New Performance Modeling Techniques for Photovoltaic Modules and Different Types of Wind Turbines

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Abstract. This paper presents new modeling techniques for evaluating the performance of photovoltaic (PV) panels, vertical-axis wind turbines (VAWT), and horizontal-axis wind turbines (HAWT). Two methods are implemented to evaluate and simulate the designed models based on actual data points from various manufacturing manuals. The first technique is based on curve fitting while the artificial neural network (ANN) is the second method. The developed models can predict the operating performance characteristics of PV, VAWT and HAWT based only on the demand power. Hence, it can easily assist the designer to select a suitable unit before the installation process. The PV model can predict the short circuit current, open circuit voltage, voltage and current at maximum power, module efficiency and the module cost for a power range from 5W to 350W per module. Moreover, the wind turbine models can predict the cut-in wind speed, rated speed, rotor diameter, rotor speed, hub height and the turbine cost for a power range of 0.1kW to 100kW for VAWT and from 0.5kW to 8000kW for HAWT. The results show that the ANN method provides a higher match with the actual data compared to the curve fitting method. The models are conducted via Matlab/Simulink.

1. Introduction
Nowadays, renewable energy systems are of great importance due to their multiple benefits such as reliability, efficiency, sustainability, and the ability to reduce environmental problems [1-4]. Moreover, many countries are investing in renewable energy potential and related infrastructures around the world either on an experimental or industrial scale [5]. Wind and solar energy are both abundant, clean, efficient, and promising energy resources for off-grid power generation at zero fuel cost [6].

Considering the performance principles, wind turbines are generally in common and can be classified into two well-known classes, horizontal axis turbines (HAWT) and vertical axis turbines (VAWT) [7]. The HAWT type rotates around a horizontal axis and the rotor is placed parallel to the flow while the VAWT generates power by rotating around the vertical axis with an orthogonal shaft across the flow [8]. Although HAWTs have greater energy extraction capacity, depending on the material [9] and the method of their manufacture [10], the use of vertical axis wind turbines is very cost effective. VAWTs are classified into two types which are the Darrieus rotor and Savonius rotor types [11]. The operating principle of the Darrieus rotor is that it rotates around a mid-axis due to the lift produced by the rotating aero foils, but in the case of
Savonius the rotor is rotating due to the drag caused by its blades. The Darius rotor can be divided into three classes which are the D type, H type and helical type [12]. Savonius turbines are among the most popular turbines for wind applications due to their cost effectiveness, low noise, environmental side effects, and ease of manufacture [13, 14]. A review of VAWT test performance and methodology compared to HAWT was presented in [15]. The review discussed key comparison factors such as aspect ratio, overlap ratio, number of blades, shaft interference, influence of stator, and rotor shape. Several researchers have proposed to increase the efficiency, by modifying the blade geometry [16, 17]. In [18], the authors carried out a computational investigation of its operation using different blade geometries and proved that the performance of elliptical blade geometry is better than that of the semicircular blades. Recently, it has been reported that the use of spline blade geometry increases the obtained power coefficient in compression with the conventional semicircular blades [19]. A detailed review of HAWTs was presented in [20] for wind turbine blade design, including theoretical maximum efficiency, thrust, practical efficiency, and blade loads that provided a complete picture of wind turbine blade design and the dominance of modern turbines demonstrated the almost exclusive use of horizontal axis rotors.

In the field of renewable energy generation, solar photovoltaic (PV) technology plays a vital role in covering the energy shortage in the country. The modeling, simulation, and analysis of a solar photovoltaic (PV) generator is a vital stage before installing a photovoltaic system in any location, which helps to understand the behavior and characteristics in the real climatic conditions of that location [21]. Several studies have been implemented by many researchers to model PV technology with different procedures and to evaluate the number of parameters using a variety of simulation software [22-24]. From previous investigations, there is a broad scope in simulation, modeling and analysis of PV modules. However, there are some obstacles to the proper implementation of solar energy in the country such as the lack of assessment of solar resource data, the needs of easy-to-use calculation and simulation tools to analyze the PV solar system, and the calculation of the appropriate size of the PV system [25, 26]. To overcome the barrier and understand real system behavior, software packages are required for model authentication. There are lots of software packages in the field of modeling, simulation and analysis of PV system such as Solar Pro, PV-Design Pro, PV-Spice and PV CAD software [27]. But these packages have some drawbacks such as expensive software, only commercially available package, the problem of interacting with the electronic power system and proprietary available packages [25, 27]. Therefore, in this paper, new performance models are implemented via Matlab/Simulink to estimate the performance operating parameters for PV, VAWT and HAWT systems. The proposed models have the advantages of ease of use, flexibility, and accurate model development based on actual data points from manufacturing manuals. The models are implemented using the curve fitting and ANN methods which give the best estimated performance parameters.

2. Performance modelling techniques

2.1. Curve fitting technique

Curve fitting is the process of fitting models to data and analyzing fit accuracy. Designers use data fitting techniques, including mathematical equations and nonparametric methods, to model acquired data [28]. Regression analysis of actual data points for PV, VAWT, and HAWT models is performed using the curve fitting toolbox. The best fit of the data can be obtained using linear and nonlinear equations. To improve the quality of fit, the toolbox provides optimized solver parameters and starting conditions. After fitting the data, the goodness of fit is evaluated using R-squared value. It is a statistical measure of goodness of fit between the actual data and the estimated data in a regression model.

The mean value of the actual data set ($\bar{y}$) of $n$ values can be calculated as follows:

$$\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i$$  \hspace{1cm} (1)

The total sum of squares (proportional to the variance of the data) can be calculated as follows:
The residual sum of squares can be expressed as follows:

$$SS_{res} = \sum_i (y_i - f_i)^2 = \sum_i e_i^2$$  \hspace{1cm} (3)

Then, the R-squared coefficient can be calculated as follows:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$ \hspace{1cm} (4)

The R-squared value typically ranges from 0 to 1, with a value closer to 1 being the best case indicating that the modeled values exactly match the actual values.

The block diagram of PV model is shown in Figure 1 with the input parameter being the PV module power ($P_{PV}$) and the estimated output parameters being the open circuit voltage ($V_{oc}$), the short circuit current ($I_{sc}$), the voltage at maximum power ($V_{mp}$), the current at maximum power ($I_{mp}$), the module efficiency ($\eta_m$), and the module cost ($C_m$). Moreover, the VAWT and HAWT models are shown in Figures 2 and 3. The input parameters for each model are the VAWT turbine power ($P_{VAWT}$) and the HAWT power ($P_{HAWT}$). The output parameters to be estimated are the cut-in wind speed ($V_{cw}$), rated wind speed ($V_{rw}$), rotational speed ($RPM_r$), rotor diameter ($D_r$), height ($H$), blade length ($BL$), and the turbine cost ($C_t$).

2.2. Artificial neural network (ANN) technique

An artificial neural network (ANN) can be used in this study to predict a set of numeric targets based on a single input. The main steps of our study are to collect data points from datasheets, establish the network, configure the network, train the network, validate the network, and finally evaluate its performance using regression analysis and mean square error. Network configuration can be determined by the number of neurons, the number of layers, and the types of connections between the layers. The feed-forward multilayer network is the most common configuration to use which consists of an input layer, one or more hidden layers, and one output layer as shown in Figure 3. Only one input parameter to the network which is the power demand with six estimated outputs for each model. The hidden layer consists of 4 neurons and the output layer consists of 6 neurons. The network will be trained with Levenberg-Marquardt backpropagation algorithm which is the best choice due to fast training process, more parameters, and reduced network output.
error. The actual data points are classified as 80% used for training, 10% for validation, and the last 10% for network testing.

![Image of neural network configuration](image)

**Figure 3.** Neural network configuration.

After training the network, the performance is evaluated in terms of the mean square error shown in Figure 4. The total number of iterations is 1000 and the final mean square error is 0.012 (very small). It can be seen that the test and validation set errors have similar characteristics and the best validation performance occurs at epoch 1000. In addition, the training state of the neural network is shown in Figure 5 in terms of the square error function gradient and the momentum update (mu) control parameter which affect the error convergence. Moreover, the regression analysis is shown in Figure 6, where there is a linear regression between the corresponding targets and the network outputs. This means the outputs track targets very well for training, testing and validation, and the R value equals 1 for the overall response which is the best fit response.

![Image of mean square error](image)

**Figure 4.** Mean square error of neural network.

![Image of training state](image)

**Figure 5.** Training state of neural network.
3. Results and discussion

3.1. PV model

This section presents the simulation results of the PV performance model based on the curve-fitting and ANN methods. By applying the curve-fitting method to the actual data points from PV datasheets, the best fitness relations for the PV performance parameters are given in terms of the PV module power ($P_{pv}$) only as follows:

$$V_{oc} = 9.053 \exp^{-0.023P_{pv}} + 14.3 \exp^{0.003P_{pv}}$$

(5)

$$I_{sc} = 14.73 \exp^{-0.001P_{pv}} - 15.54 \exp^{-0.008P_{pv}}$$

(6)

$$V_{mp} = 7.768 \exp^{-0.02P_{pv}} + 10.96 \exp^{0.003P_{pv}}$$

(7)

$$I_{mp} = 26.14 \exp^{-0.002P_{pv}} - 26.96 \exp^{-0.006P_{pv}}$$

(8)

$$\eta_m = 13.87 \exp^{-0.0004P_{pv}} + 7.395 \times 10^{-5} \exp^{0.0026P_{pv}}$$

(9)

$$C_m = 1.02 \times 10^5 \exp^{5.389e-06P_{pv}} + 1.02 \times 10^5 \exp^{-5.389e-06P_{pv}}$$

(10)

This means that the designer can use the above equations to predict the PV module performance parameters without the need for datasheets based only on the power demand. The results are validated using ANN method and compared to the actual data points as shown in Figures 7-12. It can be seen that for all figures, ANN matches more closely with the actual data than with the curve-fitting method. The variation of $V_{oc}$
against PV module power is shown in Figure 7. Since the module power ranges from 5 to 350 W, the open circuit voltage varies from 20 to 47 V. Figure 8 shows the variation of $I_{sc}$ against PV module power and the short circuit current does not exceed 10 A. The $V_{mp}$ increases with increasing the module power and reaches its highest value approximately 43 W at the maximum power value of 350 W as shown in Figure 9. Variation of the current at maximum power with the power of the PV module is shown in Figure 10 with the highest current value not exceeding 9 A. As depicted in Figure 11, the module efficiency changes randomly between 14 and 17% by changing the module power. Finally, it can be seen that the cost of the PV module varies linearly with the module power as shown in Figure 12.

Figure 7. Variation of open circuit voltage with PV module power.

Figure 8. Variation of short circuit current with PV module power.

Figure 9. Variation of voltage at maximum power with PV module power.

Figure 10. Variation of current at maximum power with PV module power.

Figure 11. Variation of module efficiency with PV module power.

Figure 12. Variation of module cost with PV module power.
3.2. VAWT model

The simulation results of the VAWT performance model based on the curve fitting and ANN methods are presented in this section. By applying the curve fitting method to the actual data points from VAWT datasheets, the best fitness relations for the VAWT performance parameters are given in terms of the turbine power ($P_{VAWT}$) only using equations (11)-(16) as follows:

\[
\begin{align*}
V_{cw} &= 3.187 \exp^{-0.0017P_{VAWT}} - 1.709 \exp^{-0.2441P_{VAWT}} \\
V_{tw} &= 12.08 \exp^{-0.0006P_{VAWT}} - 1.652 \exp^{-0.376P_{VAWT}} \\
RPM_c &= 173.7 \exp^{-0.239P_{VAWT}} + 18.57 \exp^{-0.012P_{VAWT}} \\
D_r &= 6.594 \exp^{0.007P_{VAWT}} - 5.281 \exp^{-0.14P_{VAWT}} \\
BL &= 12.78 \exp^{0.005P_{VAWT}} - 10.77 \exp^{-0.05P_{VAWT}} \\
\tau &= 1.07 \times 10^4 \exp^{0.01P_{VAWT}} + 1.04 \times 10^4 \exp^{-0.02P_{VAWT}}
\end{align*}
\]

This means that the designer can use the above equations to predict the VAWT performance parameters based only on the VAWT power without the need for datasheets. The results are validated using the ANN method and compared to the actual data points as shown in Figures 13-18. The main aspect of all Figures is that ANN matches more closely with the actual data than the curve fitting method and all results are only based on VAWT unit power ranging from 0.1 to 100 kW. Figure 13 shows the variation of cut-in wind speed with VAWT unit power as the speed increases with increasing power gradually until it reaches its maximum value of 3.3 m/s and decreases to 2.5 m/s at 100 kW power. As shown in Figure 14, the maximum rated wind speed is 12.5 m/s and remains constant till 100 kW. The variation of the rotational speed with the power of the VAWT unit is shown in Figure15 where the rotor speed starts at a maximum value and with the increase in power, the rotor speed decreases to its lower value of 18 rpm at 15 kW. Figure 16 shows the relationship between the rotor diameter and turbine power. The rotor diameter gradually increases from 1 to 14.2 m, which is the highest value of the rotor diameter corresponding to the power value of 100 kW. Figures 17 and 18 show that the blade length of the turbine and the turbine cost are directly proportional to the unit power.

![Figure 13. Variation of cut-in wind speed with VAWT unit power.](image)

![Figure 14. Variation of rated wind speed with VAWT unit power.](image)
3.3. HAWT model

The performance model of the HAWT is the same as VAWT model. By applying the curve fitting method, the performance regression equations are given as follows:

\[ V_{cw} = 6.43 \exp^{-0.0004P_{HAWT}} - 3.57\exp^{-0.00026P_{HAWT}} \]  
(17)

\[ V_{rw} = 18.55 \exp^{0.0002P_{HAWT}} - 8.68\exp^{-0.0003P_{HAWT}} \]  
(18)

\[ \text{RPM}_r = 296.7 \exp^{-0.36P_{HAWT}} + 134.2\exp^{-0.005P_{HAWT}} \]  
(19)

\[ D_r = 66.21 \exp^{0.00012P_{HAWT}} - 60.02\exp^{-0.0013P_{HAWT}} \]  
(20)

\[ H = -51.02 \exp^{-0.0017P_{HAWT}} + 59.6\exp^{0.0001P_{HAWT}} \]  
(21)

\[ C_t = 1.24 \times 10^6\exp^{0.0001P_{HAWT}} - 1.21 \times 10^6\exp^{-0.0005P_{HAWT}} \]  
(22)

Equations (17)-(22) can be used to predict the HAWT module performance parameters based only on the HAWT module power without the need for datasheets. The results are validated using the ANN method and compared to the actual data points as shown in Figures 19-24 which indicates that the ANN matches more closely with the actual data than with the curve fitting method for the power range 0.5 to 8000 kW. Figure 19 shows the variation of cut-in wind speed which increases gradually till 4.5 m/s at 7500 kW. While the rated wind speed increases rapidly up to 17 m/s in the low power range and increases slowly in the high power range from 500 to 8000 kW as shown in Figure 20. It can be seen that the rotor speed is inversely proportional to the power of the HAWT unit as shown in Figure 21. The variation of rotor diameter, hub height, and turbine cost are shown in Figures 22, 23 and 24, respectively. It can be observed that D_r, H, and C_t are directly proportional to the HAWT unit power.
4. Conclusion
This paper has presented new modeling techniques to evaluate the performance of PV, VAWT and HAWT systems using actual data points from different manufacturing manuals. The mathematical models were implemented using curve fitting and neural network techniques. The operating performance characteristics of these models were accurately predicted based on the demand power only. The models are characterized by flexibility, ease of use and simplicity. The results show that the ANN method provides a higher match with the actual data compared to the curve fitting method. When the PV module power varies from 5 to 350 W, $V_{oc}$ varies from 20 to 47 V, $I_{sc}$ varies from 1 to 10 A, $V_{mp}$ varies from 7 to 40 V, $I_{mp}$ varies from 1 to 9
A, $\eta_m$ varies from 13 to 17%, and $C_m$ varies from 5 to 400 $. Moreover, for 0.1-100 kW power range of VAWT, $V_{cw}$ varies from 1.5 to 3 m/s, $V_{rw}$ varies from 10.5 to 12.5 m/s, rotor speed varies from 200 to 40 rpm, $D_r$ varies from 1 to 14 m, $B_L$ varies from 0.5 to 22 m, and $C_t$ varies from $1000$ to $3.5 \times 10^4$ $. In addition, for 0.5-8000 kW power range of HAWT, $V_{cw}$ varies from 2.5 to 4.5 m/s, $V_{rw}$ varies from 10 to 22.5 m/s, rotor speed varies from 400 to 40 rpm, $D_r$ varies from 1 to 140 m, $B_L$ varies from 1 to 130 m, and $C_t$ varies from $0.5 \times 10^6$ to $3.5 \times 10^6$ $.$

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