Vol. 4, No. 6 June 2014 ISSN 2225-7217
ARPN Journal of Science and Technology
©2011-2014. All rights reserved.

http://www.ejournalofscience.org

Wind Turbines Design and Simulation Aspects for Renewable Energy Applications

[1] Adel El Shahat, [2] Ahmed M. Soliman, [3] Mohamed A. Sharaf
[1] Visiting Assistant Professor, Deprtment of Electrical and Computer Engineering at University of Illinois, Chicago (UIC), USA
[1] Assistant Professor, Engineering Science Dept, Faculty of Petroleum & Mining Engineering, Suez University, Suez, Egypt
[2] Assistant Professor, Engineering Science Dept, Faculty of Petroleum & Mining Engineering, Suez University, Suez, Egypt
[3] Assistant Professor, Engineering Science Dept, Faculty of Petroleum & Mining Engineering, Suez University, Suez, Egypt

[1] asayed2@uic.edu; adel.elshahat@ieee.org; adelalshahat.ahmed@suezuniv.edu.eg;

ABSTRACT

Wind energy plays a vital role in the quest for renewable and sustainable energy as well as in reducing carbon emission. There are a lot of numerical techniques that are performed in order to design and simulate the wind turbines. However; such numerical techniques are focused on structure, blade design, blade fatigue, aerodynamics analyses, etc. In this work, new correlations are implemented for the design and simulation of different types of wind turbines (Horizontal and Vertical). The numerical correlations are performed by the use of Mat Lab/SimuLink tool box. Moreover; Artificial Neural Network (ANN) numerical technique is used to simulate and evaluate the designed modules. The implemented correlations may help the designer and\or investor in order to elect a specified wind turbine according to the demanded load and design the wind farm. The results reveal that the implemented correlations show a very good matching with the actual commercial data points of the wind turbines.

Keywords: *Horizontal wind turbines; Vertical wind turbines; Mat Lab/SimuLink; Artificial Neural Networks (ANN).*

1. INTRODUCTION

Wind turbines demonstrated their importance and viability in comparable with other renewable energy resources. Wind turbines are inspiring structures of human responsiveness to, and awareness of, depleting fossil fuel resources and global warming. They are, essentially, grouped into two configurations based on their rotational rotor axis with respect to the ground: (i) the older generation, lower–power vertical axis and (ii) the higher power, horizontal-axis at wide commercial deployment. A wind turbine consists of the rotor blades that convert the wind's kinetic energy into rotational shaft energy. The rotor's blades are aerofoil shape that creates imbalanced pressure gradients between the pressure side and suction side as the air passes by the rotor sweep area. Process simulation has become an accepted tool for the performance, design, and optimization calculations for wind turbines. Solving the mathematical models representing these units and systems is a tedious and repetitive problem [2].

Iterative procedures are used to solve these models. To tackle the mathematical problems, several researchers have developed different methods, techniques, and computer programs for the simulation of a very wide range of variety for wind turbines. At the same time; there are many methodologies for the simulation of wind turbines. Jafarian [3] uses fuzzy modeling techniques and Artificial Neural Networks (ANN) to estimate annual energy output for wind turbine in different regions. He has been found that the accuracy of this method is better than the accuracy of conventional methods. Jafarian [3] model was built based on three main inputs: average wind speed, standard deviation of wind speed, and air density of the region. Jafarian work was built based on performance technique of simulation not for design technique. Vinay [4] presents comparative study of various methods for mathematical modeling of wind turbines, with reference to three commercially available wind turbines, with the help of an algorithm developed. Models by Vinay [4] are performed based on a presumed shape of power curve, though simple to use, also lack the desired accuracy; however, they give satisfactory response for higher annual average wind speeds. However; Vinay [4] work was concluded about limited range of power of wind turbines. S. Bououden [5] used fuzzy model based multivariable predictive control for wind turbine generator. One of the several advantages of the Bououden's [5] technique is that the behavior of the model is predicted based on past measurements and computed future inputs. However; the Bououden case study was performed based on performance method of modeling. For the same way of modeling technique, the different approaches to structural modeling of wind turbines are addressed by Hansen [6]. 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 [7].

In optimized placement of wind turbines the following statements must were considered; the influence of wind turbines on each other (the wake), the variation of wind in direction and intensity and the final placement for wind turbines should produce the maximum energy with the minimum cost for installation and terrain. Also A. Kusiak and Z. Song [8] presented a model for wind turbine placement based on the wind distribution to maximize the wind energy capture. The model considers wake loss, which can be calculated based on wind turbine locations, and wind direction. The model that was developed by [8] is performed based on a specific case study of wind turbine. It is obvious for

©2011-2014. All rights reserved.

literature that the most of presented mathematical models were performed based on the performance technique not the design technique. Moreover; it was built for special cases and not for a wide range of operating conditions. In the performance method, the variables associated with the wind stream and all design parameters (such as hub height, hub diameter, RPM, etc.) are assumed to be known. The variables associating the internal and outputs are the unknowns such as the developed power and efficiency or coefficient of performance. However, in the design method, design parameters (such as hub height, rotor diameter, rotor speed, etc.) are left unspecified and become unknown. At the same time, the developed power and power coefficient are known and specified. In This work; design and simulation of different types of wind turbines is performed and analyzed based on design method of modeling. The developed power by the turbine unit is assigned in order to calculate the rest of design parameters such as minimum wind speed, average wind speed, rotor diameter, hub height, rotor speed and the unit cost. A new Graphical User Interface (GUI) for the modeling of the turbines is built by the use of Mat Lab/SimuLink software browser. The GUI model is performed based on non-liner correlations built by curve fitting tool box. Moreover; ANN algorithm is used to simulate the turbines and to compare the results with the correlations and the test data from the manufacture manual. The aim of this work may be concluded into the following points:

- Mat Lab/SimuLink (GUI) and ANN are utilized for the simulation procedure.
- Designing and simulation of different types of wind turbines based on a wide range of operating conditions (0.5kW-8000kW for HWT & 0.3kW-10kW for VWT).
- Driving out new correlations for different types of wind turbines based on GUI model and ANN algorithm.
- Comparing the correlations results with the test data from the manufacture manual of the turbine units.

This modular program has great capabilities to overcome previous programming problems and limitations such as the recycle streams. The units are modeled to present a good example of the proposed modular program. Moreover; the new code may help the user or the designer to select a suitable turbine unit based on the demanded power.

2. PROCESS ANALYSIS

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 the following:

- ✓ Starting wind speed, m/s.
- ✓ Average wind speed, m/s.
- ✓ Hub height, m (HWT) and fin length, m (VWT).
- ✓ Rotor diameter, m.
- ✓ The rotor speed, RPM.
- ✓ The unit cost, $.
- ✓ Number of blades in case of vertical type.

Mat Lab tool box [9] is used to predict the characteristics correlations based on non-liner and Artificial Neural Network (ANN) techniques.

2.1 Mat Lab/SimuLink GUI

SimuLink [10] is a general-purpose software program for dynamic systems. This program has been selected to carry out the task of wind turbines modeling and simulation because it offers excellent performance qualities for designing regulation algorithms. SimuLink encourages users to try things out. User can easily build models from scratch, or modifying an existing model. For modeling, SimuLink provides a graphical user-interface (GUI) for building models as block diagrams, using click-and-drag mouse operations. With this interface, the user can draw the models just as it would with pencil and paper.

User can also customize and create his own blocks. SimuLink can also utilize many Mat Lab features. The Library Browser displays the SimuLink block libraries installed on the user system. User builds models by copying blocks from a library into a model window. SimuLink can also utilize many Mat Lab features. Mat Lab is a high-performance language for technical computing [9]. As an example of the SimuLink use, Sharaf et al. [11] developed a new visual library for solar desalination systems. Based on the same idea, turbine model is designed and simulated via the same platform. A visual library is embedded into the SimuLink browser via GUI modeling. Figure (1) shows the photograph of the wind turbine library under SimuLink browser.

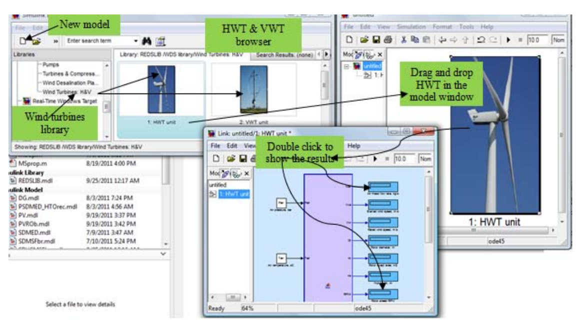

Fig 1: Wind turbines library browser under Mat Lab/SimuLink platform.

2.1.1 Horizontal wind Turbine (HWT) Analysis

The Horizontal Wind Turbine (HWT) is modeled according to the specification data obtained from the manufacture manual for many watt points. The watt points are varying from 0.5kW to 8000kW

Vol. 4, No. 6 June 2014 ISSN 2225-7217
ARPN Journal of Science and Technology
©2011-2014. All rights reserved.
http://www.ejournalofscience.org

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. The model is presented and correlated as a functional of wind turbine power (*HP*) as follows:

The starting wind speed m/s as a function of turbine power (*HP* kW):

$$Vw_s = 13.37 \times e^{\left(1.698^{-5} \times HP\right)} - 10.72 \times e^{\left(-0.008214 \times HP\right)} \ldots (1)$$

The average wind speed m/s:

$$Vw_a = 9.378 \times \left(HP^{0.09862}\right) \ldots (2)$$

The rotor diameter m:

$$Dr = 2.573 \times \left(HP^{0.4414}\right) \ldots (3)$$

The tower (Hub) height m:

$$Hh = 1.487 \times \left(HP^{0.8046}\right) + 5.854 \ldots (4)$$

Air density kg/m^3 is calculated based on air and pressure temperature:

$$\rho_{air} = \frac{P_{air} \times 100}{0.287 \times (T_{air} + 273.15)} \ldots (5)$$

Where P_{air} is in bar and T_{air} is in ^{o}C.

The rotor swept area m^2 is then calculated based on the rotor diameter *Dr*:

$$Ar = \pi \times (Dr/2)^2 \ldots (6)$$

The air mass flow rate kg/s is then calculated based on the density, rotor swept area and average wind speed:

$$M_{air} = \rho_{air} \times Ar \times Vw_a \ldots (7)$$

The required wind power kW:

$$HP_w = \frac{\left(\frac{1}{2} \times \rho_{air} \times Ar \times \left(Vw_a^{\,3}\right)\right)}{1000} \ldots (8)$$

The power coefficient is calculated from the assigned power *HP* and the aerodynamic power *HPw*:

$$CP = \frac{HP}{HP_w} \ldots (9)$$

The rotor speed in RPM:

$$RPM_r = 347.6 \times \left(HP^{-0.2909}\right) - 16.91 \ldots (10)$$

The rotor torque in N.m based on the power of the turbine and ω:

$$\omega = \frac{(2 \times \pi \times RPM_r)}{60} \ldots (11)$$

$$Tor = \frac{(1000 \times HP)}{\omega} \ldots (12)$$

The turbine unit cost \$:

$$C_t = (HP \times 310.985) + 390.8 \ldots (13)$$

The number of wind turbines can be calculated related to the total demanded power (*THP* kW) from the wind farm:

$$NWT = \frac{THP}{HP} \ldots (14)$$

2.1.2 Vertical wind turbine (VWT) analysis

Vertical wind turbines are modeled based on power range of 0.3kW up to 10kW. The correlations below show the curve fitting of different design parameters that should be obtained at a specified power. The starting wind speed m/s as a function of turbine power (*HP* kW):

$$Vw_s = 2.615 \times e^{(0.009563 \times HP)} - 2.242 \times e^{(-2.288 \times HP)} \ldots (15)$$

The average wind speed m/s:

$$Vw_a = \left(4.17 \times HP^{0.3762}\right) + 3.346 \ldots (16)$$

The rotor diameter m:

$$Dr = 1.806 \times \left(HP^{0.4011}\right) \ldots (17)$$

The fin length m:

$$F_l = 2.145 \times \left(HP^{0.3628}\right) \ldots (18)$$

The rotor swept area m^2 is then calculated based on the rotor diameter *Dr*:

$$Ar = \pi \times F_l \times Dr \ldots (19)$$

The required wind power kW:

$$HP_w = \frac{\left(\frac{1}{2} \times \rho_{air} \times Ar \times \left(Vw_a^{\,3}\right)\right)}{1000} \ldots (20)$$

Vol. 4, No. 6 June 2014 ISSN 2225-7217
ARPN Journal of Science and Technology
©2011-2014. All rights reserved.
http://www.ejournalofscience.org

The power coefficient is calculated from the assigned power *HP* and the aerodynamic power *HPw*:

$$CP = \frac{HP}{HP_W} \ldots (21)$$

The rotor speed RPM based on power parameter:

$$RPM_r = 4.759 \times (HP^{-1.693}) + 143.1 \ldots (22)$$

The rotor torque in N.m based on the power of the turbine and ω:

$$\omega = \frac{(2 \times \pi \times RPM_r)}{60} \ldots (23)$$

$$Tor = \frac{(1000 \times HP)}{\omega} \ldots (24)$$

The number of wind turbines can be calculated related to the total demanded power (*THP* kW) from the wind farm:

$$NWT = \frac{THP}{HP} \ldots (25)$$

The number of blades (*NOB*) as a function of turbine power is expressed as following:

$$NOB = -0.02366 \times HP^2 + 0.5014 \times HP + 4.52 \ldots (26)$$

2.2 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) toolbox provides tools for designing, implementing, visualizing, and simulating neural networks. ANN is used for applications where formal analysis is difficult [9]. ANN is composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. User can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The next figure illustrates such a situation. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. The used technique here is illustrated, used, tested and verified in [13] – [27]. Typically, many such input/target pairs are needed to train a network.

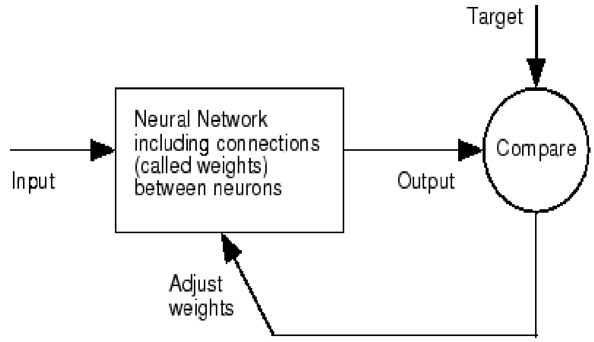

Fig 2: Schematic diagram of ANN concept.

2.2.1 Horizontal wind turbine (HWT) ANN analysis

The regression model for the HWT that performed by the ANN method is presented in this subsection. 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. Figure (3) shows the neural network model concept for the HWT.

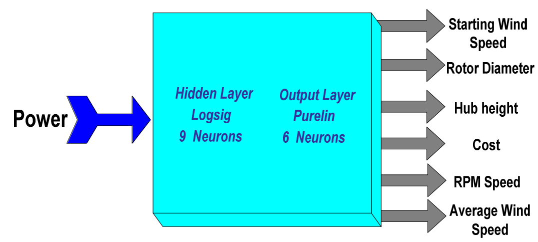

Fig 3: HWT Neural Network Model concept.

The ANN Regression equations are presented as following;

$$P_n = \frac{P - 753.6348}{1.6935^3} \ldots (27)$$

Where P_n presents the normalized input for the power and the following equations lead to the required derived equation.

Equation (27) 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 hidden layer in neural network, and *Fi*: Output from each node in hidden layer to output layer according to transfer function.

Vol. 4, No. 6 June 2014 ISSN 2225-7217
ARPN Journal of Science and Technology
©2011-2014. All rights reserved.
http://www.ejournalofscience.org

$$\left.\begin{aligned}
E1 &= -5.9236 \times P_n + 46.7085\\
E2 &= -9.9346 \times P_n + 39.4127\\
E3 &= 5.1501 \times P_n - 3.0470\\
E4 &= -238.6727 \times P_n + 24.3577\\
E5 &= -3.2422 \times P_n + 3.7053\\
E6 &= -59.8291 \times P_n + 78.8676\\
E7 &= -7.2582 \times P_n + 3.2749\\
E8 &= -20.1764 \times P_n - 1.9335
\end{aligned}\right\} \ldots (28)$$

$$E9 = 804.8057 \times P_n + 365.3206$$

$$F_{1\ldots 9} = \frac{1}{\left(1 + e^{-E_{1\ldots 9}}\right)} \ldots (29)$$

The normalized starting wind speed relation from ANN is then presented in equation (30).

$$Vw_n = 10^3 \times [-3.8299 \times F1 - 2.9017 \times F2 + 8.5491 \times F3 - 2.0946 \times F4 + 7.3592 \times F5 - 2.293 \times F6 + 7.2199 \times F7 - 0.0619 \times F8 + 0.4402 \times F9 - 3.8263] \ldots (30)$$

Also the normalized rotor diameter relation from ANN is found in equation (31).

$$Dr_n = 10^3 \times [-0.0866 \times F1 + 1.1334 \times F2 - 0.4651 \times F3 - 2.7738 \times F4 - 3.2725 \times F5 + 1.4052 \times F6 + 3.6699 \times F7 - 0.1222 \times F8 + 0.1254 \times F9 - 0.0908] \ldots (31)$$

The hub normalized hub height by the ANN is found by equation (32).

$$Hh_n = 10^3 \times [-0.1375 \times F1 + 1.0748 \times F2 - 0.2275 \times F3 - 2.9003 \times F4 - 3.1328 \times F5 + 1.3696 \times F6 + 3.9662 \times F7 - 0.1268 \times F8 + 0.0178 \times F9 - 0.1428] \ldots (32)$$

The normalized cost relation from ANN is presented in equation (33).

$$Ct_n = 10^3 \times [-0.0353 \times F1 + 0.4173 \times F2 - 0.1202 \times F3 - 1.0839 \times F4 - 1.2123 \times F5 + 0.5244 \times F6 + 1.4655 \times F7 - 0.0480 \times F8 + 0.0064 \times F9 - 0.0389] \ldots (33)$$

The normalized rpm speed relation from ANN is formulated by equation (34).

$$RPM_n = 10^3 \times [0.4985 \times F1 - 2.8698 \times F2 + 3.2212 \times F3 + 4.4604 \times F4 + 8.0036 \times F5 - 3.1991 \times F6 - 4.6696 \times F7 + 0.2045 \times F8 - 2.9357 \times F9 + 0.5314] \ldots (34)$$

The normalized average wind speed is existed by equation (35).

$$Vw_{a_n} = 10^3 \times [-1.3939 \times F1 + 0.9427 \times F2 + 1.2284 \times F3 - 4.3178 \times F4 - 2.9426 \times F5 + 1.4554 \times F6 + 6.691 \times F7 - 0.1833 \times F8 + 1.143 \times F9 - 1.4083] \ldots (35)$$

Then un-normalized outputs are performed as following;

$$Vw_s = 10^3 \times 0.000975 \times Vw_n + 10^3 \times 0.000098 \ldots (36)$$
$$Dr = 10^3 \times 0.0004 \times Dr_n + 10^3 \times 0.0003 \ldots (37)$$
$$H = 10^3 \times 0.0003 \times H_n + 10^3 \times 0.0003 \ldots (38)$$
$$Ct = 10^3 \times 8.8069 \times Ct_n + 10^3 \times 4.6983 \ldots (39)$$
$$RPM_{r_n} = 10^3 \times 0.0012 \times RPM_n + 10^3 \times 0.0014 \ldots (40)$$
$$Vw_a = 10^3 \times 0.000049 \times Vw_{a_n} + 10^3 \times 0.0001 \ldots (41)$$

2.2.2 Vertical wind turbine (VWT) ANN analysis

The regression model equations for the VWT that performed by the ANN method are presented in this subsection. Based on the available data units; the hidden layer would be a five neurons and the output layer would be six neurons. The input is one parameter (Power) and the outputs are six parameters. Figure (4) shows the neural network model concept for the VWT.

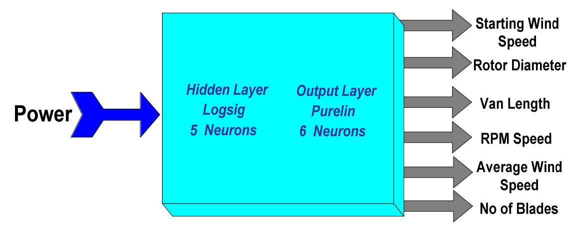

Fig 4: VWT Neural Network Model

$$P_n = \frac{P - 3.4875}{3.3413} \ldots (42)$$

Equation (42) presents the normalized input for the power and the following equations lead to the required derived equation. The parameter *n*: Subscript denotes normalized parameters, *Ei*: Sum of input with input weight and input bias for each node in hidden layer in neural network, and *Fi*: Output from each node in hidden layer to output layer according to transfer function.

$$\left.\begin{aligned}
E1 &= 14.3068 \times P_n - 10.3654\\
E2 &= 73.1157 \times P_n + 28.5540\\
E3 &= -15.7584 \times P_n + 12.4635\\
E4 &= -15.5755 \times P_n - 2.2160\\
E5 &= -194.9201 \times P_n - 188.1823
\end{aligned}\right\} \ldots (43)$$

Vol. 4, No. 6 June 2014 ISSN 2225-7217
ARPN Journal of Science and Technology
©2011-2014. All rights reserved.
http://www.ejournalofscience.org

$$F_{1\ldots8} = \frac{1}{\left(1 + e^{-E_{1\ldots8}}\right)} \ldots (44)$$

The normalized starting wind speed for VWT by ANN model is found as equation (44).

$$Vw_{s_n} = 10^4 \times [0.0002 \times F1 - 0.9548 \times F2 + 1.0105 \times F3 - 1.9654 \times F4 - 0.0001 \times F5] + 10^3 \times 9.5471 \ldots (44)$$

The rotor diameter is presented by the ANN equation (45).

$$Dr_{r_n} = 10^4 \times [0.0001 \times F1 - 0.3115 \times F2 + 0.3298 \times F3 - 0.6414 \times F4 - 0.0001 \times F5] + 10^3 \times 3.1154 \ldots (45)$$

The fin length normalized correlation by the ANN model is found as equation (46)

$$F_{l_n} = 10^4 \times [0.0001 \times F1 - 0.1130 \times F2 + 0.1197 \times F3 - 0.2329 \times F4 - 0.0005 \times F5] + 10^3 \times 1.1306 \ldots (46)$$

The rotor RPM is then presented by the ANN model as following;

$$RPM_{r_n} = 10^4 \times [-0.0001 \times F1 + 0.0103 \times F2 - 0.0109 \times F3 + 0.0213 \times F4 + 0.0023\ F5] + 10^3 \times -0.1037 \ldots (47)$$

The average wind speed is also presented by the ANN model as following;

$$Vw_{a_n} = 10^4 \times [0.0001 \times F1 - 0.1943 \times F2 + 0.2057 \times F3 - 0.4001 \times F4 - 0.0004 \times F5] + 10^3 \times 1.9431 \ldots (48)$$

The number of blades is also calculated as following;

$$NOB_n = 10^4 \times [-0.000047 \times F1 - 0.000045 \times F2 - 0.0002 \times F3 - 0.0001 \times F4 + 0.000040 \times F5] + 10^3 \times 0.0015 \ldots (49)$$

The un-normalized out puts for the proposed parameters for the VWT by the ANN model is introduced as following;

$$Vw_s = 0.7190 \times Vw_{s_n} + 2.9375 \ldots (50)$$

$$Dr_r = 1.2059 \times Dr_{r_n} + 2.6625 \ldots (51)$$

$$F_l = 1.2658 \times F_{l_n} + 3.0250 \ldots (52)$$

$$RPM_r = 13.3631 \times RPM_{r_n} + 150 \ldots (53)$$

$$Vw_a = 2.5466 \times Vw_{a_n} + 9.5125 \ldots (54)$$

$$NOB = 1.0351 \times NOB_n + 5.75 \ldots (55)$$

3. RESULTS AND COMMENTS

Results for two types of wind turbines are presented and highlighted in this section. Figures (5-a,b,c,d) represents the data results comparisons between the actual data, the polynomial correlations, and the ANN model based on starting wind speed, rotor diameter, hub height, and rotor speed. It obvious from the figure that the actual data are highly matched with the polynomial (poly) correlations and the ANN correlations. The similarity results revel that the polynomial and ANN results are quite matched with the actual data. The wind speed, hub height and the rotor diameter are increased by the increase of the unit power (kW). However; the normal vice versa of the power increasing is the decreasing of the rotor speed (rpm) thence; the torque is increasing by the increasing of the power. Figure (6) shows the behavior of the correlations based on the turbine cost and the average wind speed. The curves show that the correlations results are very matched with the actual data of the turbine. The cost is normally increasing by the increase of the power demanded. The average wind speed is noticed constant by the use of high rated power turbines. Figure (7) is implemented for the data results comparisons for the VWT based on (a) starting wind speed, (b) rotor speed, (c) rotor diameter, and (d) vane length.

It is obvious form Figure (7) that the behaviors of the curves are the same like the HWT. The curves for VWT show a very good matching with actual data. Both ANN model result and polynomial result are confirmed with the actual data. Figure (8) shows the comparison results for the (a) average wind speed and the, (b) the number of blades (vanes). It becomes very easy for the designer to select the operating point based on the demanded power. The normal scenario for any designer that the demanded power is known therefore; the minimum wind speed or even the rotor speed becomes very easy to be calculated thence the category of the wind turbine. The meteorological data would play as an important parameter side by side with the selected power.

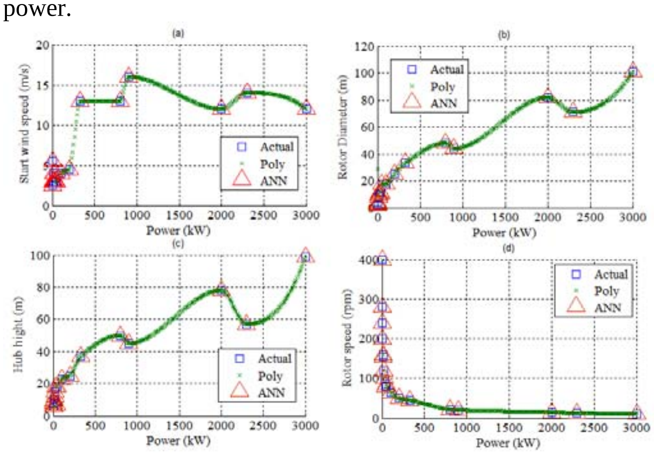

Fig 5: Data results comparisons for HWT based on (a) start wind speed, (b) rotor diameter, (c) hub height, (d) rotor speed.

ARPN Journal of Science and Technology
©2011-2014. All rights reserved.

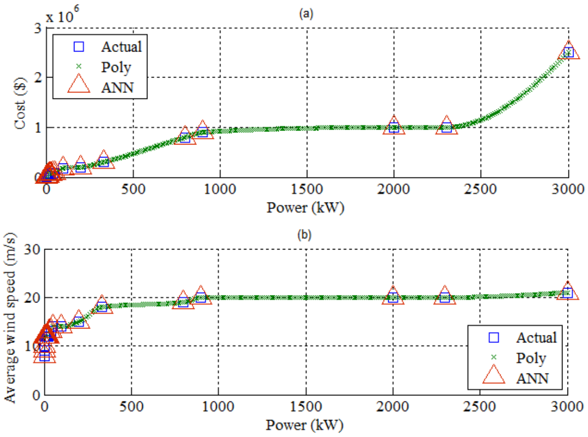

Fig 6: Data results comp.s for HWT based on (a) wind turbine cost, (b)

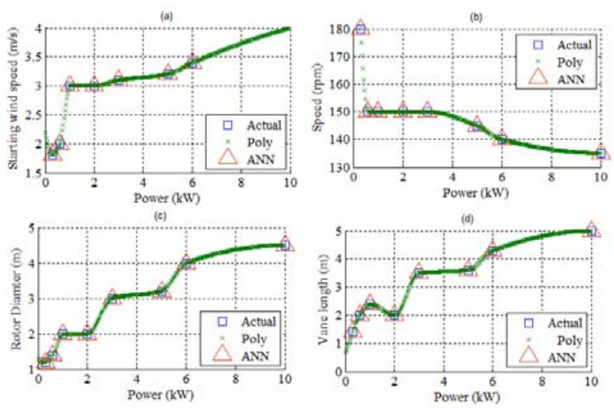

Fig 7: Data results comparisons for VWT based on (a) start wind speed, (b) rotor speed, (c) rotor diameter, (d) vane length

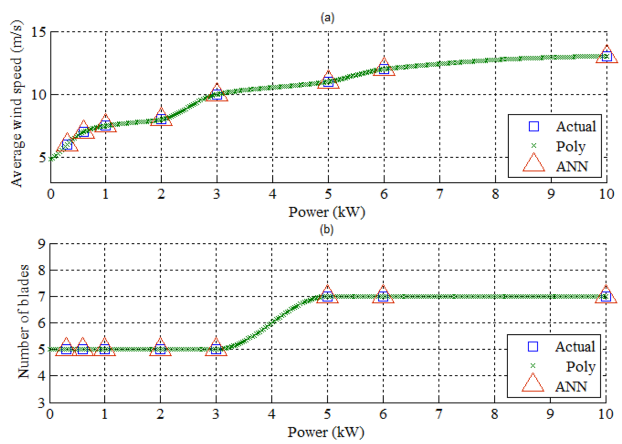

Fig 8: Data results comparisons for VWT based on (a) average wind speed, (b) number of blades.

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 [12]). The input power is about 7500 kW based on E-126 model [12]. Table 1 shows the data results for polynomial and ANN methods compared vs. the actual data from reference [12]. The Table 1 results show a very good agreement with the actual data.

Table 1: HWT data comparison between the developed models and Reference [12]

Parameters	**ENERCON [12]**	**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, RPM	5-11.7	9	9.2
Ar, m^2	12668	13704.83	13478
ρ_{air}, kg/m^3	1.225	1.221	1.22

It become very easy to the investor/designer to specify the domain area or the location of the operation based on the results obtained. The developed models (ANN or Polynomial via GUI) have many features such as;

- ✓ Easy modeling manipulation: User can easily copy & paste the equations then obtain the results.
- ✓ The model is so accurate enough to cover a wide range of power as presented (0.5kW-8000kW for HWT and up to 10kW for VWT).
- ✓ The developed models are built based on the real data from more than 50-100 manufacturing manuals for wind turbines.
- ✓ The developed model are then be ready to be combined with another technologies or units as a hybrid systems such as desalination, or auxiliaries power generation, or Photovoltaic (PV) technologies.

4. CONCLUSION

The need for sufficient power leads to use wind energy for power generation. Wind turbine market is very wide according to many issues such as type, configuration, and the wide range of operating conditions. Therefore; it becomes too difficult to the investor/designer to specify accurately the specific point of design (power, wind speed, design limits). Thence; the need for an accurate software programming package to make a selection based design and simulation of different types of wind turbines is essential. Therefore; two techniques of modeling (GUI and ANN) are used in this work in order to design and simulate horizontal and vertical wind turbines. The neural network 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. The ANN regression function for each unit is introduced to be used directly without operating the neural model each times. The

©2011-2014. All rights reserved.

required models are investigated and compared with the actual data from the manufactures manuals of the turbines. Results revel that the actual data are matched with the models data results. The models have many features such as;

- Easy model construction.
- Covering a wide range of power.
- Easy of combination with other technologies such as desalination and/or photovoltaic.
- Easy of converting the models codes into C++ or Visual Basic software programming.
- It becomes very easy to the designer to specify the power point and simply elect the turbine from the market based on the model data results.

5. NOMENCALTURE

A	Area, m^2
ANN	Artificial Neural Network
Ar	Rotor swept area, m^2
Ct	Turbine cost for HWT case, $
CP	Power coefficient, %
Dr	Rotor diameter, m
Ei	ANN parameter
Fi	ANN parameter
F_l	Fin length, m
GUI	Graphical user interface
Hh	Hub height, m
HP	Power, kW
HPw	Wind power, kW
HWT	Horizontal wind turbine
M_{air}	Air mass flow rate, kg/s
NOB	Number of blades
NWT	Number of wind turbine
P	Power, kW
Poly	Polynomial
Pn	Normalized power by ANN, kW
Tor	Torque, N.m
V	Velocity, m/s
Vw_s	Starting wind speed, m/s
Vw_a	Average wind speed, m/s
VWT	Vertical wind turbine
Subscripts	
air	Air
a	Average
i	Number
h	Height
l	Length
n	Normalized
r	Rotor
s	Start
w	Wind
Greek	
ρ_{air}	Density, kg/m^3
ω	Omega, rad/s

REFERENCES

[1] 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.

[2] 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.

[3] 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.

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

[5] 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.

[6] 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.

[7] 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.

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

[9] http://www.mathworks.com/index.html.

[10] William J. Palm, SIMULINK, Introduction to MATLAB7 for Engineers, Version 7, 2005.

[11] 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.

[12] http://www.enercon.de/de-de/

[13] Adel El Shahat, "PM Synchronous Machine New Aspects; Modeling, control, and design", LAP Lambert Academic Publishing, 2012.

[14] Adel El Shahat, "Artificial Neural Network (ANN): Smart & Energy Systems Applications", Scholar Press Publishing, 2014.

©2011-2014. All rights reserved.

[15] Adel El Shahat, “PV Module Optimum Operation Modeling", Journal of Power Technologies, Vol. 94, No 1, 2014, pp. 50–66.

[16] Adel El Shahat, “DC-DC Converter Duty Cycle ANN Estimation for DG Applications”, Journal of Electrical Systems (JES), Vol. 9, Issue 1, March 2013.

[17] Adel El Shahat, and Hamed El Shewy, “High Fundamental Frequency PM Synchronous Motor Design Neural Regression Function”, Journal of Electrical Engineering, Article 10.1.14, Edition 1, March, Vol. 10 / 2010.

[18] 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.

[19] 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.

[20] Adel El Shahat, Ahmed. M. Soliman, Mohamed A. Sharaf, “Solar Photovoltaic Modules Modeling Based Design Technique”, The International Conference on Industry Academia Collaboration, IAC 2014, 3 – 5 March 2014, Cairo, Egypt.

[21] Adel El Shahat, "Horizontal Axis Wind Turbines Modeling", Sixteenth International Middle East Power Systems Conference Cairo, Egypt, 23-25 December 2014 (MEPCON'14), IEEE Xplore included; Accepted.

[22] 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; Accepted.

[23] 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, IEEE Xplore included.

[24] Adel El Shahat, “Capacitive Deionization (CDI) Operational Conditions Nonparametric Modeling ”, International Conference on Industry Academia Collaboration, IAC 2014, 3 – 5 March 2014, Fairmont Heliopolis, Cairo, Egypt.

[25] Adel El Shahat, “Neural Network Storage Unit Parameters Modeling”, International Journal of Industrial Electronics and Drives, Vol. 1, No. 3.

[26] 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.

[27] 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.

AUTHOR PROFILE

Dr. Adel El Shahat is currently a Visiting Assistant Professor, Department of Electrical and Computer Engineering at University of Illinois, Chicago (UIC), Laboratory for Energy and Switching-Electronics Systems (LESES) (2014:Present). Assistant Professor in Engineering Science Department, Faculty of Petroleum and Mining Engineering, Suez University, Egypt (2011:2014). Previously, he was Visiting Researcher, ECE Dept., Mechatronics-Green Energy Lab, The Ohio State University, USA (2008: Sept.2010). His interests are: Photovoltaic power, Wind Energy, Electric Machines, Artificial Intelligence, Renewable Energy, Power System, Control Systems, Power Electronics, and Smart Grids. He was Associate Lecturer (2004:2008) in Faculty of Petroleum & Mining Engineering, Suez Canal University, Egypt, and Teaching Assistant (2000:2004) in the same faculty. His Education: PhD in Electrical Engineering (2011), Through Joint Supervision between Ohio State University, USA and Zagazig University, Egypt; M.Sc. in Electrical Engineering 2004, and B.Sc. in Electrical Engineering 1999 from Faculty of Engineering, Zagazig University. He has many publications between international Journals papers, refereed conferences papers, books, book chapters and abstracts or posters. He is a Member of IEEE, IEEE Computer Society, ASEE, IAENG, IACSIT, EES, WASET and ARISE. Also, he is member of editorial team and reviewer for six international journals. He gains honors and recognitions from The Ohio State University, USA 2009, Suez Canal University Honor with university Medal in 2012, 2006, Merit Ten Top-up Students Award of each Faculty from Arab Republic of Egypt, in 2000, and EES, 1999, Egypt, and also student distinguished awards (1994:1999) from Helwan, and Zagazig University, Egypt.