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Estimation of Wind Power Output Curve using Artificial Neural Network

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Abstract

Accurate estimation of wind turbine power curve has an important role in monitoring of conditioning and controlling of wind turbines in wind power plants. Artificial neural network (ANN) was used in this study in the prediction of horizontal axis wind turbine output power (P) in terms of climatic data and turbine rotational speed (Ω). Artificial neural network (ANN) involved the input parameters including the wind speed (V), atmospheric air temperature (T) and the rotational speed (Ω) of wind turbines which they were obtained from an operating power plant. According to the derived results for the testing process, minimum mean absolute percentage of error (MAPE) and maximum correlation coefficient (R) values were determined for an optimum rotational speed (Ω). MAPE and R values were respectively determined as 1.47% and 0.9991 in the case of the ANN study. These results indicated well that ANN approach provided a simple and accurate forecasting in the determination of wind turbine output power (P). Wind turbine power curve of a considered site can be rapidly predicted in a successful way with a little error under the utilization of the ANN method when the parameters of the climatic data including the wind speed (V) and the atmospheric air temperature (T); and as well rotational speed (Ω) of wind turbines in a wind farm are available. Thus, this method is rather convenient during the decision stage of new wind power plant installations.

Keywords: Artificial neural network, Atmospheric temperature, Linear and non-linear regression, Rotational speed, Wind power, Wind speed

INTRODUCTION

Evaluation of wind turbine efficiency requires the wind turbine capacity factor [1]. Additionally, the turbine performance specification and an indication of wind turbine service life can be deduced from the power characteristics curve. Generally speaking, theoretical wind turbine power characteristics curves are based on ideal meteorological and topographical conditions. In reality, however, the ideal conditions for wind power generation are never realised in practice. The location of turbines, air density, and the distribution of wind speed and as well wind direction can each significantly affect the power characteristics curve [2]. Estimation of the power curve equation and related aerodynamic parameters have recently increased its validity [3]. In addition, the forecasting of the wind power and the planning of wind farm expansion require accurate computation of power characteristics curves [4,5].

A number of methods have been mentioned in the literature for forecasting wind turbine performance parameters over different duration of time and including a variety of physical models, statistical methods, hybrid physical–statistical methods, artificial intelligence and neuro-fuzzy processing, along with more recent methods [6,7]. Li and Shi (2010) have made a comparative study of three types of neural networks, the adaptive linear element, back propagation and the radial basis function, enabling the prediction of hourly wind speed [8]. They have confirmed that no single neural network model is superior to the others in terms of its entire evaluation capability. The main advantage of the neuro-fuzzy model is in combining neural network and fuzzy logic systems, giving an increased capability in both areas. Fuzzy logic enables a better representation of the behavior of a given system by the use of a simple rule set, although it is unable to make use of the knowledge contained in numerical data [9]. In addition, it has been shown that artificial neural networks (ANN) are in general capable of training virtually any smooth nonlinear function, and a high degree of accuracy generally results from the application of ANN. Nevertheless, ANN has only limited capability in dealing with linguistic information.

It has been shown that artificial neural networks (ANN) are in general capable of training virtually any smooth nonlinear function, and a high degree of accuracy generally results from the application of ANN. Nevertheless, a drawback of ANN is the limited capability in dealing with linguistic information.

Horizontal axis wind turbines are the major type of large turbines in use today, and have received a great deal of attention both among researchers and in commercial terms [10,7]. In the present study, turbine power output values have been modelled in relation to hub-height wind speed (V), local temperature measured at the nacelle (T), and the rotational speed (Ω), using ANN approach. Power curves obtained by this modelling method can be used in the planning of new installations and for computation of total wind power generation for an existing wind farm. The main advantage of ANN model is to operate with fewer variables in forecasting of power extraction (P) from wind turbines. Wind turbine power (P) output can be predicted using required hub-height wind speed (V), local atmospheric temperature (T) and the rotational speed of the rotors (Ω) without comprehensive knowledge of the turbine operation or its control scheme. Furthermore, wind power (P) output can also be estimated satisfactorily without knowledge of other turbine characteristics, or meteorological and topographical data is the desired process of power (P) computation with less input variables.

MATERIALS and METHODS

Definition of artificial neural networks

Complex, analytically ill-defined, nonlinear or stochastic problems can be tackled using basic computational operations [11,12]. Complex problems such as non-analytical, nonlinear, non-stationary and stochastic types can be solved with limited programming knowledge when ANN structure is used. In particular, a variety of problems can be solved without re-programming or other interference in the program itself [13,14,15,16,17,18].

According to the literature, ANN methods include feed-forward neural networks (FFNN), radial-basis neural networks (RBNN) and generalised regression neural networks (GRNN). However, the back-propagation (BP) algorithm is the most widespread supervised training algorithm in multilayered FFNNs. Networks of BP algorithm involves information processed in the forward direction in a path of input layer, hidden layer and final output layer. The purpose of the BP network is to establish the optimum weight generating an output vector as close as possible to the target values, with accuracy determined by minimizing a predetermined error function [11,12,13,14].

A neural network comprises neurons constituting the basic processing elements. The back-propagation algorithm (BP) starts by computing output layer, since this is the only one for which output is available. Outputs for the intermediate layers are unavailable, as shown in Figure 1 [19].

Operating principle of ANNs

Modelling of the analytically impossible and complex problems using artificial neural networks are trained to eliminate the conventional approach limitations. Thus, this caused a significant rise on the interest focused to ANN method. Researches utilize the ANN method in many scientific areas including engineering, mathematics, economics, psychology, medicine, meteorology, etc. Besides, forecasting of mineral exploration sites, load predictions in electricity and thermal science, robot controlling and other branches of science use ANN method successfully.

A neuron is the basic processing element considering a neural network. Mathematical expressions defined in Equation 1 and 2 present a neuron, j.

$$U_j = \sum_{i=0}^{p} W_j X_i \quad (1)$$

As well,

$$Y_j = \varphi(U_j - \theta_j) \quad (2)$$

The upper limit of summation sign presented in Equation (1), p gives the amount of sources nodes in the input layer or the number of output layer neurons. Set of inputs or signals (X) having a specific weight (W) are received by the artificial neuron and a weighted average of them (U) is calculated by the summation function. Latter, some activation function (φ) is used to generate an output (Y). Threshold (θ) usage has the influence of an affine transformation application defined on the output (u) of the linear combiner. A function referred as sigmoid logistic non-linear is presented by Equation 3 [20].

$$\varphi(x) = \frac{1}{1+e^{-x}} \quad (3)$$

RESULTS and DISCUSSION

Study region, data and turbine technical specifications

The data used in the present study were taken from a wind power plant (WPP) which is in current operation. The altitude of this wind farm is 400 m above sea level. By the year 2008, the wind farm was in operation and comprised 17 identical wind turbines, each having an equal rated capacity of 2 MW. The hub-height of the identical wind turbines is 67 m, and the rotor diameter 80 m. The total swept area of a single wind turbine is thus 5027 m2. The technical specification of identical wind turbines is given in Table 1. The turbines operate at a cut-in speed of 4 m/s, a cut-out speed of 25 m/s and a nominal wind speed of 15 m/s. The present wind turbines are pitch-regulated upwind turbines with active yaw and a three-bladed rotor.

The turbines employ the OptiTip and variable speed functions, making it possible to maintain the rated power at very high wind speeds, regardless of air temperature and density. The OptiSpeed generator allows the turbine rotor speed to run at rotational speeds ranging from 9 rpm to19 rpm. The OptiTip system can be employed at low free-stream wind speeds, and the variable speed function can therefore maximise the output power (P) by optimising the rotational speed (Ω) and pitch angle.

Five wind turbines, T1, T2, T3, T4 and T5, were selected for the present study. For each of the turbines, the data taken from the WPP included power output (P, kW), hub-height wind speed (V, m/s), atmospheric air temperature (T, ºC) and turbine rotational speed (Ω, rpm). Table 2 illustrates the relationship between the input and output parameters and their correlation with wind power output (P).

It is obvious from the table that hub-height wind speed, V, is the most effective factor in wind power output (P) forecastig. In addition, V has a directly proportional relationship to wind power output (P). On the other hand, an increase in atmospheric air temperature (T) inversely affects wind power output (P), since an increase in T results in expansion of the atmospheric air. This means that a lower mass flow rate ($\dot{m}$) of air interacts with the rotor blades. Furthermore, the absolute correlation ratio with atmospheric air temperature (T) is lower in comparison with hub-height wind speed (V). The absolute magnitude of the correlation ratio of rotational speed (Ω) with the wind power output (P) is smaller when compared to the hub-height wind speed (V), but greater than the absolute value of the atmospheric air temperature, T. As can be seen from Table 2, when the minimum value of the wind power output (P) was 2.63 kW, the maximum output power (P) obtained was 2000.63 kW. The minimum and maximum values of hub-height wind speed (V) were 2.87 m/s and 24.50 m/s, respectively. The data also revealed that while the average minimum atmospheric air temperature (T) for the five turbines was 6 ºC, the maximum value was reported as 27 ºC. On the other hand, the average rotational speed (Ω) of five turbines varied, with a minimum value of 12.43 rpm and a maximum of 16.4 rpm.

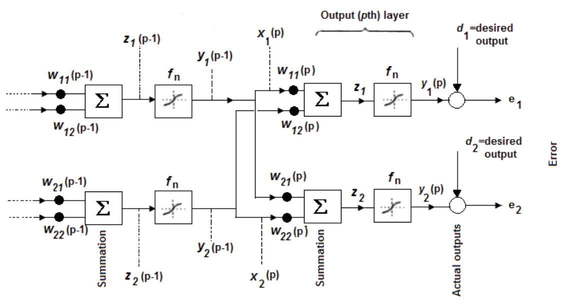

Figure 1. A schematic representation of a multi-layer perceptron

Table 1. Technical properties of wind turbines

Equipment	**Properties**
Rotor	
Diameter	80 m
Area swept	5027 m2
Nominal revolutions	16.7 rpm
Operational interval range	9-19 rpm
Number of blades	3
Power regulation	Pitch/OptiSpeed
Air brake	Full blade pitch by three separate hydraulic pitch cylinders
Tower	
Hub-height	67 m
Operational data	
Cut-in wind speed	4 m/s
Nominal wind speed	15 m/s
Cut-out wind speed	25 m/s
Generator	
Type	Asynchronous with OptiSpeed
Rated power output	2000 kW
Operational data	50 Hz, 690 V
Gearbox	
Type	Planet / parallel axles
Control	
Type	Microprocessor-based control of all the turbine functions with the option of remote monitoring. Output regulation and optimization via OptiSpeed and OptiTip pitch regulation

Table 2. Interval range of variables and related statistical parameters

Input and output variables	**Unit**	**Min**	**Max**	**Mean**	**Standard deviation**	**Correlation with P**
P	kW	2.63	2000.63	1187.23	679.32	1.000
V	m/s	2.87	24.50	12.48	5.57	0.896
T	°C	6.00	27.00	17.08	4.47	–0.640
Ω	rpm	12.43	16.40	14.67	1.58	0.703

The data was accumulated in the year 2013 and included data for the entire year. Measurements were taken over periods of 10 minutes. The data were initially composed of 52560 measurements (365 × 24 × 6 quantities) for each parameter related to V, T, Ω and P. Initially, original data for rotational speed, Ω was classified within limit ranges such as 1.00–2.99 [rpm], 3.00–4.99 [rpm], 5.00–6.99 [rpm], 7.00–8.99 [rpm], 9.00–10.99 [rpm], 11.00–12.99 [rpm], 13.00–14.99 [rpm], and 15.00–16.99 [rpm]. The probability distribution of rotational speed, Ω was calculated as shown in Figure 2. The average value in terms of rotational speed, Ω corresponding to each class mark of probability distribution for five turbines was calculated. Hence, average class marks of probability distribution considering all turbines were calculated as 2.02 [rpm], 4.10 [rpm], 6.05 [rpm], 8.08 [rpm], 10.10 [rpm], 12.44 [rpm], 13.94 [rpm], and 16.14 [rpm] in terms of rotational speed, Ω. Accordingly, designated class marks, including multi-data, were then performed for all turbines, and parameters such as V, T and P were defined with respect to each class mark of rotational speed, Ω. In this way, in terms of rotational speed (Ω), an average value corresponding to each class mark involved variation in the values of parameters such as V, T and P.

Pre-filtering was performed in order to eliminate power data given at zero or negative wind power (P) values. These improper data probably arose from rapid alterations in wind speed (V), vortices forcing a change in position of the rotor, or maintenance of the wind turbines. For these reasons power generation could not be assessed at high wind speeds. Thus, the probability density of rotational speed, Ω, corresponding to a value of 0, i.e. unrotational case was 22%. It should be observed that these data were omitted from the present computations.

As shown in Figure 2, it was satisfactory that half the data were observed, corresponding to a nominal rotational speed (Ω) of the rotor of 16.14 rpm. Also, pre-filtered data involving rotational speeds (Ω) below 12.44 rpm were filtered a second time, since data within the rotational speed range 2.02 rpm ≤ Ω ≤ 10.10 rpm (Ω) corresponded to only 2% of the total data. Finally, the remaining 76% of the data were used for the forecasting ANN model.

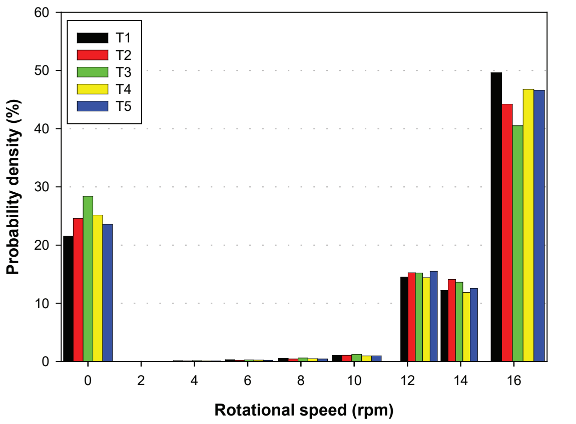

Figure 2. Probability density representation of rotational speed (Ω)

ANN forecasting results

For the development of forecasting ANN model, the total of 660 data for each parameter was used. This data set was divided into two subsets described as training and testing. The training data set included 532 data covering turbines T1, T2, T3 and T4, representing approximately 80% of the total data. The testing data set included only the turbine T5, consisting of 128 data representing approximately 20% of the total. So, wind turbine power output (P) can be characterized as a function of V, T and Ω. The relationship between wind turbine power output (P) and these independent variables can be expressed as:

$$P = f(V, T, \Omega) \tag{4}$$

The selected independent variables determined the structure of the forecasting ANN model and influenced the results of the model and the weighted coefficient, W. For this reason, the selection of the most suitable independent variables becomes a very important factor in forming a satisfactory forecasting ANN model. The ANN architecture used in the study is shown schematically in Figure 3. As seen in this figure; V, Ω and T were used as input variables. The parameters V and T are the most important climatic factors influencing performance of wind turbine power output (P), thus it is the reason that they considered. These parameters are readily available both in this region and all over the world. Moreover, they can easily be obtained and measured and in any considered region of the world.

In order to determine the optimal network architecture, various structures of forecasting models were designed using MATLAB software. For this reason, the predictions were performed by considering a different number of hidden layer neurons between 1 and 15. The ANN model was assessed by testing a data set not used during the training process. The best result was obtained by working with different training algorithms, leading to the adoption of the Levenberg–Marquardt (LM) learning algorithm. In the model of ANN formed, neurons in the input layer have no transfer function. Logistic sigmoid transfer function (logsig) and linear transfer function (purelin) were applied in the hidden layers and output layer of the network as an activation function, respectively. The ANN architecture consists of an input layer, an output layer and one hidden layer with nine neurons. In the training procedure, the maximum epoch number was set to 200, and the mean square error goal was set at 5 × 10–5.

The structure used in this study had an input layer, a hidden layer and an output layer consisting of 3, 9 and 1 nodes, respectively. While four turbines were used for training the MATLAB simulation, data from one turbine was considered adequate for testing the results. The general construction of the MATLAB codes, consisting of Levenberg–Marquardt back-propagation algorithm and logsic (logistic function) and purelin (linear transfer) functions, were used in the study.

The prediction model was trained and tested to compare and evaluate the performance of ANNs. Figures 4 and 5 present the comparison between prediction of ANN and measured results for the training data set. According to the results derived, based on the testing data set, the scatter diagrams of the network predictions against the actual values of power output (P) were drawn in order to evaluate the performance of the ANN model. As seen in Figures 6–8, the results of the prediction were in fairly close agreement with the actual values of power output (P), especially in the case of 16.14 rpm rotational speed. This indicated that used ANN artificial intelligence model can be a useful tool for accurate forecasting wind turbine power output (P); based on hub-height wind speed (V), atmospheric air temperature (T) and rotational speed, Ω.

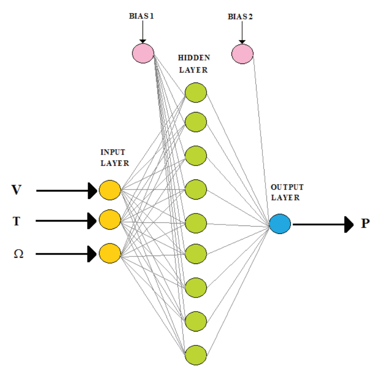

Figure 3. Schematic representation of the ANN frame-work used in the present study denoting of layers and nodes

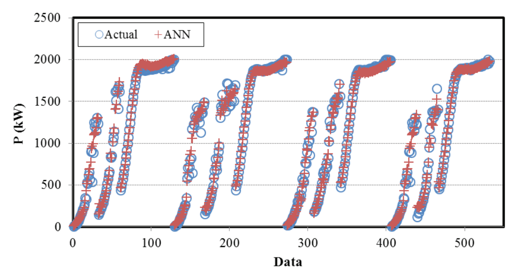

Figure 4. Comparison between prediction of ANN and measured results for the training data set in terms of studied data

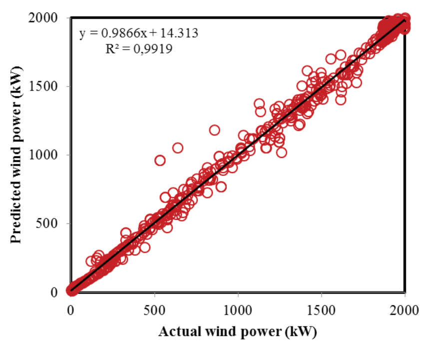

Figure 5. Comparison of actual and predicted power, P values for training data set

Table 3. MAPE and R results of the forecasting model estimations

Ω	Training process								Testing process	
	MAPE (%)				R				MAPE (%)	R
	T1	T2	T3	T4	T1	T2	T3	T4	T5	T5
12.44	21.35	30.00	13.88	21.00	0.9762	0.9866	0.9863	0.9775	16.94	0.9901
13.94	6.37	6.63	4.83	10.56	0.9901	0.9928	0.9914	0.9951	6.48	0.9898
16.14	2.05	1.44	1.83	1.54	0.9980	0.9994	0.9993	0.9995	1.47	0.9991
whole	7.78	10.58	5.68	8.57	0.9958	0.9958	0.9967	0.9963	6.31	0.9970

Error results of ANN referenced to actual power output (P)

Table 3 gives the mean absolute percentage error (MAPE) and correlation coefficient (R) results for the training and testing process depending on the forecasting computations for the actual data set of power output (P). According to the results obtained from the testing process, the interval range of MAPE was 1.47–16.94% for rotational speeds (Ω) of 12.44 rpm ≤ (Ω) ≤ 16.14 rpm. The corresponding interval range of correlation coefficient, R values for this interval of rotational speed (Ω) was 0.9898 ≤ R ≤ 0.9991. The MAPE and R results for rotational speeds (Ω) over the whole data of 12.44, 13.94, and 16.14 rpm rotational speeds were determined as 6.31% and 0.9970, respectively.

Table 3 reveals that accurate forecasting estimates were obtained especially, with 16.14 rpm of optimum rotation (Ω). When the whole data set of the three rotational cases is taken into consideration, it is seen that the MAPE result was insufficient in the forecasting ANN model. On the other hand, in terms of the correlation coefficient (R), the values showed acceptable results for each classes of rotational speed (Ω) as well considering whole classes of rotational speeds, Ω. Thus, the overall correlation coefficient (R) results of the estimations was determined a value of 0.9970.

During training of the program, MAPE values were higher for optimum rotational speed, apart from Ω = 16.14 rpm when compared with the actual power values of the wind turbines studied as presented in Table 3. Considering the results of the testing stage, ANN results clearly revealed that the estimated power output (P) values were all among the lower and upper values of MAPE according to the training forecasting results obtained from the four turbines. There was a slight difference between the results of correlation coefficient (R) in ANN estimations according to different classes of rotational speed (Ω). Both training and testing data indicated higher results of correlation coefficient (R). The comments were therefore based on the MAPE results.

The MAPE results did not indicate the same degree of success of the method, regardless of its value during the training stage, since the aim of the training was to obtain the true logic in terms of the computer program to present good estimates at the testing stage. MAPE values remained higher in training stage of estimations at 12.44 rpm; on the other hand, at 13.94 rpm and 16.14 rpm resulted MAPE at lower values during the training process. In addition, when whole classes of rotational speeds (Ω) are considered, ANN estimations of T3 turbine during training stage performed the best forecasting result based on MAPE. Estimation of T3 turbine also showed the best performance compared to others in terms of the overall correlation coefficient (R) taking whole classes of rotational speed (Ω) into account.

These results indicated that the performance of the ANN model was generally useful tool for accurate forecasting wind turbine power output, P estimation. Estimations with respect to the actual power output (P) values was illustrated in Figures 6–8 using scatter diagrams to demonstrate the results of predictions based on ANN model especially for optimum rotational (Ω) case was in fairly close agreement with the corresponding actual wind turbine power output (P) data.

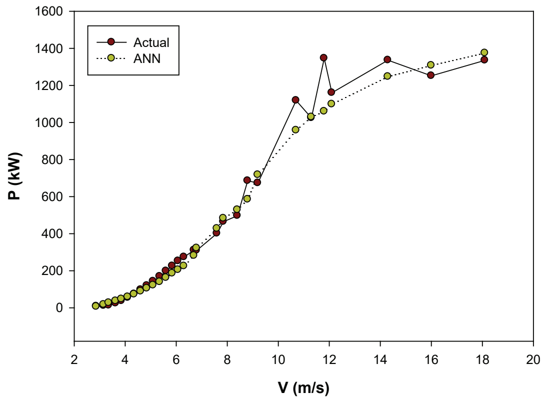

Figure 6. Comparison of actual power (P) and the forecasted computational results at 12.44 rpm

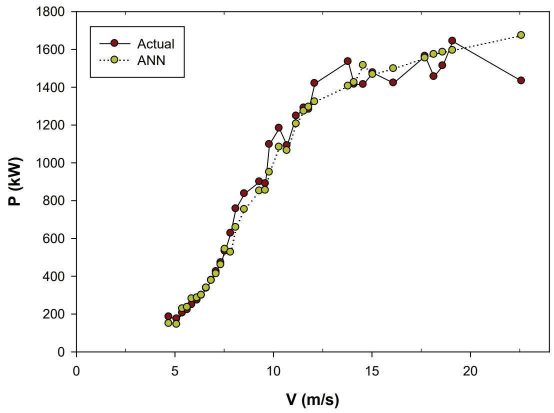

Figure 7. Comparison of actual power (P) and the forecasted computational results at 13.94 rpm

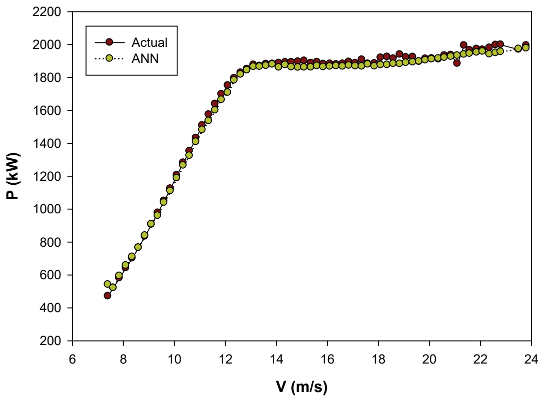

Figure 8. Comparison of actual power (P) and the forecasted computational results at 16.14 rpm

CONCLUSIONS

In the present study, the power output (P) of a horizontal axis wind turbine was predicted using ANN tool and compared the results with the actual average values obtained from five turbines. The results obtained from this forecasting model compared to actual data of power output, P were in good agreement especially for optimum rotational speeds (Ω). According to the prediction model, the MAPE values at rotational speeds (Ω) of 13.94 rpm and 16.14 rpm were found to be 6.48% and 1.47%, respectively. For the testing process, the maximum value of correlation coefficient (R) was obtained for the optimal rotational speed (Ω) conditions of the turbine, estimated as R=0.9991. Similarly, the MAPE values obtained at the optimum rotational speed (Ω) of 16.14 were better than those at rotational speeds of 12.44 and 13.94 rpm. Consequently, the advantage of this forecasting ANN model is that wind turbine power output (P) can be predicted, regardless of detailed knowledge of turbine operations and topographical data, and can provide successful results when the required hub-height wind speed (V), atmospheric air temperature (T) and turbine rotational speed (Ω) data are available. Furthermore, the wind turbine power curve of any site can be successfully estimated with a high degree of accuracy using this ANN estimation model suggested utilizing the wind speed (V), atmospheric air temperature (T) and rotational speed (Ω).

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