Performance prediction of Savonius Wind Turbine using adaptive neuro-based fuzzy inference system (ANFIS)

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Abstract. Savonius wind turbine has got the upper hand in comparison to other wind turbine in terms of simplicity in construction and better opening torque at low wind speeds. In this background, models based on adaptive neuro-based fuzzy inference system (ANFIS) have been prepared in order to predict the output performance parameters like tip speed ratio and actual torque of Savonius wind turbine in response to the input parameters like number of blades in the turbine and wind speed. The current work utilizes the experimental data of Savonius wind turbine which has been mentioned in the literature. In the literature, Savonius wind turbine with 2, 3, and 4 blades are tested at different wind speed using wind tunnel to determine the tip speed ratio and actual torque delivered by them. The results predicted from the ANFIS models are substantially close to the experimental results. Moreover, the statistical pointers like $R^2$, RMSE and MAPE are found to be 0.90, 0.066 and 18.26 for prediction of tip speed ratio and 0.97, 0.004 and 14.23 for prediction of actual torque, which highlight the precision of the models. Hence, it is finally realized that the developed ANFIS models are capable of finding the output parameter like tip speed ratio and actual torque of Savonius wind turbine with 2, 3, and 4 blades.

1. Introduction

Growing energy demand and ever-increasing fossil fuel prices combined with environmental pollution has led the researchers to look for alternative sources of energy. Energy resources like solar, wind, biomass, geothermal and tidal energy are renewable and pollution free. Among the different renewable energy, wind energy is the outstanding one, since it is easily available throughout the earth’s surface. In order to harvest the dynamic energy of wind into mechanical energy wind turbines are utilized. Wind turbines are usually divided into two primary groups i.e.; vertical axis wind turbines (VAWTs) and horizontal axis wind turbines (HAWTs) in which VAWTs have lesser efficient. In contrast, VAWTs are having the capacity to produce enough power at comparatively lesser wind velocity. These turbines are having the advantages like, simple erection, easy to maintain, less possibility to damage the bird’s life, omni-directional. Figure 1 represents a Savonius wind turbine which falls in the group of VAWT.
The performance of Savonius wind turbine are generally indicated by means of torque coefficient ($C_t$) and coefficient of power ($C_p$) in connection with the tip speed ratio (TSR). TSR is a criterion that relates the diameter of wind turbine to the rated wind speed. Whereas, $C_t$ is expressed as the proportion of the actual torque created by the turbine to the hypothetical torque feasible at a particular wind speed [1]. Thirty distinct models of savonius wind turbine were examined by Savonius, a Finnish engineer who invented the turbine, in open-air and wind tunnel [2]. He informed that on testing the turbine in open-air, a highest $C_p$ of 0.37 was achieved whereas, a highest $C_p$ of 0.37 was achieved for wind tunnel testing. In the past fifty years, number of investigators had experimentally examined numerous type of savonius wind turbine from which it was seen that the $C_p$ of the turbines within 0.35 to 0.15 [2-5]. However, in the last decade, it is seen that few number of researches have basically used neural network in prediction of performance of savonius wind turbine. Sargolzaei [6] in his research used artificial neural network (ANN) approach in order to prediction the torque in savonius wind turbine and power factor. From the research, he concluded that the overlap ratio of 0.2 to be the best and he also demonstrated that increase in the speed of the wind leads to serious rise of power output. Sargolzaei and Kianifar [7] predicted the torque of seven prototype savonius wind turbines and their power factor are using ANNs created on the basis of experimental data that have been gathered from wind tunnel testing. As per the experimental results and ANNs, the authors concluded that with the rise in the TSR, torque and power ratio of the turbines increases. They also concluded that a minimum and maximum quantity of torque occur at angle of 120° and 60° respectively. Sargolzaei and Kianifar [7] also forecast the torque and $C_p$ for 2-bucket Savonius wind turbine using ANN model using the experimental data. The results from the model indicated sensible estimations and predictions of the highest power from the 2-bucket Savonius wind turbine. Biswas et al. [8] presented ANN models for assessment of $C_t$ and $C_p$ of a combination of 3-bucket-Savonius and 3-bladed-Darrieus wind turbine. The researchers highlighted that the models can be utilized for getting more data on the performance of the turbine within the range of input data.

Therefore, the objective of the present paper is to develop two number of ANFIS models utilizing the experimental data of Savonius wind turbine which has been mentioned in the literature by Wenehenubun et al. [9] in order to predict the TSR and actual torque of the turbine. In this literature, Savonius wind turbine with 2, 3, and 4 blades are tested at different wind speed using wind tunnel to determine the tip speed ratio and actual torque delivered by them. Moreover, in the present study ANFIS method has been used because from the recent literatures it is seen that the performance of ANFIS models are superior in comparison with ANN models [10-12].

2. Adaptive neuro-fuzzy inference system (ANFIS)
In the current work, two ANFIS models are developed for establishment of correlation between input and output which is highlighted in figure 2. Figure 3 represents the architecture of each ANFIS model use in the current work which comprises of five layers with two inputs and one output. For ANFIS
model-I, input variables are number of blades in the turbine and wind speed and output is TSR. Whereas, for ANFIS model-II, input variables are number of blades in the turbine and wind speed and output is actual torque (T). In the current architecture of the ANFIS models, Takagi-Sugeno-Kang type system is utilized as Fuzzy Inference System (FIS). This is due of the fact that on using Takagi-Sugeno-Kang type FIS, unfluctuating performance of ANFIS is achieved with more precise results [13]. Moreover, in the proposed ANFIS models, hybrid learning algorithm is employed for fine-tuning of the FIS. The least square method and backpropagation algorithm are combined together to form hybrid learning algorithm. Thus, on consideration of 1st order Takagi-Sugeno-Kang type FIS with single output and dual inputs, the fuzzy “if-then rule” can be written as [16]:

Rule 1: If \( Z_1 = T_1 \) and \( Z_2 = S_1 \); then \( O_1 = x_1 Z_1 + y_1 Z_2 + v_1 \)

Rule 2: If \( Z_1 = T_2 \) and \( Z_2 = S_2 \); then \( O_2 = x_2 Z_1 + y_2 Z_2 + v_2 \)

where \( Z_1 \) and \( Z_2 \) represent the inputs and \( T_1, T_2, S_1, S_2 \) can be considered as the membership functions for inputs. \( x_1, y_1, v_1, x_2, y_2, v_2 \) are the output (O) function parameters. The functions node for the ANFIS structure used in this study can be written as:

Output of the layer 1: \( O^1_i = \mu_{T_i}(Z_1) = \mu_{S_i}(Z_2) = \frac{1}{1+\left(\frac{x_i-c_i}{a_i}\right)^{b_i}}, \quad i = 1,2 \)

Output of the layer 2: \( O^2_i = w_i = \mu_{T_i}(Z_1) \times \mu_{S_i}(Z_2), \quad i = 1,2 \)

Output of the layer 3: \( O^3_i = \bar{w}_i = \frac{w_i}{w_i + w_{i+1}}, \quad i = 1,2 \)

Output of the layer 4: \( O^4_i = \bar{w}_if_i = \bar{w}_i(x_iZ_1 + y_iZ_2 + v_i), \quad i = 1,2 \)

Output of the layer 5: \( O^5_i = \sum \bar{w}_if_i = \bar{w}_1f_1 + \bar{w}_2f_2, \quad i = 1,2 \)

In this study, Bell-shaped membership function (MF) is used where \( a_i, b_i, c_i \) are the parameters set. Bell-shaped MF has been selected in this study since, number of recent literatures reported that the performance of ANFIS model got better on using this MF [14-16]. The membership function diagrams is shown in figure 4

![Figure 2. Schematic configuration of ANFIS models](image)

![Figure 3. ANFIS model structure](image)
3. Assessment of Performance of the ANFIS models

These in order to assess the performance of the ANFIS models, several statistical criteria are used that include root mean square error (RMSE), coefficient of determinant ($R^2$) and mean absolute percentage error (MAPE). These statistical criteria are generally described by the means of prediction error (i.e., the variation between the predicted and actual values) utilizing the equations given below [17]:

$$R^2 = \frac{\sum^n_{i=1}(J_i - J_{mean})^2}{\sum^n_{i=1}(J_i - J_{mean})^2} - \frac{\sum^n_{i=1}(J_i - J_p)^2}{\sum^n_{i=1}(J_i - J_{mean})^2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum^n_{i=1} (J_i - J_p)^2}$$

$$\text{MAPE} = \left( \frac{\sum^n_{i=1} |J_i - J_p|}{n} \right) \times 100$$

where $J_i$ and $J_p$ are the actual and predicted data and $n$ represents the quantity of data points.

4. Result and Discussion:

First of all, the input dataset for the both the ANFIS model is randomly divided into three parts for training, testing and validation. In this study, 70% of the total data for the dataset is used for training whereas, 15% of the total dataset for the dataset is used for testing and remaining 15% is used for validation [15, 17]. In addition to it, the performance of ANFIS models is also checked with training, testing and validation data of 60%, 20% and 20%. On completion of the training of the ANFIS models, the performance of the models is evaluated on the basis of testing data using the statistical criteria like $R^2$, RMSE and MAPE as discussed in the previous section. The performance of the models is assessed by using testing data because for a model it is quite expected that it will give better outcomes for training data due to over training [15]. Moreover, a model, is considered to be better when the $R^2$ value associated to it approaches one, RMSE valve is closed to zero and MAPE valve is less than or equal to 20 % [18].

| Table 1. ANFIS model performance with 70%, 15% and 15% training, testing and validation |
|---------------------------------|-----------------|-----------------|
| Statistical Criteria           | ANFIS Model-I   | ANFIS Model-II  |
| $R^2$                          | 0.90            | 0.97            |
| RMSE                           | 0.066           | 0.004           |
| MAPE                           | 18.26%          | 14.23%          |

| Table 2. ANFIS model performance with 60%, 20% and 20% training, testing and validation |
|---------------------------------|-----------------|-----------------|
| Statistical Criteria           | ANFIS Model-I   | ANFIS Model-II  |
| $R^2$                          | 0.878           | 0.92            |
| RMSE                           | 0.079           | 0.012           |
| MAPE                           | 19.66%          | 17.18%          |
In Table 1 and Table 2, the performance of the ANFIS models in terms of \( R^2 \), RMSE and MAPE has been highlighted. From this table, it is found that the ANFIS models with 70% training, 15% testing and 15% validation have \( R^2 \) values as 0.90 & 0.97 (i.e., close to one), RMSE values as 0.066 & 0.004 (i.e., close to zero) and MAPE values as 18.26 and 14.23 (i.e., less than or equal to 20%). Therefore, the developed ANFIS models with 70% training, 15% testing and 15% validation can be considered to be a good one for prediction of TSR and actual torque with input parameters like wind speed and number of blades of a savonius wind turbine having aspect ratio of 1 and overlap ratio of 0.15. Finally, 15% of the total data for the dataset is utilized for validation which is presented in Figure 5 and 6.

![Figure 5. Predicted ANFIS TSR vs experimental results](image1)

![Figure 6. Predicted ANFIS actual torque vs experimental results](image2)

5. Conclusion
In the current study, two ANFIS models have been demonstrated so as to give a precise connection between input parameter like wind speed and number of blades and output performance parameter like tip speed ratio and actual torque of a Savonius wind turbine having aspect ratio of 1 and overlap ratio of 0.15. The results predicted from the ANFIS models are substantial close to the experimental results. Moreover, the statistical pointers like \( R^2 \), RMSE and MAPE are found to be 0.90, 0.066 and 18.26 for prediction of tip speed ratio and 0.97, 0.004 and 14.23 for prediction of actual torque, which highlight the precision of the models. Hence, it is finally realized that the developed ANFIS models are capable of finding the output parameter like tip speed ratio and actual torque of Savonius wind turbine with 2, 3, and 4 blades.
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