2015

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Recommended Citation

El-Shahat, Adel, Rami J. Haddad, Youakim Kalaani. 2015. "Wind Energy Estimation Functions for Future Homes." *Journal of Power Technologies*, 95 (3). source: http://papers.itc.pw.edu.pl/index.php/JPT/article/download/605/664
https://digitalcommons.georgiasouthern.edu/electrical-eng-facpubs/19

Open Access Journal
Journal of Power Technologies XX (X) (2015) X–X
journal homepage:papers.itc.pw.edu.pl

Wind Energy Estimation Functions for Future Homes

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Abstract

Wind energy is ideally suited for distributed generation systems to meet growing demand for electricity that find applications especially in developing countries. The motive of this study is to develop an efficient method to help identify and select the best sites to harvest the wind energy in Egypt. In this paper, a novel approach is proposed to estimate and appraise wind energy resources using Artificial Neural Network (ANN). To achieve this goal, an ANN-based algorithm was created and trained using relevant data collected from several wind monitoring posts installed across the country. Parameters such as latitude, longitude, elevation, and monthly wind speed were recorded for use as inputs and outputs for the ANN system. A key advantage of this model lies in its ability to predict and make interpolation between the learning curves data without the need for additional training runs. This feature was attainable using back-propagation techniques to estimate the model parameters with the aid of MATLAB. Another advantage of this proposed model is the derivation of closed-form input/output relationships which permitted to obtain fast and accurate results with excellent regression factors. Simulation results were presented in 3D plots and validated with real system data. Finally, The Horizontal Axis Wind Turbine (HWT) is modeled by many actual data from various manufacturers' manuals. Results have shown that the actual data was closely matched confirming the merits of this proposed model. Many other desirable features that researchers can find useful to quantify wind energy resources such as easy model construction, integration with other technologies, and converting into Visual Basic or C++ codes were also identified with this model.

Keywords: Simulation, Artificial Neural Networks (ANN), Wind Turbines, Wind energy, Egypt homes, estimation, site stations and MATLAB.

1. Introduction

Wind energy generation has attracted much interest in the last few years in modeling and control for hybrid systems [1-6]. Solving the mathematical models is a tedious and repetitive problem [7]. Jafarian [8] uses fuzzy modeling techniques and Artificial Neural Networks (ANN) to estimate annual energy output. Vinay [9] presents a comparative study of various methods of mathematical modeling of wind turbines. S. Bououden [10] used fuzzy model based multivariable predictive control of wind turbine generator. 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 using Genetic algorithm approach [12]. A. Kusiak and Z. Song [13] presented a model for wind turbine placement based on the wind distribution. 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. N. G. Mortenson et al. [18], studied the wind atlas for the Gulf of Suez, Egypt. H. K. Ahmed et al. [19], Studied the utilization of wind energy in Egypt in remote areas. M. N. El-Kordy et al. [20], Studied the economical evaluation of electricity generation considering externalities. 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], studied the potential of electricity generation at the east coast of Red Sea in Egypt. 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. 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. In this paper; ANN algorithm is used to simulate HWT in order to compare the results with the test data from the manufacture manuals. Moreover; the new code may help the user or the designer to select a suitable HWT unit based on the power demanded by the application system. A new Graphical User Interface (GUI) for the modeling of the HWT is built too.

2. 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.

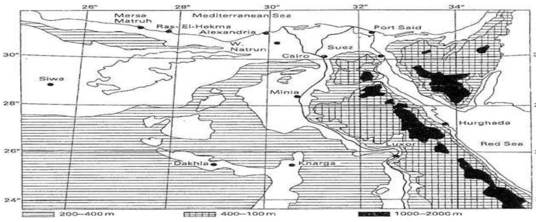

Fig. 1. Orography of the Egyptian Region [26]) [31].

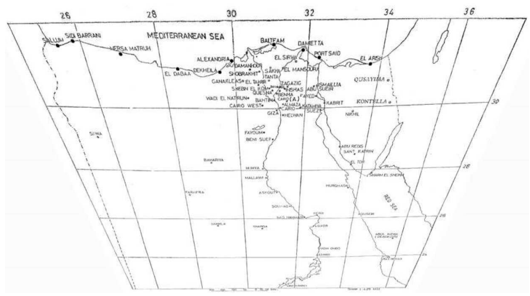

Fig. 2. Distribution of stations over Egypt [31].

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.

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].

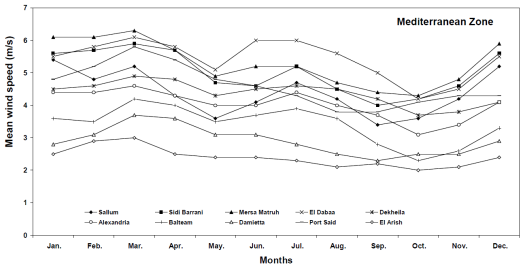

Fig. 3. Monthly variation of wind speeds for stations [31].

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.

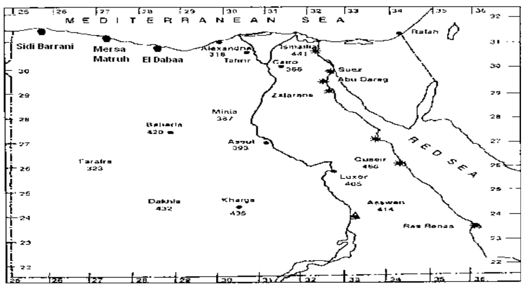

Fig. 4. Distribution of some stations over Egypt [31].

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.

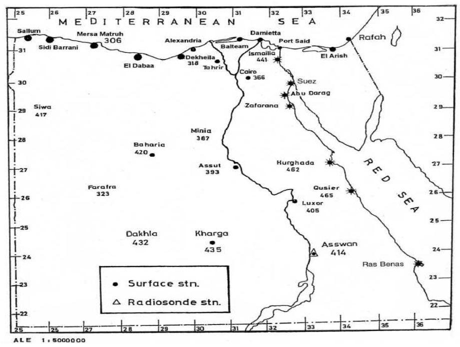

Fig. 5. Distribution of stations over Egypt [30], [31].

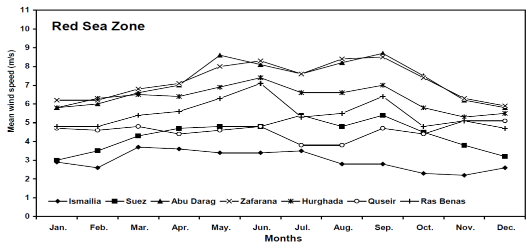

Fig. 6. Monthly variation of wind speeds for stations [31].

3. ANN Wind Estimation Function

The wind regression model is performed by the ANN method illustrated and validated in [32-42], [44] 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 has to be the same as the output variables number. Number of neurons in hidden layer is selected by inspection 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 excellent regression constant.

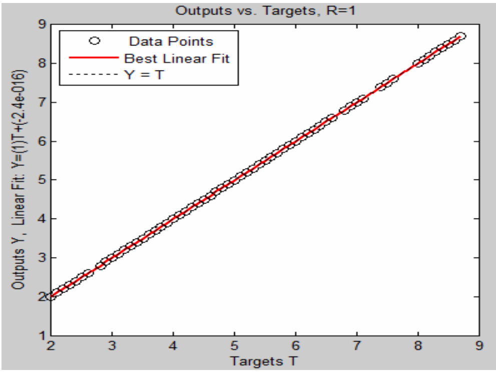

Fig. 7. Output VS Target for ANN Model training data

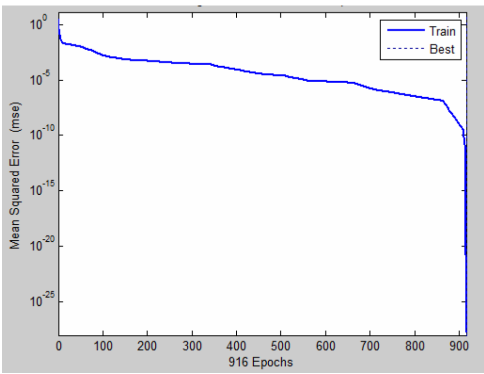

Fig. 8. Performance for the Model

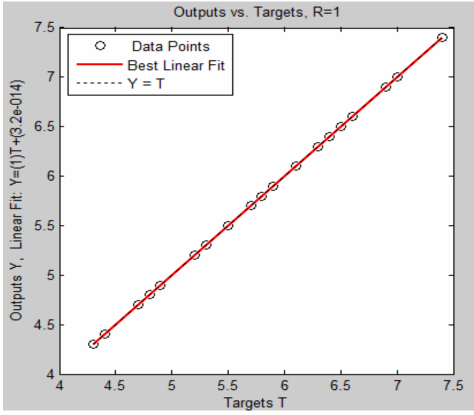

Fig. 9. Output VS Target for ANN Model testing data

The ANN Regression equations are presented as follows; (n denotes normalized variable):

$Latitude_n$ = (Latitude – 29.7929) / 2.1699 (1)

$Longitude_n$ = (Longitude – 30.8935)/2.8941 (2)

$Elevation_n$ = (Elevation – 8.9588) / 9.1365 (3)

$Month_n$ = (Month – 6.5000) / 3.4605 (4)

$$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)$$

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

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 (7)

The un-normalized out put

Windspeed = 1.4859 Windspeed$_n$ + 4.7064 (8)

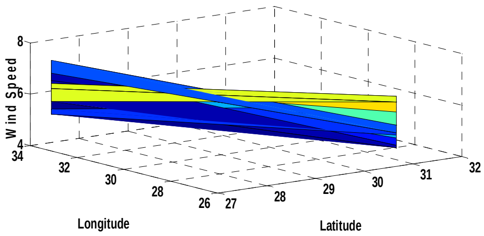

Fig. 10. Wind Speed, Longitude with Latitude for test data

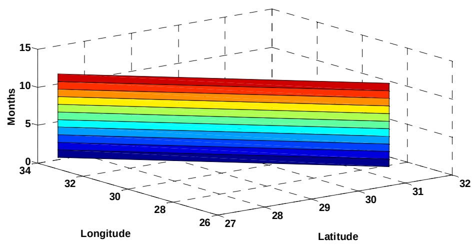

Fig. 11. Months, Longitude with Latitude for testing data

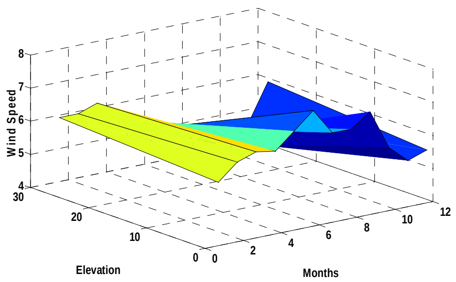

Fig. 12. Wind speed, Elevation with Months for testing data

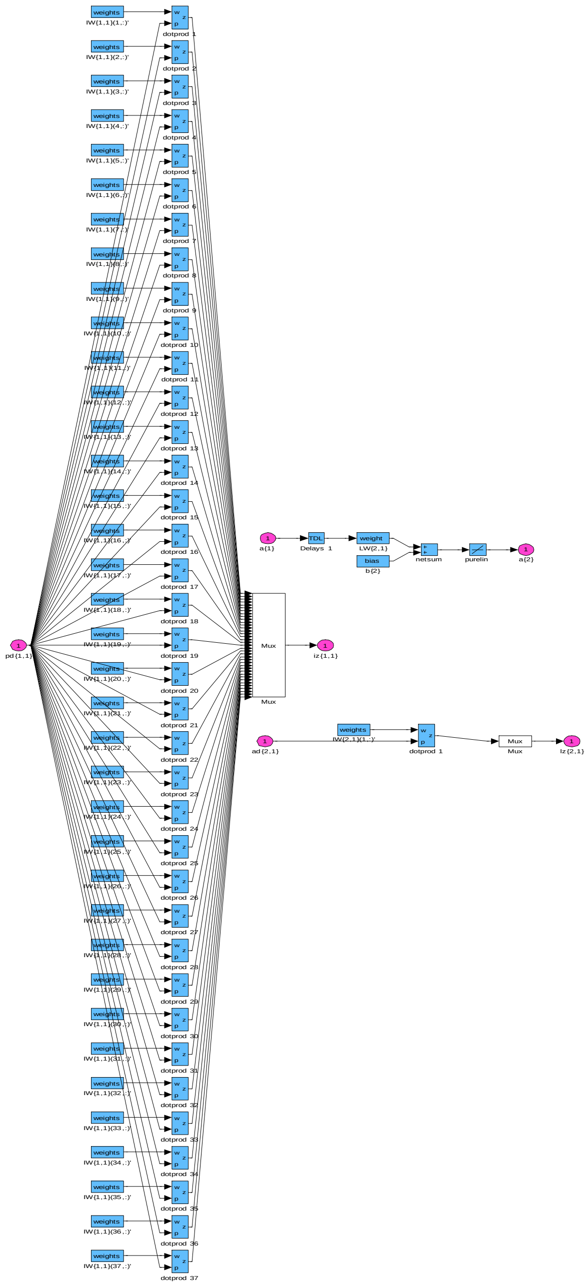

Fig. 12. ANN Model with its layers, neurons, weights, and structures.

Table 1 shows the performance of the trialed ANN model to check its validation. This is done by making a comparison with the real data and error percent for three wind station.

Table 1: Performance of the ANN model

station	latitude	longitude	elevation	month	orginal data	ANN data	E-F	Error%
sallum	31.32	25.11	4	1	5.4	5.40011	-0.00011	0%
	31.32	25.11	4	2	4.8	4.79997	3.03E-05	0%
	31.32	25.11	4	3	5.2	5.199998	2.06E-06	0%
	31.32	25.11	4	4	4.3	4.300072	-7.2E-05	0%
	31.32	25.11	4	5	3.6	3.600112	-0.00011	0%
	31.32	25.11	4	6	4.1	4.100046	-4.6E-05	0%
	31.32	25.11	4	7	4.7	4.700008	-7.6E-06	0%
	31.32	25.11	4	8	4.2	4.200125	-0.00012	0%
	31.32	25.11	4	9	3.4	3.40039	-0.00039	0%
	31.32	25.11	4	10	3.6	3.600339	-0.00034	0%
	31.32	25.11	4	11	4.2	4.200113	-0.00011	0%
	31.32	25.11	4	12	5.2	5.199809	0.000191	0%
sidi barani	31.38	25.38	21	1	5.6	5.600346	-0.00035	0%
	31.38	25.38	21	2	5.7	5.70015	-0.00015	0%
	31.38	25.38	21	3	5.9	5.90014	-0.00014	0%
	31.38	25.38	21	4	5.7	5.699965	3.54E-05	0%
	31.38	25.38	21	5	4.7	4.699735	0.000265	0%
	31.38	25.38	21	6	4.6	4.599625	0.000375	0%
	31.38	25.38	21	7	5.2	5.199939	6.14E-05	0%
	31.38	25.38	21	8	4.5	4.500244	-0.00024	0%
	31.38	25.38	21	9	4	4.000183	-0.00018	0%
	31.38	25.38	21	10	4.2	4.200084	-8.4E-05	0%
	31.38	25.38	21	11	4.6	4.600067	-6.7E-05	0%
	31.38	25.38	21	12	5.6	5.600175	-0.00018	0%
mersa matruh	31.2	27.13	28.3	1	6.1	6.099913	8.7E-05	0%
	31.2	27.13	28.3	2	6.1	6.10019	-0.00019	0%

4. HWT Mathematical Model

In order to simulate and predict the characteristics of different types of wind turbines; a lot of real data are taken from the manufacture manual of each type. It is proposed that by identifying the output power from the turbine unit, the design limits would be calculated. The design limits are summarized as follows: Starting wind speed (m/s), Average wind speed (m/s), Hub height (m), Fin length (m), Rotor diameter (m), Rotor speed (r.p.m), Unit cost ($) and number of blades in case of vertical type. The mathematical model could be correlated based on the actual data. The watt points are varying from 0.5kW to 8000~10,000kW according to many companies. The data were obtained from about fifty different companies working in the field of manufacturing of wind turbines. The data points are fitted by two methods. The first method is done by the curve fitting tool box, and the second is done by the Neural Network technique.

5. Neural Network Modeling for HWT

The regression model for the HWT that performed by the ANN method [32-45] is presented in this section. Based on the available data units; the hidden layer would be a nine neurons and the output layer would be six neurons. The input is one parameter (Power) and the outputs are six parameters. 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 has to be the same as the output variables number. Number of neurons in hidden layer is selected by inspection and minimum error until reaching the desired performance goal, and accuracy. Fig. 15 shows the neural network model concept for the HWT.

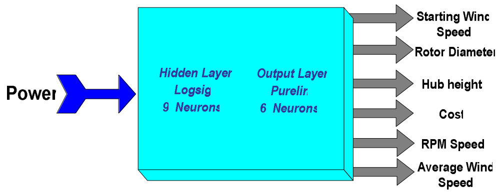

Fig. 14. HWT Neural Network Model concept.

The ANN Regression equations are presented as follows:

$$P_n = (P - 753.6348)/1693.5 \quad (9)$$

Where P_n presents the normalized input for the power and the following equations lead to the required derived equation. Eq. (9) presents the normalized input for the power and the following equations lead to the required derived equation where *n*: Subscript denotes normalized parameters, *EI*: Sum of input with input weight and input bias for each node in a hidden layer in a neural network, and *Fi*: Output from each node in a hidden layer to output layer according to transfer function.

$$E1 = -5.9236P_n + 46.7085$$

$$F1 = 1/(1 + \exp(-E1))$$

$$E2 = -9.9346P_n + 39.4127$$

$$F2 = 1/(1 + \exp(-E2))$$

$$E3 = 5.1501P_n - 3.0470$$

$$F3 = 1/(1 + \exp(-E3))$$

$$E4 = -238.6727P_n + 24.3577$$

$$F4 = 1/(1 + \exp(-E4))$$

$$E5 = -3.2422P_n + 3.7053$$

$$F5 = 1/(1 + \exp(-E5))$$

$$E6 = -59.8291P_n + 78.8676 \tag{10}$$
$$F6 = 1/(1 + \exp(-E6))$$
$$E7 = -7.2582P_n + 3.2749$$
$$F7 = 1/(1 + \exp(-E7))$$
$$E8 = -20.1764P_n - 1.9335$$
$$F8 = 1/(1 + \exp(-E8))$$
$$E9 = 804.8057P_n + 365.3206$$
$$F9 = 1/(1 + \exp(-E9))$$

Normalized starting wind speed from ANN is presented in (11).

$$Vw_n = -3829.9F1 - 2901.7F2 + 8549.1F3 - 2094.6F4 + 7359.2F5 - 2293F6 + 7219.9F7 - 61.9F8 + 440.2F9 - 3826.3 \tag{11}$$

Normalized rotor diameter from ANN is found in (12).

$$D_{rn} = -86.6F1 + 1133.4F2 - 465.1F3 - 2773.8F4 - 3272.5F5 + 1405.2F6 + 3669.9F7 - 122.2F8 + 125.4F9 - 90.8 \tag{12}$$

The hub normalized hub height by the ANN is found by (13).

$$H_{hn} = -137.5F1 + 1074.8F2 - 227.5F3 - 2900.3F4 - 3132.8F5 + 1369.6F6 + 3966.2F7 - 126.8F8 + 17.8F9 - 142.8 \tag{13}$$

Normalized cost relation from ANN is presented in (14).

$$C_{tn} = -35.3F1 + 417.3F2 - 120.2F3 - 1083.9F4 - 1212.3F5 + 524.4F6 + 1465.5F7 - 48F8 + 6.4F9 - 38.9 \tag{14}$$

Normalized r.p.m speed from ANN is formulated by (15).

$$r.p.m_n = 498.5F1 - 2869.8F2 + 3221.2F3 + 4460.4F4 + 8003.6F5 - 3199.1F6 - 4669.6F7 + 204.5F8 - 2935.7F9 + 531.4 \tag{15}$$

The normalized average wind speed is existed by (16).

$$Vw_{an} = -1393.9F1 + 942.7F2 + 1228.4F3 - 4317.8F4 - 2942.6F5 + 1455.4F6 + 6691F7 - 183.3F8 + 1143.F9 - 1408.3 \tag{16}$$

Then un-normalized outputs are performed as follows:

$$Vw = 1.0\exp(5)(0.000975Vw_n + 0.000098) \tag{17}$$
$$D_r = 1.0\exp(5)(0.0004D_{rn} + 0.0003) \tag{18}$$
$$H_h = 1.0\exp(5)(0.0003H_{hn} + 0.0003) \tag{19}$$
$$C_t = 1.0\exp(5)(8.8069\ C_{tn} + 4.6983) \tag{20}$$
$$r.p.m = 1.0\exp(5)(0.0012r.p.m_n + 0.0014) \tag{21}$$
$$Vw_a = 1.0\exp(5)(0.000049Vw_{an} + 0.0001) \tag{22}$$

6. The Model Validation

Results for HWT type of wind turbines are presented in this section. Figures 15 and 16 represent the data results comparisons between the actual data, the polynomial correlations. It's obvious from the figure that the actual data are highly matched with the polynomial (poly) correlations and the ANN correlations.

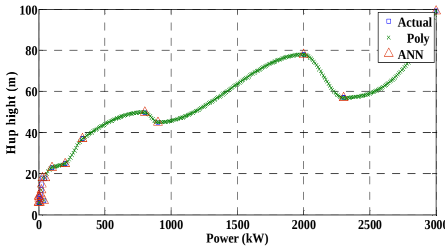

Fig. 15. HWT Comparisons based on hub height.

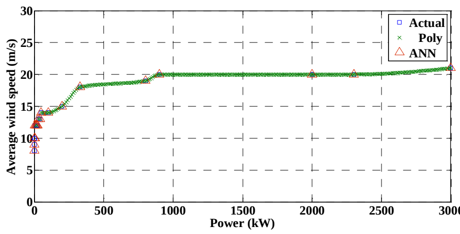

Fig. 16. HWT Comparisons based on average wind speed

Using the neural network technique in implementing a neural model to connect between the variables that: entering the Rated Power, V_w and Power ranges as inputs to generate *CP*, D_r, H_h, and rpm. Some of training data are well depicted in the following 3D figures for all inputs and targets (outputs). The GUI model equations of the ANN are presented.

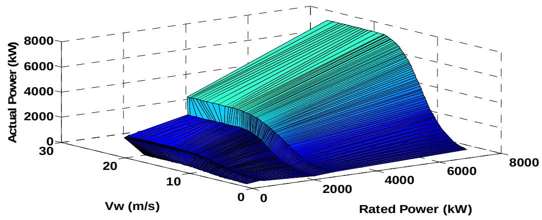

Fig. 17. The effect of wind speed, m/s and rated power on the demanded actual power, kW.

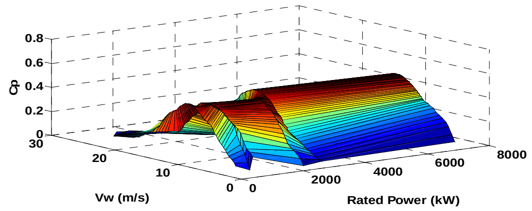

Fig. 18. The effect of wind speed, m/s and rated power, kW on the power coefficient of the HWT.

The neural model (HWT example) details, regression are presented in the following:

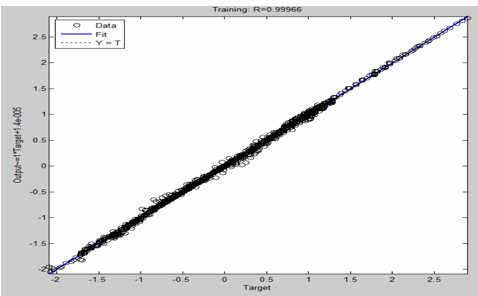

Fig. 19. Regression analysis (R =0.99966).

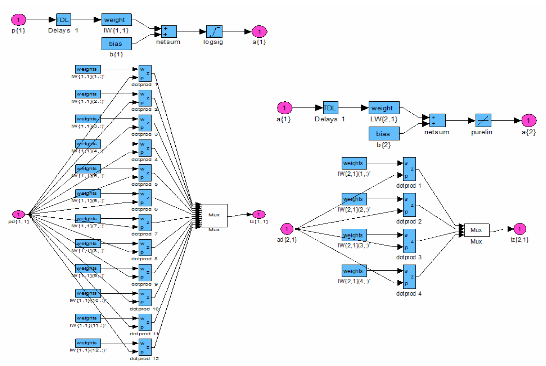

Fig. 20. ANN Model with its layers, neurons, weights, and structures.

As a case study investigation for a real turbine unit, the model is utilized to calculate the operating conditions for 7500 kW power from reference (ENERCON [43]). The input power is about 7500 kW based on E-126 model [43]. Table 1 shows the data results for polynomial and ANN methods compared vs. the actual data from reference [43]. The Table 2 results show a very good agreement with the actual data.

Table 2: HWT data comparison between the developed models and Reference [43]

Parameters	ENERCON [43]	Polynomial	ANN model
HP, kW	7500	7500	7500
Vw_s, *m/s*	16	15.19	15.08
Vw_a, *m/s*	25	22.61	22.38
Dr, m	127	132.1	131.44
Hh, m	135	135	134.89
Rotor speed, r.p.m	5-11.7	9	9.2
Ar, m^2	12668	13704.83	13478
ρ_{air}, kg/m^3	1.225	1.221	1.22

7. Conclusion

Estimation of wind energy in Egypt is well proposed. This is done based on real data from many stations in Egypt using 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. Then checked 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. The modeling technique and the proposed circuit model are useful for power electronics designers. A simple, fast, accurate, and easy-to-use modeling method is adopted. This function will help in wind turbines installation. The required models are investigated and compared with the actual data from the manufacturer's manuals of the turbines. If we have the wind speed of the location, you can simply, specify the suitable wind turbine for this location. The neural networks units are implemented, using the back propagation (BP) learning algorithm due to its benefits. 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 mean square error optimization technique. The models have many features such as: Easy model construction; Covering a wide range; Easy of combination with other technologies.

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