.1016/j.simpat.2009.05.003.
- [23] B.K. Debnath, R. Das, Prediction of performance coefficients of a three-bucket Savonius rotor using artificial neural network, *Journal of Renewable and Sustainable Energy*, vol. 2, no. 4, 2010, p. 043107.
- [24] M. Al-Ghriybah, H. Çamur, M.F. Zulkafli, M.A. Khan, Y. Kassem, E. Esenel, Study of multiple half blades effect on the performance of Savonius rotor: *experimental study and artificial neural network (ANN) model*. *Indian Journal of Science and Technology*, vol. 11, no. 38, 2018, pp. 1-2. DOI: 10.17485/ijst/2018/v11i38/129966
- [25] Y. Kassem, H. Gökçekuş, H. Çamur, Artificial neural networks for predicting the electrical power of a new configuration of Savonius rotor, *International Conference on Theory and Application of Soft Computing, Computing with*

Words and Perceptions, Springer, Cham, 2019, pp. 872-879.

- [26] M. Buscema, Back propagation neural networks: *substance use and misuse*, Taylor and Francis, vol. 33 no. 2, 1998, pp.233-270.
- [27] S.P. Siregar, A. Wanto, Analysis of artificial neural network accuracy using backpropagation algorithm in predicting process (forecasting). *Int. J. of Information System and Technology*, vol. 1, no. 1, 2017, pp.34-42.