21, rue d'Artois, F-75008 PARIS
http : //www.cigre.org

CIGRE US National Committee
2014 Grid of the Future Symposium

Site Wind Energy Appraisal Function for Future Egyptian Homes

A. EL SHAHAT
Electrical Engineering Department, Georgia Southern University
United States

SUMMARY

Wind energy systems are ideally suited for distributed generation systems especially in Egypt to solve the energy problem in future homes. This paper proposes identification and estimation of wind energy in Egypt to present a simple method for the calculation and appraisal of the wind energy potential available in Egypt. This is done based on real data from many stations in Egypt with the aid of Artificial Neural Network (ANN). The Neural Network is created and trained by the data of many wind energy stations in Egypt like: Sallum, Sidi Barrani, El Dabaa, Dekheila, Alexandria, Balteam, Damietta, Port Said, and El Arish stations; then checked and tested for Marsa Matroh and Hergada stations to show its validity. The neural network' inputs are: Latitude, Longitude, Elevation and Month; the output is the monthly wind speed. This Simulink Model (GUI) or the algebraic equations could be used directly without the need of Network training every time. ANN model is created with suitable numbers of layers and neurons, which trained, simulated, and checked with excellent regression constant. This neural model has the ability to predict values in – between learning values, also make interpolation between learning curves data. The validity of the model is achieved from comparison between target and output and model excellent regression factor. This work aims to identify good sites in Egypt for new wind turbine installations and predict for other sites too to help in designing wind family homes. All results and simulations data are well depicted in the form of 3D figures.

KEYWORDS

Wind energy, Egypt homes, estimation, site stations and Artificial Neural Network (ANN).

aahmed@georgiasouthern.edu; adel2029@yahoo.com .

INTRODUCTION

Wind energy generation has attracted much interest in the last few years in modeling and control for hybrid systems [1-5]. It is estimated that their indirect carbon dioxide emissions are paid back within nine months of operation for offshore turbines [6]. Solving the mathematical models is a tedious and repetitive problem [7]. To tackle the mathematical problems (forward and backward streams), several researchers have developed different methods, techniques, and computer programs for the simulation of a very wide range of variety of wind turbines. Jafarian [8] uses fuzzy modeling techniques and Artificial Neural Networks (ANN) to estimate annual energy output for wind turbines in different regions. Vinay [9] presents a comparative study of various methods of mathematical modeling of wind turbines, with reference to three commercially available wind turbines, with the help of an algorithm developed. S. Bououden [10] used fuzzy model based multivariable predictive control of wind turbine generator. In the same way of modeling technique, the different approaches to structural modeling of wind turbines are addressed by Hansen [11]. The placement of wind turbines in wind farm has been resolved with a new coding and also a novel objective function in Genetic algorithm approach by Emami [12]. Also A. Kusiak and Z. Song [13] presented a model for wind turbine placement based on the wind distribution to maximize the wind energy capture. Isam [14] investigated the aerodynamic flow simulation of wind turbine. Lubov [15] investigated the wind flow deformation inside the wind farm. Ekonomou [16] estimated the optimal number and power produced in the wind farm by the use of ANN model. Fouad Kamel [17], Investigated a small locally produced windmill for electric power generation as a model for small industry. N. G. Mortenson et al. [18], Studied the wind atlas for the Gulf of Suez, Arab Republic of Egypt. H. K. Ahmed et al. [19], Studied the utilization of wind energy in Egypt in remote areas. The study based on three costal and remote desert areas. M. N. El-Kordy et al. [20], Studied the economical evaluation of electricity generation considering externalities. A full analysis for the cost of the kWh of electricity generated from different systems actually used in Egypt is presented. A. S. Ahmed Shata and R. Hanitsch [21], Studied the evaluation of wind energy potential and electricity generation at the coast of the Mediterranean Sea in Egypt. A. S. Ahmed Shata and R. Hanitsch [22], The potential of electricity generation at the east coast of Red Sea in Egypt was studied. A. S. Ahmed Shata and R. Hanitsch [23, 25], Studied the application of electricity generation along the western coast of Mediterranean Sea in Egypt. A. S. Ahmed Shata and R. Hanitsch [24], Studied the electricity generation and wind potential assessment at Hurghada, Egypt. In this paper; ANN algorithm is used to deduce Wind Energy Appraisal Function based on Site information from various Egyptian wind stations. A simple method for the calculation and estimation of the wind energy potential available in Egypt is presented with the aid of Artificial Neural Network (ANN). The Neural Network is created and trained by the data from: Sallum, Sidi Barrani, El Dabaa, Dekheila, Alexandria, Balteam, Damietta, Port Said, and El Arish stations; then checked and tested for Marsa Matroh and Hergada stations to show its validity.

WIND ENERGY POTENTIAL IN EGYPT

This data analysis [21-31] will help to identify good sites for new wind turbine installations at the selected sites in Egypt. Egypt occupies a geographical zone between 220 and 320N latitude and 250 and 360E longitude. The Egyptian area is about 998,000 km2, only 3.5% of it can be said to be permanently settled, while the remainder being desert. The orography of the region has an important role in accelerating and deflecting the wind as shown in fig. 1.

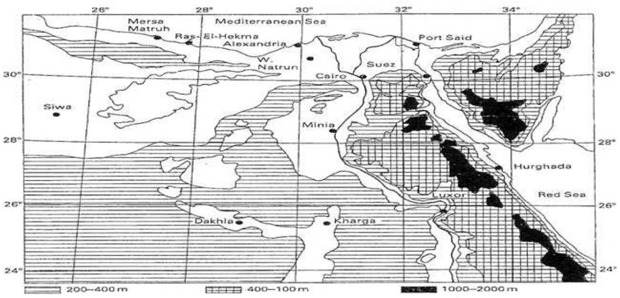

Fig. 1. Orography of the Egyptian Region (obtained from Ref. [26]) [31].

Fig. 2. shows the location of 10 chosen stations along the coast of Mediterranean Sea zone in Egypt. The present study is based on measurements of monthly wind speed, air temperature and air pressure data were taken at a height of 10 m above ground level, in open areas and over roughness class 0 (water). The Egyptian Meteorological Authority provided the data for a period of more than 10 years.

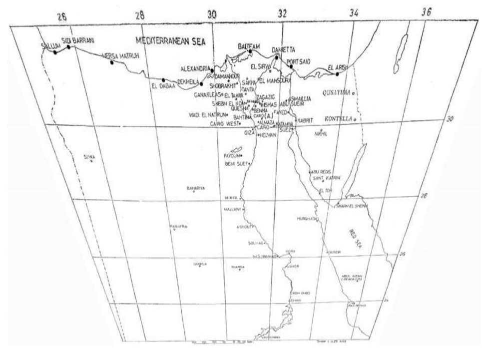

Fig. 2. Distribution of meteorological stations over Egypt [31].

The analysis of this region showed that the typical features of Mediterranean coasts are strong winds aloft or strong thermal/pressure gradients [27]. The Mediterranean zone is characterised by a wide flat coastal area along the sea and existence of Maryout plateau in the northwest area [28]. Fig. 3. illustrates the monthly mean of wind speed for all stations. It clear from the figure that the Mediterranean zone is windy. The wind speed has a maximum value of 6.3 m/s at Mersa Matruh in March, and a minimum value of 2.0 m/s at El Arish in October. This zone characterized by sea-land winds. Also from Fig. (3–3), it can be taken that high wind speeds occur in the winter and spring seasons. This may be a result of the Mediterranean Sea secondary depressions [29].

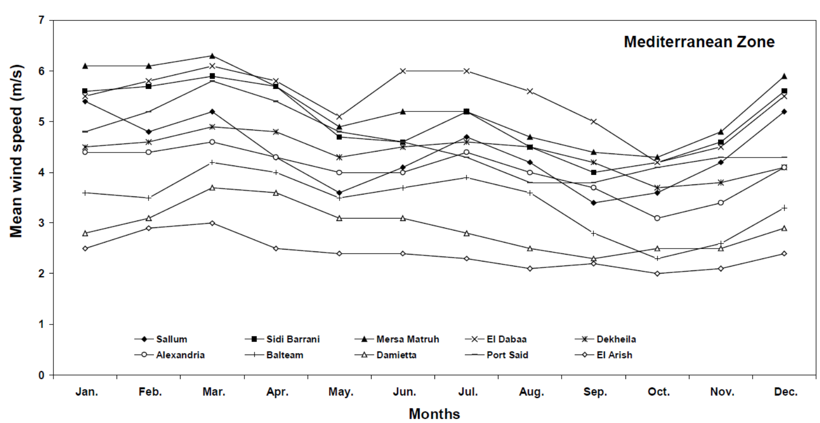

Fig. 3. Monthly variation of wind speeds of the year for selected stations [31].

Mean monthly wind speeds for different seasons of the year are plotted in Fig. 4. During *winter season*, the wind speed level at three stations Sidi Barrani, Mersa Matruh and El Dabaa reaches high values of 5.5–6.1 m/s. The maximum mean wind speed occurs at Mersa Matruh during January and February with 6.1 m/s. In *spring season*, four stations (Sidi Barrani, Mersa Matruh, El Dabaa and Port Said) have high values of wind speed 4.8–6.1 m/s, where the maximum value is recorded in Mersa Matruh with 6.3 m/s during March. In *summer season*, the wind speed level reaches 6.0 m/s at El Dabaa during June and July. For *autumn season*, the maximum mean wind speed is recorded as 5.0 m/s at El Dabaa.

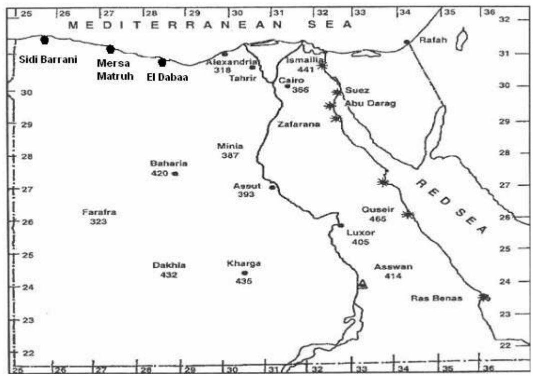

Fig. 4. Distribution of some meteorological stations over Egypt [31].

It can be taken that high wind speeds occur in the winter and spring seasons. This may be due to the Mediterranean Sea secondary depression [29]. During *winter season*, the wind speed level at the three stations reaches high values of 5.5–6.1 m/s. The maximum mean wind speed occurs at Mersa Matruh during January and February with 6.1 m/s. *In spring season*, the three sites have high values of wind speed 4.8–6.1 m/s, where the maximum value is recorded in Mersa Matruh with 6.3 m/s during March. During *summer season*, the wind speed level reaches 6.0 m/s at El Dabaa during June and July. *For autumn season,* the maximum mean wind speed is recorded as 5.0 m/s at El Dabaa in September. Deserts have a number of characteristics that make them almost ideal for wind energy applications: the pressure on the land is low, access is easy, and construction work is relatively simple. Furthermore, the surface roughness tends to be done low and uniform, so siting of wind turbines can be done primarily with optimization of the energy production–and minimization of cost–in mind. Large desert regions exist with a very promising wind potential. One region with these features is the coast along the Red Sea in Egypt [18]. Fig. 5. shows the locations of these seven stations along Red Sea zone in Egypt. The period of observations that was used equal more than 10 years except two stations (Abu Darag and Zafarana), 5 years. Data was obtained from the Egyptian Meteorological Authority and New & Renewable Energy Authority in Egypt.

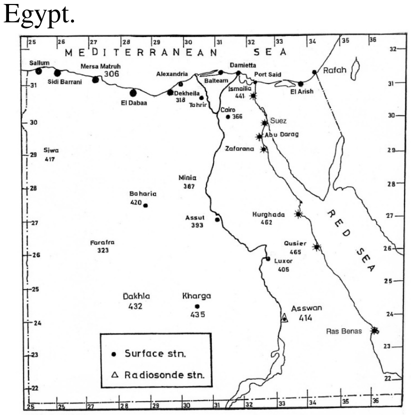

Fig. 5. Distribution of some meteorological stations over Egypt [30], [31].

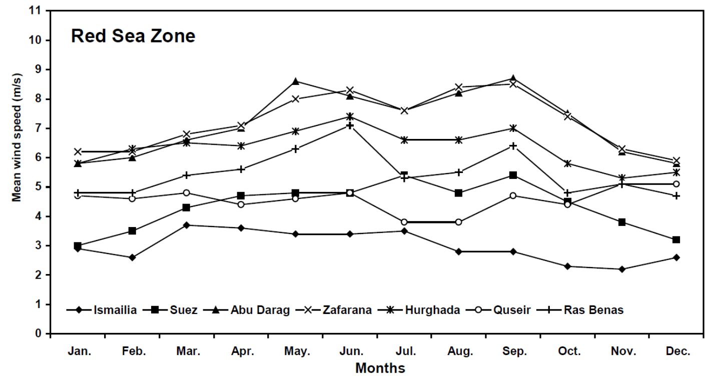

Fig. 6. Monthly variation of wind speeds of the year for selected stations [31].

ANN WIND ESTIMATION FUNCTION

The wind regression model is performed by the ANN method illustrated and validated in [32-42] is presented in this section. Based on the available data units; the hidden layer would be a 37 neurons and the output layer would be one neurons. The neural network' inputs are: Latitude, Longitude, Elevation and Month; the output is the monthly wind speed. The configuration here is a general approximator to any function with a log-sigmoid function in the hidden layer and pure- line for output layer. Number of neurons in output layer have to be the same as the output variables number. Number of neurons in hidden layer is selected by inspection or by try and error until reaching the desired performance goal, accuracy, minimum error with little time for training and with low number of neurons as possible. This Simulink Model (GUI) or the algebraic equations could be used directly without the need of Network training every time. ANN model is created with suitable numbers of layers and neurons, which trained, simulated, and checked with excellent regression constant.

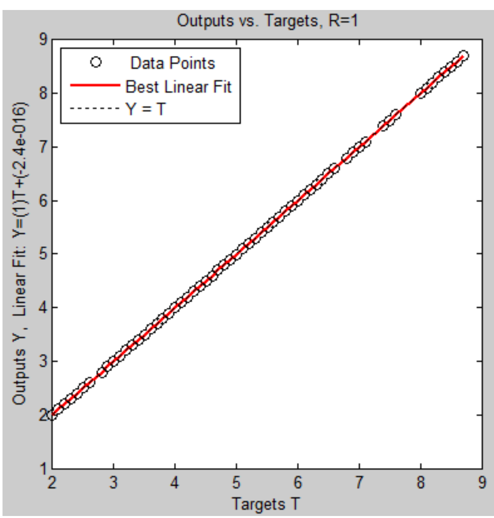

Fig. 7. Output VS Target for ANN Model training data

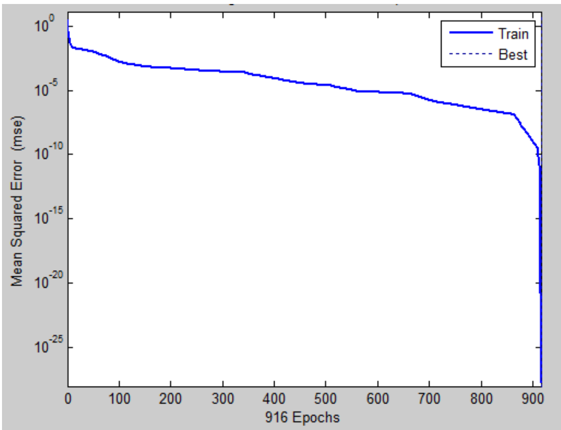

Fig. 8. Performance for the Model

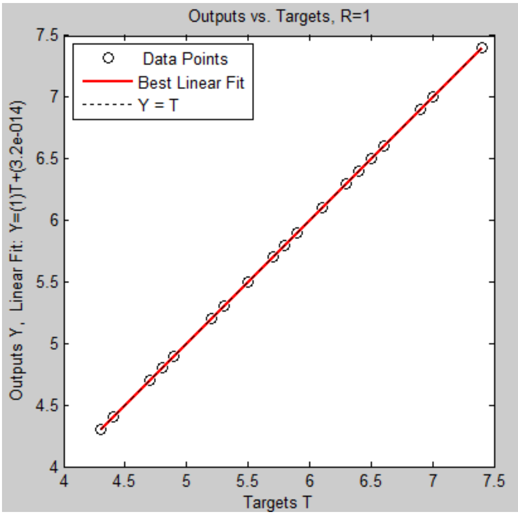

Fig. 9. Output VS Target for ANN Model testing data

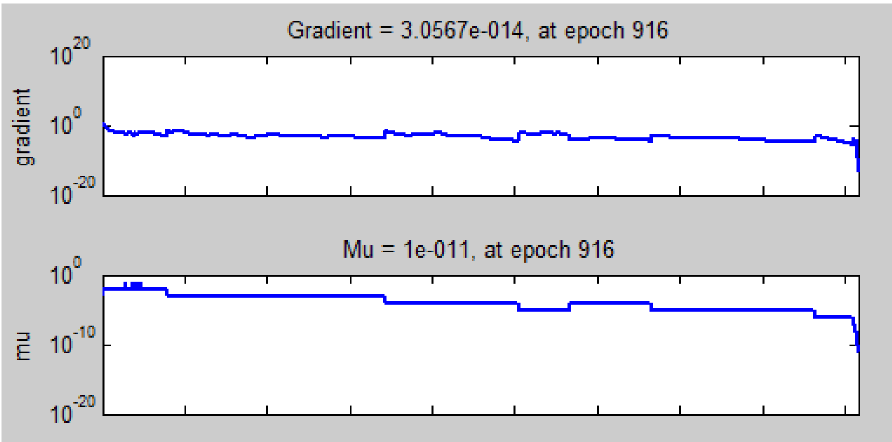

Fig. 10. Training state

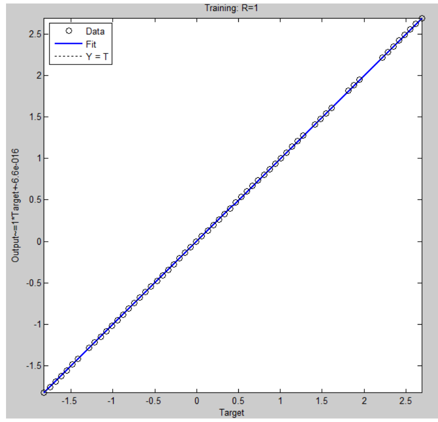

Fig. 11. Regression (R=1) for ANN Model

The ANN Regression equations are presented as follows:

$$Latitude_n = (Latitude - 29.7929) / 2.1699 \quad (1)$$

$$Longitude_n = (Longitude - 30.8935) / 2.8941 \quad (2)$$

$$Elevation_n = (Elevation - 8.9588) / 9.1365 \quad (3)$$

$$Month_n = (Month - 6.5000) / 3.4605 \quad (4)$$

The previous Equations present the normalized inputs (subscript n denotes normalized variable):

$$E = \begin{bmatrix} 0.6396 & 1.7471 & -0.6547 & 10.7274 \\ 3.8388 & 1.8295 & -0.2010 & 8.1984 \\ -0.0014 & 1.6007 & -1.7180 & 4.4499 \\ 0.6574 & 15.7247 & -0.6711 & -14.5684 \\ 3.9752 & 8.4089 & -1.0063 & -5.0979 \\ -4.3993 & 5.5209 & -7.3705 & -13.8017 \\ -1.4445 & -3.4076 & 0.2363 & 13.9397 \\ -3.2226 & 4.3336 & 6.9290 & 4.9608 \\ -1.6385 & -6.8753 & -0.4421 & -0.0521 \\ 1.9207 & -12.0107 & 3.2032 & -0.7662 \\ 2.5774 & 9.2207 & 5.4978 & -1.7696 \\ 14.6010 & 7.7009 & 0.3930 & -10.8569 \\ -1.0794 & 0.4928 & 1.2320 & 2.4442 \\ 11.4851 & 7.1752 & 13.0946 & -6.8885 \\ 2.3234 & -2.1758 & -4.4652 & -3.3138 \\ 2.7262 & -1.1075 & -1.9147 & 9.1774 \\ -0.3619 & 6.0620 & 3.6032 & 5.3536 \\ 4.1085 & -0.9830 & -1.7143 & 11.8227 \\ 8.2118 & -1.6681 & 6.6795 & -14.8795 \\ -24.4035 & 2.6200 & 7.9527 & -12.5354 \\ 0.9567 & 10.4662 & -0.2216 & 1.7240 \\ 14.7541 & 3.8684 & 13.7256 & -0.4884 \\ -0.5210 & -4.3984 & -2.8106 & -3.9145 \\ -4.0715 & 1.3964 & -0.7247 & -6.6795 \\ -2.0625 & 2.4753 & 6.6938 & 6.8036 \\ 2.0076 & -0.9915 & 4.0430 & -3.7045 \\ -8.5372 & -0.7810 & -13.3020 & 10.5343 \\ -4.4550 & -0.2966 & -1.9832 & 6.5876 \\ -6.1481 & 7.5041 & -2.1220 & -5.2759 \\ -3.8167 & -0.8801 & -1.1000 & 4.8134 \\ -2.3042 & -4.2086 & -3.7192 & 6.9408 \\ 4.3253 & 2.8406 & 1.1728 & 11.4908 \\ 3.8204 & -0.2882 & 3.5823 & 2.7588 \\ -6.6415 & -0.5181 & -2.1048 & 5.3027 \\ 0.1600 & 4.2205 & 2.9439 & -8.4838 \\ 0.7797 & 2.2422 & 9.3573 & -12.9151 \\ -8.0808 & -4.0563 & -11.8823 & 8.2312 \end{bmatrix} \begin{bmatrix} Latitude_n \\ Longitude_n \\ Elevation_n \\ Month_n \end{bmatrix} \begin{bmatrix} 13.8405 \\ -13.1492 \\ 6.1709 \\ -23.2526 \\ -9.2339 \\ 18.2249 \\ -12.9798 \\ 3.4329 \\ 3.1377 \\ 6.4560 \\ -3.8536 \\ 4.8699 \\ 0.5142 \\ 9.1335 \\ -2.6794 \\ 3.0427 \\ -2.0523 \\ 3.7346 \\ 17.8160 \\ -19.4547 \\ -10.4799 \\ 1.8920 \\ 2.0945 \\ -7.2365 \\ -3.9351 \\ -13.8135 \\ -25.0362 \\ -5.3209 \\ -12.7860 \\ -4.8994 \\ -9.4211 \\ -18.2145 \\ 5.7881 \\ -15.3119 \\ 19.2701 \\ -30.0884 \\ -19.5553 \end{bmatrix} \quad (5)$$

$$F_{1:33} = 1 / (1 + \exp (- E_{1:33})) \quad (6)$$

$$\begin{aligned} Windspeed_n = {} & 3.6139\ F1 + 21.9593\ F2 - 11.7991\ F3 + 1.3770\ F4 + 1.1708\ F5 + 2.8611\ F6 - 0.6264\ F7 \\ & + 16.8955\ F8 + 19.8342\ F9 - 16.7641\ F10 + 13.4811\ F11 - 3.7711\ F12 + 14.4935\ F13 - 4.4601\ F14 + \\ & 28.6591\ F15 + 5.4886\ F16 - 13.6707\ F17 - 4.0305\ F18 + 8.1823\ F19 + 4.2012\ F20 - 13.0403\ F21 + \\ & 10.3183\ F22 - 13.0129\ F23 - 9.8727\ F24 - 6.2241\ F25 - 13.3637\ F26 - 12.7769\ F27 - 11.0904\ F28 - \\ & 13.7870\ F29 + 20.2839\ F30 - 6.8401\ F31 - 12.6040\ F32 - 20.6121\ F33 + 17.7477\ F34 + 9.0585\ F35 + \\ & 5.5217\ F36 + 8.1274\ F37 - 10.1474 \end{aligned} \quad (7)$$

The un-normalized out put

$$Windspeed = 1.4859\ Windspeed_n + 4.7064 \quad (8)$$

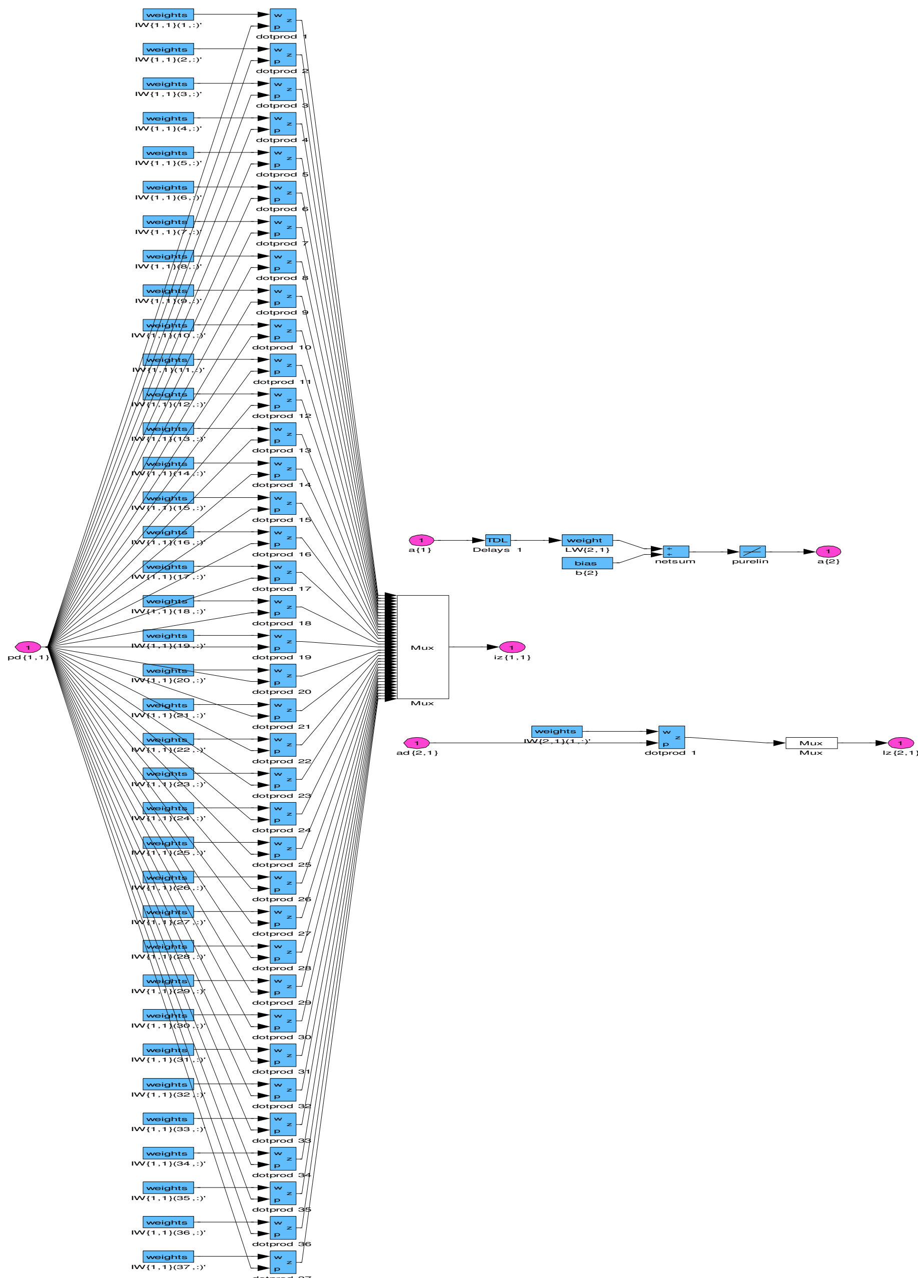

Fig. 12. ANN Model with its layers, neurons, weights, and structures.

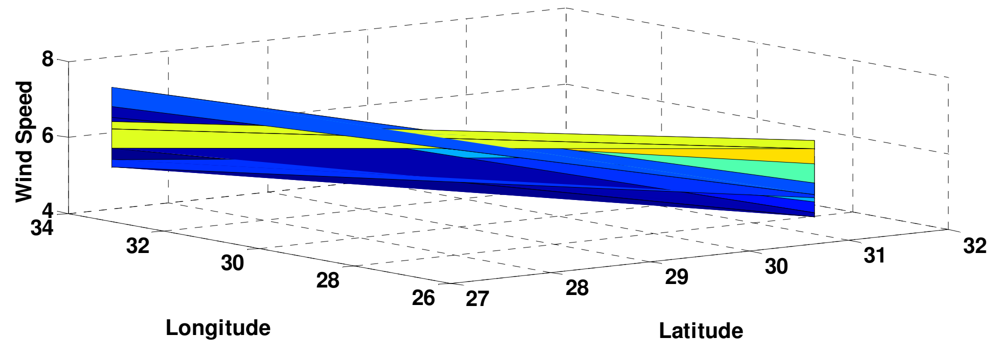

Fig. 13. 3D relation for Wind Speed, Longitude with Latitude for testing data

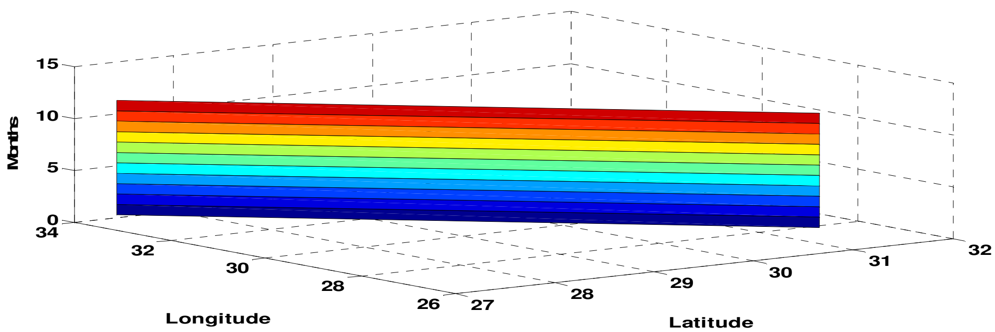

Fig. 14. 3D relation for Months, Longitude with Latitude for testing data

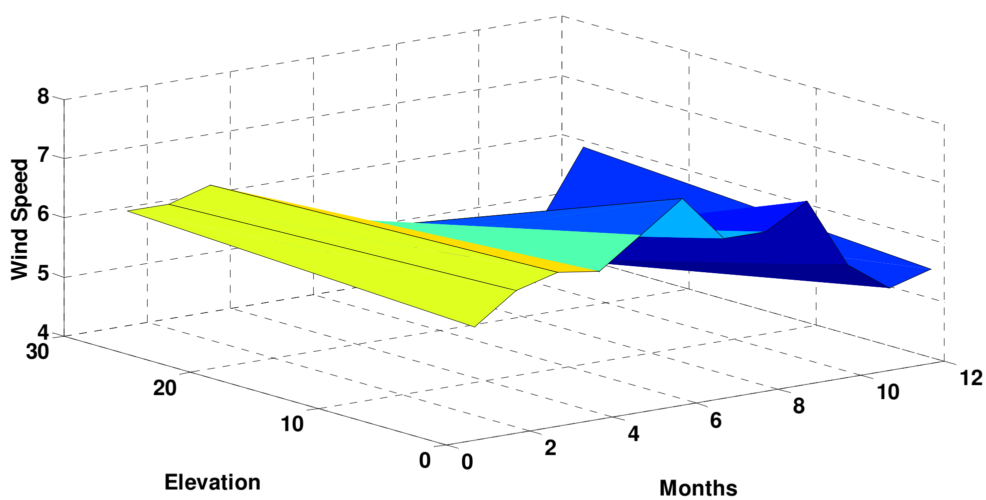

Fig. 15. 3D relation for Wind speed, Elevation with Months for testing data

CONCLUSIONS

The ANN regression function is introduced to be used directly without operating the neural model each time. Results reveal that the actual data are matched with the model data results. The models have many features such as: Easy model construction; Covering a wide range; Easy of combination with other technologies; Ease of converting the model codes into C++ or Visual Basic software programming; and The developed model is very easy to be used instead of the using the complicated equations. The neural networks units are implemented, using the back propagation (BP) learning algorithm due to its benefits to have the ability to predict values in – between learning values, also make interpolation between learning curves data. This is done with suitable number of network layers and neurons at minimum error and precise manner. Number of neurons and layers are selected to give more accuracy to the model with back- propagation technique with two layers one hidden layer and the other output layer. This configuration is considered to be as a general approximator to any function with a log-sigmoid function in the hidden layer and pure- line for output layer. Number of neurons in output layer has to be the same as the output variables number. Number of neurons in hidden layer is selected by inspection or by try and error until reaching the desired performance goal, accuracy, minimum error with little time for training and with low number of neurons as possible with the aid of MATLAB, and toolbox. Identification and estimation of wind energy in Egypt is proposed to present a simple method for the calculation and appraisal of the wind energy potential available in Egypt. This is done based on real data from many stations in Egypt with the aid of Artificial Neural Network (ANN) to help in future wind energy family homes. The Neural Network is created and trained by the data of many wind energy stations in Egypt like: Sallum, Sidi Barrani, El Dabaa, Dekheila, Alexandria, Balteam, Damietta, Port Said, and El Arish stations; then checked and tested for Marsa Matroh and Hergada stations to show its validity. The neural network' inputs are: Latitude, Longitude, Elevation and Month; the output is the monthly wind speed.

BIBLIOGRAPHY

[1] Ghassan Halasa, "Wind-Solar Hybrid Electrical Power Generation in Jordan," Jordan Journal of Mechanical and Industrial Engineering (JJMIE), Volume 4, Number 1, Jan. 2010, Pages 205 - 209

[2] S. Chen, L. Li, "3D Modeling and Finite Element analysis of Dynamic Characteristics for Blades of Wind Turbine", Power and Energy Engineering Conference (APPEEC), 2010 Asia-Pacific, 28-31 March 2010, pp. 1 – 4.

[3] Z. Yao; L. Xiao; X. Wei; C. Gong, "A High-Reliability and High-Efficiency Off-Grid Inverter Suitable for Direct-Driven Wind Generator Systems", Power and Energy Engineering Conference (APPEEC), 2010 Asia-Pacific, 28-31 March 2010, 10 – 30.

[4] J. G. Massey, "Douby Fed Induction Machine Control For Wind Energy Conservation," Master's Thesis, Naval Postgraduate School, 2009.

[5] A. El Shahat, H. El Shewy, "Neural Unit for PM Synchronous Machine Performance Improvement used for Renewable Energy", Paper Ref.: 910, Global Conference on Renewable and Energy Efficiency for Desert Regions (GCREEDER2009), Amman, Jordan.

[6] Isam Janajreh, Rana Qudaih, Ilham Talab, Chaouki Ghenai. Aerodynamic flow simulation of wind turbine: Downwind versus upwind configuration. Energy Conversion and Management, 51 (2010) 1656–1663.

[7] A.S. Nafey, M.A. Sharaf, Lourdes García-Rodríguez. A new visual library for design and simulation of solar desalination systems (SDS). Desalination 259 (2010) 197–207.

[8] M. Jafarian, A.M. Ranjbar. Fuzzy modeling techniques and artificial neural networks to estimate annual energy output of a wind turbine. Renewable Energy 35 (2010) 2008–2014.

[9] Vinay Thapar. Gayatri Agnihotri. Vinod Krishna Sethi. Critical analysis of methods for mathematical modeling of wind turbines. Renewable Energy 36 (2011) 3166-3177.

[10] S. Bououden. M. Chadli. S. Filali. A. El Hajjaji. Fuzzy model based multivariable predictive control of a variable speed wind turbine: LMI approach. Renewable Energy 37 (2012) 434-439.

[11] M.O.L. Hansen. J.N. Sorensen. S. Voutsinasb. N. Sorensenc. H.A. Madsen. State of the art in wind turbine aerodynamics and aero-elasticity. Progress in Aerospace Sciences 42 (2006) 285–330.

[12] Alireza Emami. Pirooz Noghreh. New approach on optimization in placement of wind turbines within wind farm by genetic algorithms. Renewable Energy 35 (2010) 1559–1564.

[13] Andrew Kusiak. Zhe Song. Design of wind farm layout for maximum wind energy capture. Renewable Energy 35 (2010) 685–694.

[14] Isam Janajreh, Rana Qudaih, Ilham Talab, Chaouki Ghenai. Aerodynamic flow simulation of wind turbine: Downwind versus upwind configuration. Energy Conversion and Management 51 (2010) 1656–1663.

[15] Lubov A. Ivanova, Ekaterina D. Nadyozhina. Wind flow deformation inside the wind farm. Journal of Wind Engineering and Industrial Aerodynamics 74-76 (1998) 389-397.

[16] L. Ekonomou, S. Lazarou, G.E. Chatzarakis, V. Vita. Estimation of wind turbines optimal number and produced power in a wind farm using an artificial neural network model. Simulation Modeling Practice and Theory 21 (2012) 21–25.

[17] Fouad Kamel. A small locally produced windmill for electric power generation as a model for small industry. Renewable Energy;6(5):629-32, 1995.

[18] Mortensen NG, Usama Said Said. Wind Atlas for the Gulf of Suez, Arab Republic of Egypt. Measurements and modelling 1991-95. European Wind Energy Conference. Sweden (Göteborg): H. S. Stephens & Associates Ltd; p.623-6, 1996.

[19] Ahmed HK, Abouzeid M. Utilization of wind energy in Egypt at remote areas. Renewable Energy;23:595-604, 2001.

[20] El-Kordy MN, Bader MA, Abed KA, Said M.A. Ibrahim. Economical evaluation of electricity generation considering externalities. Renewable Energy; 25:317-328, 2002.

[21] Ahmed Shata AS, Hanitsch R. Evaluation of wind energy potential and electricity generation on the coast of Mediterranean Sea in Egypt. Renewable Energy;31:1183-1202, 2006.

[22] Ahmed Shata AS, Hanitsch R. The potential of electricity generation on the east coast of Red Sea in Egypt. Renewable Energy;31:1597-1615, 2006.

[23] Ahmed Shata AS, Hanitsch R. Applications of electricity generation on the western coast of Mediterranean Sea in Egypt. 10th Portuguese-Spanish Conference in Electrical Engineering (XCLEEE), Madeira (Funchal), Portugal, 5-7 July, 2007.

[24] Ahmed Shata AS, Hanitsch R. Electricity generation and wind potential assessment at Hurghada, Egypt. Renewable Energy;33:141-148, 2008.

[25] Ahmed Shata AS, Hanitsch R. Applications of electricity generation on the western coast of the Mediterranean Sea in Egypt. International Journal of Ambient Energy;29(1):35-44, 2008.

[26] Rizk M. Wind characteristics and the available wind energy in Egypt. Solar & Wind Technology;4(4):491-9, 1987.

[27] Renne DS, Elliott DL, Holst BD, El-Bassyouni K. Wind energy resource assessment activities in Egypt. EWEC'86, Proceedings of European Wind Energy Association Conference and Exhibition. Italy (Rome): A. Raguzzi, Bookshop for Scientific Publications; p.299-304, 1986.

[28] Ahmed Shata AS. Site potential of Egypt for wind energy applications. M.Sc. thesis submitted to physics department, Faculty of Science, Zagazig University, Egypt; 2000.

[29] Salem AI. Characteristic of surface wind speed and direction over Egypt. Solar Energy for Sustainable Development. Romania;4(2):56-63, 1995.

[30] Mayhoub AB, Azzam A. A survey on the assessment of wind energy potential in Egypt. Renewable Energy;11(2):235-247, 1997.

[31] Ahmed Shata Ahmed Shata, "Theoretical investigation and mathematical modelling of a wind energy system Case study for Mediterranean and Red Sea" Elektrotechnik und Informatik der Technischen Universität Berlin zur Erlangung des akademischen Grades Doktor der Naturwissenschaften, wissenschaftlichen Aussprache: 26.6.2008, PhD thesis, Berlin 2008.

[32] Adel El Shahat, Book "Artificial Neural Network (ANN): Smart & Energy Systems Applications", ISBN 978-3-639-71114-1, Scholar Press Publishing, 2014.

[33] Adel El Shahat, "Neural Network Storage Unit Parameters Modeling", International Journal of Industrial Electronics and Drives, Vol. 1, No. 3; In Press.

[34] Adel El Shahat, "Empirical Capacitive Deionization ANN Nonparametric Modeling for Desalination Purpose", Journal of Engineering Research and Technology, Vol. 1, No. 2, June 2014, pp. 58 -65.

[35] Adel El Shahat, "PV Module Optimum Operation Modeling", Journal of Power Technologies, ISSN: 2083-4187, E-ISSN: 2083-4195, Vol. 94, No 1, 2014, pp. 50–66.

[36] Adel El Shahat, Fathy Abdul Kader, Hamed El Shewy, "ANN Interior PM Synchronous Machine Performance Improvement Unit", Journal of Automation & Systems Engineering, (JASE), ISSN 1112-8542, Volume 7, Issue 4, P3, December 2013, pp. 164-175.

[37] Adel El Shahat, "DC-DC Converter Fed Maximum Power Modeling and Simulation of Distributed Generation for Photovoltaic Applications, Elixir International journal, ISSN 2229 - 712X, July 2013, 31.
[38] Adel El Shahat, “DC-DC Converter Duty Cycle ANN Estimation for DG Applications”, Journal of Electrical Systems (JES), ISSN 1112-5209; Vol. 9, Issue 1, March 2013.
[39] Adel El Shahat, and Hamed El Shewy, “High Fundamental Frequency PM Synchronous Motor Design Neural Regression Function”, Journal of Electrical Engineering, ISSN 1582-4594; Article 10.1.14, Edition 1, March, Vol. 10 / 2010.
[40] A. El Shahat, and H. El Shewy, “PM Synchronous Motor Control Strategies with Their Neural Network Regression Functions”, Journal of Electrical Systems (JES), ISSN 1112-5209; Vol. 5, Issue 4, Dec. 2009.
[41] Adel El Shahat, “Parameters Estimations for Storage Unit based on Performance Characteristics”, 9th International Conference on Electrical Engineering, 27-29 May, 2014, Military Technical College, Egypt.
[42] Adel El Shahat, "Storage Device Unit Modeling", The second International Conference on Engineering and Technology (ICET 2014), German University in Cairo (GUC), April 19 -20, 2014, Cairo, Egypt.