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WindSpeedandDirectionForecastingUsing Artificial Neural Networks And Autoregressive Integrated Moving Average Methods

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ABSTRACT:*In this paper, Feed Forward Back Propagation Neural Network method based in Artificial Neural Networks (ANN) and Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) method are used to forecast the average wind speed and wind direction.We take wind speed and wind direction data between years 2014, January and 2017, December from Meteorology in Samsun (Turkey). Feed Forward Back Propagation Neural Networkand ARIMA methods are compared in terms of mean square error (MSE) criteria. We see that Feed Forward Back Propagation Neural Network method gives better solution in MSE than ARIMA method. We forecast wind speed and wind direction for last three months of 2018.*
KEYWORDS:*Feed forward back propagation neural network, ARIMA,Forecasting,Wind speed, Wind direction****.***

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I. INTRODUCTION

Traditional sources of energy, such as oil, coal and natural gas, harm the environment and human health.Renewable energy sources such as wind, solar, biomass, hydroelectric and geothermal can provide sustainable energy services based on the use of existing resources continuously.Therefore, renewable energy sources plays an important role in reducing dependence on traditional energy sources [7].

Wind energy has emerged as one of the safest, cleanest and fastest growing renewable energy in the recent years [12].There may be three main reasons of strong growth in wind production capacity worldwide: 1. Increasing public awareness on climate change and environmental issues; 2.Awareness about depletion of oil and gas reserves and the predicted global peaking of oil production; 3. the strong growth of wind power is due to improvements in wind turbine technologies resulting in lower costs [9].

Today, important studies have been carried out to estimate wind speed. The methods used in these studies can be divided into four categories: Physical modeling methods, Hybrid methods, Time Series models and Artificial Neural Networks (ANNs)[18]. Physical models forecast wind speed using physical parameters such as temperature, pressure. Since these methods require large computational time, they are not suitable for short-term wind speed estimation.Hybrid methods are used widely to forecast wind speed based on historic data. These methods involves the combination of physical and statistical techniques [12].Time series models forecast wind speed through analyzing historical data. These models are autoregressive (AR), Algebraic Curve Fitting (ACF), Autoregressive Moving Average (ARMA), ARMA with exogenous inputs (ARMAX), Autoregressive Integrated Moving Average (ARIMA)etc.[12;18].ANNs are a useful tool for modelling and forecasting the wind speed. They are also an alternative technique to overcome complex problems. They can learn examples and after training, can perform forecast and generalization at high speed[5;22].The advantages of the ANN is to learn the relationship between input and output without any mathematical formulations [12].More and Deo (2003) present the technique of neural networks in order to forecast daily, weekly and monthly wind speeds at two coastal locations in India. They find that the neural networks forecasting is found to be more accurate than traditional time series model of ARIMA.Torres et al. (2005) use the ARMA models to forecast the hourly average wind speed in Navarre (Spain).They showed that ARMA models outperform in RMSE.Palomares-Salas et al.(2009) compare ARIMA and the back propagation neural networks modelsfor time-series forecast for wind speed data.When analyzes are made with the data obtained from a unit located in Southern Andalusia,they have shown that ARIMA models have given a few very similar results.Ucar and Balo (2009) evaluate the monthly and yearly wind characteristics for Erzurum, Elazığ, Bingöl, Kars, Manisa and Niğde in Turkey.Fadare (2010)suggests ANN model to forecast wind speed in Nigeria. It predicts monthly wind speed range and annual mean wind speed.Akpınar (2013) has statistically analyzed wind power potentials with data taken from six meteorological stations at the North Eastern of Turkey.Velo et al. (2014) use neural networks method for determining the annual wind speed. They also use multilayer perceptron with three layers as neural network and the supervised learning algorithm used is backpropagation. Chang (2014) presents a review on forecasting of wind speed and power under different time-scalesand gives major methods of wind forecasting.Cadenas et al. (2016) compare the impact of the various meteorological variables on the performance of the multivariate model (nonlinear autoregressive exogenous artificial neural network-NARX model) of wind speed prediction with respect to the high performance univariate linear model (ARIMA). They showed that NARX model give better results the ARIMA model.Ho(2016) shows the prospect of wind energy development in Malaysia. It gives past andpresent wind studies. It also gives the Global wind energy development.Noorollahi et al. (2016) present the prediction of wind speed in both temporal and spatial dimensions using ANNs in Iran.

In this study, we use ARIMA and Feed Forward Back Propagation Neural Networkmodels to forecast wind speed and wind direction for Samsun (Turkey). The rest of this paper is organized as follows: In Section 2 and Section 3 we present ARIMA and Artificial Neural Networkmodel, respectively. In Section 4,the results of the analyses are given. Finally, we give Conclusion in Section 5.

II. ARIMA MODEL

In case of stationary time series, one of the models of Autoregressive Model (AR), Moving Average Model (MA) and Autoregressive and Moving Average (ARMA) models is suitable for series. However, in practice, most of time series are nonstationary. That's why, the difference process is applied to make stationary.This process is called as Autoregressive Integrated Moving Average (ARIMA) model that is also known Box-Jenkins [2] method.

If autoregressive level,p, moving average level,q, and d times difference import process are applied, the model is called ARIMA (p, d, q)that is generally formulized in Equation (1).

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots + \phi_p z_{t-p} + \delta + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \theta_q a_{t-q} \quad (1)$$

In Equation (1), $z_t, z_{t-1}, z_{t-2}, \dots, z_{t-p}$ are d-order difference observations, $\phi_1, \phi_2, \dots, \phi_p$ are coefficients for d-order difference observations, δ is constant value, $a_t, a_{t-1}, a_{t-2}, \dots, a_{t-q}$ are error values, $\theta_1, \theta_2, \dots, \theta_q$ arecoefficients for errors.

Algorithm 1: ARIMA model-building algorithm or Box-Jenkins process is given as below:

Step 1: Model Identification:The series is stationary or not can be determined by the graph of Autocorrelation Function (ACF). If a graph of ACF for the time series values cuts off fairly quickly or dies down fairly quickly, the time series can be considered stationary. If a graph of ACF dies down extremely slowly, the time series can be considered non-stationary. When the series is not stationary, the original series is transformedto differenced series for obtaining stationary series.ARMA model is obtained by using differenced series.

Step 2: Model Estimation:Parameters for selected model in Step1 are estimated.

Step 3: Model Checking: The model must be checked for adequacy by using graphs of ACF and Partial Autocorrelation Function (PACF) or must be checked obtainingLjung-Box Q statistic. In the test, if the p-value associated with the Q statistic is small than α(p-value $<\alpha$), the model is considered inadequate. In this case, go Step 1 and determine new model.

Step 4: Model Selecting:One or one more than tentative models can be determined. In this case, for selecting best model, model performance criteria such as Akaike Information Criteria (AIC), Schwarz Information, Mean Square Error (MSE), Root Mean Square Error (RMSE) etc. are used. In this study, MSE and RMSE are used for selecting best model and they are given in Equation (2) and Equation (3).

$$\mathbf{MSE} = \frac{1}{N}\sum_{t=1}^{N}(\mathbf{d_t} - \mathbf{z_t})^2 \quad (2)$$

$$\mathbf{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\mathbf{d_t} - \mathbf{z_t})^2} \quad (3)$$

Where, $\mathbf{N}$ is the number of forecasting periods, $\mathbf{d_t}$ is the actual observation at period t, and $\mathbf{z_t}$is the forecasting at period t.

Step 5:Forecasting with the Model:For one period or several periods into the future with the parameters are forecasted by using selected best model [14].

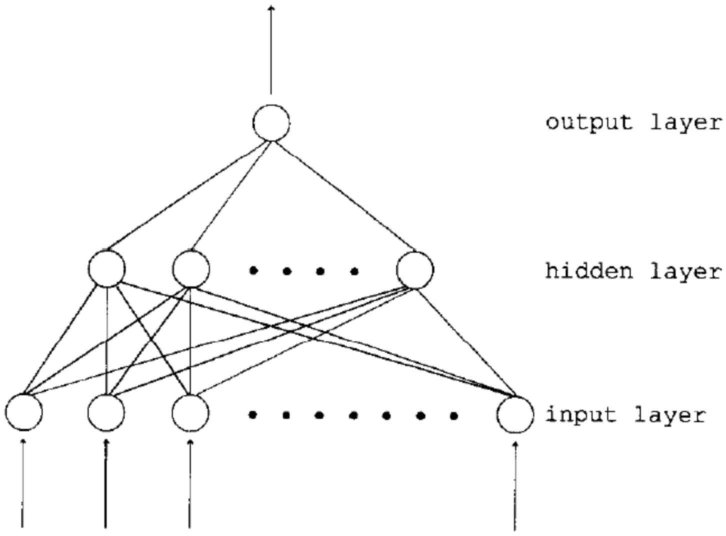
III. ARTIFICIAL NEURAL NETWORK (ANN)

Traditional models like ARIMA are commonly used in linear time series. However, time series may not be linear all the time in practice. In recent years, artificial neural network, which is one of the artificial intelligence techniques especially used to estimate nonlinear time series, is used more frequently. Artificial network is inspired by human brain and is a processor which includes studies about computer learning. This processor, which is based on calculating human brain, is a highly, extremely complex nonlinear parallel processor [6].

ANN does not need any pre-knowledge about input and output variables. It can form nonlinear models without having any assumptions [10]. Input values and output values correspond to these input vales are given to the network and network is learnt the relation between input and output is learned in network. Thereby training of networks is carried out. This method is a supervised learning method and is preferred frequently [6]. In this study, one of the supervised learning algorithm, Back Propagation Learning Algorithm, which is used frequently in literature, and as a network structure, Forward Feeding Network is used.

Back-propagation algorithm and Forward-Feeding Networks

Forward feeding networks allow for one-way proceeding from input to output. This means that there are no backward feedings. A typical ANN consists of an input layer, usually one or two middle layer (hidden layer) and an output layer. In each layer, there exist neurons (nerve cells) that vary in number according to interested problem [23]. Forward feeding networks are networks which signals are transmitted from input layer to output layer in one way as shown as below.



Forward Feeding Network Structure [19]

In ANN, effect of inputs are different from those for outputs are different and determined using weights. While data are transmitted through one layer to other, each data is multiplied by its weight. In back propagation learning algorithm, training of network is based on the principle of minimization of error by changing these weights. Levels of this algorithm are proceeding of information from input layer to output layer, calculation and back propagation of errors in outputs and changing of weights based on the error propagated backward. This algorithm finds the weights that are going to produce the best solution for given training set. This process of changing weights is based on steep descent rule and Newton method [11]. Training of network is carried out using minimization of error function (4). t_s and o_s are real output and output produced by network respectively. The amount of change is obtained differentiating of this function.

$$E = \frac{1}{2}\sum_{s=1}^{S}(t_s - o_s)^2 \qquad (4)$$

Algorithm 2: MLP algorithm is given as below:

<u>Step 1:</u> Samples are collected beforehand for the case which we want network to solve. Then structure of network is determined. Input, number of hidden layers, number of units in this hidden layers and number of output units are determined. Parameters like learning coefficient, momentum coefficient, activation function are determined.

Step 2: Initial values of weights are assigned randomly and stopping criterion is determined. Until stopping criteria is reached, step 3-10 is repeated.
Step 3: For each input-output in training set, step 4-9 is repeated.
Step 4: Samples in training set are shown to network. Inputs are transmitted from input layer to hidden layer.
Step 5: During learning, forward calculations are carried out using absolute input and activation function and sent to output layer.
Step 6: Absolute input go through activation function in output layer and produces its own output.
Step 7: For each output, errors are calculated. Therefore connections, which connect hidden layer to output layer, and amount of change in threshold term weights are calculated.
Step 8: Absolute error input for each hidden layer neuron is calculated. Error information value for each hidden neuron is obtained using absolute error input. In this way, the amount of change of threshold terms and connections that connects input layer to hidden layer is calculated.
Step 9: Weights are changed for each output neuron and hidden layer.
Step 10: It is checked whether stopping criteria is reached or not [16].

IV. RESULTS AND DISCUSSION

In this study, average daily “wind speed” and “wind direction” data between 01.01.2014-31.12.2017 taken from Samsun 10th Meteorological Service are used. Time series plots for wind speed and wind direction data belonging to each year and the data taken from last 3 months period of years between 2014 and 2017 are obtained using “IBM SPSS 22” package program and given in Figure 1-10. When the time series plots of wind speed and wind direction are examined, it is generally seen that the increase and decrease are following each other, but these increases and decreases are not periodic. Also, it is seen that there exists a low level increasing or decreasing trend.

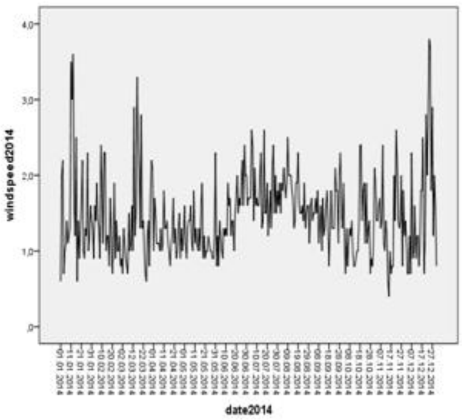


Fig.1. Wind speed time series, 2014

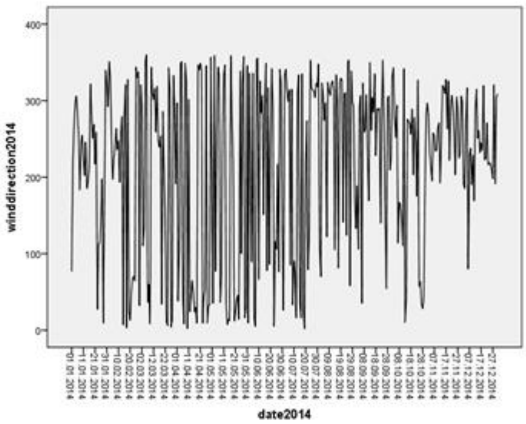


Fig.2. Wind direction time series, 2014

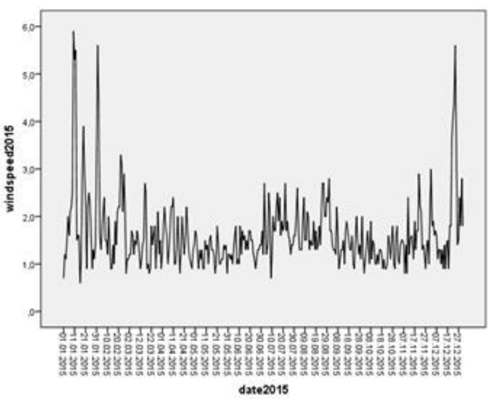


Fig.3. Wind speed time series, 2015

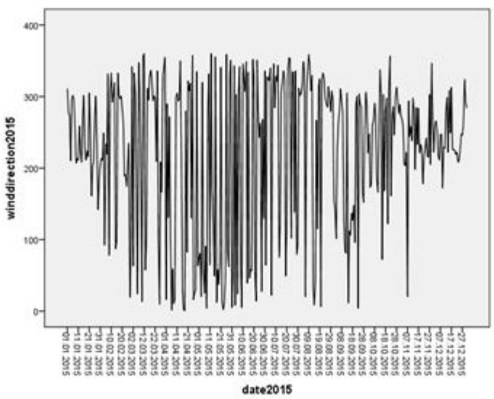


Fig.4. Wind direction time series, 2015

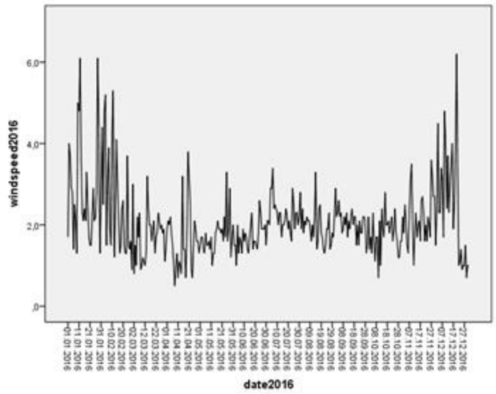


Fig.5. Wind speed time series, 2016

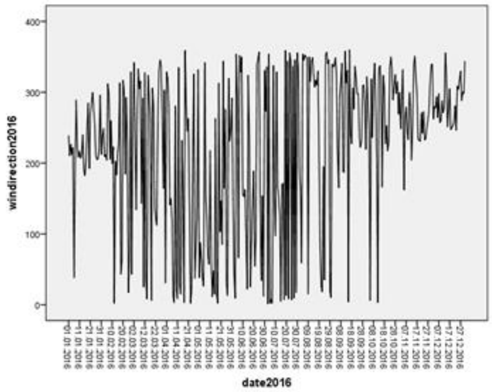


Fig.6. Wind direction time series, 2016

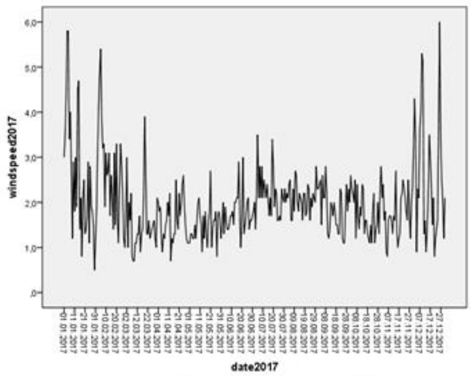


Fig.7. Wind speed time series, 2017

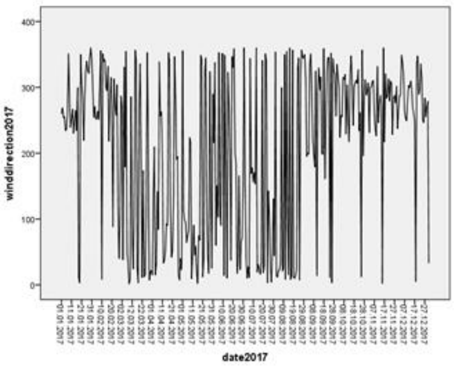


Fig.8. Wind direction time series, 2017

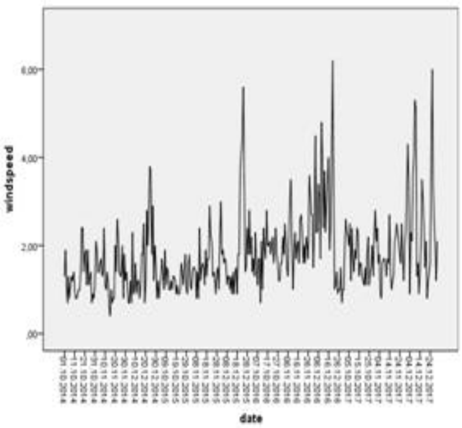


Fig.9. Wind speed time series for the last 3 months, 2014-2017

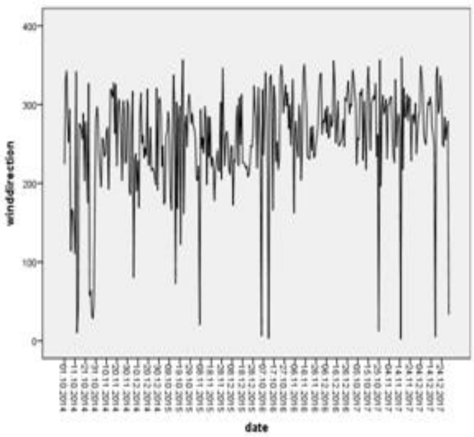


Fig.10. Wind direction time series for thelast 3 months,2014-2017

In the application, Box-Jenkins ARIMA model, which is commonly used in estimation of time series, and Feed Forward Back Propagation Neural Network, which is also commonly used in estimation of times series, is one of the artificial intelligence methods, and also is able to form both linear and nonlinear models, are used. Wind speed data for years between 2014-2017 and wind speed and wind direction data for last 3 months of years between 2014-2017 are modelled according to period observations using ANN. The best ANN topology is chosen according to MSE criteria. Also, wind speed and wind direction data for the last 3 months of years between 2014-2017 are modelled using ARIMA. The best ARIMA model is chosen according to RMSE. Both of the obtained models are compared according to their MSE criteria and based on chosen method, wind speed and wind direction of last 3 months of 2018 is estimated. Analyses are conducted using IBM SPSS 22 and Matlab 2015 package programs.

It is seen from time series graphs that the data are not stationary but also there is no seasonality when modelled using ARIMA. The wind direction data for the last 3 months of years between 2014-2017 are modelled using automatic model selection and the best model is found ARIMA (1,1,1) with the best RMSE=64,760. To test the lack of fit of the model, Ljung-Box Q test is used and the model is accepted for wind direction in the 95% confidence level (p=0,067). Time series plot of the estimation and the real values of wind direction are given in Figure 11 and it is seen that estimations and observations are compatible.

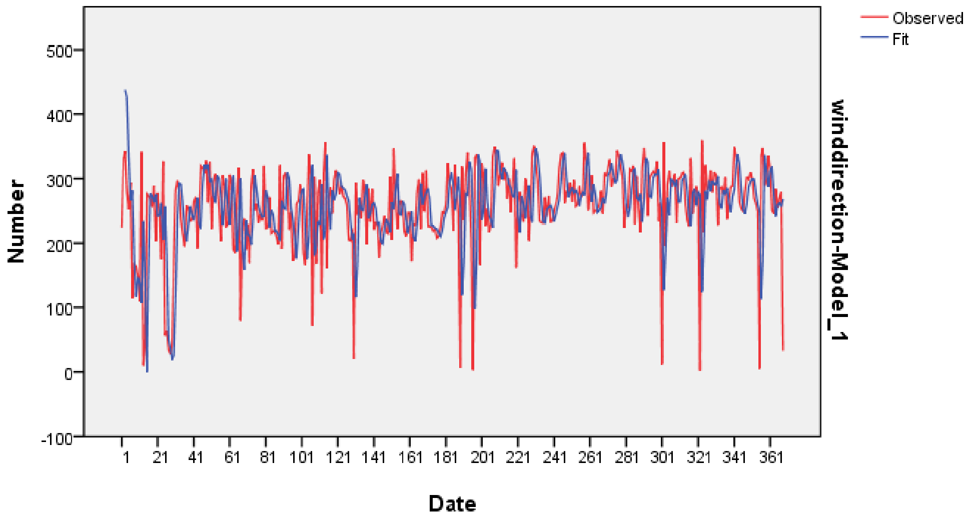


Fig.11. Time series plot of estimation and real values for wind direction

Automatic model selection is carried out for ARIMA modelling of wind speed and ARIMA (1,2,1) model with RMSE = 0,724 is chosen as the best model. To test the lack of fit, Ljung-Box Q test is used and the chosen model is accepted for the wind speed in 95% confidence interval level (p=0,230). Time series plot of estimation and real data values of wind speed is given in Figure 12. In this plot, it is seen that observations are compatible.

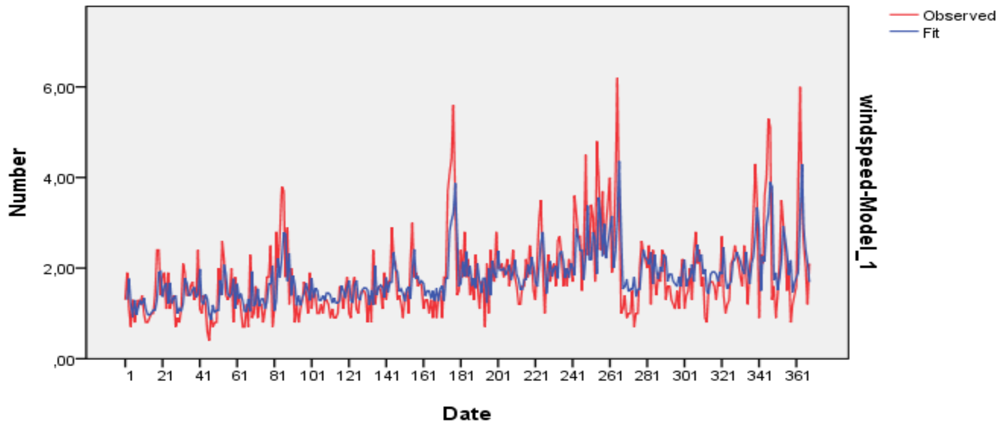


Fig. 12. Time series plot of estimation and real values for wind speed

Before modelling with ANN, wind speed and wind direction data for years between 2014-2017 are used. 70% of the data is used as training data, 15% as validation data and 15% as test data in ANN. Levenberg-Marquardt learning algorithm is used as learning algorithm. As activation function, tansig function is used. Thus the data is normalized using Equation (5).

$$X^* = \frac{X+\min X}{\max X - \min X} \tag{5}$$

Maximum iteration number and repeat number are taken as 1000 and using trial and error method, the best structure is determined with 8-9-10-11-12 hidden layer neuron numbers. In order to prevent Levenberg-Marquardt algorithm to converge to local minimum, program is run 100 times for each topology and the best MSE value is determined and given in Table 1. According to this, the best ANN topology is determined as (3-10-1) with the lowest MSE value.

Table 1. MSE values according to number of hidden layer neurons for wind speed data for years between 2014-2017.

Number of hidden layer neurons	MSE
8	0,0150
9	0,0159
10	**0,0127**
11	0,0140
12	0,0132

Wind speed and wind direction data for the last 3 months of years between 2014-2017 are modelled using Feed Forward Back Propagation Neural Network. The best model is found using MSE criteria, 1000 repeats, 1000 maximum iteration number and hidden layer neuron number 8-9-10-11-12. The best ANN topologies for wind speed and wind direction are given in Figure 13 and Figure 14. According to these, topology (3-11-1) and MSE = 0.0422 is chosen for wind direction and topology (3-10-1) and MSE = 0.000739 is chosen for wind speed. Also, when we look at regression values, it is seen in Figure 15 and Figure 16 that chosen models for wind speed and wind direction are both good.

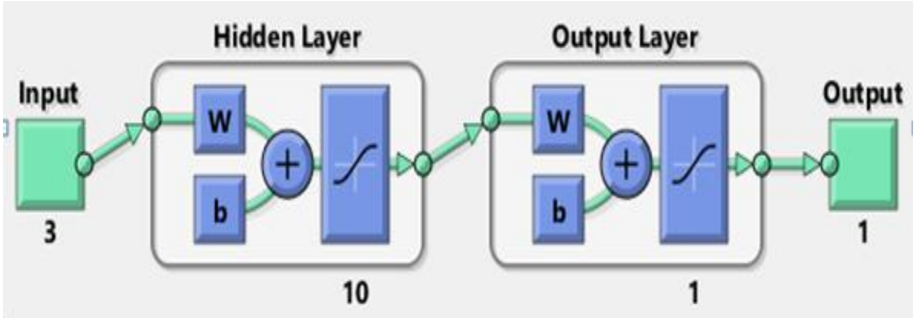


Fig. 13. The Best ANN topology of the wind speed data for the last 3 months of years between 2014-2017

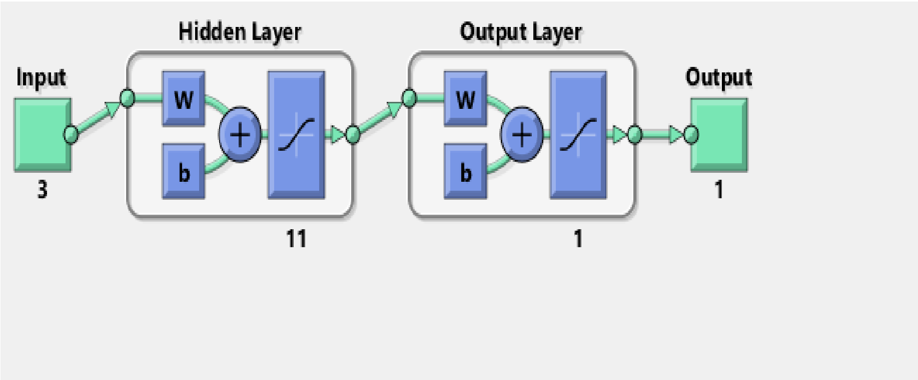


Fig. 14. The Best ANN topology of the wind direction data for the last 3 months of years between 2014-2017

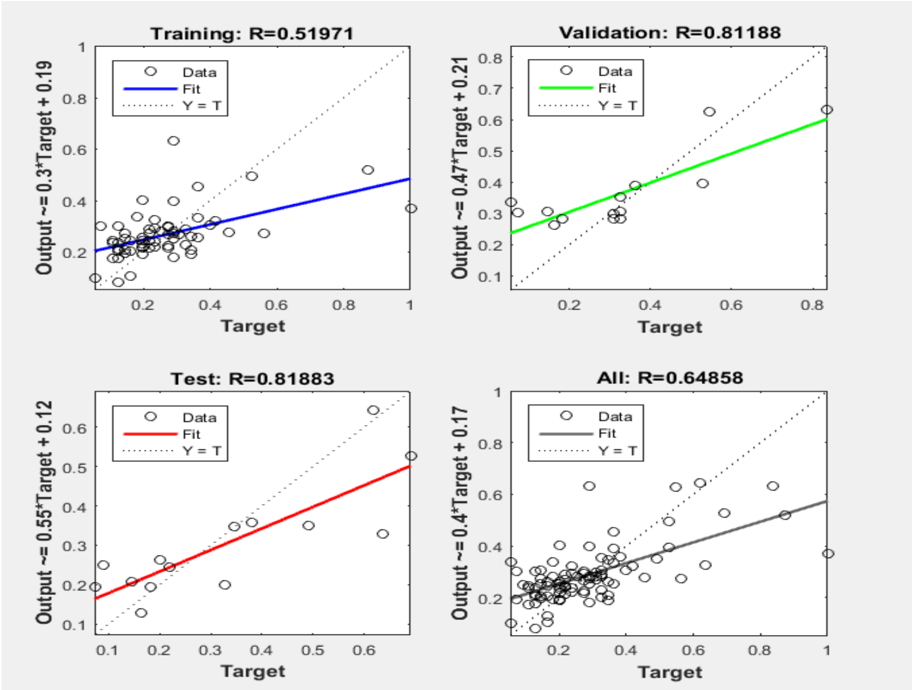


Fig. 15. Regression graphs of wind speed data for the last 3 months of years between 2014-2017

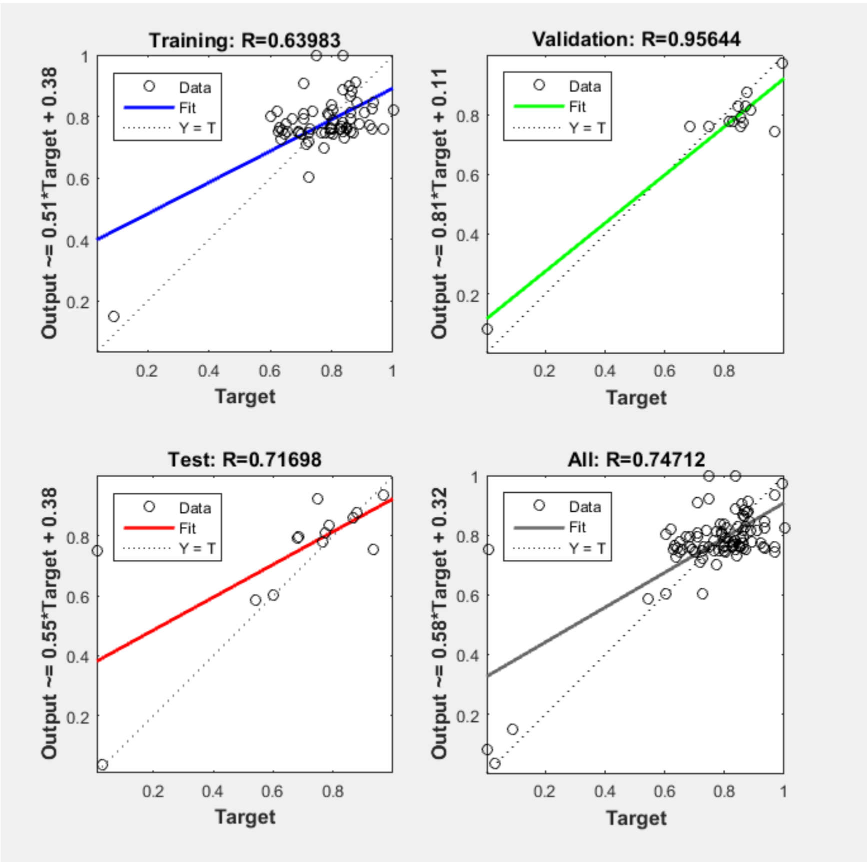


Fig. 16. Regression graphs of wind direction data for the last 3 months of years between 2014-2017

Obtained ARIMA and ANN models are compared for the data for the last 3 months of years between 2014-2017. Normalized data is denormalized and transformed into original data again for ANN. This way, it is seen that ANN gives better results as the wind speed and wind direction MSE values are found as 0.0149 and

0.276 respectively. Using the chosen ANN model, wind speed and wind directions for the last 3 months of 2018 are estimated. Obtained results are given in Appendix.

V. CONCLUSION

In this study, average daily "wind speed" and "wind direction" data taken from Samsun 10th Meteorological Service in the central Black Sea region of Turkey are used. For each year, time series plots of wind speed and wind direction are obtained. When these plots are examined, it is seen that series are not stationary and there are slightly increasing or decreasing trends. It is also seen that there is no seasonality in the series. In order to estimate the time series, Feed Forward Back Propagation Neural Networkand Box-Jenkins ARIMA methods are used.

While modelling using ARIMA, wind direction data for the last 3 months of years between 2014-2017 is modeled by automatic model selection and the best model is obtained as ARIMA (1,1,1) with RMSE=64,760. For ARIMA model of the wind speed, the best model is obtained as ARIMA (1,2,1) with RMSE=0.724. The models chosen for wind speed and wind direction are accepted by Ljung-Box Q test. When plots for wind speed and wind direction are examined, it is observed that the real values are compatible with the estimates.

The best ANN topologies for the wind speed and the wind direction are topology (3-10-1) with MSE=0.000739 and topology (3-11-1) with MSE=0.0422 respectively. Also, when regression graphs are examined, it is seen that the chosen models for both wind speed and wind direction are good in test data. The best models obtained for each method are compared according to MSE criteria. For wind speed and wind direction, it is observed that ANN method gave better results compared to ARIMA model with MSEs 0.0149 and 0.276 respectively. Wind speed and wind direction estimations for the last 3 months of 2018 are estimated using the chosen ANN models.

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APPENDIX: ForecastingValues of WindSpeedandWindDirectionfortheLast 3 Months of 2018 in Samsun.

Date	Forecasting Values of Wind Speed	Forecasting Values ofWindDirection
1.10.2018	1,681959964	286,6821352
2.10.2018	1,268955603	359,9980372
3.10.2018	1,281866052	280,3538761
4.10.2018	1,464243561	273,389349
5.10.2018	1,934252156	6,89570088
6.10.2018	1,375368457	204,2366842
7.10.2018	2,228452982	276,5743858
8.10.2018	1,71701298	38,95081362
9.10.2018	2,021285489	359,9999723
10.10.2018	1,143030943	277,1222605
11.10.2018	1,918527675	265,0247402
12.10.2018	1,994675842	86,11138428
13.10.2018	1,26262856	267,1948451
14.10.2018	1,279069376	359,9991775
15.10.2018	2,047461107	17,76224604
16.10.2018	2,00174381	320,3992366
17.10.2018	2,046477423	301,3038891
18.10.2018	2,033325739	72,83251598
19.10.2018	1,991838479	286,5917237
20.10.2018	2,051022923	287,1931668
21.10.2018	1,995549002	298,1252776
22.10.2018	1,987135747	352,8433634
23.10.2018	1,853988032	329,9320501
24.10.2018	1,40363896	357,1815533
25.10.2018	2,012715283	325,1825735
26.10.2018	2,047529733	352,8083269
27.10.2018	2,279959891	281,9784571
28.10.2018	1,819061055	23,25082694
29.10.2018	2,196993703	83,22104491
30.10.2018	1,266279677	56,70504966
31.10.2018	1,502332806	281,7853138
1.11.2018	1,701019944	91,35557494
2.11.2018	1,269932553	274,5127755
3.11.2018	1,982137529	240,4991922
4.11.2018	2,015703613	359,9996348
5.11.2018	2,240378569	269,5991751
6.11.2018	2,089073329	292,6664825
7.11.2018	2,035788097	336,4313796
8.11.2018	1,985119654	278,9732751
9.11.2018	2,22536319	278,7435997
10.11.2018	1,981276321	271,9002698
11.11.2018	5,174461274	271,6307151
12.11.2018	2,037505601	289,3818499
13.11.2018	2,04246867	276,9333888
14.11.2018	1,46273519	359,9839029
15.11.2018	2,106712011	322,3591903
16.11.2018	2,00950784	359,999994
17.11.2018	2,323421167	273,7077064
18.11.2018	1,992631724	276,2765219

19.11.2018	2,070260477	269,4273781
20.11.2018	1,498774301	269,336112
21.11.2018	3,151921423	310,2140587
22.11.2018	2,106071881	268,4246097
23.11.2018	2,031531882	291,7673543
24.11.2018	1,992013112	272,9608547
25.11.2018	2,071320368	275,5751517
26.11.2018	1,295262389	271,6095257
27.11.2018	2,065068209	281,968255
28.11.2018	1,996064856	285,4149488
29.11.2018	2,022691403	15,21024144
30.11.2018	1,323914224	89,26235282
1.12.2018	4,147587413	359,2440372
2.12.2018	5,835091546	276,6591996
3.12.2018	5,999999999	283,1579401
4.12.2018	2,152593381	115,7355904
5.12.2018	1,393224727	350,6728204
6.12.2018	3,952834134	297,8206715
7.12.2018	5,999999674	282,419477
8.12.2018	1,565236729	268,6736333
9.12.2018	5,999945353	267,8498325
10.12.2018	5,999976062	288,738926
11.12.2018	1,98379171	291,4173757
12.12.2018	2,19117757	282,3796492
13.12.2018	1,983625887	359,9999905
14.12.2018	2,004233322	359,9475388
15.12.2018	2,116580443	282,626057
16.12.2018	5,999999996	274,4370908
17.12.2018	1,514615227	278,00968
18.12.2018	1,26070458	288,1846595
19.12.2018	3,414440278	293,1370166
20.12.2018	3,055845251	293,7065845
21.12.2018	0,500000016	277,5288791
22.12.2018	0,85283042	291,2457262
23.12.2018	0,514448573	294,0316033
24.12.2018	0,500733727	358,2890431
25.12.2018	0,722532481	288,3670993
26.12.2018	1,478801692	254,0335473
27.12.2018	1,532004273	350,2657597
28.12.2018	2,602818094	276,6728707
29.12.2018	1,01787642	278,8716846
30.12.2018	5,989983499	266,1543709
31.12.2018	1,593107242	326,4822599

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