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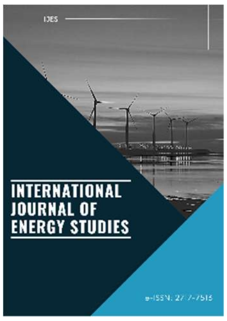

Research Article

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Estimation of the electricity to be generated at different wind speeds and turbines through fuzzy logic and ANN, A case study of Balıkesir

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Highlights

- Addressing energy production with the help of Wind Power Plants (WPP), an environmentally friendly, renewable energy source.
- Using monthly wind speed, temperature, and pressure measurement data obtained from the current sample WPP in production.
- Measuring the amounts of electricity obtained from different turbine types and using the data obtained as a result of the output data.
- Creating an electrical energy production prediction model using Artificial Neural Network (ANN) and Fuzzy Logic (FL) methods, and comparing of the prediction results obtained by ANN and FL.

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ABSTRACT

One of the most significant factors determining the development level of the world's countries in the economic domain is energy. As technology makes progress, the need of countries for energy continuously increases in parallel with that. Meeting such increasing energy demand with fossil fuels for many years has damaged the living standards of all living beings. Both of these two circumstances have caused an increase in demand for Renewable Energy Resources (RER), with wind power being one of them. In the present study, monthly wind speed, temperature, and pressure measurement data obtained from the Wind Power Plant (WPP) located in the Gonen District of Balikesir Province were averaged out. Using this data and the output data of electricity amounts from different turbine types, an electric power production estimation model was formed through the Artificial Neural Network (ANN) and Fuzzy Logic (FL) methods. It was intended to determine the electric power required to be generated by the model formed through ANN and FL. When the estimations obtained by the ANN and FL were compared, it was observed that the results were correct and coherent.

Keywords: RER, WPP, Artificial neural network, Fuzzy logic

1. INTRODUCTION

In recent years, the gradual increase in population and further developments in the technological domain have caused an increase in electric power requirements. Today, a great part of the energy requirement is met by fossil fuels such as coal, petroleum, and natural gas in most countries. Such fossil fuels cause air pollution around the world as well as global warming. Moreover, they also cause forest damage along with an increase in acid rain and ozone layer depletion [1-6]. World countries have begun to resort to Renewable Energy Resources (RER) due to the damage fossil fuels cause to nature and their near depletion. Depending on the increase in demand for energy day by day, it has been recognized that it is possible to meet the required energy demand from RER with sustainable and clean energy resources [7,8]. Generating electricity using wind power, which is one of the RER, provides environmental, social, and economic advantages. Due to the advantages it provides, it is the fastest-developing energy resource in terms of installed power [9]. One of the clean RER that is found in great amounts in all parts of the world, that is cost-efficient, and that is the most efficient in commercial terms is wind power [10-12]. Wind power is one of the most significant RER that shows the fastest development with its technology and usage, and it is able to compete with conventional energy resources with its economy [13,14]. Wind power's cleanliness and impossibility of depletion, capacity for decreasing foreign-source dependency, possibility of installation of its power plants, and great independence from the world market due to its regionalism are its greatest advantages [15]. This circumstance has led to the performance of various scientific studies in the domain of wind power today. In the studies performed, it was mainly referred to the importance of wind power, potential of wind power, and usage of wind power [16-18]. In order to estimate wind power generation, an adaptive fuzzy inference system was used. This model made use of wind speed, wind direction, wind vector, and other different parameters in order to estimate the wind. Along with force, the advantages and disadvantages of the aforementioned ones were pointed out [19]. For the estimation of short-term wind power, the Adaptive Neuro-Fuzzy Inference System approach was also used [20]. Accurate estimation of wind speed is difficult due to its changeable and stochastic nature. For that reason, the estimations were tried to be made using various estimation or measurement methods. An the Artificial Neural Network (ANN) is a model focused on outstanding data used in estimation problem. The ability to learn and generalize, adaptability to different problems, and lack of fault tolerance are the most important characteristics of ANN [21-25]. It has been observed that the ANN method is frequently used in the estimation of wind power. ANN is one of the methods of estimation generally used for estimating energy generation. Mostly the net energy consumption of the researches was estimated [26,27]. Estimation of electric power consumption [28], research of electric power consumption [29], estimation of energy demand and economy [30], determination of the total energy demand [31], energy demand for the domain of transportation, and estimation of energy consumption in lodgings and industry sectors were performed with ANN [32]. Wind information and its complex coordinates were expressed with complex figures, and they were used as the input information for a neural network with complex values. This estimation model was trained using a complex backpropagation algorithm, and thus the error of estimation was decreased [33]. In the study performed with Fuzzy Logic (FL), a short-term wind farm output power estimation model was developed using fuzzy modeling obtained from the raw data of the wind farm. But the model formed didn't provide good estimation accuracy. It just provided an interpretable model construct covering a few rules so that the estimation system may reveal its useful qualitative definition [34]. Some estimation studies performed with FL are physical estimation models, and they are based on numerical weather forecasts [35-37].

Considering the research performed, it was observed that it is generally concentrated on load estimation along with electric power demand estimation through ANN and that examinations are being performed on the electric power efficiency of specific devices or places. The FL method was found in electric demand estimation and load estimation. In this study, the FL method was preferred in addition to to the ANN in the solution of our problem due to its ability to obtain high results in terms of accuracy rate regarding the determination of the electric power amount of turbines at Wind Power Plant (WPP). A change was made to the literature by comparing the results obtained from these two methods.

2. MATERIAL AND METHOD

In the present study, the wind turbines of the WPP installed in Gonen District of Balıkesir Province were taken as models. The wind speed, temperature, and pressure data for the area were averaged out and used. Using this data, it was tried to estimate the electricity amount (kW/h) values that will be generated as against such wind power values by the wind turbines having different features through ANN and FL. A satellite image of the place of measurement is shown in Figure 1.

Figure 1. Satellite image of the location of Balıkesir WPP wind turbines

2.1. Implementation of Estimation through ANN

As ANN output data, the electric power amount in kW generated by wind turbines of different brands as per the average wind speed was obtained, and the properties of the turbines were obtained from the catalogues of producer companies. The turbine brands used in the estimation of ANN were named X, Y, Z, A, B, and C brand turbines. Turbine brands to be used in the estimation are the most preferred brands today, and they are wind turbines of very high quality in terms of efficiency. In this study, the change graph of the average input and output values to be used in prediction with ANN according to days is as shown in Figure 2.

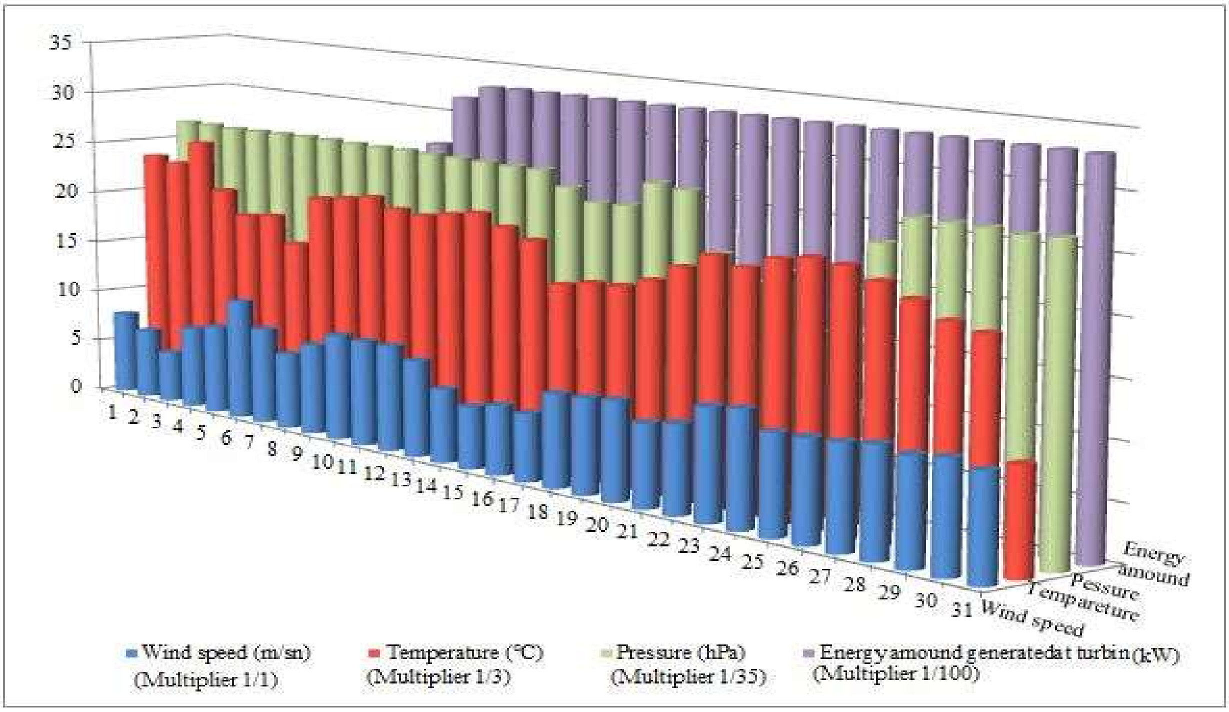

Figure 2. Average change graph of input and output data by days

Three input (weight) layers, eight neurons in the covert layer, and one output (target) layer were used. 1116 input data in total, consisting of 372 (31x12) data points for wind speed (m/s), 372

(31x12) data points for temperature, and 372 (31x12) data points for pressure, and 186 (31x6) output data points for the electric power amount (kW) generated by the turbines against the wind speeds (m/s), were used. And eight neurons were used in the covert layer. Tan-sigmoid was used as the transfer function in ANN. The ANN weight and target values formed for wind energy estimation are seen in Figure 3.

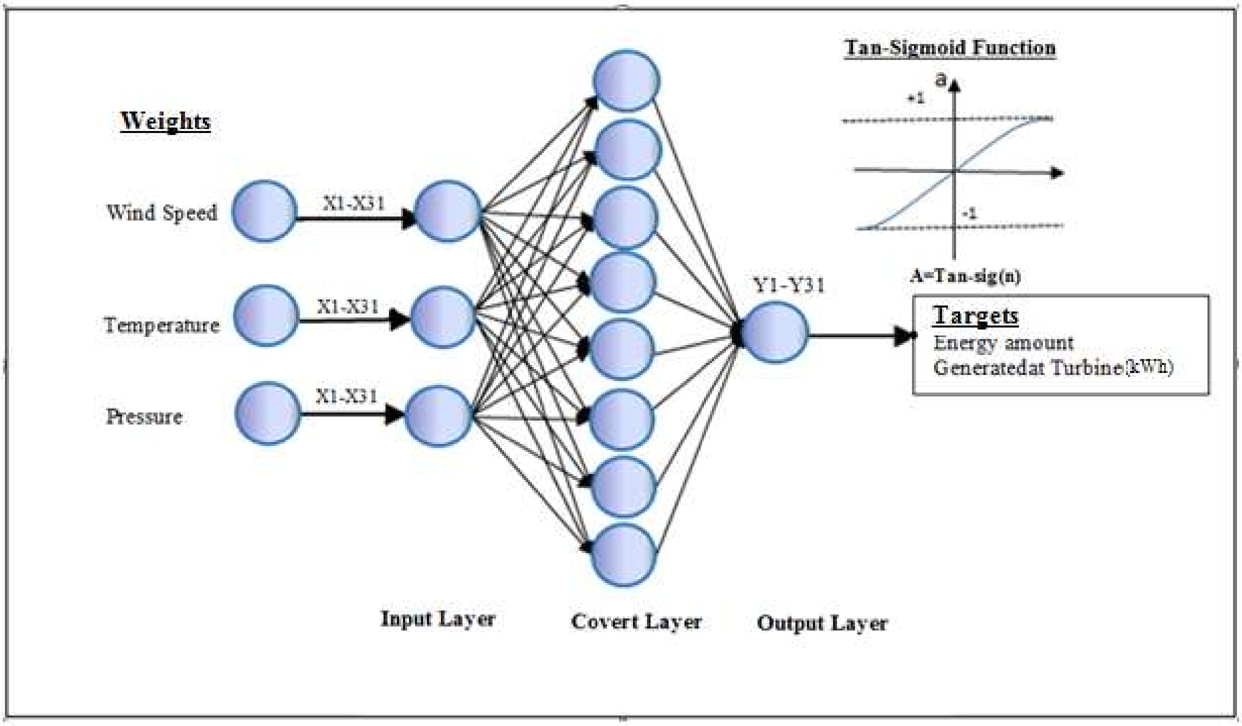

Figure 3. Weight and target values used in ANN for wind speed estimation

The backpropagation algorithm of ANN aims to minimize the difference, which is the error between the desired output from the network and the output produced. In the calculation of feedforward ANN, the input values coming to the input layer are arranged with weight matrices, and the output values are determined. Then according to the training algorithm, the difference between the network output and the actual output is found; that is, the error is propagated backward again and the network weights are rearranged. This process continues until the desired output is obtained from the network. In the training phase, one of the various model algorithms is selected for the input and target values, and the forward output values for the *j and i*'s in the "*q*" layer are calculated according to equations (1)-(5). Here, *q* represents the unit output result in layer *i* [38].

$$y_i^q = f\left(\sum_i y_i^{q-1} w_{ij}^q\right) \tag{1}$$

The error calculation of the output units is given in equation (2).

$$\delta_i^Q = \left(y_i^Q - y_i^q\right) f'\left(H_i^Q\right) \tag{2}$$

The backpropagation error calculation for units *i* in the layers is given in equation (3).

$$\delta_i^{q-1} = f'\left(H_i^{q-1}\right)\left(\sum_i \delta_i^q w_{ij}^q\right) \tag{3}$$

The w_{ij} weights connecting unit *i* in layer *q* to unit *j* in layer *q* are given in equations (4) and (5).

$$w_{ij}^{new} = \left(w_{ij}^{old} + \Delta w_{ij}^q\right) \tag{4}$$

$$\Delta w_{ij}^q = \left(\eta\, \delta_i^q\, y_i^{q-1}\right) \tag{5}$$

In the present study, following the normalization operation of the data used for the training of the ANN, the real values were found by making an inverse transformation. Graphical change graphs of normalized input and output values used in the ANN training are shown below. The change graph of normalized ANN input and output data is as seen in Figure 4.

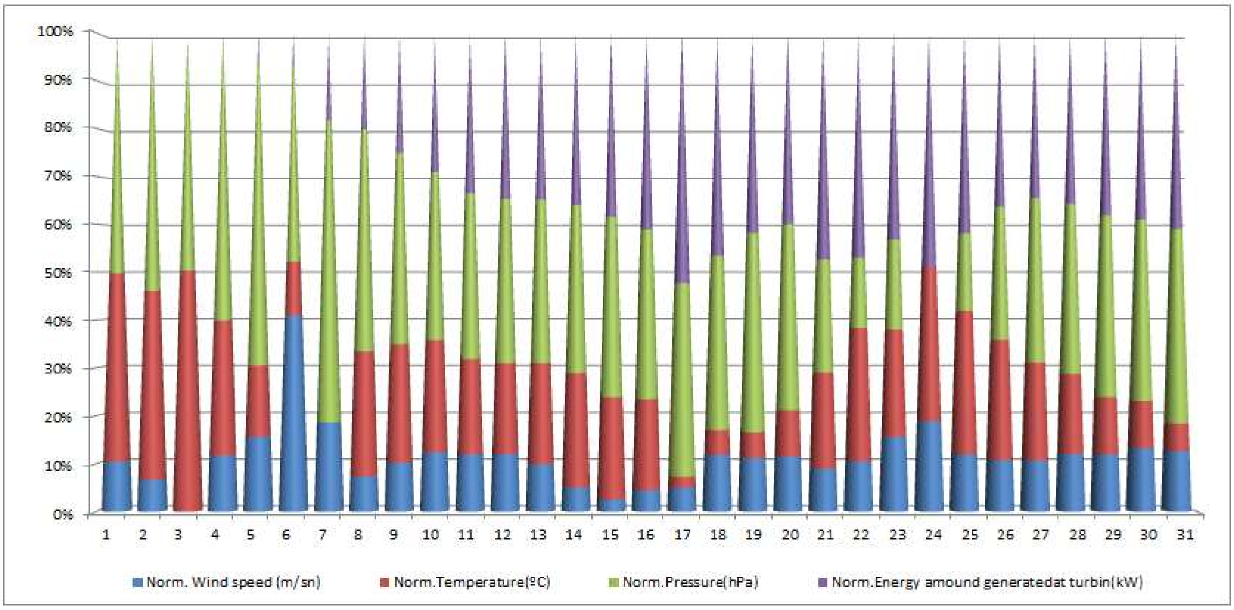

Figure 4. Change of normalized input and output data as per months

The variation graph of the normalized wind speed (m/s) with respect to the normalized amount of energy (kW) produced per month depending on the wind turbine models is shown in Figure 5.

Until the margin of error is reduced to a predetermined number close to zero these calculations are repeated at each step. When the error is minimized until it reaches the desired value, the learning of the network is complete.

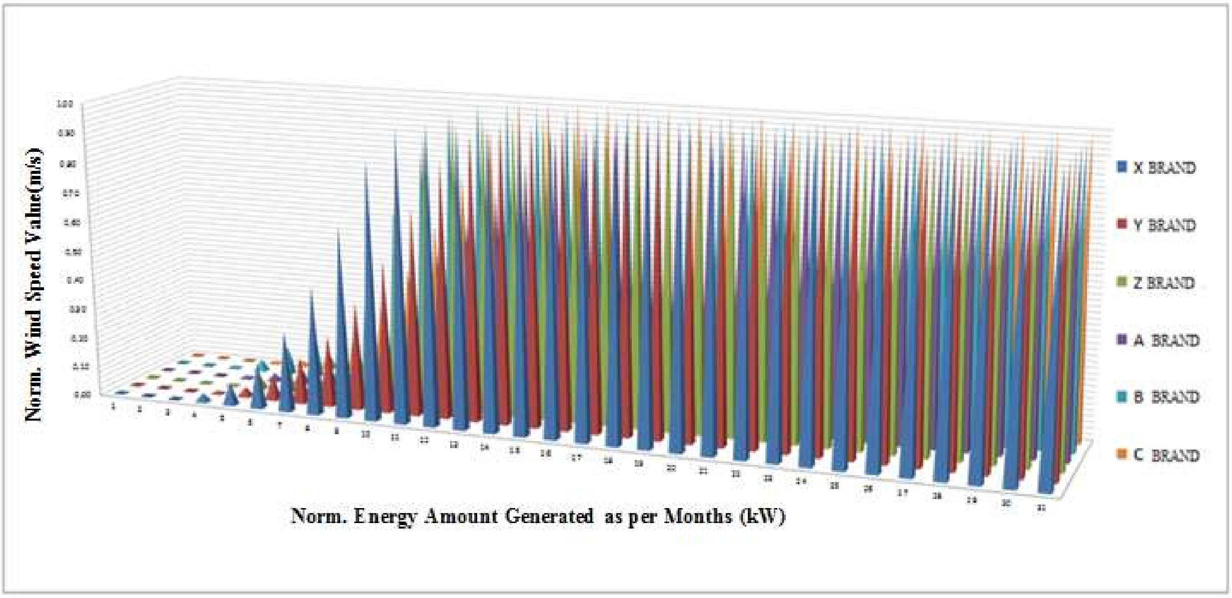

Figure 5. Normalized energy amount and wind speed change graph by month with different turbine models

In ANN, the verbal data was transformed into numerical data. The Levenberg-Marquardt (LM) algorithm was preferred in ANN training. The main reason for this is the speed and stability it provides. The main reason for this is the speed and stability it provides. The graph showing the error rate of the ANN model created with the Matlab R2015b program is shown in Figure 6.

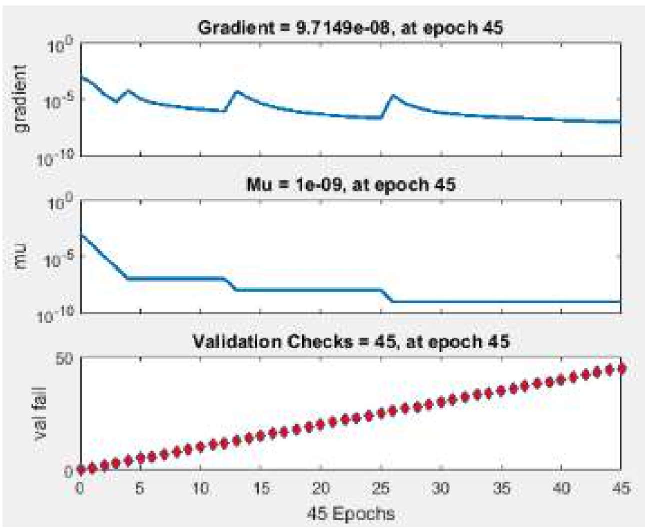

Figure 6. A graph showing the errors of the created ANN model

As seen in Figure 7, the desired result was obtained and recorded in the 45th iteration for the minimum error rate as a result of network training. As seen in Figure 5, the ANN training value of the weight values was carried out with a regression of 0.99752. The validation value of the created ANN prediction was 0.99121, and the test regression values of the target values were 0.998 with high validity. The regression value of the entire entry was found to be 0.99768. In this situation, it was observed that the education values were correct at a rate of 99.752%.

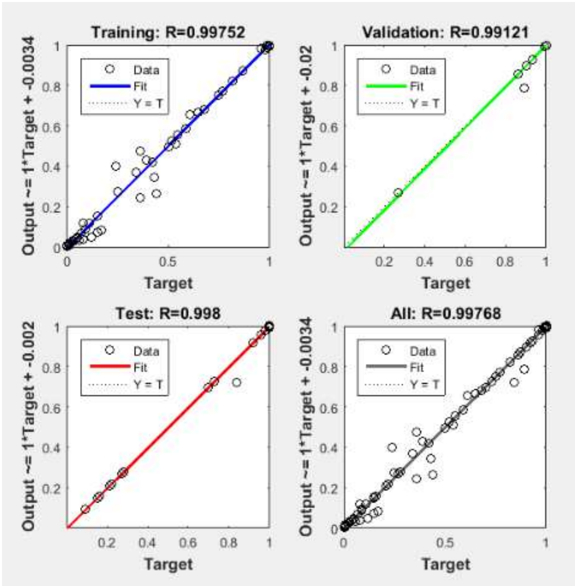

Figure 7. Training, validation, test, and all values in the estimation made

As seen in Figure 8, the best performance value in the developed model was determined to be 0.050493. Since the correlation value is equal to 1, it can be seen that there is a perfect similarity between the network output and the target output.

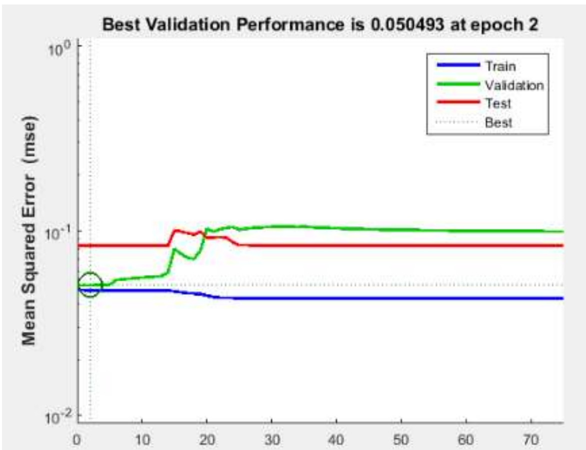

Figure 8. Best validation performance of the created ANN

Figure 9 shows the 3D view of the data resulting from the ANN prediction. Here, the brighter and clearer yellow color scale indicates that energy production values are increasing, and the closer it gets to the darker blue color, the more energy production values are decreasing.

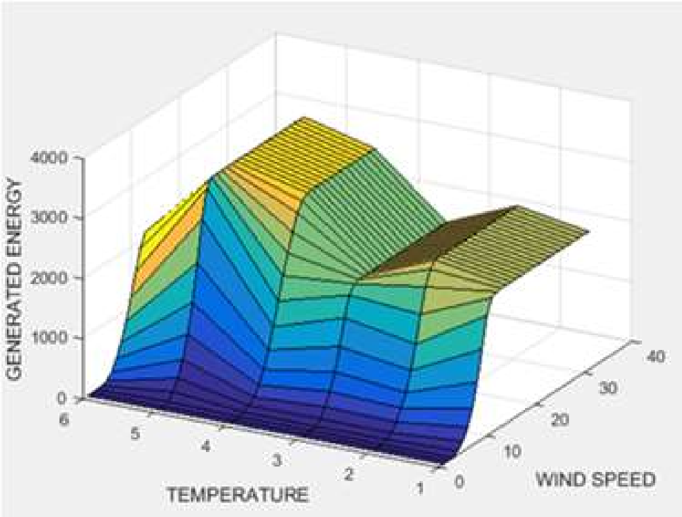

Figure 9. 3D image and glare distribution of the prediction result obtained in ANN

2.2. Estimation through Fuzzy Inference System

In the estimation made through the FL method, three input parameters and one output parameter were used. The parameters used were determined by taking the previous studies as reference. The data used as input data in ANN was also the input parameter of the FL model. The estimated energy generation amount is the output parameter. A FL view of the model formed is shown in Figure 10.

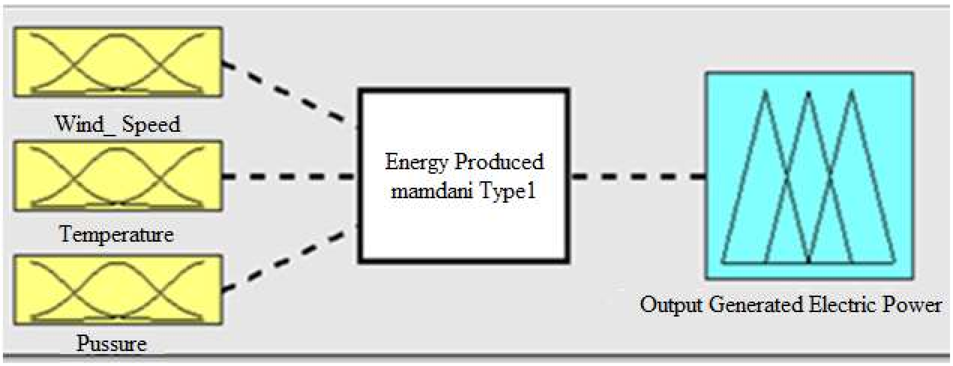

Figure 10. FL view of the model formed

Table 1 shows the effect of wind speed and temperature input values on the energy output value as follows:

Table 1. The effect of wind speed and temperature input values on the generated electric power output value

Wind Speed / Temparature	VVL	VL	L	N	H	VH	VVH
VVS	VS	VS	VVS	VVS	VVS	VVS	VVS
VS	VS	VS	VS	VVS	VVS	VVS	VVS
S	N	S	S	VS	VS	VS	VS
N	N	N	N	N	N	N	N
B	VB	B	B	N	N	N	N
VB	VB	VB	VB	VB	VVB	VVB	VVB
VVB	VVB	VVB	VVB	VB	VVB	VVB	VB

In the designed study, it was intended to determine the amount of electric power required to be generated on a daily basis as output using the input values. Membership functions were formed for input and output parameters determined in the FL practice. While forming the membership functions in the parameters used, the membership functions extensively used in the electricity demand estimation model in the literature were preferred. The membership functions shown in Figures 11-14 define fuzzy clusters identified as Ai and Bi. For the input and output variables; the triangular membership function is used in equation (6), and the Gaussian membership function is used in equations (8),(9). The defined clusters in the figures have been verified by membership functions with equations (7) [39, 40].

$$\mu_A = \mu_A(x; a, b, c) = \left\{ \begin{array}{ccc} \frac{(x-a)}{(a-b)} & if & a \le x < b \\ \frac{(c-x)}{(c-b)} & if & b \le x \le c \\ 0 & if & x > c \quad or \quad x < a \end{array} \right\} \tag{6}$$

$$\sum_i^n \mu_{A\frac{(x_i)}{x_i}} \Rightarrow \{(x, \mu_A(x))\}\ x \tag{7}$$

According to the Gaussian perspective, the degree of membership function of the output is $\left(\frac{x-c}{\sigma}\right)^2$;

$$gassian(x; c, \sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2} \tag{8}$$

$$(x) = e^{-\frac{1}{2}\left(\frac{x}{\sigma}\right)^2} \tag{9}$$

The wind speed measured was formed with a Gaussian membership function, and it consists of 7 groups: Very Very Small (VVS), Very Small (VS), Small (S), Normal (N), Big (B), Very Big (VB), and Very Very Big (VVB). The range values in the membership functions are shown in Table 2. The rules in the FL method were determined as per the group numbers from the membership functions of the input parameters. 112 rules were formed as there were 7 groups in the wind speed parameter, 7 groups in the temperature parameter, and 7 groups in the pressure parameter.

Table 2. Range values in the membership functions formed

		Group Name	Smallest Value	Biggest Value
Inputs	Measured Wind Speed (m/s)	Very Very Small	0	4
		Very Small	1	6
		Small	4	9
		Normal	6	12
		Big	9	15
		Very Big	12	18
		Very Very Big	15	20
	Temperature (°C)	Very Very Low	0	10
		Very Low	3	20
		Low	10	35
		Normal	20	42
		Hight	31	50
		Very high	42	58
		Very Very High	50	60
	Pressure (hPa)	Very Very Small	0	200
		Very Small	50	320
		Small	190	500
		Normal	320	630
		Big	500	800
		Very Big	630	920
		Very Very Big	790	950
Outputs	Generated Energy Amount (kW)	Very Very Small	0	700
		Very Small	200	1200
		Small	600	1800
		Normal	1300	2300
		Big	1800	2800
		Very Big	2300	3200
		Very Very Big	2800	3500

The membership function for the wind speed parameter is shown in Figure 11. The data in the function is in kW, and it was formed by simplifying by 100.

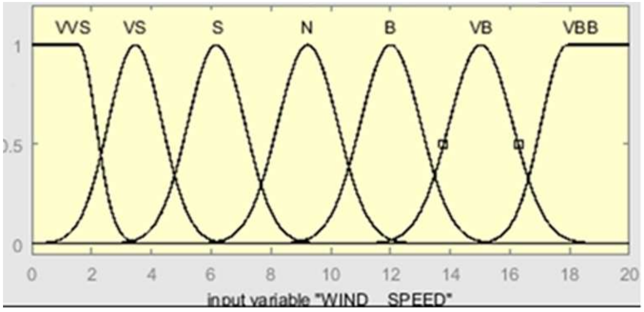

Figure 11. Membership function for the wind speed parameter

The gaussian membership function of the temperature parameter was formed of 8 groups: VVLow, VLow, Low, High, VHigh and VVHigh. The membership function for the temperature parameter is seen in Figure 12.

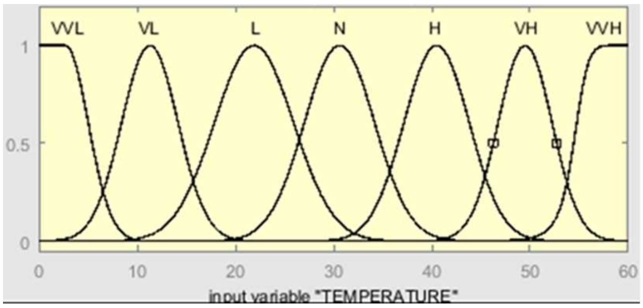

Figure 12. Membership function for the temperature parameter

The gaussian membership function of the pressure parameter was formed of 7 groups: Very Very Small, Very Small, Small, Normal, Big, Very Big, and Very Very Big. The membership function for the pressure parameter is seen in Figure 13.

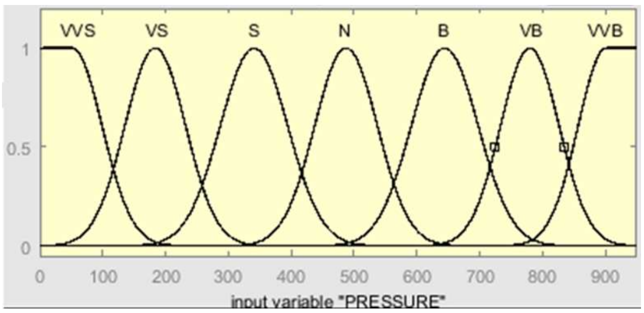

Figure 13. Membership function for the pressure parameter

The generated energy amount parameter covers 7 groups as being Very Very Small (VVS), Very Small (VS), Small (S), Normal (N), Big (B), Very Big (VB), and Very Very Big (VVB) through triangular and trapezoid membership functions. The membership function for the energy generation amount parameter is seen in Figure 14. The data in the function is in kW, and it was formed by simplifying by 100.

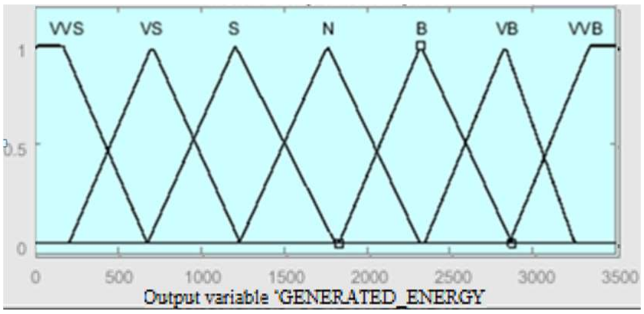

Figure 14. Membership function for the energy generation amount parameter

The 3D graph resulting from the energy (kW) value estimates produced after entering the rules in FL is shown in Figure 15. As can be seen here, there is less prediction similarity compared to the values obtained in ANN. An approximately correct result was obtained, but it is less clear than ANN.

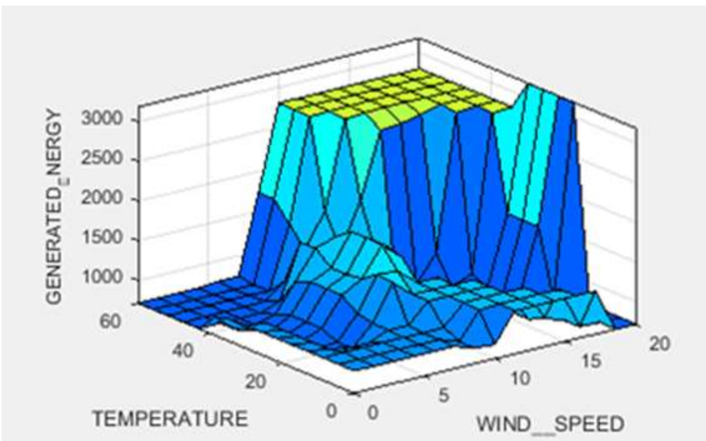

Figure 15. Result and distribution of the estimates of produced energy (kW) values

3. FINDINGS AND DISCUSSION

It can be seen in Figure 16 that the desired values and the predicted values in the training carried out with the ANN here coincide exactly with the reference values. A successful prediction was achieved with a validation value of 0.99121 for the ANN prediction.

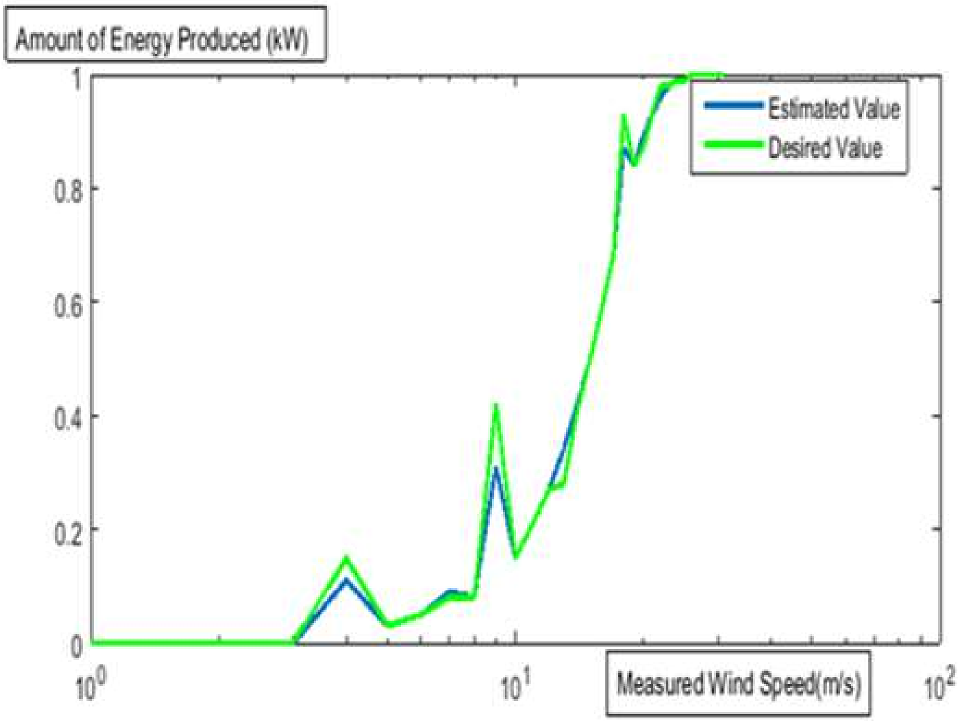

Figure 16. The graph indicating the congruence of the requested energy generation amount (kW) and the estimated energy generation amount (kW)

Tests were performed using numerous different data values in order to find values from ANN that overlapped with their normal values. ANN actualized its estimation with a verification value of 0.99121. The test regression value of values, determined as the target, was actualized with a high validity of 0.998. All input regression values were found to be 0.99768. We observed that the training values were accurate at a rate of 99.752%. It was observed that it was found correct in ALL cases, namely in total, at a rate of 99.768%. As the correlation value was equal to 1, it was observed that there is a perfect similarity between network output and target output. It was observed that the closest value was guessingly obtained at the 45th iteration. In the model developed, the best performance value was determined to be 0.050493. As the output powers required in reality and the regression values of the output powers estimated by ANN for the results of training, verification, and test data were close to 1, it indicated that the trained ANN was successful. As a result of the values tested by training the network, a new output variable that was closest to the ideal values was found. The accuracy rate of the prediction corresponding to the rules defined in FL was found to be 97.867%, and a part of the image of the results obtained by using different input values in addition to the defined rules is shown in Figure 17.

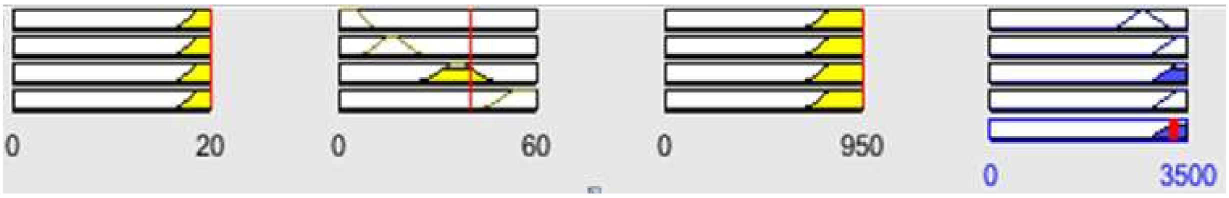

Figure 17. Membership function for the generated electric power (kW) estimation parameter

The number of members was determined through the classification of numeric data as per qualitative properties in FL, and the membership range was formed by the Mamdani method. A rules list was formed by the rule editor for the operation of the system. The membership was tested by the rules formed. The output, indicating the results, was formed. The values used as input and output data are between -2 and 3500. Membership functions were tested with 112 rules. Fuzzy rule bases were created based on the data obtained, and membership functions were adapted based on this data. Excessive compatibility between the trained data and the obtained data was checked. Prediction results were evaluated by statistical checking. The output, showing the results, was created. Looking at the prediction results, it was seen that the error rate was 1.533%. The verification rate was found to be 97.867%, based on the data obtained as a result of trying different input test values. The fact that the error rate is 1.533% shows that there is a perfect similarity between the desired result and the result obtained. It was observed that the closest value to the prediction was obtained as a result of the 105th trial. As a result of the experiment by entering more different values, a graph was created and it was observed that the result was perfect, as seen in the graph.

4. CONCLUSION

In this study, the values found using ANN and FL methods were compared. ANN made its prediction with a validation value of 99.768%. The test regression value of the target values was achieved with a high validity of 99.80%. The entire input regression value was found to be 99.121%. We see that the training values in Training are 99.752% correct. It is observed that the prediction was 99.768% correct in total. When the results obtained in the prediction made with FL were tested with the approximate values given, it was seen that it was realized at a rate of 97.867%. 2.133% of the errors were obtained depending on the defined rules. As a result of the predictions made by classifying numerical data according to qualitative characteristics in FL, the accuracy rate in prediction with FL was found to be 98.43%. Approximately 1.57% incorrect results were obtained depending on the defined rules. According to the results of both prediction methods, the accuracy rate in the calculation with ANN was found to be approximately 99.768% and in the calculation with FL was approximately 98.43%. By virtue of accurate estimation, both how much electricity would be generated by the turbines of different companies and the most efficient one were determined by comparing the methods used. The present study indicated that the most efficient result may be obtained in power generation estimation through ANN and FL, and it is considered that it will provide a significant contribution to the literature.

NOMENCLATURE

f' : Activation function,

w_{ij}^{q} : Weight values from access to hidden layer

y_i^q : i′th output value

δ_i : Output unit error calculation

q : Unit output result in layer I

H_i : Hessian matrix

I : Error signal of the nerve

Q : Number of training pairs

μ_A : Membership degree

a,b,c: Boundary ranges of fuzzy sets

x : searched variable

σ : learning rate

DECLARATION OF ETHICAL STANDARDS

The authors of the paper submitted declare that nothing that is necessary for achieving the paper requires an ethical committee permission and/or legal-special permission.

CONTRIBUTION OF THE AUTHORS

Onur Akar: Design and execution of the experiments; implementation and analysis; and interpretation of the results.

Zuleyha Ok Davarcı: Execution and conduct of the experiments; writing the article.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

REFERENCES

[1] Ilkilic C. Wind energy and assessment of wind energy potential in Turkey. Renewable and Sustainable Energy Reviews 2012; 16(1): 1165–1173.

[2] Wai RJ, Wang WH, Lin CY. High - Performance Stand - Alone Photovoltaic Generation System. IEEE Transactions on Industrial Electronics 2008; 55(1): 240-250.

[3] Zhang S, Zhu C, Sin JKO, Mok PKT. A novel ultrathin elevated channel low-temperature poly-Si.TFT. IEEE Electron Device Lett 1999; 20: 569–571.

[4] Memis S, Karakoc O. An Application of Soft Decision-Making Methods to Energy Planning of Turkey. In Proceedings of the 2nd Rumeli Energy and Design Symposium for Sustainable Environment, İstanbul, Türkiye, 17–18 February 2022; 146–157.

[5] Horosan MB, Kilic HS. A multi-objective decision-making model for renewable energy planning: The case of Turkey. Renewable Energy 2022; 193: 484-504.

[6] Aksoy A. Integrated model for renewable energy planning in Turkey. International journal of green energy 2019; 16(1): 34-48.

[7] Wegmuller M, von der Weid JP, Oberson P, Gisin N. High resolution fiber distributed measurements with coherent OFDR. in Proc. ECOC'00 2000; 11(4): 109.

[8] Azad K, Rasul MG, Islam R, Shishir IR. Analysis of wind energy prospect for power generation by three weibull distribution methods. Energy procedia 2015; 75: 722-727.

[9] Monfared M, Rastegar H, Kojabadi HM. A new strategy for wind speed forecasting using artificial intelligent methods. Renewable Energy 2009; 34(3): 845–848.

[10] Kose R, Ozgur M, Arif EO, Tugcu A. The analysis of wind data and wind energy potential in Kutahya, Turkey. Renewable and Sustainable Energy Reviews 2004; 8: 277–288.

[11] Aslan M. Archimedes optimization algorithm based approaches for solving energy demand estimation problem: a case study of Turkey. Neural Computing and Applications 2023; 35(26): 19627-19649.

[12] Mayilsamy G, Palanimuthu K, Venkatesweren R. et. al. A Review of State Estimation Techniques for Grid-Connected PMSG-Based Wind Turbine Systems. Energies 2023; 16(2): 634.

[13] Jiang Z. Installation of offshore wind turbines: A technical review. Renewable and Sustainable Energy Reviews 2021; 139: 110576.

[14] Da Rosa AV, Ordonez JC. Fundamentals of renewable energy processes. Academic Press 2021.

[15] Erdogdu E. On the wind energy in Turkey. Renewable and Sustainable Energy Reviews 2009; 13(6-7): 1361-1371.
[16] Togrul IT, Ertekin CA. Statistical Investigation on the Wind Energy Potential of Turkey's Geographical Regions Energy Source. Part A: Recovery, Utilization, and Environmental Effects 2011; 33(15): 399- 1421.
[17] Bilgili M, Sahin B, Kahraman A. Wind energy potential in Antakya and İskenderun regions, Turkey. RenewableEnergy 2004; 29: 1733–1745.
[18]IRENA (International Renewable Energy Agency) Wind Energy, 2022.
[19] Negnevitsky M, Potter C. Innovative short-term wind generation prediction techniques. Proceedings of the IEEE/PES general meeting, Montreal, Canada, June 18–22. 2006.
[20] Pousinho HMI, Mendes VMF, Catalao JPDS. A hybrid PSO–ANFIS approach for short-term wind power prediction in Portugal. Energy Convers Manage 2011; 52: 397–402.
[21] Akpinar EK, Akpinar S. An assessment on seasonal analysis of wind energy characteristics and wind turbine characteristics. Energy Conversion and Management 2005; 46(11-12): 1848-1867.
[22] Sareen K, Panigrahi BK, Shikhola T, Sharma R. An imputation and decomposition algorithms based integrated approach with bidirectional LSTM neural network for wind speed prediction. Energy 2023; 278: 127799.
[23] Jin LV. Summary of Artificial Neuron Model Research. Industrial Electronics Society. 33 rd Annual Conference of the IEEE, 5-8 Nov. 2007.
[24] Fausett LV. Fundamentals of neural networks: architectures, algorithms and applications. Pearson Education India, 1993.
[25] Sozen A, Arcaklıoglu E, Ozkaymak M. Turkey's net energy consumption. Applied Energy 2005; 81(2): 209-221.
[26] Sozen A, Arcaklıoglu E. Prediction of net energy consumption based on economic indicators (GNP and GDP) in Turkey. Energy Policy 2007; 35(10): 4981-4992.
[27] Kavaklıoglu K, Ceylan H, Ozturk HK, Canyurt OE. Modeling and prediction of Turkey's electricity consumption using Artificial Neural Networks. Energy Conversion and Management 2009; 50(11): 2719-2727.
[28] Geem ZW, Roper WE. Energy demand estimation of South Korea using artificial neural network. EnergyPolicy 2009; 37(10): 4049-4054.
[29] Ekonomou L. Greek long-term energy consumption prediction using artificial neural networks. Energy 2010; 35: 512-517.

[30] Limanond T, Jomnonkwao S, Srikaew A. Projection of future transport energy demand of Thailand. Energy Policy 2011; 39(5): 2754-2763.

[31] Geem ZW. Transport energy demand modeling of South Korea using artificial neural network. Energy Policy 2011; 39(8): 4644-4650.

[32] Akar O. Estimation through ANN of Voltage Drop Resulting from Overloads on Power Transformers. European Journal of Technique 2022; 12(2): 198-203.

[33] Kitajima T, Yasuno T. Output prediction of wind power generation system using complex-valued neural network. SICE Annual Conference 2010.

[34] Zadeh LA. Fuzzy Sets. Information and control 1965; 8(3): 338-353.

[35] Zhu B, Chen MY, Wade N, Ran L. A prediction model for wind farm power generation bas-ed on fuzzy modeling. Procedia Environmental Sciences 2012; 12: 122-129.

[36] Landberg L. A mathematical look at a physical power prediction model. Wind Energy: An International Journal for Progress and Applications in Wind Power Conversion Technology 1998; 1(1): 23-28.

[37] Landberg L. Short-term prediction of the power production from wind farms. Journal of Wind Engineering and Industrial Aerodynamics 1999; 80(1-2): 207-220.

[38] Kelesoglu O, Firat A. Determination of Heat Loss in Brick Wall and Installation with Artificial Neural Networks. Firat University Science and Engineering 2006; 18(2): 133-141.

[39] Özdem B. Determination and Evaluation of Electric Power Generation Strategy with Fuzzy Logic Method. Master's Thesis, Karabük University, 2022.

[40] Ahmad I. et. al. Fuzzy logic control of an artificial neural network-based floating offshore wind turbine model integrated with four oscillating water columns. Ocean Engineering 2023; 269: 113578.