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# Application of adaptive neuro-fuzzy methodology for performance investigation of a power-augmented vertical axis wind turbine

W.T. Chong <sup>a, \*\*</sup>, M. Gwani <sup>a, b</sup>, S. Shamshirband <sup>c, \*</sup>, W.K. Muzammil <sup>a, d</sup>, C.J. Tan <sup>a</sup>, A. Fazlizan <sup>a</sup>, S.C. Poh <sup>a</sup>, Dalibor Petković <sup>e</sup>, K.H. Wong <sup>a</sup>

<sup>a</sup> Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, 50603, Kuala Lumpur, Malaysia

<sup>b</sup> Department of Physics, Kebbi State University of Science and Technology, Aliero, 1144, Kebbi State, Nigeria

<sup>c</sup> Department of Computer System, Faculty of Computer and Information Technology, University of Malaya, 50603, Kuala Lumpur, Malaysia

<sup>d</sup> Faculty of Engineering, Universiti Malaysia Sabah, Jalan UMS, 88400, Kota Kinabalu, Sabah, Malaysia

<sup>e</sup> University of Niš, Faculty of Mechanical Engineering, Department for Mechatronics and Control, Aleksandra Medvedeva 14, 18000, Niš, Serbia

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#### ABSTRACT

Wind power is generating a lot of interest in many countries as a way to produce sustainable and lowcost electrical power. Since the power in the wind is known to be proportional to the cubic power of the wind velocity approaching the wind turbine, this means that any slight increase in wind speed can lead to a substantial increment in the energy output. Power augmentation device is an interesting option in this respect. The aim of this study is to determine the accuracy of a soft computing technique on the rotational speed estimation of a Sistan rotor vertical axis wind turbine with PAGV (power-augmentationguide-vane) based upon a series of measurements. An ANFIS (adaptive neuro-fuzzy inference system) was used to predict the wind turbine rotational speed. The ANFIS network was developed with three neurons in the input layer, and one neuron in the output layer. The inputs for the network were time (t), wind velocity (v) and presence of the PAGV (0 with PAGV and 1 without PAGV). The precision of ANFIS technique was assessed against the experimental results using RMSE (root-mean-square error) and coefficient of determination ( $R^2$ ).

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#### 1. Introduction

Recently, the number of research related to applications of renewable energy sources have increased. This is due to the extensive depletion of fossil fuel reserves drove by the high demands of energy [6]. Nowadays, one of the main topics in renewable energy research is on how to harness and utilize wind energy [12]. The significant improvements achieved by wind energy devices in operating efficiencies, make them more economically competitive than other energy generation techniques [32]. Wind energy has zero emission with minimal impacts on landscapes, biodiversity and watersheds, presently, it is considered as one of the leading renewable energy sources [20]. The Technology of wind energy has attained an outstanding development status with a significant progress in the electronic equipment and battery construction sectors [10]. Over the decades, various designs of wind energy conversion systems have been studied and reported by many researchers, these include the HAWT (horizontal axis wind turbines) and the VAWT (vertical axis wind turbine). The VAWT is further divided into two distinct types, the lift type (Darrieus rotor, H-type) and the drag type (Savonius rotor). The VAWTs are considered as one of the most cost-effective and attractive solutions for on-site wind energy generation system [12]. The VAWTs have many advantages which include capturing wind from any direction, generating power at lower wind speed as well as low level of noise and environmental friendly [14].

Wind power is known to be proportional to the cubic power of the wind velocity approaching wind turbines [1]. This means that any slight increase in wind velocity approaching the wind turbine can lead to a substantial increase in the power output [28]. Therefore, enclosing a wind turbine in a specially designed shroud will increase its output power [9,16]. Power-augmentation-device is one of the most promising concepts for extracting wind energy.

<sup>\*</sup> Corresponding author.

<sup>\*\*</sup> Corresponding author. Tel.: +60 12 723 5038; fax: +60 3796 75317. *E-mail addresses:* chong\_wentong@um.edu.my (W.T. Chong), shamshirband1396@gmail.com (S. Shamshirband).

The concept of power-augmentation-device is to increase the approaching wind speeds before the wind stream interacts with the wind turbine, this will eventually increase the power output of the wind turbine [33]. Power-augmentation-device has an important influence on average wind speed and output power of wind turbine over a certain period of time. It plays a role to collect and accelerate the approaching wind [28]. Different designs of poweraugmentation-devices have be studied and reported by many researchers using experiments, and numerical simulations or the combination of the two to evaluate the effectiveness of these designs [10]. A lot of researches have been carried out to enhance the performance of HAWT in Refs. [1,15,16]. Ohya et al. [26] presented a study on a shrouded wind turbine with a brimmed diffuser for power augmentation, the results shows that the shrouded wind turbine has power augmentation by a factors of approximately 2-5compared with a bare wind turbine.

Similarly, many studies have been conducted on the poweraugmentation-devices for the VAWT. Altan et al. [5] reported that the performance of the Savonius rotor is improved by 38.5% if a curtain arrangement is introduced in front of a Savonius rotor, moreover, the negative torque opposite the rotor is prevented. The effect of a guide vane geometry on the performance of straight bladed VAWT was reported by Takao et al. [37]. The results showed an increment of 1.5 times of the power coefficient of the straightbladed VAWT with the guide vane. Irabu and Roy [19], reported that the coefficient of a Savonius rotor can be improve by a factor of 2.3 times, by adjusting the inlet mass flow rate with a rectangular guide-box tunnel. Nobili et al. [25] reported that the introduction of an omni direction stator around the VAWT increases the power coefficient by 1.35 times compared to the open case. Chong et al. [11] asserted that the introduction of an innovative poweraugmentation-guide-vane that surround the VAWT increased the rotor torque by 2.8 times and the power output by 5.8 times. Tourlidakis et al. [38] presented a numerical study on a VAWT (bare and shrouded), the results showed that a significant improvement on the performance of the shrouded wind turbine can be achieved. The technique of using an augmentation device to improve rotors performance is not limited to wind turbines. Alidadi and Calisal [4] in their study of hydro-current vertical axis turbine reported that the power output from a turbine can be increased significantly up to 74% when it is enclosed within a well-designed duct than in a free stream condition.

The wind systems are nonlinear power sources that need accurate on-line identification point for accurate estimation and prediction of wind energy systems. Therefore, a more robust methodology like the soft computing techniques are preferred [36]. In recent years, many new soft computing techniques such as the FL (fuzzy logic) [41], ANN (artificial neural network) [3,8], neuro-fuzzy and SVM (support vector machines) [24] have been utilized to predict and estimate the performance of wind energy systems. Bilgili et al. [7] reported that monthly average wind speed of any target stations can be predicted with ANN (artificial neural network) using mean monthly wind speed from neighbouring stations indicated as the reference stations. Petkovic et al. [34] estimated building augmented power and wind velocity using ANFIS (adaptive neuro-fuzzy inference system). They analyzed various building geometries and their effects on poweraugmentation with a simplified turbine model. Their results demonstrated the effectiveness of the developed method. Mohendes et al. [24] compared the performance of MLP (multilayer perception) and SVM (support vector machine) in wind speed prediction. Their results indicated that SVM performs better than MLP for all systems with orders ranging from 1 to 11. A comparative study for estimation of wind turbine power coefficient using soft computing methodologies was reported by Sharmshirband et al. [36]. They used a polynomial and RBF (radial basis function) as kernel function for SVR (support vector regression) to estimate the optimal power coefficient value of the wind turbines. The obtained results indicated that SVR approach can achieve an improvement in predictive accuracy and capability of generalization in comparison to other soft computing methodologies. Sharmshirband et al. [35] presented a study on the wake added turbulence in wind turbine using ANFIS (adaptive neuro-fuzzy inference system). The effectiveness of the developed method was confirmed by the simulation results.

The ANFIS technique has been previously used in several engineering systems [16,17]. ANFIS, as a hybrid technique, has the proficiency to automatically learn and adopt [29-31]. ANFIS is a unique neural network which has good learning and predicting capabilities [22]. Because of these capabilities, ANFIS is a very effective instrument to deal with when encountering doubts in any system [29–31]. Due to its estimation accuracy, many studies have been conducted on real-time identification and estimation for many different systems using the application of ANFIS [13,18,23]. The main core of ANFIS is the FIS (fuzzy inference system). The FIS can be used to predict the behaviour of several systems that are uncertain as it is based on skill which is expressed in 'IF - THEN' rules. One of the advantages of FIS is that the precondition for its applications does not need knowledge of fundamental physical procedure. Therefore, the ANFIS incorporates the FIS through neural network back-propagation learning algorithm. With this method, the fuzzy logic has the ability to familiarize with the parameters of the membership function which allows the given input and output data to be tracked by the related FIS [2.17.40].

The aim of this study is to apply a soft-computing methodology for prediction and estimation of the rotational speed of a poweraugmented vertical axis wind turbine. The study evaluates the influence of PAGV (power-augmentation-guide-vane) on the performance of VAWT using ANFIS, as a robust soft-computing methodology. Since the process is uncertain and nonlinear, analyzing the data could be time consuming. Therefore, the study attempts to estimate the effects of the PAGV in changes of wind turbine rotational speed using ANFIS.

#### 1.1. PAGV (power-augmentation-guide-vane)

PAGV is a device consisting of several guide vanes. The guide vanes are used to guide the oncoming wind stream into the wind turbine with a better angle of attack. Also, venturi effects are created through the guide vanes which increase the speed of the oncoming wind, thereby improving the VAWT performance. Furthermore, the PAGV is designed to increase the energy generation of the wind turbines in low wind speed areas. Moreover, the compact design of the system permits the use of small wind turbines on high rise buildings or structures without affecting the building architecture [10].

## 2. Methodology

ANFIS model was established in this study to investigate the performance of a power augmented vertical axis wind turbine. Three ANFIS networks were modelled since there are three inputs (time (t), velocity and presence of PAGV). Training and checking data for the ANFIS networks was extracted from the experimental study of the PAGV. With a proper training scheme and fine filtered data-sets, ANFIS is capable of accurately estimating the rotational speed of power augmented vertical axis wind turbine since it learns from the training data.

## 2.1. Adaptive neuro-fuzzy application

ANFIS (adaptive neuro-fuzzy inference system) can be used as a basis for constructing a set of fuzzy 'If-Then' rules with an appropriate membership to generate the stipulated input—output pairs. In this study, the ANFIS system that is functionally equivalent to the first-order Sugeno fuzzy model was used. A typical rule set with a fuzzy 'If-Then' rule can be expressed as:

$$\text{if } x \text{ is } A \text{ then } f_1 = p_1 x + t \tag{1}$$

The ANFIS architecture for three inputs of x, y and z (wind speed, time, and PAGV) is shown in Fig. 1. Nodes at the same layer have the same purposes.  $O_{l,i}$  denotes the output of the i th node in layer l.

The input variable membership functions (MFs) is in the first layer, which supply the next layer with the input values. The adaptive node can be a function of:

$$O_{l,i} = \mu(x, y, z)_i$$
 for  $i = 1, 2$  (2)

Where  $x_i y = i$ th node input and  $\mu(x_i y_i z)_i$  = membership functions. The MFs can be defined by a bell-shaped function:

$$f(x;a,b,c) = \frac{1}{1 + \left(\frac{x-c}{a}\right)^{2b}}$$
(3)

Where  $\{a,b,c\}$  is the parameter set.

The second layer (membership layer) sends the product out after it multiplies the incoming signals from the first layer. The output of every single node signifies the firing power of a rule or weight:

$$O_{2,i} = w_i = \mu(x)_i \cdot \mu(x)_{i+1}, \quad i = 1, 2$$
(4)

The rule layer which is the third layer is non-adaptive, in this layer, The ratio of the rule's firing strength to the sum of all rules' firing strength is calculated by every node i:

$$O_{3,i} = w_i^* = \frac{w_i}{w_1 + w_2}$$
, where  $i = 1, 2$  (5)

This layer's output is called normalized firing strengths or normalized weights. The defuzzification layer which is the fourth layer provides the output values which results from the inference rules, where each node i is an adaptive node with node function.



Fig. 1. Three inputs, one output and two rules ANFIS structure.

$$O_{4,i} = w_i^* \cdot f_i = w_i^* (p_i x + q_i y + r_i)$$
(6)

Where  $\{p_i, q_i, r_i\}$  is consequent parameters.

The classification results of the fuzzy were converted into a crisp output after all the inputs from the fourth layer is sums up by the fifth layer. The overall output of all the incoming signals was computed by the node in the fifth layer which is no adaptive:

$$O_{5,i} = \sum_{i} w_i^* \cdot f_i = \frac{\sum_{i} w_i \cdot f_i}{\sum_{i} w_i}$$
(7)

## 2.1.1. Evaluation of model performances

To assess the performance of the developed ANFIS model, the following statistical indicators are utilized:

(a) RMSE (root-mean-square error)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (O_i - P_i)^2}{n}}$$
(8)

(b) Coefficient of Determination  $(R^2)$ 

$$R^{2} = \frac{\left[\sum_{i=1}^{n} \left(O_{i} - \overline{O}_{i}\right) \cdot \left(P_{i} - \overline{P}_{i}\right)\right]^{2}}{\sum_{i=1}^{n} \left(O_{i} - \overline{O}_{i}\right) \cdot \sum_{i=1}^{n} \left(P_{i} - \overline{P}_{i}\right)}$$
(9)

Where  $O_i$  is the predicted value by ANFIS technique,  $P_i$  is the measurement value,  $\overline{O_i}$  is the mean values of  $O_i$ ,  $\overline{P_i}$  is the mean values of  $P_i$ , and n is the total number of test data. It should be noted that the smaller values of RMSE represent further accuracy in the predictions and in an ideal case it is zero. Also, the  $R^2$  ranges between 0 and +1. The  $R^2$  values around +1 indicates that there is a perfect linear relationship between the estimated values and measured ones whereas  $R^2$  around zero shows that there is no linear relationship.

#### 2.2. Experimental study of the PAGV

Using a drag type Sistan rotor wind turbine, a test was performed for the small scale PAGV device with the geometry and measurements as shown in Fig. 2 to ascertain the possibility of incorporating the wind turbine with the PAGV. The experiments were performed for the following cases: (i) the case where the wind turbine is integrated with the PAGV and, (ii) the case without the PAGV. Three industrial fans were arranged in parallel to generate the wind stream. Two different experiments were conducted with two different average wind speeds. The first experiment was conducted using a wind speed of 4.24 ms<sup>-1</sup> and the second experiment was conducted using a wind speed of 4.63 ms<sup>-1</sup>. The wind rotor performance was measured using the laser tachometer over time, and a continuous measurement of the rotational speed was carried out until the data stabilized.

#### 2.2.1. Sistan rotor

Wind energy is the kinetic energy of the wind which can be extracted by using wind turbines to produce electric power. The wind kinetic power can be presented as follows:



Fig. 2. Fabricated PAGV model with dimensions [10].

$$P_{\rm w} = \frac{1}{2} \dot{m} v^2 \tag{10}$$

Where  $\dot{m}$  is the mass flow rate of air which can be expressed as;

$$\dot{m} = \rho A v \tag{11}$$

Where  $\rho$  is the density of air, *A* is the wind turbine swept area and v is the velocity, the combination of Eqs. (10) and (11) is the power extracted from a Sistan rotor *P*<sub>S</sub>, expressed as:

$$P_{\rm S} = C_P \frac{1}{2} \rho A v^3 \tag{12}$$

The power coefficient,  $C_P$  presented in Eq. (12) is the ratio of the real power extracted to the power that is available in the wind. Furthermore, Eq. (12) shows that the resulting power that can be extracted from a wind turbine is proportional to the cubic power of the wind velocity. However, the theoretical Betz limit sets the amount of power that can be extracted from a wind turbine to about 59% of the total wind power (refer Fig. 3) [21]. The purpose of the PAGV is to improve the performance of the wind turbine by increasing the rotational speed of the rotor, which eventually increased the amount of energy that can be extracted from the wind turbine [10].



Fig. 3. A typical wind turbine power extractable limit [21].

Sistan rotors produce mechanical energy from the conversion of wind kinetic energy by using the drag principle. As shown in Fig. 4, the oncoming air hits the surface of a Sistan rotor blade, *S* at velocity of  $V_0$ . Thus, the extractible power from the Sistan rotor using the principle of the drag force can be expressed as:

$$P_{\rm S} = F_{\rm D} V_{\rm S} \tag{13}$$

Where  $F_D$  is the drag force and  $V_S$  is the wind surface velocity. The drag force produced by the Sistan rotor can be calculated as follows:

$$F_D = C_d \frac{\rho}{2} (V_0 - V_S)^2 S$$
(14)

Where  $C_d$  is the coefficient of drag of the blade, by combining



Fig. 4. Single-bladed Sistan rotor.

Eqs. (13) and (14), the resultant power extracted at  $0^{\circ}$  azimuth angle from this wind turbine can be expressed as:

$$P_{\rm S} = C_d \frac{\rho}{2} (V_0 - V_{\rm S})^2 S V_{\rm S} \tag{15}$$

Using Eq. (7), the various azimuth angles can be calculated as:

$$P_{S} = C_{d} \frac{\rho}{2} S \left( \overrightarrow{V_{0}} - \overrightarrow{V_{S}} \right)^{2} \cdot \overrightarrow{V_{S}}$$
(16)

By summing up all the power extracted from the Sistan rotor at every azimuth angle in a single blade revolution, the average power extracted  $P_{S(avg)}$  can be calculated from the Eq. (17) as:

$$P_{S(avg)} = \frac{1}{2\pi} \sum_{i=0}^{2\pi} \left\{ C_d \frac{\rho}{2} S\left(\overrightarrow{V_{0_i}} - \overrightarrow{V_{S_i}}\right)^2 \cdot \overrightarrow{V_{S_i}} \right\}$$
(17)

It should be noted that in Eq. (16) the assumption was made that the blade is purely driven by the air drag force. No other aerodynamic behaviours such as the turbulence flow and edge vortex generated after the moving fluid interacts with the Sistan rotor blade were considered. Through the use of CFD (computational fluid dynamics) software, the average power extraction and behaviour of the VAWT can be simulated and predicted.

#### 3. Results and discussion

### 3.1. Experimental results

The experiments were conducted with and without the presence of the PAGV for different wind speeds. Fig. 5 illustrates the results from the experiments.

The experimental results without the PAGV show that the wind turbine cannot self-start by itself, hence requiring an external force to be applied on the rotor to enable the turbine to start. This is the reason why the rotational speed for the case of a wind turbine without the PAGV starts at about 20 RPM to 30 RPM. However, when the wind turbine was integrated with the PAGV, it was able to self-start without the influence of any external force. Furthermore, with the presence of PAGV, the average increments of the Sistan rotor wind turbine rotational speed is 29% for wind speeds of 4.24 ms<sup>-1</sup> and approximately 25%. For wind speed 4.63 ms<sup>-1</sup>.

#### 3.2. Input variables for the ANFS model

The data shown in Fig. 5 was used for generating the ANFIS model. To get a more reliable evaluation and comparison, the ANFIS model is tested by evaluating a data set that was not used during



Fig. 5. Wind turbine rotational speed and time (with PAGV and without PAGV) for different wind speeds.

the training process. The statistical parameters (wind speed, and rotor rotational speed with and without the presence of PAGV) for data sets are calculated and given in Table 1.

## 3.3. ANFIS model analysis

#### 3.3.1. Training of data set

Training is a learning process of the developed model. The model is trained until the results are obtained with minimum error. To design an ANFIS system for real world problems, it is essential to select the parameters for the training process and testing of data set [39]. In this study, approximately 70% of the data generated for the ANFIS model was used for training purposes, and the remaining 30% was used for testing purposes of the ANFIS model. Three bell-shaped membership functions were used to fuzzify the inputs of the ANFIS. After the training process, the ANFIS networks were tested to determine the wind turbine rotational speed without the presence of the PAGV and with the presence of the PAGV. The predicted data is used to correlate with the rotor rotational speed test data extracted from the experiment (Fig. 5).

The average computation time for the ANFIS modelling was around 300s for 1000 training epochs using a PC with the Intel Core Duo CPU E7600 @3.06 GHz and 2-GB RAM. For the ANFIS modelling, MATLAB software was used.

The predicted rotor rotational speed values using ANFIS model for a wind turbine without the PAGV are presented in Fig. 6(a) and (b). Whereas, Fig. 7(a) and (b) illustrate the predicted values using ANFIS model for a wind turbine with the PAGV. As seen in the figures, the  $R^2$  correlation coefficients are very high. Therefore, the ANFIS model used for the study has a very good correlation with the wind turbine model with and without the PAGV. Note that the  $R^2$ correlation is higher for the wind turbine with the PAGV, which translates to a better correlation.

The output from the ANFIS shows that the model can be used to predict the wind turbine performance for any future sites. By feeding the site's wind speed data into the ANFIS model, the output of rotor rotational speed for wind turbine models with and without the PAGV can be predicted. To illustrate, Fig. 8(a) and (b) show the predicted rotor rotational speed data extracted from the ANFIS model for a period of 240 s. The predicted data output from the ANFIS model can be used as an efficient indicator to evaluate a site's wind performance, therefore reducing time and cost. For the current study, the ANFIS model is trained with a wind speed of 4.24 m/ s and 4.63 m/s only. However, for future study, the ANFIS model can be trained and tested with larger range of wind speed.

The evaluation of the ANFIS model performance for the estimation of the rotor rotational speed was also conducted in a tangible manner based on RMSE and  $R^2$ . The output from the ANFIS testing phase confirms the RMSE statistics as shown in Table 2. The presented results in Table 2 shows average results after many iterations in order to find optimal results. It therefore shows that the proposed ANFIS model can be used for forecasting wind turbine rotational speed with high reliability.

ANFIS already has shown high prediction accuracy for power augmented wind turbines. For example in article [42] ANFIS

able 1				
Statistical	parameters	for	data	sets

Average wind speed $(ms^{-1})$	Rotational speed (RP	Rotational speed (RPM) <sup>a</sup> of the rotor		
	Without PAGV	With PAGV		
4.24	70	90		
4.63	80	100		

<sup>a</sup> Stabilized rotor rotational speed.



**Fig. 6.** Scatter plots of predicted and experimental data of rotational speeds (RPM) without PAGV using ANFIS model for wind speed (a)  $4.63 \text{ ms}^{-1}$  and (b)  $4.24 \text{ ms}^{-1}$ 



**Fig. 7.** Scatter plots of predicted and experimental data of rotational speeds with PAGV using ANFIS model for wind speed (a)  $4.63 \text{ ms}^{-1}$  and (b)  $4.24 \text{ ms}^{-1}$ .

methodology for estimation of building augmented wind turbine performances was presented where ANFIS was used to determine factors of wind and power increasing due to building augmentation of the wind turbine performances. However in article [42] different



Fig. 8. ANFIS forecasting of wind turbine rotational speed for wind speeds (a)  $4.63 \text{ ms}^{-1}$  and (b)  $4.24 \text{ ms}^{-1}$ .

 Table 2

 Performance statistics of the ANFIS model in wind turbine rotational speed estimation.

	RMSE	R <sup>2</sup>
Wind speed 4.63 ms <sup>-1</sup> ; w/o PAGV	1.386773	0.9382
Wind speed 4.24 ms <sup><math>-1</math></sup> ; w/o PAGV	1.023119	0.9226
Wind speed 4.63 ms <sup><math>-1</math></sup> ; with PAGV	1.230114	0.9757
Wind speed 4.24 ms <sup><math>-1</math></sup> ; with PAGV	0.906654	0.9787

inputs are used in comparison with this study. In another similar research [43] ANFIS was used to estimated diffuser effect on wind turbine performances. ANFIS was used to determine power and torque coefficient changing of the wind turbine with a diffuser. It was also estimated the wind turbine rotational performances according to wind speed and blade solidity (the number of wind turbine blades in percentage). The investigation [43] also concluded that ANFIS prediction has better results with slower wind speeds which confirms results in this investigations also where one can see in Table 2 that ANFIS has better performances for wind speed of 4.24 ms<sup>-1</sup> than for wind speed of 4.63 ms<sup>-1</sup>.

## 4. Conclusion

Power augmentation device is one of the most promising concepts to extract wind energy. The power augmentation device improves the output power of a wind turbine by accelerating the wind velocity that approaches the wind turbine. Since wind power is known to be proportional to the cubic power of the wind velocity, thus any slight increase in wind velocity approaching the wind turbine can lead to a substantial increase in power output. Therefore, enclosing a wind turbine in a specially designed shroud will increase its output power. In this work, a new application of ANFIS method was presented to test the accuracy in the estimation of wind turbine rotational speed using the PAGV. Basically, the main advantages of the ANFIS technique are computational efficiency and adaptability. In this study, it was investigated that how accurate wind turbine rotational speed could be estimated using ANFIS technique for both cases of with and without the presence of PAGV. In the developed ANFIS model, three parameters of time, wind speed and the presence of PAGV for a given site were utilized as inputs. The study results indicated that the ANFIS technique can be used to model the rotational speed of the wind turbine. The study proved that the ANFIS model can be used for forecasting wind turbine rotational speed with high reliability. Furthermore, applying the ANFIS approach for a wind turbine integrated with the PAGV shows better accuracy. Therefore, the study results suggested that the proposed ANFIS model can be embedded effectively for estimation of wind turbine rotational speed for both cases of with and without the presence of PAGV.

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