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The Effect of Varying Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System Parameters on Wind Energy Prediction: A Comparative Study

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Abstract: Owing to the development of technology, the majority of nations throughout the world now rely on fossil fuels and nuclear power plants to meet their energy needs. However, as academic research on this subject has shown, it has become clear that alternative energy uses are necessary due to the gradual depletion of these fuels and their significant negative effects on the environment. In order to ensure energy diversity and end the energy shortage, the development of renewable energy sources is crucial. The prediction of wind power is crucial for effectively utilizing the potential of wind energy. In this study, an adaptive neuro-fuzzy inference system (ANFIS) and an artificial neural network (ANN) have been developed for the prediction of wind power. In this study, data sets were created by taking the daily average wind speeds of the selected wind turbine, the daily average power values it produces, and the daily average wind speed values in the Velimese region. By creating single-hidden layer and multi-hidden layer ANN models, the network was trained multiple times with different activation functions and different numbers of neurons, and wind power prediction was performed. In the ANFIS model, the number of membership functions is kept constant, and wind power prediction is performed using different membership functions. With these ANFIS and ANN models developed with different parameter combinations, it is aimed to determine the most efficient model by performing daily average wind power prediction. Parameter combinations were tested to determine the appropriate models, and as a result, the ANN and ANFIS models were compared with each other.

Keywords: ANFIS; fuzzy logic; wind energy; prediction of wind power; artificial neural networks; renewable energy

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1. Introduction

One of the most basic human needs is energy. Energy demand is increasing all over the world, including Turkey. Providing adequate and affordable energy is essential to eradicate poverty, improve human well-being and raise living standards around the world. Thanks to the decrease in the cost of renewable energy sources over time, it has been possible to meet the demand for electricity generation in recent years. Fossil fuels have been the main source of global electricity generation. However, it is essential to increase the use of renewable energy sources for power supply in the world due to the adverse environmental effects of electricity generation from fossil fuels, climate change, the demolition of fossil fuel reserves, and fluctuating charges [1]. Alternative "clean" energy sources that are independent of fossil fuels and have a manageable environmental impact are being developed in order to satisfy the rising global energy demand while preserving the environment and leaving the possibility of the use of fossil fuels in the future [2].

Promoting the use of renewable energy sources has been identified as one of the most effective strategies to mitigate the effects of current and future climate change. Therefore, a worldwide renewable energy policy is being developed and implemented to facilitate the growth of the renewable energy sector [3]. Energy sources that can be classified as renewable include solar, geothermal, hydro energy systems such as hydroelectric, wave, tidal, and ocean thermal energy conversion systems, as well as biomass and wind energy [4]. Wind and solar systems are attracting more attention due to their significant natural potential in many parts of the world [5].

Wind energy has been the focus of attention due to its clean and environmentally friendly nature and because it is one of the most economically viable renewable energy sources. An electric current is produced when wind turbines capture the kinetic energy of air flows. Wind farms usually consist of several wind turbines covering many square kilometers of land or ocean. Developments and innovations in the wind energy sector have led not only to improvements in the design and manufacture of turbines but also to better capacity factors, resulting in lower wind energy costs, confirming that this technology is a key driver of the clean energy transition. The rapidly growing use and production of wind energy requires extensive research in various fields. The most precise technique of converting wind energy into clean electricity is provided by turbine systems, which even have lower operational and maintenance expenses. The precise prediction of wind power is considered a major contribution to large-scale wind power generation [6–9].

Artificial neural networks (ANNs) are widely accepted as a technology that offers an alternative way to overcome complex and ill-defined problems. Artificial neural networks are computer networks that aim to roughly simulate the decision-making process in neural networks of biological (human or animal) central nervous systems [10]. They can be described as a collection of processing units represented by artificial neurons connected by numerous interconnections (artificial synapses), implemented by vectors and synaptic weight matrices, and capable of acquiring and maintaining knowledge (knowledge-based) [11]. ANNs have been successfully used in a variety of domains, including mathematics, engineering, medicine, economics, meteorology, psychology, and neurology. The analysis of electromyographs and other medical signatures, the identification of military targets, pattern, voice, and speech recognition, and the detection of explosives in checked baggage are some of the most significant. They are also employed in the prediction of electrical and thermal loads, adaptive and robotic control, weather and market trends, and mineral exploration sites. Process control uses artificial neural networks because they can develop prognostic models of the process from multidimensional data that are routinely collected from sensors [12]. An ANN model comprises many nodes and their connections. Structure, transfer function, and learning algorithms define its capacity [13]. ANNs are not programmed to perform specific tasks when applied to computers. Instead, they are trained on datasets until they learn the patterns available to them. They can be trained to generate quick predictions and generalizations; are fault-tolerant in that they can deal with noisy and imperfect data; and can learn from examples. Once trained, new models can be presented to them for prediction or classification. ANNs have been used in a variety of applications in control, robotics, pattern recognition, prediction, medicine, power systems, manufacturing, optimization, signal processing, and social and psychological sciences [12].

The study of thinking systems in which the ideas of truth and falsity are handled gradually is known as fuzzy logic. Fuzzy logic examines ambiguity in natural language as well as in a number of other application domains. In essence, fuzzy logic makes it possible to characterize values that fall between assessments like high–low, yes–no, and true–false [14]. A mathematical theory called fuzzy logic uses verbal explanations to deal with datasets whose meaning does not directly correspond to a single numerical value but rather to a range of potential values. On these datasets, domain-specific functions can be designed to produce results with a sufficient degree of approximation that are relevant to the receiver. The meaning of the field-specific values of the dataset can be explained using fuzzy terms that have ambiguous definitions at their borders thanks to input membership functions. Fuzzy logic systems are knowledge- or rule-based systems built from human knowledge in the form of fuzzy IF-THEN rules. Fuzzy system theory, a systematic procedure, enables the use of the knowledge-base to transform it into nonlinear mapping. The fuzzy IF-THEN rule is an IF-THEN statement in which some words are characterized by continuous membership functions [15]. The fuzzy logic controller has five basic elements such as blurring, knowledge base, rule base, fuzzy inference, and defuzzification [16]. These steps help us define a logical framework based on linguistic values that are defined and characterized using fuzzy sets.

The adaptive neuro-fuzzy inference system (ANFIS) combines the self-learning capacity of an artificial neural network (ANN) with the language expression function of fuzzy inference. Sugeno operates in a fuzzy inference system with a structure similar to a multilayer feedforward neural network. The first fuzzy rules and membership functions are chosen based on the human knowledge of the outputs to be mimicked. ANFIS offers a variety of benefits, such as the capacity to depict the nonlinear nature of a process, adaptability, and quick learning capabilities. For the supplied input–output matches, ANFIS creates a collection of fuzzy IF-THEN rules with the relevant membership functions. A significant amount of the accessible data have been used to learn membership functions and fuzzy rules. Then, the ANFIS can alter these fuzzy IF-THEN rules and membership functions to lessen the output inaccuracy or clarify the relationship between an intricate system's inputs and outputs [17,18].

Applications of artificial neural networks include wind energy systems for forecasting, defect diagnosis and detection, design optimization, and control optimization. Although predicting wind power generation is a difficult undertaking, it is crucial that energy providers, participants in the wind energy market, owners and operators of wind farms, maintenance crews, etc., construct the best plans possible. The primary factors that must be predicted are wind power and speed [19]. The most significant approaches for predicting wind speed include physical techniques like numerical weather forecasting (NWF), statistical techniques like the ARIMA model, intelligent models with artificial neural networks, and hybrid prediction models that combine multiple types of algorithms [20,21]. While physical techniques are better at predicting wind speed over the long run, statistical and artificial intelligence models are useful at predicting wind speed in the short term. The majority of studies and wind speed forecasting techniques concentrate on very short-term forecasts. For turbine control applications, very short-term projections are relevant in the second range. As a result, the computational cost of models that will be employed in online applications is crucial. It has been claimed that multilayer perceptron (MLP) findings are more accurate when compared to wavelet-based networks and particle swarm optimization outcomes; however, this comes at a significant computational cost [22].

Monfared et al. [23] used fuzzy logic and an artificial neural network to forecast the wind speed. They pointed out that, in comparison to conventional models, the model offers a substantially smaller rule base and a greater level of anticipated wind speed accuracy. The experimental findings demonstrate the improved wind speed prediction and faster computation times of the suggested model. Galdi et al. [24] extracted the most energy possible from variable-speed wind power generation systems using an adaptive Takagi–Sugeno–Kang (TSK) fuzzy model. An integrated control approach was presented by Kaneko et al. [25] for a wind farm to lessen frequency variations in a small power system. The least squares method was used to forecast the short-term forward wind speed in order to adjust the wind farm's output power command in response to the changing wind speed. The output power command of the wind farm is multiplied by the projected wind speed using fuzzy reasoning. The model was validated by the researchers using numerical simulations. ANFIS was utilized by Mohandes et al. [26] for the wind speed profile and by De Giorgi et al. [27] for the prediction of wind power.

The objectives of the present study were to determine the most suitable model by estimating the wind power with artificial neural networks and fuzzy logic methods using the wind speed values of the Velimese region. In order to predict the wind power, it was examined which of the different activation functions applied with different numbers of neurons in ANN gave better results. With the ANFIS method, tests were carried out using different membership functions, and it was investigated in which function the best predictive values were reached. It was examined how close the results obtained from these models were to the real values.

2. Materials and Methods

MATLAB is a programming and computing language widely used in mathematics, engineering, and scientific calculations. MATLAB was invented by mathematician and computer programmer Cleve Moler. The first early version of MATLAB was completed in the late 1970s. The software was first publicly demonstrated in February 1979 at the Naval Postgraduate School in California, USA.

The study was performed in the MATLAB 2020b program. In this study, the prediction of daily average wind power from daily average wind speed by using fuzzy logic and an artificial neural network model has been attempted. Various transfer functions and numbers of neurons for ANN and Sugeno architecture for ANFIS were used.

Enercon is a wind turbine manufacturer based in Germany. The company was founded in 1984 by Aloys Wobben. Enercon is a worldwide developer and manufacturer of innovative and efficient wind turbines. Enercon's wind turbines are available in various capacities and sizes. Among the company's most popular turbine models are the E-82, E-92, E-101 and E-126. In this study, daily average wind speed and wind power values of Enercon E-92 turbine and wind speed data of Velimese region were used to estimate the average wind power.

2.1. Determination of Wind Energy

Wind energy systems are naturally energized by the flowing wind, so they can be considered a clean energy source. Wind energy is one of the lowest priced renewable energy technologies available today. However, the biggest challenge of using wind as a power source is that the wind is intermittent and does not always blow when electricity is needed. Wind energy cannot be stored, and not all winds can be utilized to meet the timing of electricity demands. The option of storing energy in battery banks is beyond economically feasible limits for large wind turbines. Although wind power plants have relatively little impact on the environment compared to other conventional power plants, there are some concerns about the noise generated by rotor blades and their esthetic (visual) impacts. Most of these issues have been resolved or greatly reduced by technological development or the appropriate siting of wind farms [28].

Wind turbines can be broadly classified as vertical-axis machines and horizontal-axis machines, depending on the direction of the rotor shaft relative to the approaching wind [29].

In a vertical-axis machine, the rotor shaft carrying the blades is oriented perpendicular to the ground. This allows the turbine to rotate regardless of changing wind direction, eliminating the need for a tail blade or yaw motor and the associated complexities. Furthermore, the gearbox, generator, and associated controls can be located close to the ground surface, allowing easy access for repair and maintenance work. Vertical axis machines are commonly installed in urban environments where wind speed is relatively low and turbulent [29].

The rotation axis of the horizontal axis wind turbines (HAWT) used in this study is parallel to the wind direction. The blades are perpendicular to the wind direction (Figure 1). In these turbines, the condition for faster rotor rotation is to reduce the number of blades. The efficiency of HAWT turbines ranges from approximately 10 to 45%. These turbines should generally be 20 to 30 m above the ground [30].

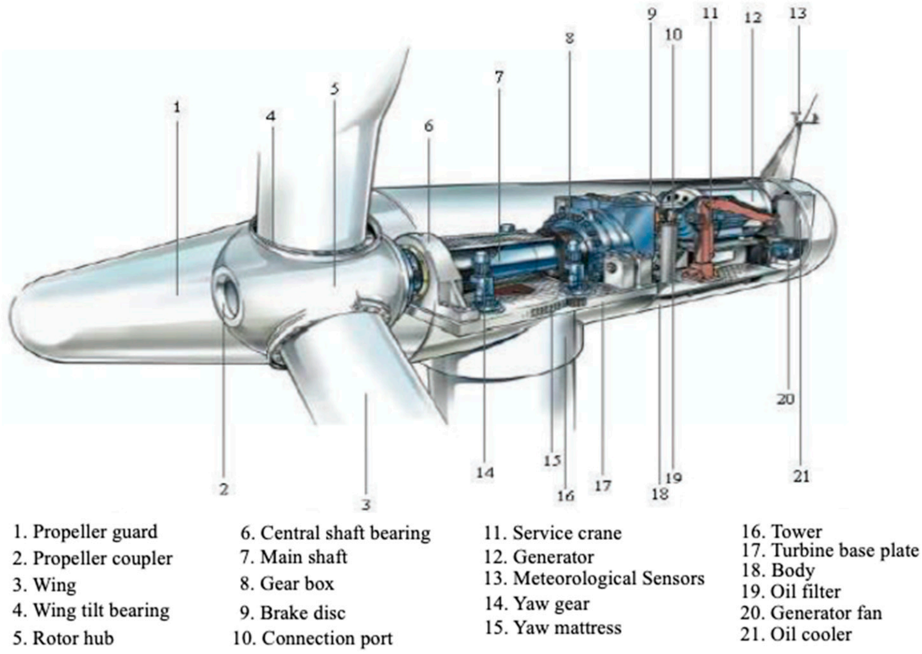

Figure 1. Structure of a horizontal-axis wind turbine [31].

A wind turbine is the most important part of a wind energy system. It converts the kinetic energy associated with the wind (wind energy) into mechanical energy and then into electrical energy (Figure 2) [32].

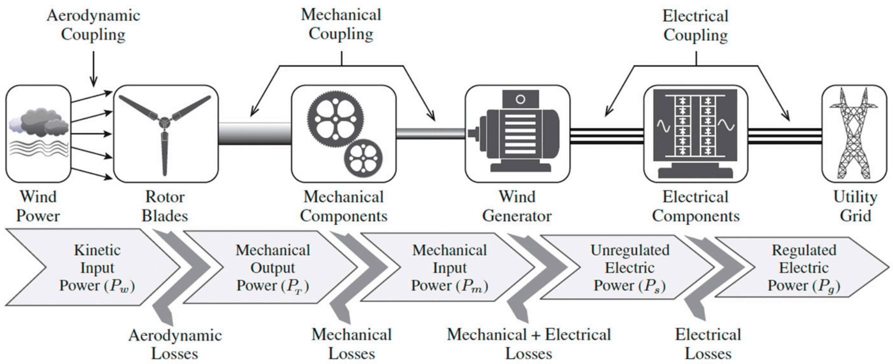

Figure 2. The conversion of wind energy into electrical energy [33].

Basically, the power equation obtained by a turbine with rotor area A_r with density p_W and speed v_∞ is given below:

$$P_W = 1/2 \times p_W \times A_r \times {v_\infty}^3, \quad (1)$$

Power is proportional to wind speed and rotor area. However, the size of the rotor, production costs, and site restrictions are all limits for large-scale wind turbines. However, areas with high wind speeds can be effectively utilized to boost the capacity of wind farms to capture energy. The theoretical power that might be produced from the wind is determined by the expression in Equation (1). Different rotor layouts in wind turbines result in different power coefficients. The Betz limit is the power coefficient's highest value, which is 0.5926 [34].

The change in volume (V) with respect to length (l) and time (t), when considering area (A) and applying a wind speed (v), is as follows:

$$\Delta V = A \times \Delta l, \quad (2)$$

$$v = \Delta l/\Delta t, \quad (3)$$

which give,

$$\Delta V = A \times \Delta t \times v. \quad (4)$$

Kinetic energy (E) is the form that the wind's energy takes. The following Equation (5) characterized the kinetic energy:

$$E = 1/2 \times m \times v^2, \quad (5)$$

where m denotes the wind mass. The relation between the change in mass and the change in energy is linear is defined as follows; i.e.,

$$m = V \times p_a, \quad (6)$$

where p_a is the specific density of air. Therefore, if we arrange the v and m yields in Equation (6), we obtain

$$E = 1/2 \times A \times p_a \times v^3, \quad (7)$$

The previous Equation (7) shows that the energy in the wind is proportional to the cube of the wind speed v:

$$P = E/t = 1/2 \times A \times p_a \times v^3, \quad (8)$$

The power shown as P is defined by Equation (8) [33].

2.2. Testing of Activation Functions

Activation functions are used specifically in artificial neural networks to convert an input signal into an output signal, which in turn is fed as an input to the next layer in the stack. In a neural network, we calculate the sum of the products of the inputs and their corresponding weights and finally apply an activation function to it to take the output of that layer and provide it as input to the next layer. The prediction accuracy of the neural network depends on the number of layers used and, more importantly, on the type of activation function used.

A neural network works like a linear regression model, where the predicted output is the same as the provided input when an activation function is not defined. The same is the case when a linear activation function is used, where the output is similar to the fed input with some errors. The limit of the linear activation function is linear, and if they are used, the network can only adapt to linear changes in the input; however, in the real world, errors have nonlinear properties along with the ability of neural networks to learn from erroneous data. Therefore, in a neural network, nonlinear activation functions are preferable to linear activation functions. The most important feature of artificial neural networks is their ability to adapt their behavior to the changing characteristics of the system [35].

The tanh and sigmoid functions are similar, but the tanh is symmetrical according to the origin. As a result, different output signals from previous layers are provided as input to the subsequent layer. With values between −1 and 1, the tanh function is continuous and differentiable. The gradient of the tanh function is steeper compared to the sigmoid function. Tanh is preferred to the sigmoid function because it has gradients that are not limited to changing in a certain direction and is zero-centered [35]. The activation functions were calculated with Equations (9) and (10) below:

tansig:

$$f(x) = \tanh(x) = (e^x - e^{-x})/(e^x + e^{-x}), \quad (9)$$

logsig:

$$f(x) = 1/(1 + e^{-x}). \quad (10)$$

2.3. Testing of Membership Functions

A member's level of accuracy inside a specified fuzzy set is defined by a membership function. They are curves that show how each point in the input space is translated to a membership degree ranging from 0 to 1 [36]. One-dimensional membership functions like triangle, trapezoid, gaussian, and sigmoidal can be utilized, depending on how the input variables behave.

The complexity and requirements of the fuzzy logic system determine the number of membership functions. More complex systems usually require more membership functions. The number of membership functions to be defined for each input variable must be determined. This is usually determined by expert knowledge or experience in the problem domain.

The representation and initial design of a fuzzy system are made simpler by linear membership functions, which also have a linear form for triangular and trapezoidal membership functions. Although more difficult to build, uniform membership functions like Gaussian and sigmoidal are more effective for automatic control [37]. The membership functions were calculated with Equations (11)–(13) below:

TriMF:

$$\mu\ (x; \alpha, \beta, \gamma) = \{(\text{if } \alpha \leq x \leq \beta, (x-\alpha)/(\beta-\alpha); \text{if } \beta \leq x \leq \gamma, (\gamma-x)/(\gamma-\beta); \text{if } \gamma \leq x \text{ or } x \leq \alpha, 0)\} \tag{11}$$

TrapMF:

$$\mu\ (x; \alpha, \beta, \gamma, \lambda) = \{(\text{if } \alpha \leq x \leq \beta, (x-\alpha)/(\beta-\alpha); \text{if } \beta \leq x \leq \gamma, 1; \text{if } \gamma \leq x \leq \lambda, (x-\lambda)/(\gamma-\lambda); \text{if } x > \lambda \text{ or } x < \alpha, 0)\} \tag{12}$$

GaussMF:

$$\mu\ (x; c, s, m) = \exp\hat{}(-1/2 \times |(x-c)/s|\hat{}m), \tag{13}$$

2.4. Data Used in the Study

While predicting the wind energy potential with ANN and ANFIS, the daily average wind speeds of the wind turbine were used as input data and output power values were used as output data. The annual daily average wind speeds of the Velimese region used to predict daily average wind power are taken from Meteoblue company which at Basel in Switzerland.

2.5. Wind Speed Data

The process of obtaining electricity from wind turbines varies depending on parameters such as the difference in turbine-specific drivetrains, mechanical components, generator losses, etc. For this reason, the amount of electrical energy generated from wind speed will vary from turbine to turbine. The wind power to be obtained from wind speed will not carry these differences. Therefore, this study is based on wind power estimation from daily average wind speed.

The fields in the data set used were preprocessed according to the wind turbine characteristics. The turbine subject to the study has some specific characteristics. The main one is that it stops when the wind speed is below 2 m/s and produces a constant value when the wind speed is above 13 m/s. For this reason, the 365-day wind speed daily averages collected from the Velimese region are ignored for wind speeds less than 2 m/s, and those higher than 13 m/s are set to 13.

The wind speed values used in the study are shown in Table 1.

Above and below a certain wind speed, the turbine is stopped and no power is produced. When the wind speed drops below 2 m/s, the Enercon E-92 wind turbine stops producing power. In addition to this, it rotates at a constant speed of over 13 m/s. These values were ignored while training ANN and ANFIS models. The amount of power produced by the Enercon E-92 wind turbine according to the wind speed between 0 and 25 m/s is shown in Table 2.

Table 1. Daily average wind speed values for the first 6 months (m/s).

Days	January	February	March	April	May	June
1	8.05	6.98	3.62	9.87	4.35	3.41
2	11.17	7.24	7.10	12.07	4.76	2.73
3	5.37	8.84	7.27	4.25	3.25	3.47
4	3.69	6.10	5.61	7.94	5.43	6.18
5	6.59	8.84	5.56	17.02	3.82	5.92
6	17.78	11.00	4.56	19.36	6.04	3.80
7	17.14	8.51	6.57	16.94	4.27	6.00
8	13.72	9.18	6.70	13.31	4.60	4.55
9	7.25	4.53	5.59	8.47	4.29	3.85
10	1.57	6.18	8.15	2.91	3.88	6.03
11	1.57	10.88	4.87	5.60	4.94	3.15
12	6.96	3.98	4.80	7.96	8.27	4.76
13	3.89	5.08	6.14	5.71	8.46	4.31
14	2.49	5.19	8.16	8.08	3.71	3.84
15	6.17	6.58	12.23	9.72	6.35	4.21
16	9.26	8.40	11.57	5.47	6.08	4.98
17	9.01	6.36	5.48	3.36	6.15	4.35
18	6.87	2.85	6.69	4.71	9.76	2.68
19	6.77	4.38	8.13	3.87	8.82	3.66
20	9.25	6.67	3.80	9.28	5.73	5.64
21	6.80	8.63	2.74	9.82	10.41	5.26
22	3.41	5.32	6.12	10.54	7.31	3.36
23	8.51	4.45	9.23	9.34	4.41	2.95
24	5.48	9.66	10.23	9.57	4.54	3.35
25	7.39	5.88	11.18	4.61	5.33	6.02
26	5.03	10.16	13.50	4.76	4.36	9.31
27	4.96	12.77	9.37	4.27	7.57	8.79
28	6.32	5.36	4.41	6.37	2.77	8.07
29	8.03	9.44	5.98	5.10	3.11	5.59
30	6.81	-	5.41	4.32	5.60	2.63
31	7.85	-	8.80	-	5.37	-

Table 2. The amount of power produced by the Enercon-E92 wind turbine according to the wind speed (kW).

Wind Speed (m/s)	Wind Power (kW)
1(−)	0
2	8
3	25
4	75
5	192
6	351
7	660
8	980
9	1395
10	1800
11	2060
12	2270
13(+)	2350

2.6. Modeling with ANN

While determining the ANN model, the model parameters were changed and the feedforward backpropagation algorithm with the highest prediction success was used. The ANN model was designed by using the traingdx algorithm, and the learngdm function as a learning function, and the tangent sigmoid (tansig) and logistic sigmoid (logsig) activation functions in training datasets.

The performance of the model was calculated with the mean square error (MSE) function. In the designed model, wind speeds are used as input data and the output power of the Enercon E92 turbine as output data. The single-layer model was first used in the network structure, and the number of neurons in the hidden layers was determined as 10, 15, and 20, respectively. After training the network with a single layer and generating predictive values, tests were conducted using two hidden layers as a multilayer model, and the number of neurons in the hidden layers were determined as 10 and 15, 10 and 20, and 15 and 20, respectively. Tests were carried out with the tansig and logsig functions as transfer functions and the number of neurons mentioned above. The model, which is multilayered from the created ANN structure and in which the number of neurons is determined as 10 and 15, is shown in Figure 3.

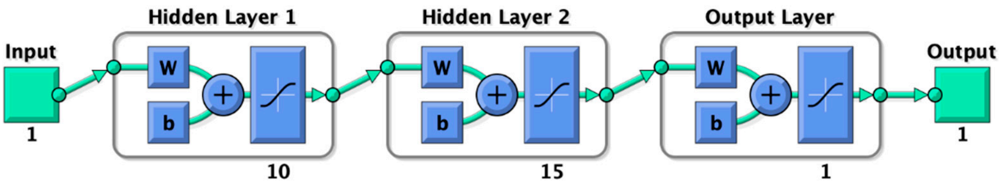

Figure 3. ANN structure with multi-hidden layers.

The training data were divided into 70% training, 15% validation, and 15% testing with the dividerand function. In the model created, the stopping criterion of "1000" iterations, the "0" error 1×10^{-5} gradient value, and the "1000" validation error number were used. The training stopped after reaching 1000 iterations in 1 s. The error performance values of the training, validation, and test data are shown in Figure 4.

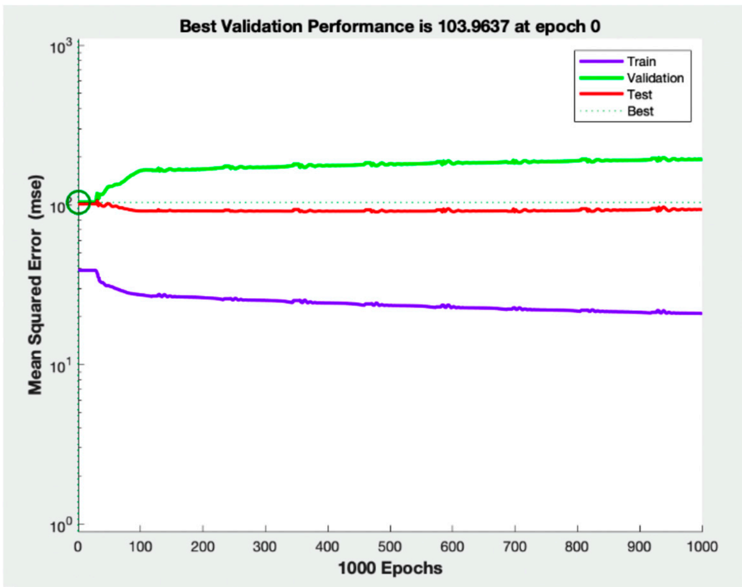

Figure 4. Validation performance values (MSE) of training, validation, and test data.

As a result of comparing the actual values and the output values produced by the network to determine the performance of the network, the regression values for all of the training, validation, and test data were close to 1. According to these results, it can be concluded that the output values of the network and the real data are close to each other. Regression curves for all data are shown in Figure 5.

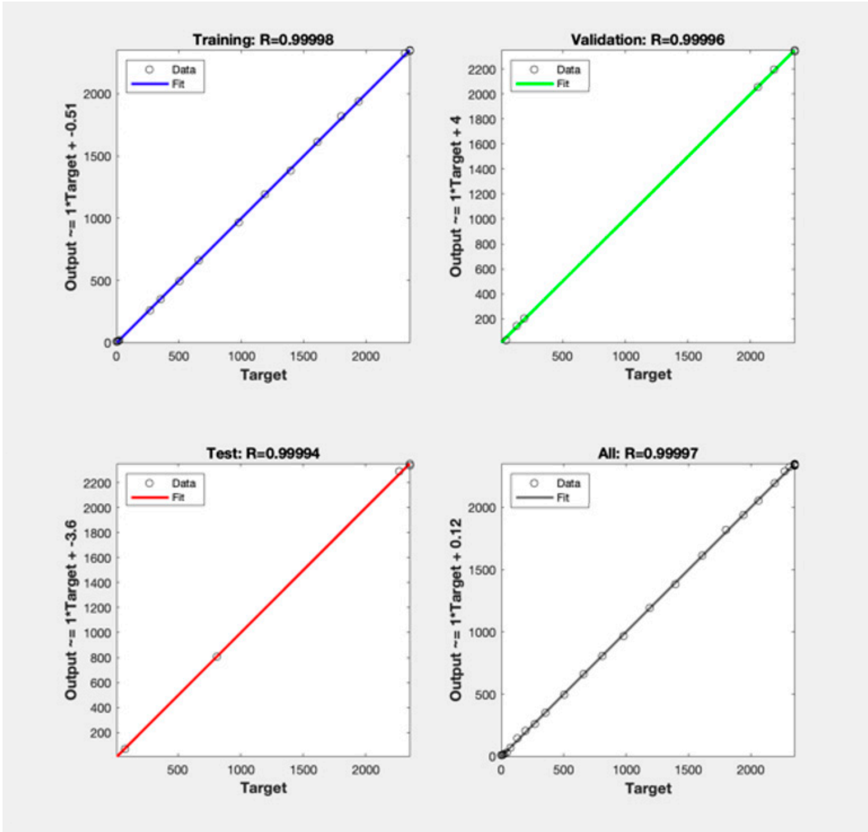

Figure 5. Regression curves of training, validation and test data.

After the ANN training, predicted test output values are produced for the input data set presented to the network for testing. Tables 3 and 4 show actual and predicted output values for the single-hidden layer ANN model and the multi-hidden layer ANN model, respectively.

Table 3. Single-hidden layer ANN model prediction values.

Wind Power (kW)	Tansig 10	Tansig 15	Tansig 20	Logsig 10	Logsig 15	Logsig 20
8	26.17	27.60	14.38	33.74	19.76	29.91
14	27.08	27.29	14.51	34.87	19.40	36.06
25	33.58	30.24	18.67	42.38	11.40	90.65
45	47.83	35.45	39.80	57.55	17.12	63.25
75	57.94	46.11	69.67	68.80	48.84	36.05
130	109.35	145.19	154.27	124.04	125.84	134.26
192	195.60	213.16	117.93	198.36	192.86	182.97
270	269.44	188.74	227.86	260.27	271.60	245.47
351	378.16	343.32	306.13	392.51	352.20	376.96
506	451.86	498.18	420.75	482.17	453.56	491.70
660	595.15	657.47	818.74	704.91	764.05	380.06
810	715.47	821.79	979.26	828.25	813.56	814.81
980	1015.56	978.25	849.16	967.57	855.58	980.07
1190	1153.57	1202.69	1070.48	1134.97	1197.56	1187.68
1395	1243.94	1376.15	1291.69	1252.28	1376.89	1370.39
1610	1620.30	1597.99	1545.73	1642.41	1543.62	1611.51
1800	1818.05	1799.18	1748.57	1819.05	1817.21	1811.21
1940	1942.18	2002.59	1889.36	1953.25	1945.22	1954.75
2060	2079.98	2215.55	2031.19	2068.31	2057.42	2065.51
2190	2157.52	2195.65	2173.06	2168.17	2190.06	2294.78
2270	2301.06	2225.55	2268.87	2309.38	2272.91	2268.18
2310	2312.67	2268.37	2283.10	2316.78	2286.02	2274.43
2350	2321.08	2307.84	2337.31	2326.45	2305.09	2327.82

Table 4. Multi-hidden layer ANN model prediction values.

Wind Power (kW)	Tansig 10_15	Tansig 10_20	Tansig 15_20	Logsig 10_15	Logsig 10_20	Logsig 15_20
8	30.22	40.51	25.17	25.13	31.13	15.54
14	30.58	42.17	25.01	27.72	31.40	15.55
25	44.30	36.65	33.97	37.43	37.60	26.41
45	60.60	49.86	47.03	60.21	59.85	42.64
75	67.45	62.47	76.14	77.66	75.92	82.31
130	127.56	104.48	127.98	128.61	124.71	123.51
192	212.38	170.31	153.97	214.90	221.64	146.39
270	260.68	259.06	271.32	254.09	263.32	272.06
351	370.84	383.50	377.72	368.70	374.91	360.78
506	483.00	467.21	506.54	478.09	491.66	506.94
660	697.10	712.49	657.24	737.91	899.82	677.52
810	819.62	825.14	824.66	809.50	813.13	823.87
980	977.89	969.51	995.75	999.26	951.07	996.38
1190	1191.47	1188.62	1191.64	1157.94	1216.23	1192.47
1395	1239.71	1352.29	1400.57	1293.28	1335.92	1418.11
1610	1637.50	1657.05	1617.93	1625.73	1646.74	1619.93
1800	1842.57	1800.66	1812.96	1800.58	1798.08	1809.58
1940	1939.00	1904.71	1925.80	2109.51	1957.88	1903.73
2060	2054.95	2067.22	2060.28	2101.20	2086.95	2060.23
2190	2182.83	2173.54	2178.86	2141.00	2160.02	2179.79
2270	2303.43	2306.11	2286.45	2300.18	2295.22	2284.77
2310	2307.30	2313.32	2312.67	2307.62	2302.72	2309.93
2350	2319.53	2322.55	2333.51	2307.27	2309.82	2331.29

After the network is trained and the predicted test values are produced, the predicted values should be compared with the actual data. In Table 5, the performance criteria of the ANN model calculated by the RMSE (root mean squared error), MAPE (mean absolute percentage error), and R^2 methods are given. The equations of performance criteria are as follows:

$$\mathrm{MAPE} = 100/n \sum{}_i^n \left(|y_i - \hat{y}_i|\right)/y_i, \tag{14}$$

$$\mathrm{RMSE} = \sqrt{}\left(1/n \sum{}_i^n (y_i - \hat{y}_i)^2\right), \tag{15}$$

$$R^2 = 1 - \sum (y_i - \hat{y}_i)/\left(\sum (y_i - \bar{y}_i)\right). \tag{16}$$

Table 5. Performance measures of ANN models.

Activation Function	Hidden Layer	Number of Neurons	RMSE	MAPE	R^2
Tansig	Single	10	45.31	20.27	0.9973
Tansig	Single	15	43.41	21.70	0.9975
Tansig	Single	20	73.58	13.87	0.9928
Logsig	Single	10	38.58	27.73	0.9980
Logsig	Single	15	40.98	17.01	0.9978
Logsig	Single	20	66.92	37.73	0.9941
Tansig	Multi	10 and 15	37.97	24.79	0.9981
Tansig	Multi	10 and 20	26.97	32.89	0.9990
Tansig	Multi	15 and 20	13.63	16.22	0.9998
Logsig	Multi	10 and 15	49.51	20.42	0.9967
Logsig	Multi	10 and 20	55.59	25.43	0.9959
Logsig	Multi	15 and 20	15.92	7.45	0.9997

As seen in Table 5, the best performance values were calculated as RMSE 13.63, MAPE 7.45, and R^2 0.9998. When the results were compared, it was seen that the two-hidden layer

ANN model with 15 and 20 neurons using the Tansig transfer function produced the closest prediction value to the real values.

Table 5 shows that the mean RMSE values of the ANN models with two hidden layers (33.27) are significantly lower than the mean RMSE values of the ANN models with one hidden layer (51.46). When the mean MAPE values are considered, it is seen that there is no significant difference between the models with one hidden layer and two hidden layers (23.05–21.2). When the average R^2 values are analyzed, it is seen that the average of the two hidden layer models (0.9982) produces slightly better results than the average of the single-hidden layer models (0.99625). When analyzed according to the number of neurons, it is understood that models with 15 neurons give better results than single-hidden layer models by looking at different activation functions. Two hidden layer models, on the other hand, confirm the number of 15 neurons in the first layer, and using 20 neurons in the second hidden layer improved the results.

2.7. Modeling with ANFIS

The data used in the development of the ANFIS model were divided into two sets: 70% for training and 30% for testing the data sets. The membership function parameters were then adjusted and used in the creation of the fuzzy inference system.

After the data were introduced in the system, the network training proceeded by sequentially selecting the membership functions to be used. The model underwent multiple training sessions utilizing triangle, trapezoidal, and Gaussian membership functions, with each membership function having three functions and a fixed number of iterations set at 1000.

After all parameters are determined, the training of the model is performed. The training interface of the ANFIS model is shown in Figure 6.

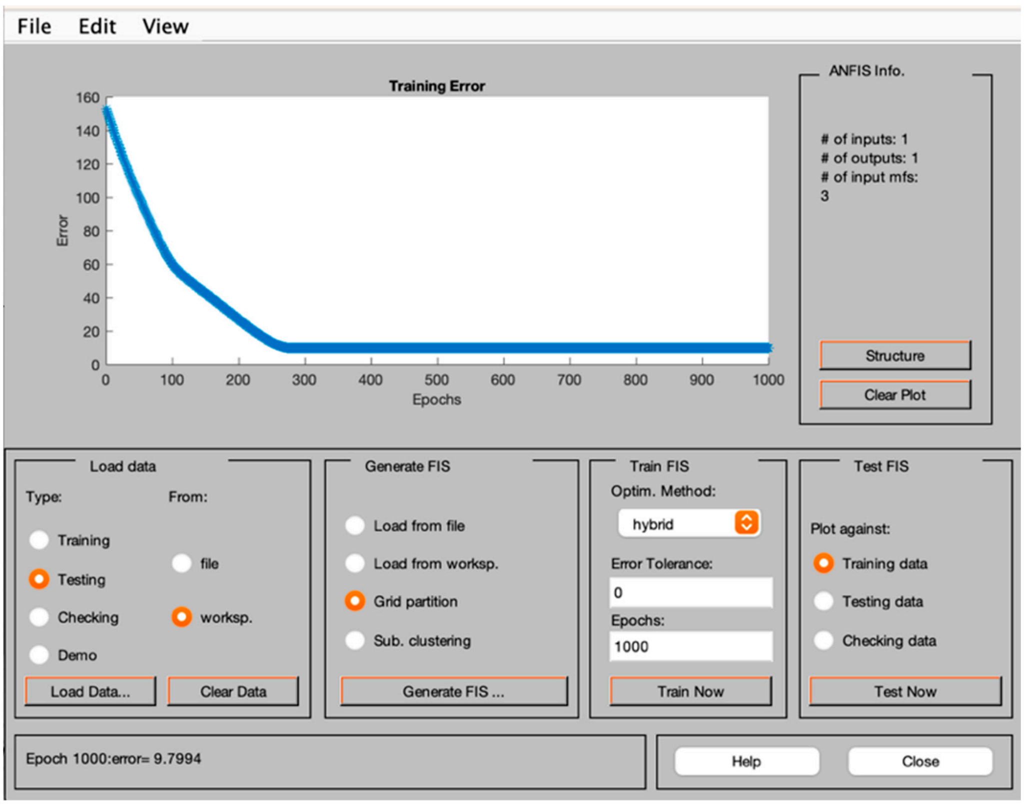

Figure 6. ANFIS training interface.

Actual values and values predicted by ANFIS are given in Table 6.

Table 6. ANFIS model prediction values.

Wind Power (kW)	TriMF	TrapMF	GaussMF
8	22.03	10.93	12.49
14	26.11	10.93	14.57
25	47.00	10.93	31.16
45	61.14	10.93	52.78
75	71.91	70.68	80.93
130	118.62	134.07	125.47
192	185.89	183.65	184.88
270	270.22	259.54	266.29
351	368.93	363.94	364.92
506	492.60	499.46	486.07
660	496.22	634.21	637.84
810	739.93	727.68	812.17
980	996.63	991.18	1002.61
1190	1217.87	1217.66	1198.21
1395	1421.48	1425.62	1401.64
1610	1621.49	1629.43	1615.60
1800	1792.31	1803.14	1799.16
1940	1948.62	1947.24	1957.56
2060	2079.45	2054.38	2076.29
2190	2193.68	2186.26	2174.36
2270	2245.96	2330.53	2264.86
2310	2261.38	2330.53	2282.77
2350	2325.79	2330.53	2333.13

After the prediction values were produced with ANFIS, the predicted values were compared with the actual data.

The model's error performance values were calculated for the predicted values produced by various functions. As a performance measure, the RMSE, MAPE, and R^2 methods were used. The model's error performance values are given in Table 7. When the error performance values were compared, it was seen that the ANFIS model, which produced the closest prediction value to the real values, was the model trained using the Gaussian membership function.

Table 7. Performance measures of ANFIS models.

Membership Function	RMSE	MAPE	R^2
TriMF	41.40	19.82	0.9977
TrapMF	26.39	10.39	0.9991
GaussMF	12.94	6.02	0.9998

Figure 7 shows the comparison of the best single-hidden layer ANN, multi-hidden layer ANN, and ANFIS results with linear fitting results. As can be seen from the figure, the differences between the ANN and ANFIS models in the linear direction are close to each other.

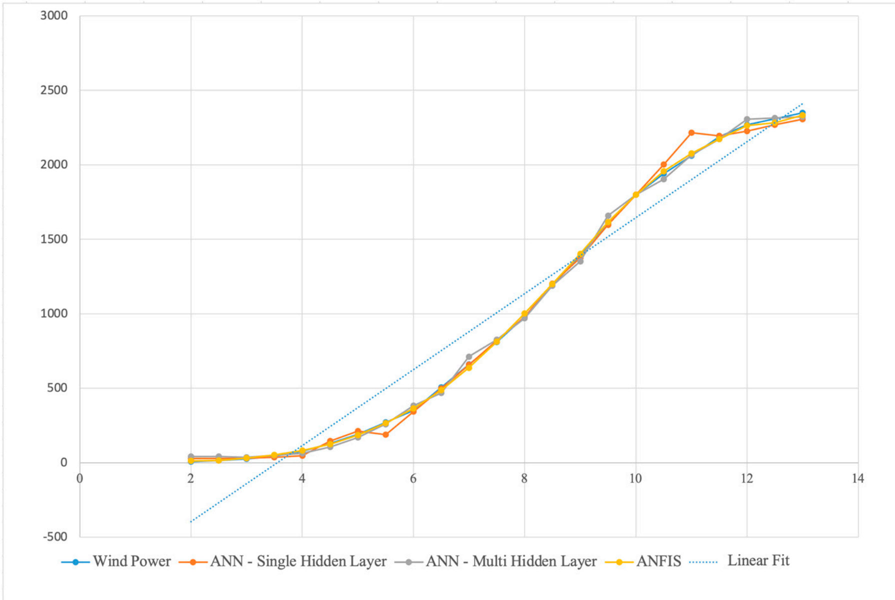

Figure 7. Comparison of single-hidden layer ANN, multi-hidden layer ANN, and ANFIS results with linear fitting results.

3. Results

In the study, average wind power was predicted using the daily average wind speed and wind power values of the Enercon E-92 turbine and the wind speed data of the Velimese region. ANN and ANFIS methods, which are frequently used as forecast models for wind energy forecasts, have been applied.

While determining the ANN model, different parameters were evaluated and tested. First, a single-layer ANN model was created, and the network was trained many times using different numbers of neurons and different activation functions. In the created model, the Tansig activation function and the number of neurons in the hidden layer were given as 10, 15, and 20, respectively, and the network was trained and the prediction results were obtained. The prediction results obtained using a single-layer network structure were compared with the actual values, and error performance values were calculated using the RMSE, MAPE, and R^2 methods. The RMSE value of the model using 10 neurons in the hidden layer was 45.31, the MAPE value was 20.27, and the R^2 value was 0.9973; the RMSE value of the model using 15 neurons was 43.41, the MAPE value was 21.70, and the R^2 value was 0.9975; the RMSE value of the model using 20 neurons was calculated at 73.58, the MAPE value was 13.87, and the R^2 value was 0.9928. By using the logsig activation function and giving the same number of neurons, the network was retrained, and predicted values were obtained. Error performance values were calculated with the RMSE, MAPE, and R^2 methods by comparing the estimated values with the actual values. The RMSE value of the model using 10 neurons in the hidden layer was 38.58, the MAPE value was 27.73, and the R^2 value was 0.9980; the RMSE value of the model using 15 neurons was 40.98, the MAPE value was 17.01, and the R^2 value was 0.9978; the RMSE value of the model using 20 neurons was calculated at 66.92, the MAPE value was 37.73, and the R^2 value was 0.9941. The model that recorded the best performance among the tests using a single-layer network was the one created using the logsig activation function with 10 neurons. A new ANN model using two hidden layers was created after the single-layer ANN model had been evaluated. The numbers of neurons in the hidden layers were 10 and 15, 10 and 20, and 15 and 20, respectively, and firstly, the network was trained using the Tansig function. In the trained network, 355 wind speed values were simulated, and predicted output values were produced. When the performance measurements were calculated by comparing the produced predictive values with the actual values, the RMSE values were 37.97 for the model using 10 and 15 neurons, 26.97 for the model using 10 and 20 neurons, and 13.63 for the model using 15 and 20 neurons; the MAPE values were 24.79 for the model using 10 and 15 neurons, 32.89 for the model using 10 and 20 neurons, and 16.22 for the model using 15 and 20 neurons; and the R^2 values were calculated as 0.9981 for the model using 10 and 15 neurons, 0.9990 for the model using 10 and 20 neurons, and 0.9998 for the model using 15 and 20 neurons. Prediction values were produced by retraining the network with the logsig activation function using the same number of neurons. The RMSE values of the models that produced predictive values using two hidden layers were 49.51 for the model with 10 and 15 neurons, 55.59 for the model with 10 and 20 neurons, and 15.92 for the model with 15 and 20 neurons; the MAPE values were 20.42 for the model with 10 and 15 neurons, 25.43 for the model with 10 and 20 neurons, and 7.45 for the model with 15 and 20 neurons; and the R^2 values were calculated as 0.9967 for the model with 10 and 15 neurons, 0.9959 for the model with 10 and 20 neurons, and 0.9997 for the model with 15 and 20 neurons. When the computational results were compared among the two-layer models, the model using the Tansig activation function with 15 and 20 neurons in the hidden layer gave the best results. When the single-layer and two-layer ANN models were compared based on the above, it was seen that the ANN model, in which the Tansig activation function was used and the number of neurons was determined as 15 and 20, produced the closest prediction values to the real values.

By determining the training parameters for the ANFIS model, the performance of three membership functions was evaluated, and the closeness of the prediction values to the real values was tested. Triangle, trapezoidal, and Gaussian functions were used as membership functions in the models created with the Sugeno inference system, and the number of functions was determined as 3 for each. After the network was trained, predicted power values were produced for 355 wind speed values. The error performance results for the predicted values were calculated with the RMSE, MAPE, and R^2 methods. The RMSE values for the models using triangular, trapezoidal, and Gaussian membership functions were 41.40, 26.39, and 12.94, respectively; the MAPE values were 19.82, 10.39, and 6.02, and the R^2 values were calculated as 0.9977, 0.9991, and 0.9998. When all membership functions were evaluated among themselves, it turned out that the membership function that produced the values closest to the real values was Gaussian.

Considering the results mentioned above, different models belonging to both techniques will be able to predict wind power close to the actual values as long as meteorological data are available. A comparison of both models showed that the difference was not significant. The graphs given in our study also confirm this. Finally, when the predicted values from the ANN and ANFIS models were compared with the actual values, it was seen that the ANFIS model produced slightly better results than the ANN model in estimating the wind power.

4. Discussion

Artificial neural networks and fuzzy logic methods are techniques that are applied in many fields, and their importance is increasing. There are many parameters, such as the number of hidden layers, the number of neurons in the hidden layers, and activation functions, when creating models of artificial neural networks. The selection of these parameters can be made by heuristic, experience-based, or trial and error methods that are generally used according to the data. Similarly, the selection of membership functions in fuzzy logic methods can be performed in the same way. The models created with the selected parameters are optimized using techniques such as cross-validation.

In this study, ANN and ANFIS models with different parameters for the prediction of average wind power were created, and research was carried out to use the most efficient model by changing the parameters.

The results were obtained by conducting many trials with the available data, and a comparison between the two methods could be made. Increasing the number of data points, enriching the study by adding new and popular methods, applying them to different fields, and making inferences according to the results obtained will form the basis of future studies.

5. Conclusions

The existing relevant literature on wind energy and predictions on impact on electricity production has been comprehensively reviewed. In addition, two popular techniques, artificial neural networks and fuzzy logic methods, and the prediction models created with these methods have also been researched in the literature. There are many parameters that need to be taken into consideration when creating a model using both methods. In order to examine the effects of these parameters on the prediction results, the field of renewable energy, which is increasingly important today, was chosen as the subject. Prediction models for wind power production with wind energy from both methods have been created. The focus of the study is to express this rationally by investigating the effect of different parameters of two artificial intelligence methods on prediction models. In the study, daily average wind power predictions were made using 1-year meteorological data from the Velimese region. The results show us that both techniques obtained very efficient results with the data and the models created, but when the proximity to the actual values was examined, it was seen that the values obtained from the ANFIS method were observed to be closer in proximity to the actual values than the values obtained with the ANN.

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References

1. Aboagye, B.; Gyamfi, S.; Ofosu, E.A.; Djordjevic, S. Status of renewable energy resources for electricity supply in Ghana. *Sci. Afr.* **2021**, *11*, e00660. [CrossRef]
2. Maradin, D. Advantages and disadvantages of renewable energy sources utilization. *Int. J. Energy Econ. Policy* **2021**, *11*, 176–183. [CrossRef]
3. Hereher, M.; El Kenawy, A.M. Exploring the potential of solar, tidal, and wind energy resources in Oman using an integrated climatic-socioeconomic approach. *Renew. Energy* **2020**, *161*, 662–675. [CrossRef]
4. Sayed, E.T.; Wilberforce, T.; Elsaid, K.; Rabaia, M.K.H.; Abdelkareem, M.A.; Chae, K.J.; Olabi, A.G. A critical review on environmental impacts of renewable energy systems and mitigation strategies: Wind, hydro, biomass and geothermal. *Sci. Total Environ.* **2021**, *766*, 144505. [CrossRef] [PubMed]
5. Mehrjerdi, H. Modeling, integration, and optimal selection of the turbine technology in the hybrid wind-photovoltaic renewable energy system design. *Energy Convers. Manag.* **2020**, *205*, 112350. [CrossRef]
6. Rahman, M.A.; Rahim, A.H.M.A. Performance evaluation of ANN and ANFIS based wind speed sensor-less MPPT controller. In Proceedings of the 2016 5th International Conference on Informatics, Electronics and Vision (ICIEV), Dhaka, Bangladesh, 13–14 May 2016; pp. 542–546.
7. Singh, U.; Rizwan, M. Analysis of Fuzzy Logic, ANN and ANFIS based Models for the Forecasting of Wind Power. In Proceedings of the 2018 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, India, 22–24 October 2018; pp. 1–7.
8. Geçmez, A.; Gençer, Ç. Wind Energy Production Estimation with ANN and ANFIS. In Proceedings of the 2021 9th International Conference on Smart Grid (icSmartGrid), Setubal, Portugal, 29 June–1 July 2021; pp. 167–173.
9. Muneer, T.; Gago, E.J.; Berrizbeitia, S.E. Solar and Wind Energy Technologies. In *The Coming of Age of Solar and Wind Power*; Springer International Publishing: Cham, Switzerland, 2022; pp. 21–103.
10. Graupe, D. *Principles of Artificial Neural Networks*; World Scientific: Singapore, 2013.

11. da Silva, I.N.; Hernane Spatti, D.; Andrade Flauzino, R.; Liboni, L.H.B.; dos Reis Alves, S.F. Artificial neural network architectures and training processes. In *Artificial Neural Networks*; Springer International Publishing: Cham, Switzerland, 2017; pp. 21–28.
12. Kalogirou, S.A. Artificial neural networks in renewable energy systems applications: A review. *Renew. Sustain. Energy Rev.* **2001**, *5*, 373–401. [CrossRef]
13. Đekić, L.; Ibrić, S.; Primorac, M. Application of artificial neural networks (ANNs) in development of pharmaceutical microemulsions. In *Focus on Artificial Neural Networks*; Nova Science Publishers, Inc.: New York, NY, USA, 2011; pp. 1–28, ISBN 978-1-61324-285-8.
14. Ozsahin, D.U.; Uzun, B.; Ozsahin, I.; Mustapha, M.T.; Musa, M.S. Fuzzy logic in medicine. In *Biomedical Signal Processing and Artificial Intelligence in Healthcare*; Academic Press: Cambridge, MA, USA, 2020; pp. 153–182.
15. Pillay, A.; Wang, J. Modified failure mode and effects analysis using approximate reasoning. *Reliab. Eng. Syst. Saf.* **2003**, *79*, 69–85. [CrossRef]
16. Cirstea, M.; Dinu, A.; McCormick, M.; Khor, J.G. Fuzzy logic fundamentals. In *Neural and Fuzzy Logic Control of Drives and Power Systems*; Elsevier: Amsterdam, The Netherlands, 2002; pp. 114–121.
17. Imran, M.; Alsuhaibani, S.A. A neuro-fuzzy inference model for diabetic retinopathy classification. In *Intelligent Data Analysis for Biomedical Applications*; Academic Press: Cambridge, MA, USA, 2019; pp. 147–172.
18. Ghenai, C.; Al-Mufti, O.A.A.; Al-Isawi, O.A.M.; Amirah, L.H.L.; Merabet, A. Short-term building electrical load forecasting using adaptive neuro-fuzzy inference system (ANFIS). *J. Build. Eng.* **2022**, *52*, 104323. [CrossRef]
19. Marugán, A.P.; Márquez, F.P.G.; Perez, J.M.P.; Ruiz-Hernández, D. A survey of artificial neural network in wind energy systems. *Appl. Energy* **2018**, *228*, 1822–1836. [CrossRef]
20. Liu, H.; Tian, H.Q.; Liang, X.F.; Li, Y.F. Wind speed forecasting approach using secondary decomposition algorithm and Elman neural networks. *Appl. Energy* **2015**, *157*, 183–194. [CrossRef]
21. García Márquez, F.P.; Pliego Marugán, A.; Pinar Pérez, J.M.; Hillmansen, S.; Papaelias, M. Optimal Dynamic Analysis of Electrical/Electronic Components in Wind Turbines. *Energies* **2017**, *10*, 1111. [CrossRef]
22. Safavieh, E.; Ardakani, A.J.; Laviani, A.K.; Pourmousavi, S.A.; Hosseinian, S.H.; Abedi, M. A new integrated approach for very short-term wind speed prediction using wavelet networks and PSO. In Proceedings of the International Conference on Power Systems, Bangalore, India, 12–14 December 2007.
23. Monfared, M.; Rastegar, H.; Kojabadi, H.M. A new strategy for wind speed forecasting using artificial intelligent methods. *Renew. Energy* **2009**, *34*, 845–848. [CrossRef]
24. Galdi, V.; Piccolo, A.; Siano, P. Exploiting maximum energy from variable speed wind power generation systems by using an adaptive Takagi–Sugeno–Kang fuzzy model. *Energy Convers. Manag.* **2009**, *50*, 413–421. [CrossRef]
25. Kaneko, T.; Uehara, A.; Senjyu, T.; Yona, A.; Urasaki, N. An integrated control method for a wind farm to reduce frequency deviations in a small power system. *Appl. Energy* **2011**, *88*, 1049–1058. [CrossRef]
26. Mohandes, M.; Rehman, S.; Rahman, S.M. Estimation of wind speed profile using adaptive neuro-fuzzy inference system (ANFIS). *Appl. Energy* **2011**, *88*, 4024–4032. [CrossRef]
27. De Giorgi, M.G.; Ficarella, A.; Tarantino, M. Error analysis of short term wind power prediction models. *Appl. Energy* **2011**, *88*, 1298–1311. [CrossRef]
28. Wagner, H.J.; Mathur, J. Wind Energy Today. In *Introduction to Wind Energy*; Green Energy and Technology Series; Springer: Cham, Switzerland, 2018.
29. Roy, A.; Bandyopadhyay, S. *Wind Power Based Isolated Energy Systems*; Springer: Cham, Switzerland, 2019. [CrossRef]
30. Bekar, G. Economic Analysis of Wind Energy Systems Investments in Turkey. Master's Thesis, Manisa Celal Bayar University, Institute of Science, Energy Department, Mechanical Engineering Division, Manisa, Turkey, 2020.
31. Terzioğlu, H.; Arslan, M.; Demirok, H.D. Rüzgar enerjisi ile elektrik üretimi. In *Research Articles in Engineering*; Gece Akademi: Ankara, Turkey, 2019; pp. 219–241.
32. Beig, A.; Muyeen, S.M. Wind energy. In *Electric Renewable Energy Systems*; Academic Press: London, UK, 2015; pp. 60–77.
33. Yaramasu, V.; Wu, B. *Model Predictive Control of Wind Energy Conversion Systems*; John Wiley & Sons: Hoboken, NJ, USA, 2016.
34. Dhiman, H.S.; Deb, D.; Balas, V.E. *Supervised Machine Learning in Wind Forecasting and Ramp Event Prediction*; Academic Press: London, UK, 2020.
35. Sharma, S.; Sharma, S.; Athaiya, A. Activation functions in neural networks. *Towards Data Sci.* **2017**, *6*, 310–316. [CrossRef]
36. Singh, H.; Lone, Y.A. Artifical Neural Networks. In *Deep Neuro-Fuzzy Systems with Python: With Case Studies and Applications from the Industry*; Apress: Berkeley, CA, USA, 2020; pp. 157–198.
37. Belyadi, H.; Haghighat, A. *Machine Learning Guide for Oil and Gas Using Python: A Step-by-Step Breakdown with Data, Algorithms, Codes, and Applications*; Gulf Professional Publishing: Oxford, UK, 2021.