International Journal of
Intelligent Systems and Applications in Engineering
ISSN:2147-6799 www.atscience.org/IJISAE
Advanced Technology and Science
Original Research Paper

Wind Power Forecasting For The Province Of Osmaniye Using Artificial Neural Network Method

Bülent YANIKTEPE *[1], Sakir TASDEMİR [2], A.Burak GÜHER[3], Sultan AKCAN[1]

Abstract: Although wind energy at certain intervals and random in nature, today it is one of the commonly utilized alternative energy source in the world. Because of sustainability and environmentally-friendly energy source, countries increasingly benefit from wind energy. Several estimation methods are applied in the determination of a region's wind energy potential. Today, one of the most commonly used prediction methods is artificial neural network (ANN) method. In this study, Estimation of wind power in Osmaniye district was investigated in method with artificial neural network (ANN) using data from meteorological measurement stations from the meteorological measurement device at the campus of Osmaniye Korkut ATA University. In order to give the best values of prediction results, several methods increasing the impact on output of different models for the input variables were investigated.

Keywords: *Wind Power, Prediction, Artificial Neuron Network.*

1. Introduction

In recent years, the importance of the renewable energy sources grows worldwide. The reasons of this growth are that the sources named as fossil fuel are exhaustible, and they have negative effects on environment. Especially as a result of the gradual increase in greenhouse gases like Carbon dioxide and Methane which have direct impact on global warming, our environment is affected negatively [1]. Although there are some saving studies worldwide considering the issue of fossil fuels in energy usage, these are not enough. Because the energy need of people and corporations increase gradually. To avoid from this deficiency, renewable energy sources are used in recent years. Renewable sources are becoming one of the leading actors all around the world in the production of electric energy. In a short time, they are foreseen to become alternatives for power plants running fossil fuels, and they will become more widespread.

When the renewable energy types are considered, the first ones to remember are wind and sun. They are also the energy sources on which the highest number of research and scientific studied are conducted. The popular method to use to produce electric energy by using solar energy is to make use of radiation. While producing energy from the wind; first, the energy turns into kinetic energy, then into electric energy. The velocity of the wind is one of the most important parameters in the production of energy from the wind. For this reason, it is a must to measure both the velocity and potential of the wind in a certain area before launching a wind power plant [2]. For this reason, the researchers developed methods to predict the wind potential in recent years. These prediction methods aim at measuring the wind power of a certain area or predicting it by using certain inputs. As it is shown in (Equation.1) the power of the wind is stated as a mathematical function in which it equals the cube of the wind velocity [3].

$$\text{Power}=\frac{1}{2}\,\rho A v3 \qquad (1)$$

Equation.1 according to the formula, it is seen that the calculated or predicted value of the wind velocity grows exponentially. Hence, the wind velocity acts as a defining factor in power calculation more than other variables in the formula. This velocity variant is taken into account in the detection of establishing wind power plant into a certain place and of the identification of their performance [3].

When we have a look at the recent studies, it can be seen that the methods used to predict the velocity and power of the wind are artificial intelligent based (ANN, Fuzzy Logic, Support Vector Machine) methods. The commonly used one is the ANN method. The studied conducted by using this method are indigenous to a definite area. A model can create using the data chosen such as the latitude, longitude, elevation, and average of wind velocity (yearly, monthly, daily, hourly), their minimum and maximum velocity values, distance to the sea level, air pressure, density and temperature. These chosen data are defined as input variants in the model. These input variants are chosen by trying as many different methods as possible to do the best predictions. There are many layers in these models. The input and output are the main layers. There are one or more hidden layers between them. There are a few neurons in each layer. When a model has been created, some of the data is used for education (learning) while some of it is used for test (prediction). The aim is to predict the wind velocity and power belonging to a certain area as output. Besides, by making use of Box-Jenkins statistical model (ARIMA-Autoregressive Integrated Moving Average) which is used to predict seasonal or non-seasonal time periods, fuzzy logic methods (ANFİS-Adaptive Network-Based Fuzzy Inference System), Genetic Algorithm based models; and by creating a hybrid or a different model with ANN, it can be used both while predicting the wind potential and while comparing the predictions. [3-11].

[1] *Osmaniye Korkut Ata University, Energy Systems Engineering, Osmaniye, Türkiye*
[2] *Selçuk University, Computer Engineering, Konya, Türkiye*
[3] *Osmaniye Korkut Ata University, Informatics Department, Osmaniye, Türkiye*
* *Corresponding Author: Email: byaniktepe@osmaniye.edu.tr*
Note: This paper has been presented at the 3rd International Conference on Advanced Technology & Sciences (ICAT'16) held in Konya (Turkey), September 01-03, 2016.

In our study, the short term wind power prediction with ANN is aimed using the data taken from the meteorological station which was mounted at the Campus of University of Osmaniye Korkut Ata. The data from the first half of 2013 is used (between January and June). With the aim of evaluating the prediction performances of a model created with ANN, three different statistical indicators are used such as coefficient of determination (R^2), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The power plant potential of Osmaniye province for the first six months has been estimated using these indicators.

2. The Structure of Artificial Neural Network

The artificial nerve nets were discovered in the second quarter of the 20. Century and they started to be used. It is an informatics technology developed by inspiring the data processing capacity of human brain. Generally it was emerged out of the inspiration of human brain and operation of central neural system. The principle of biological neural system is imitated with ANN. These nerve cells include neurons, and they create neural networks by binding themselves in different kinds. The created nets carry the potential of learning, remembering and finding relationship between data. In other words, they can find a solution to those problems requiring human beings' thinking and natural observation abilities. The created nets were successfully used in different disciplines such as mathematics, engineering, medicine, meteorology, economics, computer and electronic fields [9-12].

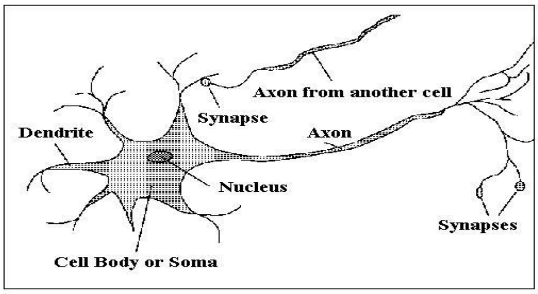

Figure 1. Biological nerve cell structure of human.

With the entrance and proliferation of computer systems into human life, the model in (Figure.1) is used for the problems seeking for attention. A mathematical model trying to imitate human brain cell's operation can be defined among artificial neural networks. It has many advantageous aspects as it can be paralleled, generalized, and as it is easy to analyze and design. One of the most important features of it is its capacity to derive as much information as possible without the need to any assistance. A mathematical model of an artificial neural network and its working principle are given in (Figure.2). This structure is the process of imitating the human brain and the process of transferring learning to the computer based systems [12].

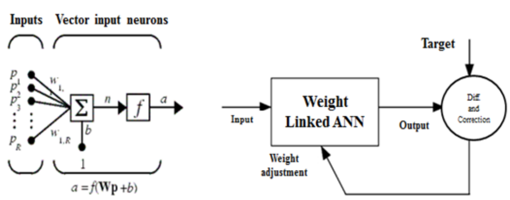

Figure 2. ANN Mathematical Model. (P) İnput Vectors, (W) Weight Matrix, (n) Total Net Entry, (a) Output of Cell, (f) Activation Function.

3. Wind Data

The data used in our study has been provided from active meteorological stations at Osmaniye Korkut Ata University. The coordination of the station is 37.05 north and 36.14 east. It is 120 meters above the sea level. The distance from the sea is 20 kilometers. The experimental date used in the study was measured by using Vantage Pro2 meteorological measuring device. This device has been planted in the elevation of 20 m. [13].

With the aim of predicting short term wind power, Wind Velocity, Temperature And Humidity data of 2013's first half (January-June) has been taken. The hourly averages of the data have been measured as the station measures the data every 5 minutes. The wind power of each input variables have been measured by using the power formula in (Equation.1) as a part of emerging results. At the same time the normalization formula given in (Equation.2) has been used to capture more accurate results in models formed with ANN.

$$Xn = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (2)$$

It is a fact that the using ANN models in measure values without doing anything gives worse performance results then using it after normalization. This situation is quite apparent in whether forecast. Min-Max normalization method is a way which provides linear normalization for data between 0 and 1. It is used commonly. It defines minimum value while describing the maximum related data's possible peak value [14].

4. The Generated Model and Validation Methods

The best models have been tried to be created in order to estimate the wind power with MATLAB, using input variables (Wind Velocity, Temperature and Humidity). Multilayer Feed-Forward (FFMLP) Backprop Network has used because of the best performance in the developed model. TRAINLM is chosen as the education function, and TRAINGDM is chosen as the learning function in this network. As an activation function, LOGSIG is used in the first layer, and TANSIG is used in the second one. Neurons are recommended to use twice as much as for the input variables at the generated hidden layer of ANN model [15]. Hence 6, 9, 12, 15, 18, 21, 24, 27, 30, 60 and 90 neurons in the hidden layer are formed, as a result of 11, 20, 16, 19, 8, 54, 101 and 236 epoch trying, smallest MSE (Mean Square Error) test error for network capable of generalization is tried to get. Both the best performance and 30 neurons model with high velocity are formed after 16 epoch model and is shown in (Figure.3).

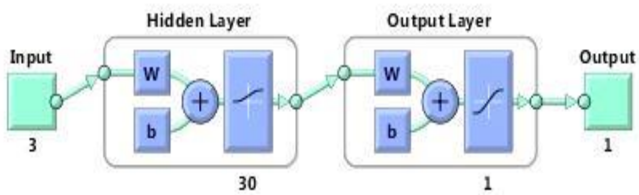

Figure 3. 3 Input 1 Output ANN model.

The achievement status for the developed model is necessary to compare statistically. When we look at the literature, the most widely used statistical error methods are Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). There are also some other methods to use. Among the statistical error methods, MAPE is the most effective one in terms of making sense without other factors when it is compared with other methods [1, 3, 7-13].

MAPE and RMSE which are the statistical error methods are used in this paper. At the same time, the models have been compared by measuring the coefficient of determination (R^2). MAPE, RMSE and R^2 formulas are given respectively in (Equation.3), (Equation.4) and (Figure.4).

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left|\frac{P_i - O_i}{P_i}\right| * 100 \qquad (3)$$

Pi, and Oi represent the calculated actual values in the equation of (Equation.3) and (Equation.4) respectively.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=i}^{n}(P_i - O_i)^2}{n}} \qquad (4)$$

Similarly, the best model is defined as a result of calculation considering with the performance success of the model and models, using statistical error formulas of the equation of (Equation.3) and (Equation.4).

$$\textit{Coefficient of Deternination} \rightarrow \quad R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$$

$$\textit{Sum of Squares Total} \rightarrow \quad SST = \sum (y - \bar{y})^2$$

$$\textit{Sum of Squares Error} \rightarrow \quad SSE = \sum (y - y')^2$$

Figure 4. Coefficient of Determination (R^2) formula. y, yı and ȳ values respectively of supplied Real, Estimate and Mean Values.

5. Model Results

In this study, 4344 data has been used between January and June considering the hourly value. The data obtained between January and May has been put into the system as education (training), and it is aimed to predict the wind power data of June. For this reason, 3624 (83.4%) rating between January and May has been used as education, and 720 (16.6%) rating within June has been used for testing purposes. R^2, RMSE and MAPE results of ANN model have been given below in Table 1.

Table 1. Ann Model Performance Value

R^2	RMSE	MAPE
0.999159	0.001467	13.79

At the end of the conducted studies, R^2 values are seen to be at 0.99 level when examining the results of Table 1. Examining MAPE, results that are above 10% are accepted to be well in success rate. Assessing the MAPE results for a prediction model or models, the values under 10% are **very good**, values between 10% and 20% are **good**, values between 20% and 50% are **acceptable** level. If the result of MAPE is over 50%, model should be considered as a wrong or failure [16]. If the RMSE value is 0.0015, it will show us that performance success of the model is a good level.

Regression graphic of concerned model in MATLAB program at 16 epoc result, it is seen as in (Figure.5).

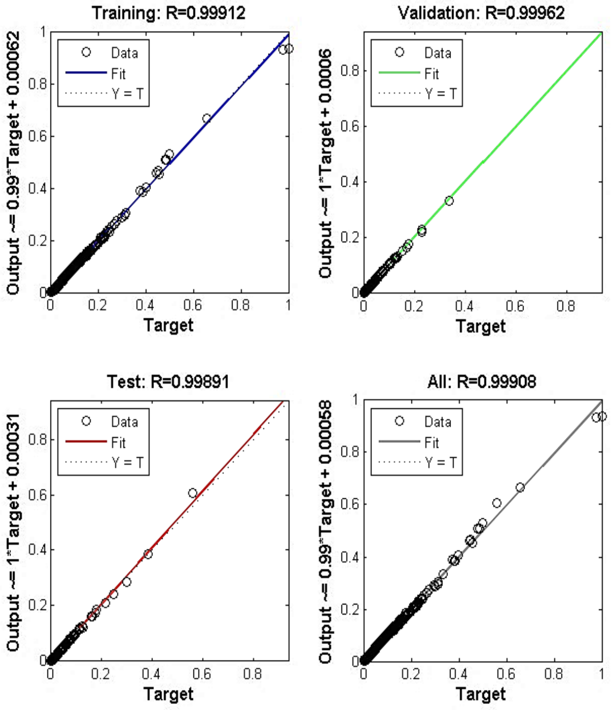

Figure 5. Regression Graphics of ANN Model

In these regression graphics; test, training and verification graphics of related model is seen. Performance graphic of developed model according to Mean Square Error (MSE) is given in (Figure.6).

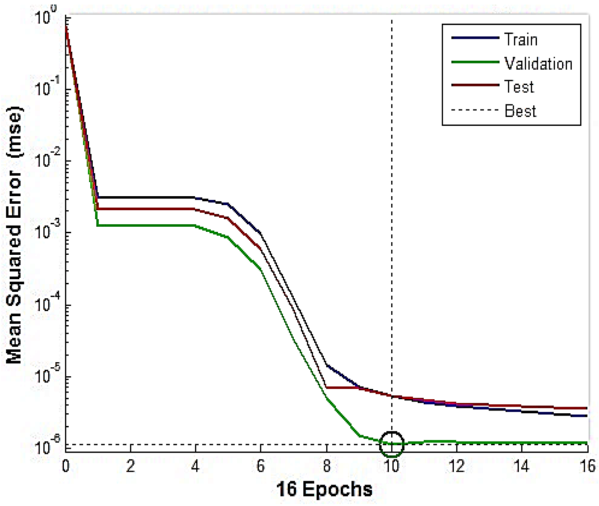

Figure 6. MSE Performance Graph

Generally speaking when compared statistically, obtained MATLAB results are approximately same. Comparison between actual calculation of 24-hour power estimation measurements of an arbitrary day (11th) in June and power rating with estimation of ANN model is given in (Figure 7).

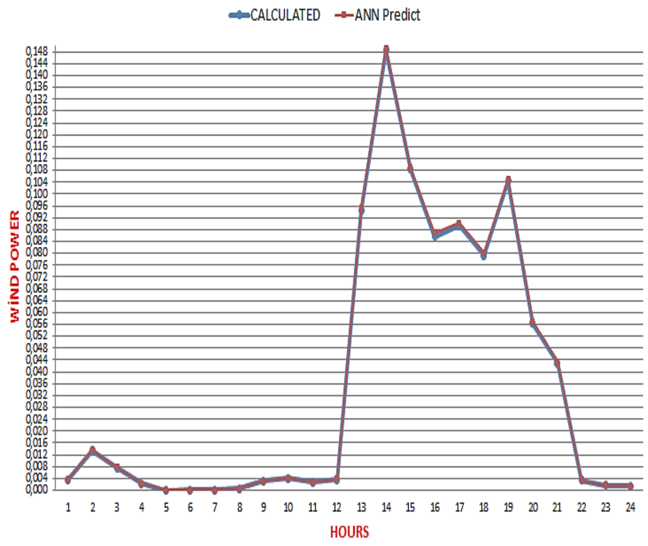

Figure 7. Comparison of 11th of June between actual and estimated ratings

As it is well understood from the (Figure.7), success rate between estimated and actual value can be seen, it is very close to each other and this figure also shows us that the prediction method gives quite good results according to the actual value.

6. Conclusion

In this conducted research to estimate potential wind power of Osmaniye city, feedback forward neural network is utilized by using MATLAB program. Wind power estimation of June is calculated by educated models by means of changing a series of parameters of model as hidden layer, learning and education function and neuron number in order to optimize the estimated results of created model. When estimated values compare with the actual values statistically, R^2 values of estimated model are quite good result and it is very close to 1 shown in Table 1, and this value determines the success rate of the estimated model substantially. Furthermore, the results of the MAPE and RMSE shows us the power of prediction of estimated model and the it is shown clearly in (Figure.7). By this means, short term wind power estimation with high success rate is made in Osmaniye.

Acknowledgements

This paper has been presented as an oral presentation at the International Conference on Advanced Technology&Sciences (ICAT'16) held in KONYA (Turkey), September 01-03, 2016 and selected for the International Journal of Intelligent Systems and Applications in Engineering (IJISAE).

References

[1] H. Mituharu and B. Kermanshahi, Application of artificial neural network for wind speed prediction and determination of wind power generation output, Proceedings of ICEE, 2001.

[2] F. O. Hocaoğlu, M. Kurban, and Ü. B. Filik, Wasp Yazılımı ile Rüzgar Potansiyeli Analizi ve Uygulama, IV, Yenilenebilir Enerji Kaynakları Sempozyumu, 2007.

[3] Y. Noorollahi, M. A. Jokar and A. Kalhor, "Using artificial neural networks for temporal and spatial wind speed forecasting in Iran," Energy Conversion and Management, vol. 115, pp. 17-25, May. 2016.

[4] M. Lei, L. Shiyan, J. Chuanwen, L. Hongling, and Z. Yan, A review on the forecasting of wind speed and generated power, Renewable and Sustainable Energy Reviews, vol. 13, pp. 915-920, May. 2009.

[5] R. Velo, P. López, and F. Maseda, Wind speed estimation using multilayer perceptron, Energy Conversion and Management, vol. 81, pp. 1-9, May. 2014.

[6] E. Cadenas, and W. Rivera, Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA–ANN model, Renewable Energy, vol. 35, pp. 2732-2738, December. 2010.

[7] G. Li, and J. Shi, On comparing three artificial neural networks for wind speed forecasting, Applied Energy, vol. 87, pp. 2313-2320, July. 2010.

[8] Z. W. Zhenga, Y. Y. Chena, X. W. Zhoua, M. M. Huoa, B. Zhaoc and M. Y. Guod, Short-Term Wind Power Forecasting Using Empirical Mode Decomposition and RBFNN, International Journal of Smart Grid and Clean Energy, vol. 2, pp. 192–199, May. 2013.

[9] S. Wang, X. Liu, Y. Jin, and K. Qu, Wind Power Short Term Forecasting based on Back Propagation Neural Network, International Journal of Smart Home, vol. 9, pp. 231-240, 2015.

[10] M. C. Mabel, and E. Fernandez, Analysis of wind power generation and prediction using ANN: A case study, Renewable Energy, vol. 33, pp. 986-99, May. 2008.

[11] M. Bilgili, B. Sahin, and A. Yasar, Application of artificial neural networks for the wind speed prediction of target station using reference stations data, Renewable Energy, vol. 32, pp. 2350-2360, Nov. 2007.

[12] S. Tasdemir, I. Saritas, M. Ciniviz and N. Allahverdi, Artificial Neural Network and Fuzzy Expert System Comparison for Prediction of Performance and Emission Parameters on a Gasoline Engine, Expert Systems with Applications (ISI), vol. 29, pp. 1471-1480, 2012.

[13] B. Yaniktepe, and Y.A. Genc, Establishing new model for predicting the global solar radiation on horizontal surface, International Journal of Hydrogen Energy, vol. 40, pp. 15278-15283, Nov. 2015.

[14] S. Yavuz, and M. Deveci, İstatiksel Normalizasyon Tekniklerinin Yapay Sinir Ağin Performansina Etkisi, Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, vol. 40, pp. 167-187, 2012.

[15] Ç. Elmas, Yapay Zeka Uygulamaları, 2 nd ed., Ed. Ankara, Türkiye: Seçkin Yayıncılık, 2010.

[16] C.D. Lewis, Industrial And Business Forecasting Methods, vol. 2, iss. 2, Ed. Borough Green, Sevenoaks, pp. 144, 1982.