Special Issue Article | ICADET 2017[c]

Turkish Journal of Electromechanics & Energy

ISSN-2547-975X

An Assessment of Energy Production Capacity of Amasra Town Using Artificial Neural Networks

Ünal Kaya[1*], Yüksel Oğuz[2], Ümit Şenol[3]

[1*]Kastamonu University, Cide Rıfat Ilgaz Vocational School, Department of Electronics &Automation, Kastamonu, 37600, Turkey
[2]Afyon Kocatepe University, Faculty of Technology, Department of Electricity & Electronics, Afyon, 03100, Turkey
[3]General Directorate of TEIAS, Department of Load Dispatch, Ankara, 06100, Turkey

Received: 10 November 2017; Revised: 22 February 2018; Accepted: 24 March 2018; Published: 1 June 2018
Turk J Electrom Energy Vol: 3 No: 1 Page: 22-26 (2018)
SLOI: http://www.sloi.org/
*Correspondence E-mail: ukaya@kastamonu.edu.tr

ABSTRACT This study aimed to estimate the amount of power can be generated using wind turbines in accordance with the wind speed data obtained from Amasra town, using Artificial Neural Networks (ANN) method. In the training of artificial neural network, wind speeds ranging between 0 and 20 m/s were used as artificial neural network input while the production data from six wind turbines (Gamesa G97-2MW, Suzlon S.88-2100, Siemens SWT-2.3-113, N100-2.5 MW, E82-3 MW, V117-3.3 MW) were used as ANN outputs. Moreover, wind speed data collected from Amasra during 2016 was used in the test phase. Hence, the energy generation capacity of Amasra was analyzed with different wind turbines.

Keywords: Artificial Neural Networks, Wind Power, Energy Potential

Cite this article: Ü. Kaya, Y. Oğuz, Ü. Şenol, An Assessment of Energy Production Capacity of Amasra Town Using Artificial Neural Networks, Turkish Journal of Electromechanics & Energy, 3(1), 22-26, (2018)

1. INTRODUCTION

Energy is one of the most important aspects in economic and social development of nations. Need for electrical power has been increasing gradually in parallel with the technological advancements. Recently, producing energy from reliable resources in an efficient and cost-effective manner has become of great importance [1]. Today, most of the countries depend on fossil fuels such as coal, oil and natural gas to meet their energy demands. Considered to be one of the reasons behind global warming, the use of fossil fuels results also in air pollution, acid rains, ozone depletion, and deforestation [2]. With the depleting fossil fuel resources and due to the damages caused by the use of such resources, nations are now seeking the ways to utilize renewable energy resources. Nevertheless, it is only possible to meet the ever-increasing demand in energy using sustainable and clean energy resources, in other words, renewable energy resources [3].

Offering a great potential, renewable energy resources have recently found their place in the energy policies of nations and are becoming even more attractive investment options as the technology develops. Wind is one of the most important renewable energy resources which can compete with conventional energy resources thanks to the current technology and advancements in its use [4]. Wind power has been harvested since the ancient times through wind mills, and utilized in water pumps, sea and river shipping, and a number of mechanically powered devices. Today we have modern turbines designed to harvest wind power which are commonly exploited in many parts of the world [5]. Wind power offers various advantages including it is a clean and inexhaustible energy source, and it reduces the energy dependency of nations, its installation time is fast, and it's highly unlikely affected by the global energy market.

Since the 1990s, wind power technology has seen significant advancements and high-capacity wind farms have been built all around the globe. The total installed capacity of wind farms was 2.16 GW by the beginning of 1990s and it reached up to 13.5 GW by the end of 1990s, increasing approximately 6-fold. The increase in installed capacity persisted also in 2000s reaching up to 33.4 GW by the end of 2003, 74 GW by the end of 2006 and 487 GW by the end of 2016 as shown in Fig. 1 [6].

[c]*Initial version of this paper was selected from the proceedings of International Conference on Advanced Engineering Technologies (ICADET 2017) which was held in September 21-23, 2017, in Bayburt, TURKEY; and was subjected to peer-review process prior to its publication.*

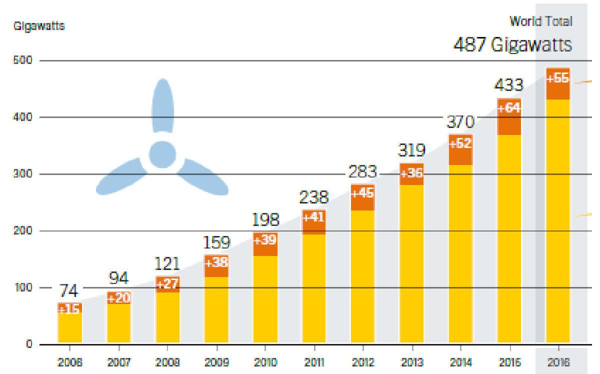

Fig. 1. The graph showing the installed wind power on Earth [6]

Turkey is a bridge between Europe and Asia, and it is surrounded by seas on its three sides. The coastal regions of Marmara, Aegean, and Eastern and Southeastern Anatolia offer a significant potential for wind energy with an average wind speeds between 4.5 to 10 m/sec. [7]. In Turkey, electricity generation based on wind energy started in 1998 with the first wind farm connected to the grid and the installed capacity and power production of wind farms has been increased significantly, especially after 2005. As of January, in 2017, the installed wind power capacity in Turkey has reached up to 6106 MW which corresponds to the 6.3% of the total installed power capacity of Turkey [8].

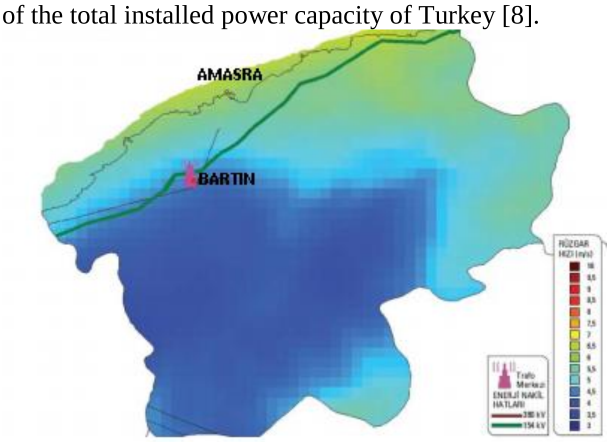

Fig. 2. A map of wind speed averages in Bartın

As shown in Fig. 2, Amasra is the district of Bartın with the highest wind potential. The reason behind the selection of Amasra in this study is that the wind speeds measured in this location reach up to 7 m/sec.

In this study, power production using wind energy was estimated by using ANN model in combination with a number of different wind turbine models. ANN was executed using Matlab software (version R2014A). The main purpose of this study was to define the wind energy potential of Amasra with minimal error using Artificial Neural Networks. Moreover, wind turbine models of Gamesa G97, Suzlon S.88, Siemens SWT2.3, Nordex N100, Enercon E82, Vestas V117 and the tower height of 90 m were selected as the ANN output data. These turbine models, output data of the ANN model, are commonly used in the industry offering significantly higher yields.

2. ARTIFICIAL NEURAL NETWORKS (ANN)

ANN is a computer system which is able to produce new information through learning, multiplexing, and exploration, just like human brain, and to perform superior skills without any kind of assistance [9]. As a result of advancement in computing algorithms and software industry, ANN modeling is now simpler and it offers convenient solutions to once hard-to-solve problems. In addition, ANN is widely used in engineering practices, especially in modeling complex problems. ANN, in short, is a set of artificial neurons developed upon inspiration of biological neurons. The most important features of ANN are its ability to model nonlinear systems, its structure with parallel distribution, error tolerance, ability to learn, generalize, and adaptability to different problems [10].

A basic ANN neuron has a much simpler structure when compared to a biological neuron. ANN model consists of an input layer, an output layer and a hidden layer. The hidden layer may consist of multiple layers and each layer contains neurons. Input layer includes a number of neurons equals to the number of variables while the output layer includes a number of neurons equals to the number of outputs. However, there are no rules dictating the number of neurons included in the hidden layer. Each neuron uses the output value of the neuron available in the previous layer as its input value. Neurons located in the interim layer and output layer process the signals they receive in accordance with a specific activation function and pass them to the next layer, if there is available. Activation functions are the functions shaping the output of ANN. An ANN model with an interim layer and sufficient amount of neurons in this layer is able to model any nonlinear function [11]. It is necessary to select the activation function corresponding to the type of the problem to be solved by ANN. The network must be required the applicable to attain the desired result in artificial neural networks. To realize this, weights with value suitable and accurate connections must be required. The network must learn the system's behavior or self-organize to meet these conditions [12].

Doğancı et al. (2016) conducted a study to estimate the wind power by measuring the wind power from several locations in Central and Western Black Sea Region. The study showed that estimates based on different parameters such as algorithm type, activation function, training function, number of layer, and number of neurons and actual measurements for Bafra, İnebolu, Zonguldak and Karabük were in agreement [13].

Kılıc & Arabacı (2016) estimated the wind speed values for the city of Burdur using ANN method. Calculations with the data obtained from Turkish Meteorological Institute showed that the ANN method is suitable methodology that can be used in similar studies [14].

Islak et al. have estimated the mechanical and physical properties of Cu-TiC composites produced by hot pressing technique with artificial neural networks (ANN) model. The output values have been selected as relative density, hardness, electrical conductivity, crossfracture strength, friction coefficient and wear rate while the input parameters have been selected as the amount of titanium carbide added copper matrix in the ANN model. As a result, the regression values were noted to be very close to the value of 1. This implies that the ANN model output is in well agreement with the real data [15].

Güleç et al. (2017) tried to estimate the wind power potential of the city of Kastamonu using two different models with several wind turbine data. The daily maximum wind speed data collected in 2015 for Kastamonu was acquired from General Directorate of Meteorology. As a result, maximum power values which can be produced per type of turbine were estimated. The estimates showed that Kastamonu offers a rather high wind potential [16].

Yiğit and his colleagues (2014) designed a web-based program to support the training of artificial neural network structures and the lesson contents. ANN model in order to test thanks to developed software and it is easier infer to understand the basics of YSA [17].

3. RESULTS AND DISCUSSIONS

In this study, the wind power production capacity of Amasra, a district of Bartın, was estimated using artificial neural networks with meteorological data. First, ANN model was trained using the responses of six different turbine models at varying wind speeds. Monthly average wind speed values measured in Amasra for 2016 were used as training input data.

Table 1. Monthly average wind speeds measured in Amasra in 2016

Months	Wind speed (m/s)
January	6.52
February	5.11
Arch	4.76
April	4.36
May	4.21
June	3.77
July	3.88
August	3.91
September	4.75
October	4.43
November	5.11
December	6.17

The production capacities of turbine types of Gamesa G97-2MW, Suzlon S.88-2100, Siemens SWT-2.3-113, N100-2.5 MW, E82-3 MW, V117-3.3 MW with respect to wind speed were used as training output data.

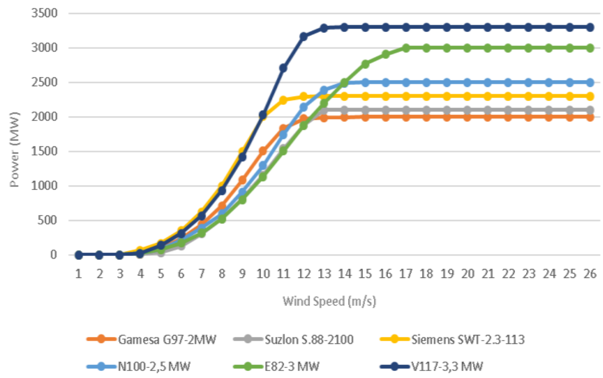

Fig. 3. The power generated by six turbines used in the ANN model with respect to the wind speed

Stopping criteria of “1,000” iterations, “0” error, gradient of 1e.-5 and number of “1,000” validation were used in the training process. Training reached at “1,000” iterations in 4 seconds and stopped. Dividend function, on the other hand, was divided in itself into two as train, validation and test in a randomized distribution of data in 70%, 15% and 15%, respectively. Mean squared error (mse) was used as the performance function. Fig. 4 shows the results of regression, validation, test data and training data. The model tends to memorize if the selected correction error gradient is high.

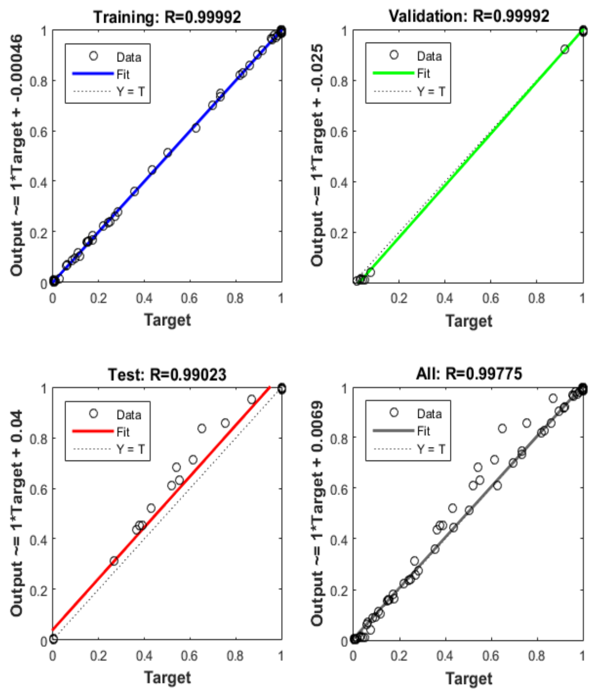

Fig. 4. Regression curves of the results of train, validation, test data and all data combined

Table 1 shows the data obtained from the Directorate of Meteorology for monthly average wind speed values measured at the city center of Amasra in 2016. Using the wind data for the city center of Amasra in the ANN model it is possible to obtain output power values corresponding to 6 turbines. These power values estimated are given in Table 2. Accordingly, it was found that Siemens SWT-2.3-113 is the most efficient turbine type.

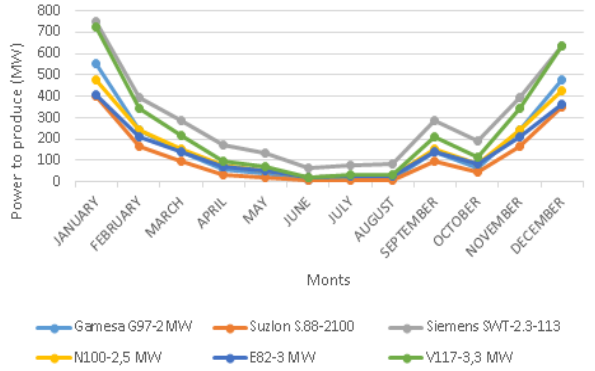

Fig. 5. The amount of power obtained for six types of turbines may generate in Amasra

Table 2: The amount of power that can be generated by six different types of turbines in Amasra

Months	Wind Turbines					
	Gamesa G97-2 MW	Suzlon S.88-2100	Siemens SWT-2.3-113	N100-2.5 MW	E82-3 MW	V117-3.3 MW
January	554.90	401.52	748.08	477.50	405.60	726.52
February	240.03	169.45	393.80	240.37	210.62	346.28
March	141.19	95.58	289.70	156.13	140.47	216.78
April	56.98	36.33	172.48	75.34	71.41	97.91
May	37.90	23.60	136.46	54.39	52.86	68.56
June	10.97	6.40	66.45	20.23	21.27	23.21
July	14.84	8.79	79.27	25.74	26.54	30.22
August	16.14	9.60	83.25	27.53	28.24	32.53
September	138.57	93.68	286.61	153.78	138.50	213.24
October	68.22	43.98	191.21	87.03	81.60	114.61
November	240.03	169.45	393.80	240.37	210.62	346.28
December	478.43	351.16	636.84	424.29	362.10	639.11

IV. CONCLUSION

The main purpose of this study was to reveal the wind energy potential of Amasra with minimal error using Artificial Neural Networks. The data obtained from Provincial Based Wind Energy Potential Atlas (Republic of Turkey Ministry of Energy and Natural Resources) shows that Amasra offers an important potential for wind [8, 18]. A closer look into the potential of Amasra comparing a number of turbines revealed that Siemens SWT-2.3-113 model turbine can generate attractive levels of energy in Amasra. The response of ANN model showed that Amasra is suitable for installation of turbines. These results are important especially in terms of the development of the city of Bartın and Western Black Sea Region.

References

[1] E. Yağcı, Comparison and error analysis of different methods used for wind speed extrapolation, M.Sc. Thesis, İstanbul University, Energy Science and Technology Department Energy Science and Technology Program, İstanbul. (2013).

[2] R. J. Wai, W. H. Wang, C. Y. Lin, High-performance stand-alone photovoltaic generation system, IEEE Transactions On Industrial Electronics, 55(1), 240-250, (2008).

[3] K. Azad, M. G. Rasul, R. Islam, I. R. Shishir, Analysis of wind energy prospect for power generation by three weibull distribution methods, Energy Procedia, 75, 722-727, (2015).

[4] U. Elibüyük, İ. Üçgül, A. K. Yakut, Wind power plant project to Suleyman Demirel University, Süleyman Demirel University, Journal of YEKARUM, 3(2), 22-32, (2016).

[5] A.V. Da Rosa, Fundamentals of renewable energy processes, 3rd ed., Amsterdam, Netherlands, Elsevier, (2013)

[6] REN21, Renewables 2017 Global Status Report, http://www.ren21.net/wp_content/uploads/2017/06/GSR2017_Full-Report.pdf, ISBN 978-3-9818107-6-9, (Accessed 2016).

[7] C. İlkiliç, İ. Türkbay, Determination and utilization of wind energy potential for Turkey. Renewable and Sustainable Energy Reviews, 14(8), 2202-2207, (2010).

[8] TUREB, Turkey wind energy statistics report Turkey wind energy association, http://www.tureb.com.tr, (Accessed 25.02.2017).

[9] E. Öztemel, Yapay sinir ağları, Papatya Yayıncılık, İstanbul, (2003)

[10] C. Hamzaçebi, Yapay sinir ağları: tahmin amaçlı kullanımı matlab ve neurosolution uygulamalı, Ekin Yayınevi, Bursa, (2011)

[11] L. Fausett, Fundamentals of neural networks: Architectures, Algorithms and Applications, Prentice Hall, New York, (1994)

[12] Ç. Elmas, Yapay Zeka Uygulamaları, Seçkin Yayıncılık, Ankara, (2011)

[13] Ö. Doğancı, M. Ertürk, A. Özsunar, A. Arcaklıoğlu, A study of the estimation of the wind energy in the central-western Black Sea region, Journal of Advanced Technology Sciences, 5(1), 153-163. (2016).

[14] B. Kılıç, E. Arabacı, Estimation of wind speed values in future of Burdur city using artificial neural networks (ANN), Dumlupınar University, Journal of Science and Technology of Dumlupınar University, 45-50, (2015).

[15] S. Islak, M, Akkaş, Ü, Kaya, H. Güleç, Estimation of mechanical and physical properties of Cu-Tic composites by artificial neural networks (ANN) Model, Technological Applied Sciences, 12, 122-129, (2017).

[16] H.G. Güleç, H. Demirel, Artificial neural network based prediction of intensity of insolation in the city of Kastamonu using meteorological data, Technological Applied Sciences, (2017).

[17] T. Yiğit, A. H. Işık, M. Bilen, Web based educational software for artificial neural networks, International Conference on Education in Mathematics, Science & Technology, May 16 – 18, 629-632, (2014).

[18] General directorate of renewable energy, http://www.eie.gov.tr/yekrepa/BARTIN-REPA.pdf (Accessed 08.03.2017).

Biographies

Ünal Kaya was born in 1986 in Fatih, İstanbul. After studying primary and high schools in İstanbul, he holds B.Sc. and M.Sc. degrees from Fırat University and was employed by Kastamonu University in 2013. Mr. Kaya specializes in artificial intelligence methods, energy and real-time control systems. Mr. Kaya is married with one child, currently employed in Cide Rıfat Ilgaz Vocational School.

E-mail: ukaya@gmail.com

Yüksel OĞUZ was born in Afyon, Turkey, in 1971. He received his B.Sc. degree from the Marmara University Technical Education Faculty, Department of Electrical Education, Istanbul, and the M.Sc. and Ph.D. degrees in Electrical Education from the Marmara University, Institute for Graduate Studies in Natural and Applied Sciences, in 2000 and 2007, respectively. He has been an assistant professor in the Electronical Engineering Department at Afyon Kocatepe University. He has worked mainly in control education, automatic control applications, electrical machines, power generation systems and control, renewable energy, and intelligent control.

E-mail: yukseloguz@aku.edu.tr

Umit Senol was born in 1989 in Sarikaya, Yozgat. After studying primary and high schools in Yozgat, he graduated from Dumlupinar University with a B.Sc. degree, and Bozok University with M.Sc. degrees. Mr. Senol specializes in renewable energy sources and artificial intelligence methods. Mr. Senol has been employed in Turkish Electricity Transmission Corporation since 2014.

E-mail: umitsenol66@gmail.com