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Estimation of Wind Power Density with Artificial Neural Network

Muhammed Yusuf Aktaç
Electrical and Electronic Engineering, Engineering Faculty/ Siirt University

Mehmet Şahin
Electrical and Electronic Engineering, Engineering Faculty/ Siirt University

Rıdvan Saraçoğlu

Electrical and Electronic Engineering, Engineering Faculty/ Yüzüncü Yil University

ABSTRACT

Industry and technology are rapidly developing with each passing day. They need energy to sustain this evolution. The demand of energy is mainly provided from fossil fuels. Unfortunately, this kind of energy reserves are consumed away day by day. Therefore, there is a need to use alternative energy sources to supply energy needs. Alternative energy sources can be listed as; solar, wind, wave, biomass, geothermal and hydro-electric power. Our country has significant potential for wind energy. Wind power density estimation is required to determine the wind potential. In this study, the wind power density was estimated by using artificial neural network (ANN) method. Forty meteorological stations were used for ANN training, while eighteen meteorological stations were used to test the trained network. Network has trained according to, respectively; trainlm, trainbfg, trainscg, traincgp traincgb, traincgf ve trainoss learning algorithms. The correlation coefficient (R) and Mean bias error (MBE) of the best developed model were calculated as 0,9767 and -0,3124 W/m2 respectively. Root Mean Square Error (RMSE) was calculated as 1,4786 W/m2. In conclusion, the obtained results demonstrate that the developed model can be used to estimate the wind power density.

Keywords: Alternative energy sources, wind power density, wind speed, artificial neural networks

1 INTRODUCTION

Today, the rapid population growth that have occurred around the world, with the facts of urbanization and industrialization increased as a result of globalization there is an increasing demand for natural resources and energy developments such as commercial facilities[1]. On the other hand used fossil resources, causing global warming and the greenhouse effect on world climate changes are caused by this unusual form. On the other hand, environmental pollution brought by energy source began to occur indirectly harm the environment and human health [2].

Due to these reasons countries of the world clean, healthy, renewable energy sources to qualify as a sustainable energy source has been forced to move toward a quick orientation. Renewable energy sources lasting, environmentally friendly, clean and plays a major role in environmental protection. At the same time, countries also provide a major contribution to economic development [3]. These circumstances has increased the interest of the people of the renewable energy sources [4]. Amongst renewable energy sources, wind energy is one of the sources which is plenty, low-cost, clean, most advanced, and sufficient in terms of commercial aspect [5]. Therefore, the use of wind energy is getting attention increasingly both in Turkey and all over the world in recent years [6, 7]. The aim of this research is to examine the activity and the practicability of ANN in detecting the potential of wind energy in Turkey. In previous studies, long-term studies which used the combination of ANN methods based on large input parameters have not been observed in Turkey.

The study has its own direction in this respect. In this study, wind power density (W/m2) will be obtained as output parameter while the month, latitude, longitude, height, soil heat (5 cm), vapour pressure, relative humidity, average temperature, average maximum and minimum temperature which are obtained from meteorological stations of 58 city centers of Turkey which representing different weather conditions are used as input parameters. The datas between 1980-2010 years are used as education datas, the datas between 2011-2013 are used as test-purpose in the study.

2 METHODOLOGY AND DATA SOURCES

Depending on the climatic conditions Turkey is divided into seven geographical regions. These are; Ege, Marmara, Karadeniz, İç Anadolu, Doğu Anadolu and Güneydoğu Anadolu regions. Each area has a unique climate. Fifty-eight selected in the study as a control point locations, with 7 smooth distributions by geographic region is provided.

Table 1 Cities which are used for testing and education

City	Height (m)	Latitude(°N)	Longitude(°E)	Geographic Region*
Adana	27	37	35,19	1
Adıyaman	679	37,45	38,16	2
Afyonkarahisar	1034	38,44	30,34	6
Aksaray	961	38,22	34	4
Amasya	412	40,39	35,5	5
Ankara	891	40,04	32,34	4
Antalya	47	36,53	30,4	1
Artvin	615	41,1	41,49	5
Aydın	58	37,5	27,5	6
Balıkesir	100	39,36	27,55	7
Bartın	23	41,38	32,2	5
Batman	610	37,53	41,07	2
Bilecik	539	40,09	29,58	7
Bitlis	1794	38,28	42,09	3
Bolu	737	40,44	31,36	5
Burdur	957	37,43	30,17	1
Bursa	100	40,13	29	7
Çanakkale	5	40,08	26,33	7
Çorum	776	40,32	34,56	5

Table 1 (continue) Cities which are used for testing and education

Denizli	450	37,46	29,06	6
Edirne	51	41,4	26,33	7
Elazığ	1093	38,4	39,13	3
Erzincan	1218	39,42	39,31	3
Erzurum	1757	39,53	41,16	3
Eskişehir	801	39,46	30,33	4
Gümüşhane	1219	40,27	39,27	5
Hatay	100	36,15	36,08	1
Isparta	997	37,47	30,34	1
İstanbul-Göztepe	28	40,54	29,09	7
İzmir	20	38,23	27,04	6
Kahramanmaraş	572	37,35	36,55	1
Karaman	1023	37,12	33,13	5
Kars	1775	40,35	43,04	3
Kastamonu	800	41,22	33,46	7
Kırklareli	232	41,44	27,13	4
Kırşehir	1007	39,09	34,1	4
Kilis	638	36,43	37,05	2
Konya	1031	37,52	32,28	4
Malatya	947	38,21	38,18	3
Manisa	70	38,36	27,24	6
Mersin	3	36,48	34,38	1
Muğla	646	37,17	28,22	6
Niğde	1211	37,28	34,41	4
Ordu	4	40,58	37,53	5
Rize	8	41,02	40,3	5
Samsun	4	41,21	36,14	5
Siirt	896	37,55	41,56	2
Sinop	32	42,01	35,09	5
Sivas	1285	39,45	37,01	4
Tekirdağ	4	40,59	27,29	7

Table 1 (continue) Cities which are used for testing and education

Tokat	608	40,18	36,33	5
Trabzon	40	40,59	39,46	5
Tunceli	979	39,06	39,32	3
Uşak	929	38,68	29,47	6
Van	1670	38,29	43,23	3
Yalova	4	40,39	29,16	7
Yozgat	1298	39,39	34,48	4
Zonguldak	154	41,27	31,47	5

* Akdeniz Region (1), Güneydoğu Anadolu Region (2), Doğu Anadolu Region (3), İç Anadolu Region (4), Karadeniz Region (5), Ege Region (6), Marmara Region (7).

3 METHODOLOGY OF WIND ENERGY

3.1 Energy of Wind Energy

Considering an air package whose mass is m, moving with a speed v. Depending on the mass and the speed of the air package, the kinetic energy will occur. The kinetic energy is shown by the following formula (Figure1).

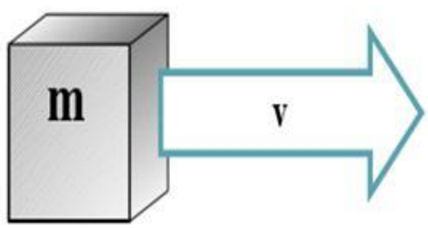

Figure 1 : Air package whose mass is m, moving with a speed v.

$$W_{KE} = \frac{1}{2} m v^2 \tag{1}$$

W_{KE} is the kinetic energy. Power moving in the air stream, the flow of the kinetic energy of flowing per unit time.

$$P = \frac{d}{dt}\left(\frac{1}{2} m v^2\right) = \frac{1}{2}\frac{dm}{dt} v^2 \tag{2}$$

The result is achieved. P is the power in the air flow. In the equation $\frac{dm}{dt}$, is defined as the mass flowing per unit time, this corresponds to a mass flow expression. Mass flow rate has $\dot{m}$ demonstration. In its final form power, equation would be (3).

$$P = \frac{1}{2}\dot{m}v^2 \tag{3}$$

Power is the energy flowing per unit time, since it is assumed that the mass of air that passes through surface A. The power flowing through surface A is shown as P_A, P can be written instead of P_A.

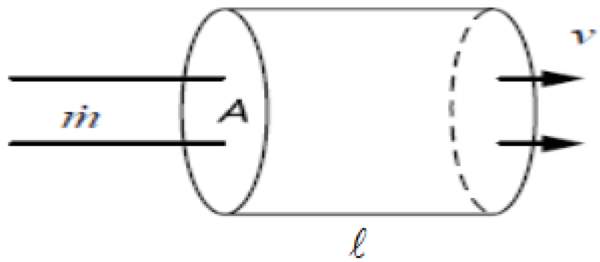

Figure 2: An air mass moving at the speed of v in a space

$$P_A = \frac{1}{2}\dot{m}v^2 \tag{4}$$

On the other hand multiplying the mass by the volume gives the density,

$$m = \rho.V \tag{5}$$

Formula can be written. ρ is the density of the air and V is the mass of the air. (5) equality in the fluid mass m 's time derivative is taken on the formula according to the mass flow rate is reached.

$$\dot{m} = \rho.\frac{d}{dt}(V) = \rho.\frac{d}{dt}(A.\ell) = \rho.A.\frac{d}{dt}(\ell) = \rho.A.v \tag{6}$$

Return to equation (4);

$$P_A = \frac{1}{2}\dot{m}v^2 = \frac{1}{2}(\rho.A.v)v^2 = \frac{1}{2}.\rho.A.v^3 \tag{7}$$

In short, we could write the equation in terms of wind power that occur throughout the area;

$$P_W = \frac{1}{2}.\rho.A.v^3 \quad \text{(Watt)} \tag{8}$$

P_W is the mechanical strength of the moving air, ρ is the density of the air, (at the sea level, for 15°C temperature used as 1,225 kg/m^3) A rotor swept area of blades (m^2). The expression of power, depending on the speed of the wind is proportional to the cube of speed as follows (figure 3).

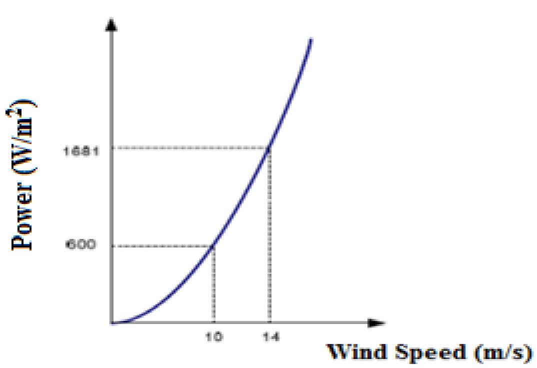

Figure 3: Wind speed and power relation

Here is the corresponding power unit is the power per m^2, and these are specific to a region of this specific magnitude (custom) is referred to as power or power density. The power density of a region is calculated by the following formula.

$$\frac{P_w}{A} = \frac{1}{2}\rho v^3 \qquad (9)$$

$\frac{P_w}{A}$ is the density of power and the unit's is W/m^2 [8].

3.2 The Effect Of The Temperature On The Air Density

Wind energy data is presented, air density is usually assumed that 1,225 kg/m^3. In other words, temperature 15°C, pressure is 1 atmospheric pressure. Using the ideal gas law, air density can be calculated easily under other conditions [8].

$$P.V=n.R.T \qquad (10)$$

In equation (10) P(atm) is pressure, V(m^3) is volume, n is number of moles, T (K) is absolute temperature and R(K^{-1} . mol^{-1} .8,2056.10^{-5} m^3 . atm) is the ideal gas constant.

Molecular weight of the gas (g/mol) is shown *MA*, air density is; ρ (kg/m^3)

$$\rho = \frac{n.MA.10^{-3}}{V} \qquad (11)$$

Is calculated.

If V volume in equation (10) taking back, equation (11) is used, equation (12) expression is obtained.

$$\rho = \frac{P.MA.10^{-3}}{RT} \qquad (12)$$

The molecular weight of air for the presence of the power density should be calculated. This is performed by using this latest (12) of equality. A mixture of air molecules is composed of nitrogen (78,08%), oxygen (20,95%), argon (% 0,93), carbon dioxide (% 0,035), neon (0,0018%) and similar components. Equivalent molecular weight of air can be calculated by using the molecular weights of the components (N_2= 28,02 g/mol; O_2= 32,00 g/mol; Ar =39,95 g/mol; CO_2= 44,01 g/mol; Ne=20,18 g/mol). Equivalent molecular weight of air have been obtained as (0,7808.28,02 + 0,2095. 32,00 + 0,0093. 39,95 + 0,00035. 44,01 + 0,000018. 20,18 = 28,97 g/mol) [8]. This result is written in equation (12) instead of *MA.* The measurement is made at the point wind speed, air pressure and temperature of the location using the same equation is also related to the density of the air is calculated.

At 0°C the density of air is approximately %5 more than the density of air at 15°C and 1 atm (1,225 kg/m^3). P_W 5 percent of the power will be greater because wind power is directly proportional to the air density. Under the pressure of 1 atm, the density of air at various temperatures is shown in table 2.

Table 2 Air temperatures under 1 atm pressure the density of air change [8].

Temperature (ºC)	Density (kg/m^3)	Density ratio for temperature change (K_T)
-15	1,368	1,12
-10	1,342	1,10
-5	1,317	1,07
0	1,293	1,05
5	1,269	1,04
10	1,247	1,02
15	1,225	1
20	1,204	0,98
25	1,184	0,97
30	1,165	0,95
35	1,146	0,94
40	1,127	0,92

3.3 Wind Speed Power Equation

Depending on the height of the wind speed equation is given in the following figure.

$$\left(\frac{v}{v_0}\right) = \left(\frac{H}{H_0}\right)^{\alpha} \tag{13}$$

v is wind speed at H height, v_0 is the wind speed at the H_0 reference height. a is the coefficient of friction. The coefficient of friction α, the topology of the surface of the ground exposed to the wind is a coefficient. α refers to Hellman coefficient. This coefficient is given for different earth topologies in table 3 [8, 9, 10].

Because wind power varies with the cube of wind speed relative wind using equation (13) in the height of power, the power at the H_0 reference height as a function of can be found.

Wind speed varies depending on the geographical conditions and altitude of the measurement point. A wind turbine is defined as the wind speed at the height of the desired tower;

$$\frac{P}{P_0} = \left(\frac{V}{V_0}\right)^3 = \left[\left(\frac{H}{H_0}\right)^{\alpha}\right]^3 \rightarrow \quad \frac{\mathrm{P}}{\mathrm{P}_0} = \left(\frac{\mathrm{V}}{\mathrm{V}_0}\right)^3 = \left(\frac{H}{H_0}\right)^{3\alpha} \tag{14}$$

Table 3 The wind shear exponent α values of different surfaces [9].

Description of land	The wind shear exponent values
Smooth, firm ground, lake, or ocean surface	0,10
Short grass on undeveloped land	0,14
The foot at the level of the floor covered with grass	0,16
Shrubs, shrubbery, floor covered with trees	0,20
Floor covered with many trees and buildings	0,22 – 0,24
The edge of the small town of woodland and neighbourhood	0,28 – 0,30
Tall buildings in urban centres	0,4

3.4 Cell Of ANN

The basic biological neuron that has much complex structure compared to cell of Ann information processing systems. The basic elements of artificial neural networks in biological neural networks, neural cell. Artificial neural cells are the basic information processing unit in ANN process. All neurons within the network receive one or more input and they give a single output. This output may be given as the output of the neural network can be used as input to other neurons. An artificial cell model consists of 5 components. These are; inputs, weights, function of combination, activation function and output [11].

Data that is received from the external environment connects to neuron by the weights. These weights determine the impact of the corresponding entry. The total function calculates the net input. The net input, inputs, and these inputs are result of multiplying the corresponding weights. The activation function calculates the net output during the process and this process at the same time, the output of the neuron. The bias with a constant b can be expressed. Concept of bias is referred as the activation function of the threshold value. In figure 4 simple structure of artificial neural cells (neurons) is shown.

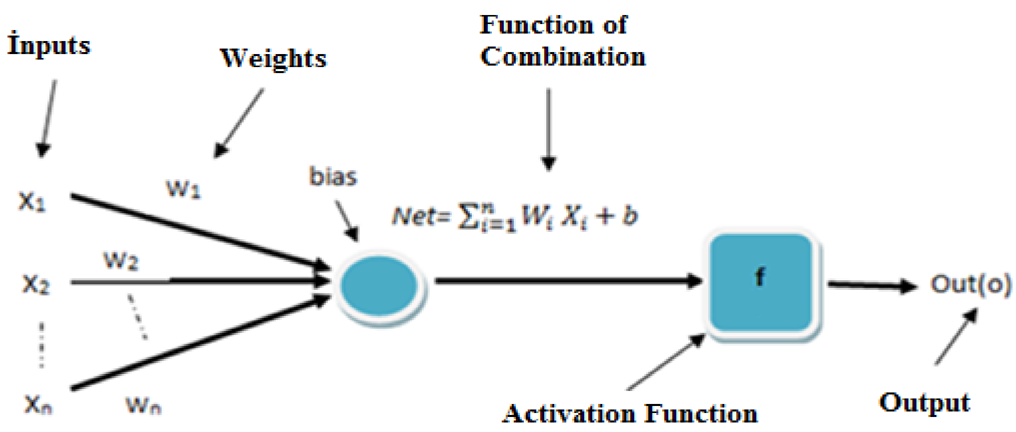

Figure 4: A simple artificial neuron structure [12].

3.5 Analyses Of The Data

Calculated all scale takes the numeric property based on each numeric feature expressed by a volume. The calculated values are done according to the standard criteria of the reviews by the critics. The results of the evaluation of the measurement according to the calculated values according to the nature of the discipline had reached the decision that the desired goal is reached. The values estimated in the studies for checking and verification purposes, compared with the actual values. Various statistical rules have been developed for comparison. These rules can be written as following;

1. $i = 1 \ldots\ldots\ldots \ldots n$, v_i is the cluster of the real values, e_i is the cluster of predicted values, $\bar{v}$ is the average of the actual values and $\bar{e}$ is the average of the predicted values, σ_v standart deviation of the real values and σ_e standard deviation of the predicted values. The difference between $\bar{v}$ and $\bar{e}$ is called 'trend' (slip). Briefly, the estimated value is the difference between the actual value [13].
2. Linear correlation coefficient R, is given as equation (15) [14].

$$R = \frac{\sum_{i=1}^{n} (v_i - \bar{v})(e_i - \bar{e})}{n \sigma_v \sigma_e} \tag{15}$$

R shows that the relation of the predicted value the actual value. New formulas can be produced according to this relationship. However, in these calculations is not sufficient for the evaluation of the success. Obtained in the first calculation of the error rate is quite high because although the rate of encountering a similar error in other calculations, the correlation coefficient can be quite successful [15].

The root mean square error (RMSE), equality is calculated with a mathematical formula given in (16) RMSE is the differentiate between the real value and the predicted value is considered to be a precise measurement. The accuracy of the value obtained in the following formula and values are evidence of the success predicted to be small.

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^{n} (e_i - v_i)^2 \right]^{\frac{1}{2}} \tag{16}$$

3. In comparison of the actual values with predicted values average bias error (MBE) is expected low value. Ideal MBE would be expected to close to zero. The MBE value may be positive or negative. This doesn't matter. MBE value is calculated by the equality (17) [16].

$$MBE = \frac{1}{n} \sum_{i=1}^{n} [e_i - v_i] \tag{17}$$

4 RESULTS AND DISCUSSIONS

In this study, artificial neural network method has been used to estimate the wind power density. First of all, retrieved wind speeds from a height of 2 m from Turkish State Meteorological Service and Hellman coefficient values in table 3. The wind speed at a height of 50 m has been calculated by using (13) equation. The air density at the corresponding location has been obtained using equation (12). The wind power density values are calculated by using wind speed and air density in (9). The wind power density datas which obtained fifty-eight city centers in Turkey between 1980-2013 years are calculated for ANN studies. The data in 1980-2010 were used for training models. The accuracy of models generated with the data 2011-2013 has been tested. The ANN models used in the study consist of input layer, hidden layer and output layer. In this study, wind power density (W/m^2) obtained as output parameter while the month, latitude, longitude, height, soil heat (5cm), vapour pressure, relative humidity, average temperature, average maximum and minimum temperature which are obtained from meteorological stations of fifty-eight city centers of Turkey which representing different weather conditions are used as input parameters.

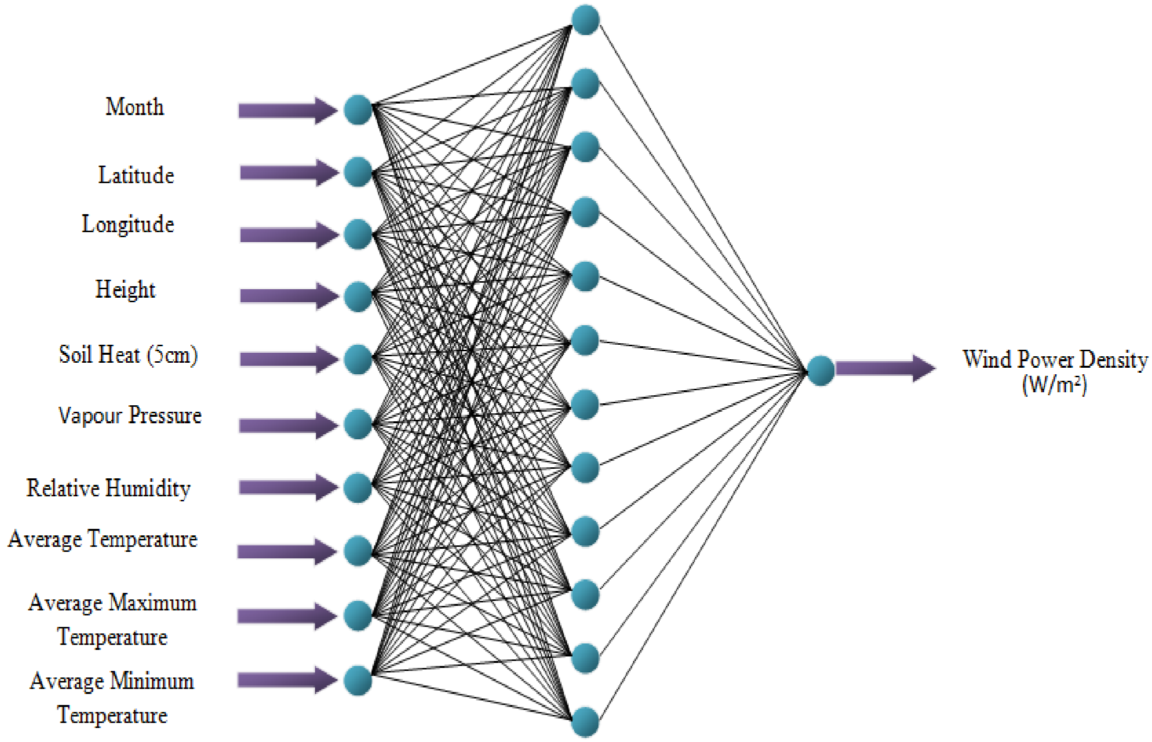

Figure 5: The architecture of ANN

There is not a mathematical formula to determine the number of the neural network with optimum hidden layer nerve cell (neuron). The number of the cell in the hidden layer (neuron) is decided by training of the network. The number of neurons in hidden layer have been replaced by increasing numbers 2-50 to obtain the most suitable neural network model in the study. Decided to appropriate neural network model as a result of attempts however the creation of the random initial weights of ANN. Trainlm, trainbfg, trainscg, traincgp traincgb, traincgf and trainoss learning algorithms have been used during the training of the network. Learning algorithms, transfer functions and number of neurons in the hidden layer, according to the best of the models developed is shown in table 4.

Table 4 The developed ANN models

Model no	Learning algorithm	Number of neuron in hidden layer	Transfer func.İn hidden layer	Transfer func. İn out layer	MBE(W/m^2)	RMSE (W/m^2)	R
1	trainbfg	28	logsig	Lineer	0,5113	10,8182	0,9771
2	trainbfg	18	logsig	Lineer	-0,1150	2,9495	0,9797
3	trainbfg	14	logsig	Lineer	-0,1169	5,0279	0,9787
4	trainbfg	24	logsig	Lineer	0,0123	3,1924	0,9796
5	trainbfg	30	logsig	Lineer	-0,1662	6,8756	0,9780
6	trainbfg	34	logsig	Lineer	0,3137	5,9796	0,9783
7	trainbfg	46	logsig	Lineer	-0,4566	9,9558	0,9773
8	trainbfg	4	tansig	Lineer	0,8176	6,1507	0,9783
9	trainbfg	10	tansig	Lineer	0,0245	3,6149	0,9793
10	trainbfg	16	tansig	Lineer	-0,2064	4,4629	0,9789
11	trainbfg	26	tansig	Lineer	-0,2388	6,8440	0,9781
12	trainbfg	32	tansig	Lineer	-0,0199	1,8917	0,9806
13	trainbfg	38	tansig	Lineer	0,7217	10,9121	0,9771
14	trainbfg	46	tansig	Lineer	-0,1635	5,2155	0,9786
15	trainbfg	50	tansig	Lineer	0,1025	7,1261	0,9780
16	trainscg	10	logsig	Lineer	-0,6243	13,5523	0,9767
17	trainscg	34	logsig	Lineer	0,6217	10,1680	0,9773
18	trainscg	4	tansig	Lineer	0,0139	1,8315	0,9807
19	trainscg	10	tansig	Lineer	-0,2112	12,1571	0,9769
20	traincgb	4	tansig	Lineer	-0,1224	3,1267	0,9796
21	traincgb	28	tansig	Lineer	0,0391	1,7932	0,9807
22	traincgb	36	tansig	Lineer	0,0006	2,7593	0,9799
23	traincgb	48	tansig	Lineer	0,0373	10,8742	0,9771
24	traincgb	18	logsig	Lineer	0,0226	6,4407	0,9782
25	traincgb	28	logsig	Lineer	-0,3687	10,3832	0,9772
26	traincgf	44	logsig	Lineer	-0,1637	12,9639	0,9768
27	traincgf	8	tansig	Lineer	-0,1527	4,5020	0,9789
28	traincgf	42	tansig	Lineer	0,6421	10,0440	0,9773
29	traincgp	10	tansig	Lineer	-0,1394	4,5163	0,9789
30	traincgp	34	tansig	Lineer	0,0158	3,6885	0,9793
31	traincgp	32	logsig	Lineer	-0,0459	12,9233	0,9768
32	trainoss	44	logsig	Lineer	0,5177	12,6459	0,9768
33	trainoss	6	tansig	Lineer	-0,0939	8,9504	0,9775
34	trainlm	12	tansig	Lineer	0,1768	3,2174	0,9796
35	trainlm	16	tansig	Lineer	-0,3124	1,4786	0,9899
36	trainlm	24	tansig	Lineer	0,0047	1,5942	0,9881
37	trainlm	28	tansig	Lineer	-0,0895	2,0861	0,9804

Table 4 (continue) The developed ANN models

38	trainlm	36	tansig	Lineer	0,1818	4,8224	0,9788
39	trainlm	40	tansig	Lineer	-0,2368	2,2365	0,9803
40	trainlm	44	tansig	Lineer	0,0598	2,5095	0,9801
41	trainlm	4	logsig	Lineer	0,1684	4,4591	0,9789
42	trainlm	10	logsig	Lineer	-0,2579	4,7216	0,9788
43	trainlm	16	logsig	Lineer	-0,1629	2,0144	0,9805
44	trainlm	28	logsig	Lineer	0,0478	3,0477	0,9797
45	trainlm	34	logsig	Lineer	-0,0941	1,7957	0,9807
46	trainlm	38	logsig	Lineer	0,1813	4,0297	0,9791
47	trainlm	42	logsig	Lineer	-0,0771	2,5495	0,9800
48	trainlm	48	logsig	Lineer	0,0075	1,8633	0,9807

When examined in table 4 calculating the correlation coefficient as the smallest of 0,9767, the largest correlation coefficient was calculated 0,9899. The largest correlation coefficient, the learning algorithm is trainlm, tansig transfer function in the hidden layer and the output layer transfer function is linear. The network in question, using 16 neurons in the hidden layer are developed. In the smallest correlation coefficient learning algorithm is trainscg, the transfer function in the hidden layer is logsig and the transfer function in the output layer is linear. The network in question is developed using 10 neurons in the hidden layer. In table 4, 1,4786 the smallest RMSE value W/m^2 is obtained, while the RMSE value of the largest 13,5523 W/m^2 was obtained.

The largest RMSE values, which learning algorithm is effective in obtaining trainscg, the transfer function in the hidden layer is logsig, the transfer function in the output layer is linear. The network in question developed by using 10 neurons in the hidden layer. Trainlm is the learning algorithm that for obtaining the smallest RMSE value, the transfer function in the hidden layer is tansig, the transfer function in the output layer is linear. The network is developed by using 16 neurons in the hidden layer. The models developed were also calculated MBE values. The MBE values in the table be positive or negative, it does not matter. The importance is that the values are close to zero. Best value in MBE is 0,0006 W/m^2 , the worst value of MBE is 0,8176 W/m^2. In the best value in MBE learning algorithm is traincgb, the transfer function in the hidden layer is tansig, the transfer function in the output layer is linear. Neuron in the hidden layer is 36. In the worst value of MBE learning algorithm is trainbfg, the transfer function in the hidden layer is tansig, the transfer function in the output layer is linear. There are 4 neurons in the hidden layer.

In the study, the datas of between the years 1980-2010, the ANN is trained the achievement is tested with the datas of between 2011-2013 years. The RMSE values are evaluated according to the success of a three-year study. In table 4, it is observed that the lowest RMSE value 1,4786 W/m^2 and it is the most successful developed model. The ANN method the most accurate results obtained from the model structure of ANN (10:16:1). This features of the model that provides the value 10 neurons in the input layer (month, latitude, longitude, height, soil temperature (5 cm), vapour pressure, relative humidity, average temperature, average maximum temperature and average minimum temperature) and there are 16 neurons in the hidden layer. There is 1 neuron (wind power density) in the output layer. The learning algorithm of the network is tarinlm, the transfer function in the hidden layer is tansig, the transfer function in the output layer is linear.

Obtained, depending on the model at the provincial level, MBE, RMSE and R values are calculated and shown in table 5.

Table 5 City-based MBE, RMSE, and R values.

Cities	**MBE(W/m^2)**	**RMSE(W/m^2)**	**R**

Sinop	0,5257	1,4874	0,9787
Rize	-0,5688	0,8506	0,8972
Artvin	0,3273	1,0048	0,9685
Kırklareli	-0,3320	0,8282	0,9969
Tekirdağ	-0,4424	0,9504	0,9895
Bolu	-0,3560	0,8420	0,9797
Kastamonu	0,0517	0,5725	0,9977
Tokat	-0,1439	0,9409	0,9997
Gümüşhane	-0,5850	0,8336	0,9991
Çanakkale	-0,3624	0,7544	0,9999
Bursa	0,0067	4,2642	0,9703
Van	-0,6140	2,3471	0,9971
Afyonkarahisar	-0,5810	1,2458	0,9893
Aksaray	-0,4324	1,1126	0,9968
Isparta	-0,4976	0,9532	0,9996
Muğla	-0,3458	0,7247	0,9934
Adana	-0,4064	0,8041	0,9993
Batman	-0,9634	1,4034	0,9881

The smallest correlation coefficient in the study is Rize with 0,8972 and the largest correlation coefficient is Çanakkale with 0,9999. The MBE values in the table be positive or negative, it does not matter. Best value in MBE is from bursa with 0,0067 W/m^2. The worst value of MBE is Batman with 0,9634 W/m^2. The best RMSE value is Kastamonu with 0,5725 W/m^2. The worst RMSE value is Bursa with 4,2642 W/m^2. The other locations of the correlation coefficients are between 0,8972 - 0,9999. RMSE values are between 0,5725-4,2642 W/m^2 the approach of MBE values are between 0,0067-0,9634 W/m^2. Wind power density is best estimated in Kastamonu with ANN method and the worst estimated in Bursa. The predicted and real data's change of average values monthly are shown in figure 6 and 7.

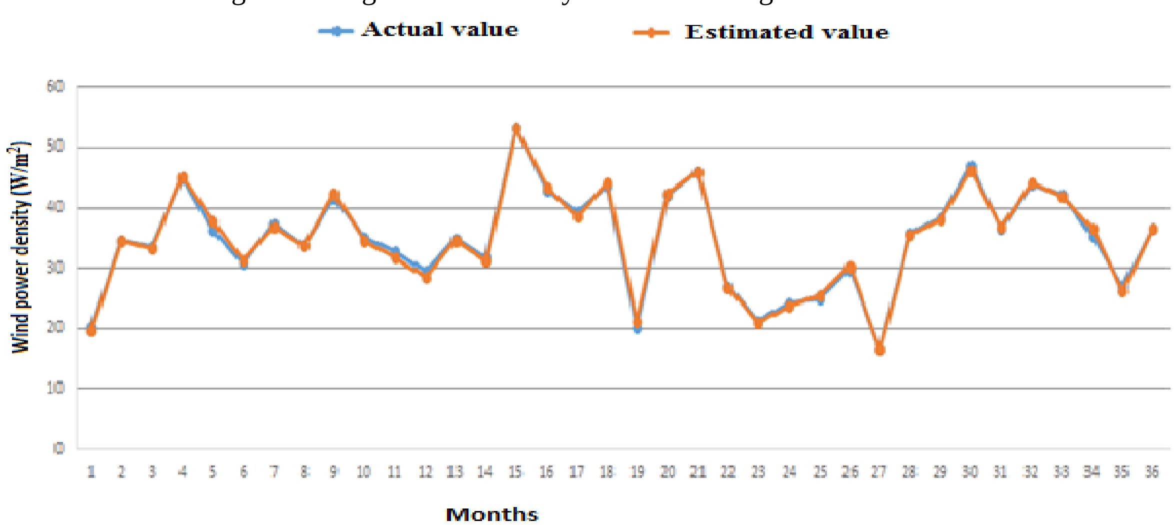

Figure 6: Power density values of Kastamonu location

It is seen that are compatible with each other the location of the real data in Kastamonu with the estimate of the data obtained from neural network method. Kastamonu location by month the difference between real data and predicted data is 0,021-1,437 W/m^2. Kastamonu location in December 2013, wind power density was estimated with minimum error. Kastamonu location in May 2011, wind power density was estimated with maximum error.

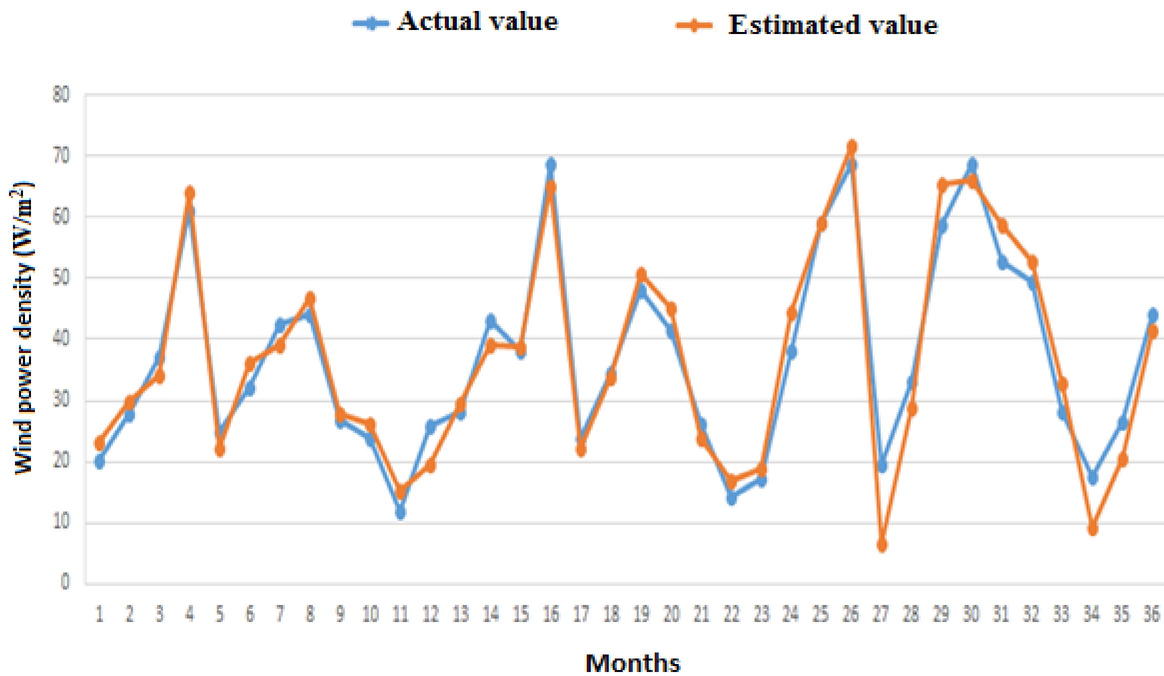

Figure 7: Power density values of Bursa location

The location of the Bursa in real data and the predicted data from the ANN method show that have not the same sensitivity about compatibility. Bursa location by month the difference between real data and predicted data is between 0,222-12,858 W/m^2. Bursa location in January of 2013, wind power density was estimated with minimum errors. Bursa location in March of 2013, wind power density was estimated maximum error.

5 CONCLUSION

Wind power density has been estimated by using meteorological data from 58 location with the help of ANN in the study. 40 Location is used to train Ann models, 18 locations were used to test the accuracy of the model. In this study, wind power density (W/m^2) will be obtained as output parameter while the month, the latitude and longitude, height, soil heat (5 cm), vapour pressure, relative humidity, the average temperature, the average maximum and minimum temperature which are obtained from meteorological stations of fifty-eight city centers of Turkey which representing different weather conditions are used as input parameters. In the training of model trainlm, trainbfg, trainscg, traincgp traincgb, traincgf and trainoss learning algorithms are used. The transfer functions used in the hidden layer are tansig and logsig'dir. The transfer function used in output layer is linear. As a result of the modeling performed (10:16:1) was observed that the model gave the best results. According to this model the correlation coefficient is 0,9899. The RMSE value is 1,4786 W/m^2, the MBE value is predicted as 0,3124 W/m^2. This model of residential location, depending on the location of Kastamonu gives the best results, the worst result in the location of the Bursa statistically. As a suggestion, development and testing of the accuracy of different combinations of input parameters by neural network models has been proposed.

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