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Forecasting Wind Power Generation Using Artificial Neural Network

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Abstract

Today, among renewable energy sources, wind energy is used effectively as a clean and sustainable energy source in electricity generation. The uncertain nature of renewable energy sources and the smart ability of the neural network approach to process complex time series inputs have allowed the use of artificial neural network (ANN) methods in the prediction of renewable energy generation. In this study, the speed and power of wind turbines and electricity generation were estimated from wind speed data using artificial neural networks. In our calculations, the real wind speed data were used in the test phase, and the speed-power data of six different types of wind turbines were used in the training phase. It has been shown that the predictions made by our ANN model from the regression curves of the training, validation, and test data obtained are quite successful and reliable. According to our results, it has been understood that the wind potential of our selected region is good enough and that the electrical energy need for this region can be met from wind energy by using the appropriate wind turbine type, so it is quite appropriate to invest in wind energy.

Keywords: artificial neural networks, renewable energy sources, artificial intelligence, wind turbines, wind speed

Yapay Sinir Ağı Kullanımı ile Rüzgar Enerjisi Üretimi Tahmini

Öz

Günümüzde yenilenebilir enerji kaynakları içerisinde rüzgar enerjisi, elektrik enerji üretiminde temiz ve sürdürülebilir bir enerji kaynağı olarak etkin olarak kullanılmaktadır. Yenilenebilir enerji kaynaklarının belirsiz doğası ve sinir ağı yaklaşımının karmaşık zaman serisi girdilerini işleme konusundaki akıllı yeteneği, yenilenebilir enerji üretimi tahmininde yapay sinir ağı (YSA) yöntemlerinin kullanılmasına olanak sağlamıştır. Bu çalışmada, yapay sinir ağlarını kullanarak rüzgâr hızı verisinden, rüzgâr türbinlerinin hızları ve güçleri ile elektrik üretimi tahmin edilmiştir. Hesaplamalarımızda test aşamasında gerçek rüzgar hızı verileri, eğitim aşamasında ise altı farklı rüzgar türbininin hız-güç verisi kullanılmıştır. Elde edilen eğitim, doğrulama ve test verilerinin regresyon eğrilerinden YSA modelimizin yaptığı tahminlerin oldukça başarılı ve güvenilir olduğu gösterilmiştir. Elde ettiğimiz sonuçlara göre, seçilen bölgemizin rüzgar potansiyelinin yeterince iyi olduğu ve bu bölgenin elektrik enerjisi ihtiyacının uygun rüzgar türbini tipi kullanılarak rüzgar enerjisinden karşılanabileceği, dolayısıyla yatırım yapılmasının oldukça uygun olduğu anlaşılmıştır.

Anahtar Kelimeler: yapay sinir ağları, yenilenebilir enerji kaynakları, yapay zeka, rüzgar türbinleri, rüzgar hızı

INTRODUCTION

With the increase in the world population, the demand for energy has increased due to the developing industry and technology in recent years (Koç E, Kaya K., 2015). The sustainability of energy resources has been one of the most important problems of our world and humanity from past to present. Factors such as the rapid depletion of energy resources; the unconscious use of non-renewable resources such as oil, coal, and nuclear energy; the pollution caused by these resources to the environment and the atmosphere have led people to use renewable energy resources (solar energy, wind energy, geothermal energy, biomass energy, and hydraulic energy) (Arslan F, Uzun A., 2017). In recent years, while the usage rates of coal (33%) and natural gas (22%) in electricity

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production have decreased, electricity production from hydroelectric, solar and wind energy has increased. Figure 1 (a) shows the change in the electricity produced in the world between 1985 and 2020 according to the energy sources.

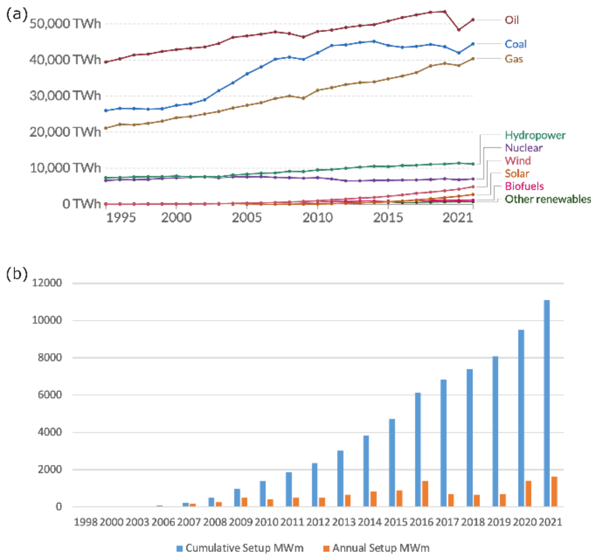

Figure 1. (a) Distribution of electricity produced between 1985 and 2020 according to sources (Our World in Data, 2021). (b) Cumulative installation and annual installation of wind power plants in Turkey (Tureb, 2021)

While there is an increase in the installed power of renewable energy power plants, it is seen that there is a decrease of 291 MW in the total installed power of the power plants that produce electricity with natural gas and other fuels. Considering the Eleventh Development Plan, it is foreseen that the total installed electricity power of Turkey will reach 109.5 GW by 2023. Considering the first nine months of 2020, the shares of energy resources in electricity generation are as follows: imported and domestic coal power plants (34%), hydroelectric power plants (29%), natural gas power plants (19%), wind power plants WPPs (8%), solar power plants (4%), geothermal power plants (3%), biomass energy power plants (2%) (TSKB, 2020). If we look at the resource distribution, the use of coal and natural gas has been decreasing in recent years clearly. Although there is a decrease, it is a serious problem that almost half of the electricity production both globally and in our country is provided by oil, coal and natural gas, which are known as fossil fuels. Considering the finite nature of fossil fuel resources, which are largely used to meet energy needs, their prices and the damage they cause to nature, there has been an increase in the demand for renewable energy resources and still continues to increase.

Among the renewable energy sources, the rate of use of wind energy in the world is constantly increasing due to its domestic, continuous and direct use. Wind energy also has advantages such as reducing gas emissions and long-term use of turbines (Bayraç, 2011). Despite the high initial installation costs of wind turbines, their ability to operate without the need for raw materials reduces operating costs. Wind energy is the fastest growing energy type among renewable energy sources globally and the most invested in the last 6 years. In 2019, approximately 15% of electricity demand in Europe and 7% in Turkey is provided by wind power plants (YEKDEM, 2020). Additionally, Figure 1(b) shows cumulative installation and annual installation of wind power plants in Turkey between 1998-2021.

Since electrical energy cannot be stored on a large scale, the electricity produced has to be consumed at the same time. This difference between production and consumption reflects negatively on the network, and for this reason, efforts are made to reduce and balance the difference between production and consumption. Since electricity generation with wind energy has a variable structure, it is more difficult to control than traditional electricity generation. In electricity markets, future production and consumption estimates and price offers are requested from the participants. When the participants cannot produce the amount they declared, they pay a penalty in proportion to the difference between their products and their estimated values. Penalties here due to forecast errors constitute approximately 10% of the revenues of wind farms. (Dukpa et al., 2010). Values such as consumption estimates received in the market, production estimates and price offers for the estimates are used in the creation of the work programs of the power plants in a way that will minimize the price of electricity in the grid. Ensuring the balance of production and consumption ensures that the uncertainty in electricity systems is reduced, optimizing the electricity price and increasing the efficiency of the system. For this reason, energy forecasting models made with wind forecasting have a crucial role to obtain reliable, economic, and

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efficient operation of wind energy resources. These forecasting models are used in power systems planning, reserve planning, maintenance and repair planning, and tenders in the electricity market. Thanks to forecasting models, one-day marketing of power plants in electricity can increase by reducing forecast errors. It can benefit from an important choice especially in the short-term wind power target, day-ahead electricity, aiming the day-ahead electricity plan from the reserve section, and the targets of the unit decisions. Problems such as short-term construction allowance paid and excess budget allocation can be loaded from the excess business and integrated into the system. Estimates of wind power can be divided into three categories according to their methodology:

1- Statistical methods: In statistical methods, a large amount of historical data are taken into account without considering meteorological data. This method is aimed to find the relationship between the measured power data. Statistical methods are more suitable for short-term wind power estimations because the error tolerance increases as the estimation time increases (Garcia and angel, 2009; Giebel et al., 2011).

2-Physical methods: It focuses on lower atmosphere or numerical weather forecasting (NWP), which uses mostly meteorological data and weather forecast data. It uses parameterizations based on a detailed physical description of the atmosphere to arrive at the best estimation method for physical systems.

3-Hybrid Methods: These are systems that use physical and statistical data as hybrids. The purpose of hybrid models is to obtain an optimal forecasting performance to take advantage of both models (Wu and Hon, 2007).

Here, we use artificial neural networks (ANN) to process wind power datas because traditional programming is insufficient to deal with unsteady wind power behaviour. Additionally, one of the biggest reasons to use ANN method is that it has great advantages such as working with incomplete information, not preventing one or more cells from producing output due to disruption, and parallel processing capabilities. In this case, in order to make an accurate estimation, the most suitable model for our data was chosen by trial and error ways. Another important feature of ANN is that it can create invisible relationships on invisible data after the learning model is created.

There are many studies on the use of wind energy with artificial neural networks (ANN) (Can, Ö. F. 2021). For example, in Ref. (Çetin F., 2003), wind intensity estimation with artificial neural networks was discussed and radial-based and feed-forward networks were used as ANN, and connection weight values in feed-forward ANN were optimized using backpropagation and Evolutionary Algorithm (EA). In another study, in Ref. (Yeşilnacar Y O., 2011), the wind speed, pressure, and temperature estimation with artificial neural networks in Bilecik province was discussed and modeling of real data, a statistical model of real data, and three different models in which odd-numbered days in real data were considered as input and even-numbered days as output were studied. Thus, they revealed that which of the ANN models was more successful for the related wind parameters (Yeşilnacar Y O., 2011). In addition to that, very recent studies in the literature are given in Table 1.

In this present work, electricity generation from wind energy was tried to be estimated with the ANN model. In our study, data of 6 different wind turbines (Gamesa G97, Suzlon S88, Siemens SWT2.3, Nordex, Enercon E82-3, and Vestas V117) were used with the tool interface of Matlab (2018b version). The place to be used as the application area in the study is located in the center of Rize, and the wind speed data of this location were used as input, and the wind power output values of 6 different wind turbines were used as output values.

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Table 1. Wind power estimation studies, estimation methods and error criteria in the recent literature

Work	Input Variables	Estimation Method	Error Criteria	Reference
Short-term wind power forecasting by stacked recurrent neural networks with parametric sine activation function	Wind power	LSTM, DA	RMSE, MAE, R2	Liu et. al. (2021)
Wind power generation probalistic modeling using ensemble learning techniques	Wind speed, wind direction, temperature, humidity	Boost, gradient boost tree, XGBoost	RMSE, R2	Banik et. al. (2020)
Uzun kısa süreli hafıza ve evrişimsel sinir ağları ile rüzgar enerjisi üretim tahmini	Wind power	CNN, LSTM	MSE	Görgel and Kavlak (2020)
Short-term wind power prediction based on imroved chicken algorithm optimization support vector machine	Wind speed, wind direction, temperature, humidity	SVR, ICSO	RMSE, RE	Fu et. al. (2019)
Short-term wind power forecasting using long-short term memory based recurrent neural network model and variable selection	Wind speed, temperature	LSTM	NRMSE	Cali and Sharma (2019)
Yapay zeka teknikleri kullanılarak kısa dönem rüzgar gücünün çok katmanlı tahmni	Wind speed, wind direction	ANFIS, YSA, SVR	NRMSE	Çevik (2019)

MATERIAL AND METHODS

ANN are computer systems that have the ability to derive and discover new information through learning, and to perform operations without self-help (Altunbey, F. And Alataş, B. 2015, Özcan, C. 2021). Artificial neural networks can also obtain results from imprecise data and have various learning features. ANNs are systems that are formed by connecting artificial nerve cells and consist of three main parts: input layer, hidden layer, and output layer which can be determined as the following.

<u>*Input layer:*</u> It contains the input data coming from data source to the ANN. From here, the inputs are transmitted to the hidden layer without any processing.

<u>*Hidden Layer:*</u> After the input layer, the data comes to this layer. The number of hidden layers may vary depending on the need. The number of neurons in the hidden layer is independent of the number of inputs and outputs.

<u>*Output Layer:*</u> Processes the data from the hidden layer and produces the outputs. In feedback networks, new weight values are calculated using the output produced in this layer. In Figure 2 (a) the schematic topological representation of an artificial neuron is represented.

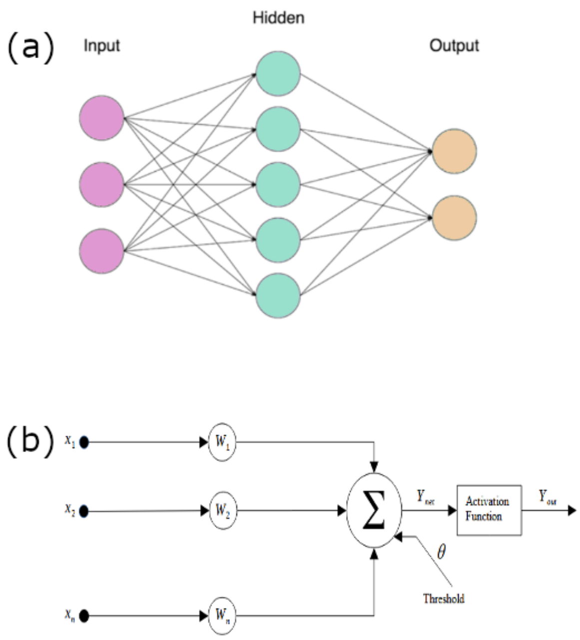

Figure 2. (a) Structure of an artificial neuron. (b) Artificial neural network model

In the structure of an ANN, weight values are determined to increase the accuracy of the outputs produced by using various transfer functions such as linear and sigmoid as illustrated in Figure 2 (b). Thanks to the training of artificial neural networks, the weights are determined using the previous examples and the relationship between the predicted variables is revealed by the input variables. After the network training is over, artificial neural networks

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can work with new data and reach a level that can produce predictions. Network performance is measured by error criteria and driven signals. The margin of error is obtained by comparing the output of the network with the output driven. It is desired to reduce the error margin rate by using the backpropagation algorithm. By repeating this process several times, the network is trained. The purpose of a network trainer is to get the best solution in performance measurements. Thanks to the training, examples are generalized, and results are produced for new data that has never been defined into the system before. The most important advantage of ANN is that there is no need for a mathematical model, and it can learn by itself (Graupe D,. 2016). ANN has applications in various fields such as prediction (Badri A, Ameli Z, Birjandi AM. 2012, Guo Z, Zhao W, LU H, Wang J. 2012, Abhishek K, Singha MP, Ghosh S, Anand A. 2012), classification (Dehuri S, Roy R, Cho SB, Ghosh A., 2012, Ghiassi M, Olschimke M, Moon B, Arnaudo P., 2012, Raeesi M, Moradzadeh A, Ardejani FD, Rahimi M., 2012), and image recognition (El-Midany TT, El-Baz MA, ABD-Elwahed M S., 2010).

In the training phase, one of several algorithms is selected for the input and the target. The join function is defined as:

$$Net = \sum_{i=1}^{n} X_i W_i + b \qquad (1)$$

Here X is the input values and W is the weights. If the n value is taken as the number of inputs presented to the model, $W_1, W_2, W_3, ..., W_n$ are the weight values that are automatically adjusted in the Matlab program, and $X_1, X_2, X_3, ..., X_n$ values are the wind speed data entries in m/s. The activation function selected among various activation functions calculates the output $o=f(Net)$ by applying the inputs taken by the model to the model, and gives the output data as follows;

$$o = f\left(\sum_{i=1}^{n} X_i W_i + b\right) \qquad (2)$$

Here, the b value is a fixed value and is called the threshold that changes according to the activation function we choose. Learning in ANN is of three types: supervised learning, unsupervised learning, and supportive (reinforced) learning.

Supervised learning; inputs and outputs vectors to the system are given as pairs. According to these given data, the system makes generalizations about the examples by collecting information from the examples that come across.

Unsupervised learning; it is a type of learning that works even though there is no previously entered data in the system. Unsupervised learning cannot obtain a definite result since no information is given about the data in the system.

Supportive (reinforced) learning; it does not require prior knowledge. The program is a type of learning that acts with its actions and knowledge and reaches the result by trial and error.

In our study, the Matlab nntool interface was used for ANN model training and the window view of the tool interface is shown in Figure 3. Our input and target data were saved in the Microsoft Excel program and transferred to the Matlab environment.

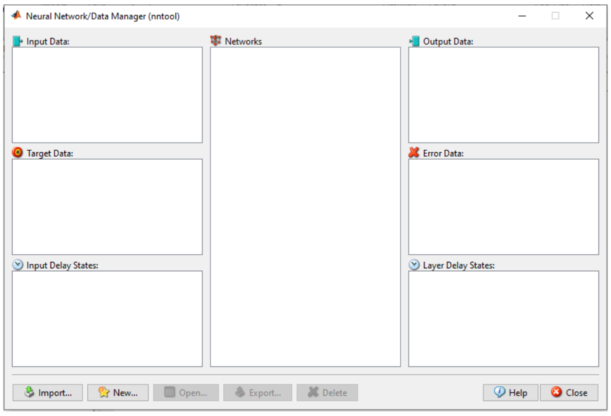

Figure 3. Matlab tool interface window view

RESULTS AND DISCUSSION

In this study we tried to predict electricity generation from wind energy using ANN. For the test of our ANN model, we aim to meet/reduce the loaded electricity consumption of the Rize Provincial Health Directorate by using renewable energy sources through the use of wind energy. In Figure 4, a suitable location for the placement of wind turbines within ~1km of Rize Provincial Health Directorate has been selected for our wind turbine positioning. While creating the ANN model training, we use one-year average daily wind speed as input data in the region we are interested in; we produce the wind power values for six different selected wind turbines (Gamesa G97, Suzlon S88, Siemens SWT2.3, Nordex

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N100, Enercon E82, and Vestas V117) as target data. The wind speed data we use here has been taken into account that the wind turbine is at the height of the tower. A cross-section (15-day-period) of the wind speed data for the location we are interested in is listed in Table 2. The wind power output values we produce for 0-25 m/s wind speed for six different wind turbine types that we are interested in in our study are listed in Table 3.

Figure 4. The location we are interested in, close to Rize Provincial Health Directorate ~1km from the center of Rize/Turkey

Table 2. A daily average wind speed data for our location in Rize/Turkey between January 2020 – December 2020 (Meteostat, 2021)

Day	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	8,3	9,5	17,9	9,7	8	7,1	8,7	8,6	6,9	12,9	13,7	8,1
2	8,2	8,4	10,1	13	7,5	7,8	7,2	15,9	7,1	13,2	6,3	6,2
3	9,5	24,4	7,6	9,9	8,7	10,7	5,5	11,1	11,4	8,4	8,7	6
4	8,7	20,7	6,3	12,5	6,3	7,2	8,7	8,3	8,1	11,4	7,2	7,5
5	7,7	15,6	5,3	5,1	7,9	10,8	6,8	7,3	11	10	4,6	6
6	7,7	22,3	12,7	10	7,7	6,4	6,6	9,6	9,6	10,9	19,5	17,7
7	4,7	14	9,8	8,9	11,4	5,3	8,6	7,8	11,3	11,5	10,8	10,2
8	9,9	18,6	5	4,3	14,9	8,5	16,1	4,9	7	8,2	10,7	12,6
9	20,7	13,1	8,6	8,1	8,1	6,5	20,2	6,1	11,1	8,7	8,9	6,5
10	10,9	14,3	13,6	7	8,1	7,7	11,7	10,1	9,8	11,4	11,7	9,1
11	7,2	11,3	10	5,3	8,3	11	9,1	11,4	6,5	5,8	16	9,6
12	7,4	16	4,9	9,6	11,8	8,1	8,4	10,3	8,7	9,1	7,2	11,6
13	14,3	12,7	7,7	11	11,4	9,5	15,3	14,5	8,8	7,4	12,9	14,2
14	10,3	17,3	10,8	7,8	11	8,9	15	18,2	7,5	5,8	9,1	8,9
15	7,8	3,2	13,6	12,7	6,5	9,1	10,7	14,9	10,3	7	17	7,8
16	8,3	8,2	14,2	9,6	12,5	7,4	10,2	13,5	7,4	6,6	13,4	21
17	7,5	7,6	11,8	13	9,5	7,5	9,3	13,4	7,2	8,3	8,4	23,1
18	13,6	9,9	5,2	5,3	10,8	8,4	9	9,6	8,5	10,8	8,8	9
19	5,8	4,5	5,5	6,5	6,2	14,7	6	9,8	13,8	12,5	11,1	10,3
20	8,7	8,1	2,7	9,6	9,8	10,7	8,5	8,8	7,5	8,3	7,1	9,3
21	18,1	4,7	4,4	12,1	11,4	9,7	16,2	10,6	5,5	9,9	12,1	10,5
22	7,5	8,6	8,3	6,4	20,3	10	11,8	11,7	13,6	8,7	11,9	13,5
23	12,7	7,5	5,3	8,8	15,2	7,8	10,1	22,3	9,5	10,9	10,1	16,1
24	15,2	6,9	7,3	10,3	10,7	12,2	13,3	12,4	6,3	7,7	9,1	15
25	15,1	21,9	4,9	8,4	12,9	11	7,9	6,9	6,6	5,7	17,2	8,6
26	5	9,8	2,9	6,7	10,8	8,8	6,3	8,5	7,5	4,1	13,4	6
27	7,6	7,7	5,6	7,9	9,4	8,2	6,7	6,8	7,7	7,7	13,4	3
28	7,1	19,2	3,1	7,4	9,4	7,9	9,9	9,2	6,1	8,7	8,3	4,4
29	10,6	9	6,5	11,2	9,5	10,7	9,5	10,4	9,7	11,5	4,7	3,8
30	15,1		7,8	7,8	8,4	15,4	9,9	7,9	14,3	8,9	7,2	3,4
31	18,9		6,3		9,2		8,5	5,5		7,8		5,3

Table 3. The amount of energy (kW) produced by the 6 different wind turbines according to the wind speed (Şenol Ü, Musayev Z. 2017)

Wind Speed (m/s)	Gamesa G97	Suzlon S.88	Siemens SWT2.3	Nordex N100	Enercon E82	Vestas V117
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	14	15	66	24	25	24
4	94	35	171	84	82	139
5	236	130	352	212	174	312
6	438	310	623	391	321	570
7	714	525	1002	599	525	936
8	1084	820	1497	912	800	1419
9	1508	1160	2005	1299	1135	2027
10	1836	1540	2246	1744	1510	2705
11	1973	1880	2296	2149	1880	3168
12	1992	2100	2300	2389	2200	3292
13	1998	2100	2300	2492	2500	3300
14	2000	2100	2300	2500	2770	3300
15	2000	2100	2300	2500	2910	3300
16	2000	2100	2300	2500	3000	3300
17	2000	2100	2300	2500	3000	3300
18	2000	2100	2300	2500	3000	3300
19	2000	2100	2300	2500	3000	3300
20	2000	2100	2300	2500	3000	3300
21	2000	2100	2300	2500	3000	3300
22	2000	2100	2300	2500	3000	3300
23	2000	2100	2300	2500	3000	3300
24	2000	2100	2300	2500	3000	3300
25	2000	2100	2300	2500	3000	3300

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While creating our ANN model, we apply Min-Max normalization process to obtain more consistent results and which is determined as;

$$x_n = \frac{x_0 - x_{min}}{x_{max} - x_{min}} \tag{3}$$

Here x_n is normalized data, x_0 is the original data, x_{min} the minimum, and x_{max} is the maximum data. In Table 4, there is a 15-day cross-section of the normalization process of our wind speed data can be found.

Table 4. A daily average normalized wind speed data for our location in Rize/Turkey between January 2020 – December 2020

Days	January	February	March	April	May	June
1	0.258065	0.313364	0.700461	0.322581	0.24424	0.202765
2	0.253456	0.262673	0.341014	0.474654	0.221198	0.235023
3	0.313364	1	0.225806	0.331797	0.276498	0.368664
4	0.276498	0.829493	0.165899	0.451613	0.165899	0.207373
5	0.230415	0.59447	0.119816	0.110599	0.239631	0.373272
6	0.230415	0.903226	0.460829	0.336406	0.230415	0.170507
7	0.092166	0.520737	0.327189	0.285714	0.400922	0.119816
8	0.331797	0.732719	0.105991	0.073733	0.562212	0.267281
9	0.829493	0.479263	0.271889	0.248848	0.248848	0.175115
10	0.37788	0.534562	0.502304	0.198157	0.248848	0.230415
11	0.207373	0.396313	0.336406	0.119816	0.258065	0.382488
12	0.21659	0.612903	0.101382	0.317972	0.419355	0.248848
13	0.534562	0.460829	0.230415	0.382488	0.400922	0.313364
14	0.35023	0.672811	0.373272	0.235023	0.382488	0.285714
15	0.235023	0.023041	0.502304	0.460829	0.175115	0.294931

In our study, during the creation of the ANN training model, we choose the most appropriate ANN parameters to ensure that the model give the lowest error. In our model, due to ease of use, convergence rate, and high forecast success in both linear and nonlinear models, we use the feed-forward back-propagation algorithm (The MathWorks, 2021). To train our data we use Trained (Variable Learning Rate Backpropagation) algorithm, a network training function that updates weight and training values according to gradient landing momentum and adaptive learning rate (The MathWorks, 2021). We use Learngdm as the learning function for our ANN model. Learngdm calculates the weight change for a given neuron from the neuron's input and error, weight (or deviation), learning rate, and momentum constant to momentum gradient descent. To activate neurons in neural networks we use activation functions, also known as transport functions. It also increases the expressiveness of the ANN model, enabling the network to learn and calculate more complex tasks. We use the tangent sigmoid transfer function (tansig) for the activation function, considering that it is a continuous and differentiable function in the selection of the function. We choose the MSE (Mean Squared Error) function as the performance function for our model.

For the ANN model we created, the daily average wind speed data between the 12 months we are interested in for the location we are working on, and the power output power values of 6 different wind turbines are taken as the target (output) data. The iteration value, which is the stopping criterion, is set to 1000. Gradient value 1.00e-05 with "0" error and validation error number of 850 is used. For the training of our model, we determine the learning rate as 0.01 and the momentum value as 0.9. The training of our model stopped by reaching 1000 iterations in 1 second time. The dividerand function is randomly divided into 70% training, 15% validation and 15% test data on Matlab. Figure5 shows the ANN model and training parameters we created in the Matlab nntool interface.

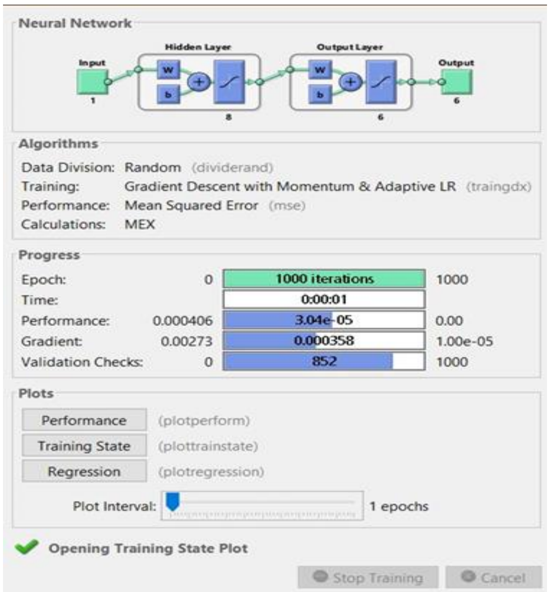

Figure 5. ANN model and training parameters created in Matlab nntool interface

The error values of the validation set obtained as a result of the training phase are used in the selection of the weights that gave the best performance values as a result of the model training. In the testing phase of the model, first of all, the values we found as a result of the training are presented to the network again, and in this way, the synaptic weights matrix and input values are presented to the network, and it was aimed

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to predict the model with the least error. As presented in Figure 6 (a), the lowest error is in the 148th iteration.

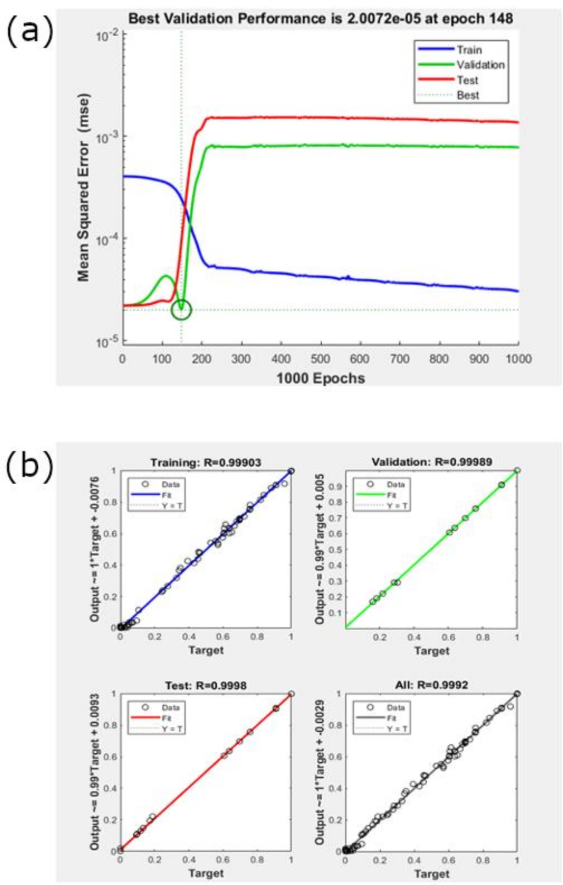

Figure 6. (a) The changes in the performance function of the validation and test data of the ANN training model we created during the training phase. (b) Regression curves of the results of the training, validation, and testing data of our ANN model

Figure 6 (b) shows the regression curves of the results of the training, validation and test data of our ANN model. As can be seen from our results the output values of our ANN model are very close to the real data.

Here, from the calculations we have made using our successful ANN model between January 2020 - December 2020 however a section of months February, August and November 2020 is presented in this study. The data of the estimated wind power output values produced from 6 different wind turbines on a daily average for February 2020 are listed in Table 5 and its graphical representation is presented in Figure 7 (a). Likewise, data on estimated power output values generated from an average of 6 different wind turbines per day for August 2020 and November 2020 were listed in Table 6 and Table 7, respectively; and their graphical representations are presented in Figure 7 (b) and 7(c), respectively.

Table 5. The expected daily average power output values (kW) from 6 different wind turbines for February 2020

February	Gamesa G97	Suzlon S.88	Siemens SWT2.3	Nordex N100	Enercon E82	Vestas V117
1	1129.689	845.46	1563.672	940.005	808.434	1461.768
2	688.974	524.667	911.823	599.511	528.198	911.526
3	1999.998	2099.658	2298.681	2499.717	2999.832	3300
4	1999.998	2099.79	2299.605	2498.628	2998.545	3300
5	1999.998	2098.239	2299.242	2496.912	2969.538	3300
6	1999.998	2099.394	2299.671	2499.42	2999.337	3300
7	1999.338	2093.124	2292.378	2490.774	2709.498	3299.967
8	1999.998	2099.79	2299.671	2496.615	2993.694	3300
9	1992.573	2055.339	2283.303	2438.997	2368.773	3298.449
10	1999.635	2095.071	2294.061	2493.282	2773.089	3300
11	1848.099	1629.243	2248.818	1852.653	1647.855	2786.289
12	1999.998	2098.635	2299.605	2497.374	2984.223	3300
13	1975.347	1981.32	2276.076	2335.311	2129.886	3282.807
14	1999.998	2099.163	2299.803	2497.704	2992.836	3300
15	0.396825	0.211652	31.74237	3.36996	2.849484	0.372207
16	639.111	482.46	858.66	558.261	489.258	846.879
17	436.359	303.0423	692.274	383.658	319.9548	577.203
18	1406.757	1072.962	1913.736	1192.62	1017.159	1855.194
19	2.133153	0.652344	56.9547	3.3099	1.764279	3.196314
20	612.381	458.964	833.613	535.59	467.346	811.668
21	2.3529	0.709104	59.2482	3.42144	1.798962	3.5805
22	739.167	564.399	975.018	639.276	564.003	974.82
23	391.017	264.6567	656.469	344.718	283.2093	517.209
24	122.6181	65.2938	385.836	115.1139	82.5396	165.7887
25	1999.998	2099.427	2299.671	2499.354	2999.304	3300
26	1337.754	1011.879	1835.658	1124.145	959.277	1750.782
27	478.434	339.603	724.911	419.958	354.75	633.171
28	1999.998	2099.922	2299.539	2495.856	2994.453	3300
29	866.085	656.337	1163.151	735.24	644.358	1130.25

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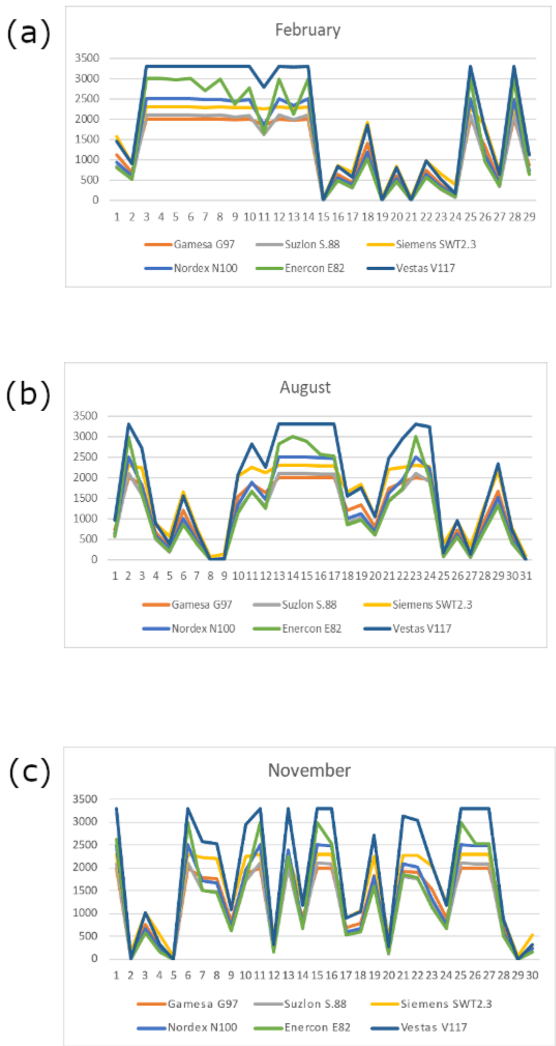

Figure 7. Graphical representation of expected daily average power output values (kW) from 6 different wind turbines for (a) February, (b) August and (c) November 2020

Table 6. The expected daily average power output values (kW) from 6 different wind turbines for August 2020

August	Gamesa G97	Suzlon S.88	Siemens SWT2.3	Nordex N100	Enercon E82	Vestas V117
1	739.167	564.399	975.018	639.276	564.003	974.82
2	1999.998	2098.569	2299.539	2497.275	2981.781	3300
3	1827.309	1589.181	2240.898	1801.536	1597.926	2710.257
4	664.389	504.174	884.466	579.348	509.388	879.879
5	294.4755	186.8823	574.893	262.2642	207.6492	390.225
6	1197.207	897.072	1657.524	996.732	854.304	1551.99
7	516.912	373.626	754.776	453.255	386.991	684.486
8	2.596044	0.778503	61.8255	3.6036	1.882716	3.9864
9	11.82027	4.30188	128.6901	13.46796	7.79526	17.4537
10	1532.553	1195.359	2039.07	1331.682	1138.599	2061.18
11	1857.24	1648.02	2251.755	1877.04	1670.394	2824.272
12	1634.094	1308.549	2123.715	1462.659	1258.851	2247.663
13	1999.734	2095.863	2295.15	2494.272	2812.92	3300
14	1999.998	2099.592	2299.77	2497.176	2993.43	3300
15	1999.899	2096.952	2297.163	2495.526	2888.622	3300
16	1997.82	2083.422	2288.517	2477.772	2561.658	3299.868
17	1997.061	2079.132	2287.428	2471.865	2520.441	3299.736
18	1197.207	897.072	1657.524	996.732	854.304	1551.99
19	1337.754	1011.879	1835.658	1124.145	959.277	1750.782
20	796.059	606.573	1056.132	682.737	601.194	1044.879
21	1738.638	1445.565	2194.929	1625.019	1417.284	2469.456
22	1883.211	1706.232	2258.355	1954.194	1736.559	2946.405
23	1999.998	2099.394	2299.671	2499.42	2999.337	3300
24	1950.828	1894.497	2270.334	2213.475	1968.879	3231.129
25	122.6181	65.2938	385.836	115.1139	82.5396	165.7887
26	713.658	544.533	941.688	619.245	546.216	942.843
27	92.6475	46.9128	339.504	88.803	61.8948	126.4131
28	955.053	718.872	1301.949	802.296	698.247	1239.48
29	1674.915	1359.039	2153.514	1521.96	1315.479	2329.701
30	551.826	404.844	782.397	483.483	416.493	731.115
31	4.08474	1.275384	76.7085	5.17209	2.750088	6.27

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Table 7. The expected daily average power output values (kW) from 6 different wind turbines for November 2020

November	Gamesa G97	Suzlon S.88	Siemens SWT2.3	Nordex N100	Enercon E82	Vestas V117
1	1998.711	2088.999	2290.299	2485.263	2630.76	3299.934
2	20.27718	8.01273	166.8018	22.03113	13.3551	29.30631
3	766.359	584.859	1012.803	660.231	582.153	1008.48
4	246.213	150.3414	529.617	221.1759	171.3195	327.1257
5	2.242284	0.679833	58.0866	3.35841	1.776258	3.3891
6	1999.998	2099.922	2299.506	2495.922	2995.113	3300
7	1783.287	1513.578	2220.042	1707.585	1501.566	2580.27
8	1762.959	1481.7	2209.053	1668.711	1461.636	2528.031
9	829.026	630.168	1105.929	707.52	621.72	1085.106
10	1883.211	1706.232	2258.355	1954.194	1736.559	2946.405
11	1999.998	2098.635	2299.605	2497.374	2984.223	3300
12	246.213	150.3414	529.617	221.1759	171.3195	327.1257
13	1986.105	2025.441	2279.871	2397.252	2250.402	3294.555
14	907.896	685.707	1228.425	766.623	669.669	1181.4
15	1999.998	2099.064	2299.803	2497.737	2992.341	3300
16	1997.061	2079.132	2287.428	2471.865	2520.441	3299.736
17	688.974	524.667	911.823	599.511	528.198	911.526
18	796.059	606.573	1056.132	682.737	601.194	1044.879
19	1827.309	1589.181	2240.898	1801.536	1597.926	2710.257
20	200.3925	117.2721	482.262	182.0973	137.7024	267.3528
21	1920.897	1804.011	2265.087	2087.646	1847.175	3124.935
22	1901.361	1751.31	2261.787	2015.277	1786.356	3035.835
23	1532.553	1195.359	2039.07	1331.682	1138.599	2061.18
24	907.896	685.707	1228.425	766.623	669.669	1181.4
25	1999.998	2099.13	2299.803	2497.737	2992.704	3300
26	1997.061	2079.132	2287.428	2471.865	2520.441	3299.736
27	1997.061	2079.132	2287.428	2471.865	2520.441	3299.736
28	664.389	504.174	884.466	579.348	509.388	879.879
29	2.3529	0.709104	59.2482	3.42144	1.798962	3.5805
30	246.213	150.3414	529.617	221.1759	171.3195	327.1257

As a result of our study, the estimated monthly average wind power output values to be obtained from 6 different wind turbines between January 2020 - December 2020 are listed in Table 8 and its graphical representation is shown in Figure 8. According to the results, it has been determined that the region is efficient in terms of wind and electrical energy production with a high capacity factor can be realized with the turbines selected appropriately. When the estimated power values are examined, it is seen that the turbine type is Vestas V117 with the best efficiency, followed by Siemens SWT2.3, Nordex N100, Enercon E82, Gamesa G97, Suzlon S88 turbines, respectively.

Table 8. *Average estimated wind power output values (kW) obtained from 6 different wind turbines between January 2020 – December 2020*

Months	Gamesa G97	Suzlon S.88	Siemens SWT2.3	Nordex N100	Enercon E82	Vestas V117
1	1054.0877	968.10459	1335.0642	1141.26	1178.0229	1599.8741
2	1264.4208	1218.6004	1543.2031	1437.6136	1554.6815	1976.2386
3	711.9908	641.71475	923.3751	750.98818	727.93165	1071.6374
4	917.43471	783.88218	1207.6929	905.75813	803.87307	1340.3832
5	1182.6043	1032.7431	1501.2201	1191.7833	1122.7005	1745.9877
6	966.72106	808.77886	1273.2491	934.77986	861.90379	1385.3484
7	1058.4021	936.7435	1359.9522	1087.1987	1083.2428	1563.2657
8	1202.9281	1084.7695	1516.5935	1260.8563	1245.7125	1805.8732
9	854.84875	724.99406	1153.9981	846.66336	784.33719	1238.2712
10	980.2851	836.54048	1263.7018	964.57373	859.98726	1432.2856
11	1237.069	1152.9837	1530.2905	1349.6847	1344.2422	1908.6095
12	965.34513	890.36172	1216.1843	1040.3027	1067.6731	1466.2394

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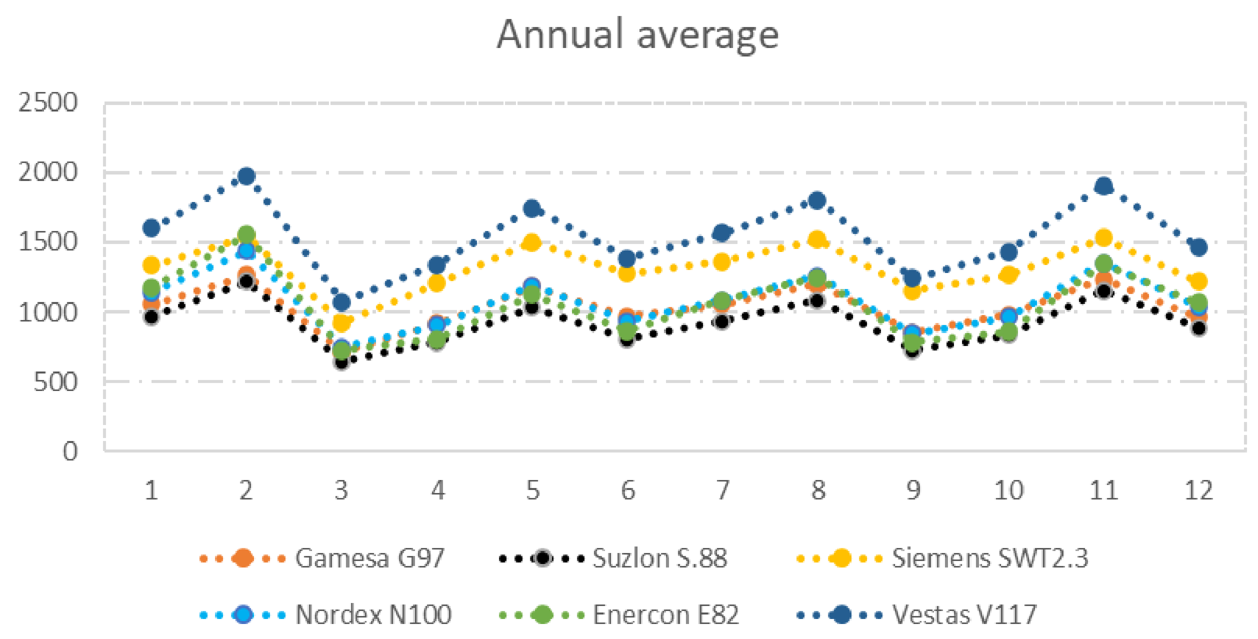

Figure 8. Graphical representation of the average estimated wind power output (kW) values obtained from 6 different wind turbines between January 2020 – December 2020

CONCLUSION

In this study, energy production from wind energy is estimated utilizing the network trained using ANN with six different wind turbines. In the created ANN model, the speed-power output values obtained from the manufacturer's catalogs for different wind turbines are entered as input layer and output layer, respectively. From the regression curves of the training, validation, and test data obtained as a result of the modeling, it is seen that the ANN model could make a successful and consistent estimation with the smallest error. The actual wind speed values of the relevant location are used as a post-training application were defined as input data to the Matlab program and the wind turbine power output values are simulated. Thus, it is concluded that the Vestas V117 turbine provided the highest power output among the six different wind turbine types, and the turbine providing the second-best power output is found to be the Siemens SWT2.3 turbine. As it is seen in the power output values, it will be quite possible, convenient, and advantageous to meet the electricity generation for the selected region from wind energy. As a result, this study will guide the investors and practitioners in the energy sector to benefit from wind energy.

CONFLICT OF INTEREST

The Authors report no conflict of interest relevant to this article.

RESEARCH AND PUBLICATION ETHICS STATEMENT

The author declares that this study complies with research and publication ethics.

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