Prediction of the power ratio and torque in wind turbine Savonius rotors using artificial neural networks

SARGOLZAEI J.
Department of chemical engineering,
Ferdowsi university of Mashhad,
P.O. Box 9177948944, Mashhad,
IRAN

Abstract: -The power factor and torque of wind turbines are predicted using artificial neural networks (ANNs) based on experimental that are collected over seven prototype vertical Savonius rotors. Unlike horizontal-axis turbines, in vertical-axis turbines rotation speed is low and torque is high. Therefore, this device could be used for local production of electricity. In this research, the rotors having different features in the wind tunnel and the tests are repeated 4 to 6 times for reducing error. All experiments are done on six blades in different Reynolds number and wind speed varied from 8 to 14 m/s. Input quantities for the prediction in neural network are Reynolds number and the tip speed ratio (TSR). Rotor's power factor and torque were simulated in different Reynolds numbers and different angles of blade in proportion to blowing wind in a complete rotation. The simulated Results were compared with the corresponding experimental data shows that the simulation has the capability of providing reasonable predictions for the maximum power of rotors and maximizing the efficiency of Savonius wind turbines. According to results, increasing Reynolds number leads to increase of power ratio and torque. For all examined rotors, maximum and minimum amount of torque happens in angle about 60^o and 120^o, respectively.

Key-Words: -Vertical Savonius rotors, Neural networks, Wind tunnel, Power factor, Torque, Tip speed ratio

1 Introduction

Wind turbine is used to change wind energy into mechanical energy (such as wind mill and moving weight) and generate electricity. These turbines are classified to two categories horizontal axis and vertical axis. The horizontal axis wind turbines have complicated structures and difficult installation. This turbine is economically valuable only in areas with permanent winds and high speeds. Although rotation speed is very high, torque is low. This turbine often is used to generate electricity. The vertical-axis wind turbines (VAWTs) have simple structure and installation. They are useful in different speed and direction of wind [1,2]. Unlike horizontal axis turbines, in vertical axis turbines rotation speed is low and torque is high [3]. These turbines are independence from wind direction. Because of low speed and high torque in these turbines, some forms of power transfer such as compressed air and hydraulic have preference to generate electricity. This device could be used for pumping water in agriculture and industry [4].

In vertical axis wind turbines or rotors, such as Savonius [5] rotating axis is perpendicular to wind direction. Therefore the surface which is moved by air, after rotating half a round, should move in reverse direction of wind. This is the reason of decreasing of power ratio. Therefore blade is an important factor in these rotors. The Savonius rotor includes two half cylinder shape blades (nominal diameter D, height S), as shown in Fig. 1. The movement is mainly the result of the different between the drag on the advancing paddle and the drag on the other one. The lift force, which normally takes place to the direction of wind velocity, produces the rotation in this type of turbine. There is high pressure before the surface whereas low pressure after it [3].

Kavamora and his colleagues in 2001 studied the flow round Savonius rotor by DDM method (Domain Decomposition Method). They examined torque ratio and power ratio of rotor in different speeds of air blow for semicircle blades [6].

All these results have leaded us to build alternative methods of predicting wind turbine performance that is function of power factor and Reynolds number. One of these methods is artificial neural networks (ANNs). Neural networking involves algorithms under which information is accumulated in programmed objects that are capable of learning through much iteration using simulated or real data [7].

ANNs have been used in renewable energy systems as well as for many other disciplines. Comprehensive reviews of ANN applications in energy systems in general [8] and in renewable energy systems in particular [9] are available.

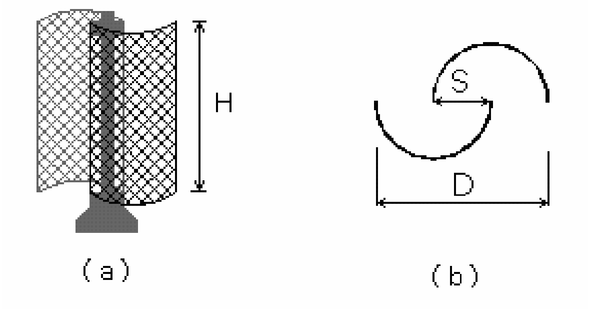

Fig. 1: Schematic of a Savonius rotor. (a) Front view; (b) Semicircle shape

In this research, ANNS have applied to simulation of rotor's power ratio in different Reynolds numbers and different angles of blade in proportion to blowing wind (in a complete rotation). Then, Results were compared with the corresponding experimental data shows that the simulation has the capability of providing reasonable predictions for the maximum power of rotors and maximizing the efficiency of Savonius wind turbines.

2 Theory

A neural network is by definition: a system of simple processing elements, called neurons, which are connected to a network by a set of weights (Fig. 2). The network is determined by the architecture of the network, the magnitude of the weights and the processing element's mode of operation. The neuron is a processing element that takes a number of inputs (p), weights them (w), sums them up, adds a bias (b) and uses the result as the argument for a singular valued function, the transfer function (f), which results in the neurons output (a). The most common networks are constructed by ordering the neurons in layers, letting each neuron in a layer take as input only the outputs of neurons in the previous layer or external inputs. To determine the weight values, a set of examples is needed of the output relation to the inputs.

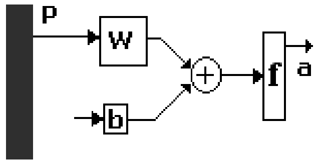

Fig. 2: The architecture of the neural network

The task of determining the weights from these examples is called training and is basically a conventional estimation problem. For this purpose, the back-propagation strategy has become the most frequently, and here, used method which tends to give reasonable answers when presented with inputs that they have never seen. Standard back-propagation is a gradient descent in which the network weights are modified by relation follow:

$$w_{ij}(n+1) = w_{ij}(n) + \eta \cdot \delta_i(n) \cdot x_i(n) \qquad (1)$$

Where $w_{ij}(n+1)$ weight of i to j element in (n+1)th step and $w_{ij}(n)$ are as same weight in nth step. $\delta_i(n)$ is local error that evaluated to $e_i(n)$ and n is step size [10] and η is the learning rate that is equal 1. The local error is corresponding of relation follow:

$$e_i(n) = d_i(n) - y_i(n) \qquad (2)$$

The typical performance function that is used for training feedforward neural networks is the mean sum of squares of the network errors between the network outputs and the target outputs [11]. In this work the batch gradient decent with momentum algorithm [12] was used as the training function. The momentum algorithm is development state of the gradient decent that weights learning obtained from relation follow:

$$w_{ij}(n+1)=w_{ij}(n)+\eta\cdot\delta_i(n)\cdot x_i(n)+\alpha\cdot(w_{ij}(n)-w_{ij}(n-1)) \qquad (3)$$

Where α is the momentum coefficient that between 0.1 to 0.9 values.

Where α is the momentum coefficient that between 0.1 to 0.9 values. The performance of the neural network model evaluated with the root mean square error (RMSE) and determination coefficient (R^2) between the modeled output and measures of the training data set that their relations are follow:

$$R^2 = 1 - \frac{\sum_P (x_{obs} - x_{est})^2}{\sum_P (x_{pred} - \bar{x}_{obs})^2} \qquad (4)$$

$$RMSE = \sqrt{\frac{\sum_P (x_{obs} - x_{est})^2}{N}} \qquad (5)$$

Where x_{obs}, x_{est} are experimental and estimated values, respectively, and N is the number of data.

3 Methods and materials

3.1 Calculating power of wind force

Kinetic energy of air is calculated by following equation:

$$P_w = \frac{1}{2}\overset{o}{m}V^2 \tag{6}$$

That $\overset{o}{m}\,(kg/s)$ is air mass flow rate and $V\,(m/s)$ is speed of blowing air. By replacing $\overset{o}{m}$ energy equation is changeable to power in surface which is swept by rotor:

$$P_w = \frac{1}{2}\rho v^3 A \tag{7}$$

$P_w\,(watt)$ is power, $\rho\,(kg/m^3)$ is air density and $A(\pi R^2)$ is surface which is swept by rotor.

Following equation is useful to calculate power produced by turbine:

$$P_t(\theta) = F(\theta).v(\theta) = T(\theta)\omega(\theta) \tag{8}$$

θ is angular position of turbine, T is torque of vertical force to blade's surface (force of air pressure), v is speed vector in force point of F, and ω is rotating speed of blade.

The power factor can be defined as the ratio between the power in turbine shaft (P_t) and the wind power (P_w) due to its kinetic energy right before the turbine plane, which yields:

$$C_P = \frac{P_t}{P_w} \tag{9}$$

Product of dot multiply in equation 8 shows that only the factor of the force with the same direction of rotation is effective to produce power. Therefore, blade's curve in vertical axis turbine is very important.

3.2 Produced samples

Savonius rotor has been tested with six different blade's curves in a square section wind tunnel to dimension $0.4\times0.4\times14$ m. In rotors I to V each blade is a semicircle to the diameter value 16 cm. Values of S distances (gap) are 0, 3.2, 3.8, 6.4, and 7.2 cm for rotors I to VI in Fig. 3, respectively.

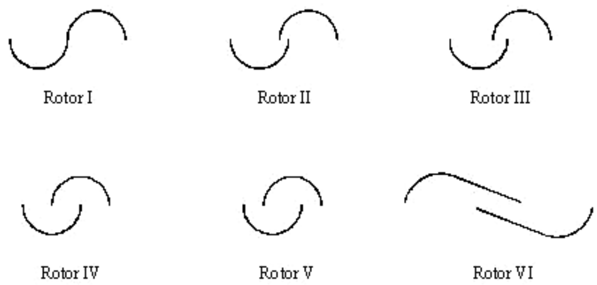

Fig. 3: Shapes of experimented rotor's blades

These gap distance change amount of drag force on back and front of blade in different angles in proportion to blowing wind. Height (H) in all produced models is about 30 cm, thickness of blade is 1 mm, and it is made of aluminum. Fig. 3 shows rotors shapes.

3.3 Experimentation of different blades in wind tunnel

Blade's power factor is calculated by measuring rotating speed of rotor round axis and outlet torque which is measured by two special dynamometer connected to the end of each blade. All experiments are done in the same situation and wind speed varies from 8 to 14 m/s.

The result of experiments for rotors I and IV are presented. Results of previous experiments make it possible to calculate and compare average power factor in a complete rotation in a specific wind speed. This comparison could be a good standard to select the rotor with the best efficiency.

Variables tip speed ratio (λ), power factor (Cp) and Reynolds number (Re) are defined with following equations:

$$\lambda = \frac{u}{V} = \frac{\omega D}{2V} \tag{10}$$

$$Cp = \frac{2Fu}{\rho V^3 DH} \tag{11}$$

$$Re = \frac{VD}{\nu} \tag{12}$$

Which V wind speed, D diameter of rotor, H height of rotor, u speed of blade's tip, ν kinematics viscosity, and ω is rotation speed of rotor.

3.4 Architecture of the neural network

In this research, the architecture of the neural network model was optimized by applying different amounts (1–7) of hidden neurons. The choice of a specific class of networks for the simulation of a non-linear and complex map depends on a variety of factors such as the accuracy desired and the prior information concerning the input–output (TSR–power factor) pairs. The most popular ANN is the feed forward multi-layer perceptron, where the neurons are arranged into an input layer, one or more hidden layers, and an output layer. Only one hidden layer was used in this study because of the proven non-linear approximation capabilities of multi-layered feed forward perceptron network for an arbitrary degree of accuracy [13].

The variation of training error with respect to the number of neurons in the hidden layer is found for rotor I that this result is enable to generalization to other rotors. As seen from Fig. 4, the RMSE (training error) is minimal when the number of neurons is six.

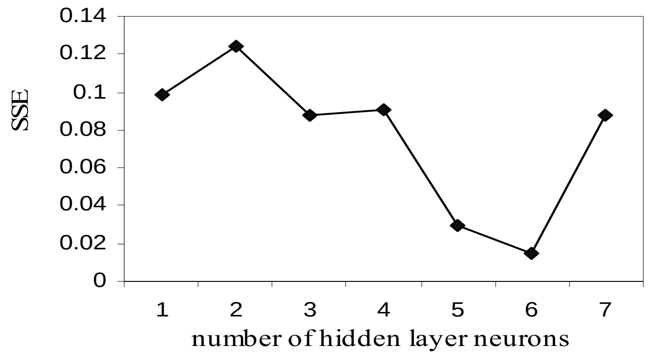

Fig. 4: The effect of number of neurons in hidden layer

In this work, the accuracy of the modeling with respect to the correlation coefficient index (R^2), standard sum error (SSE), and root mean square error (RMSE) have been presented in Table 1.

Table 1: The accuracy of the modeling with respect to the training errors

number of hidden neuron	RMSE	R^2	SSE
1	0.01835	0.96	0.099
2	0.02056	0.95	0.1243
3	0.0172	0.965	0.0875
4	0.01761	0.9658	0.09119
5	0.01007	0.987	0.02976
6	0.0071	0.993	0.01519
7	0.0173	0.967	0.0876

Each neuron consists of a transfer function expressing internal activation level. Output from a neuron is determined by transforming its input using a suitable transfer function. Generally, the transfer functions are sigmoidal function, hyperbolic tangent and linear function, of which the most widely used for non-linear relationship is the sigmoidal function [14, 15]. The general form of this function is given as follows:

$$y_J = f(x_J) = \frac{1}{1+e^{-x_J}} \tag{13}$$

The software used for the ANNs modeling was Matlab Toolbox version 7.0.

4 Results and discussions

Power factor (power ratio) for rotors I to IV in Reynolds number 1.5×10^5 by tip speed of blade (results of first experiment) are presented in Figures 5 and 6. According to results, each rotor might have an effective result in specific range of blade’s tip speed in proportion of other rotors. For example, rotors V and IV have greater power factor then rotor I in low and high speed of blade’s tip. But in average speed, rotor I has greater power factor.

In order to compare rotors and chose the best rotor curve, average power factor or total power factor is useful. In Fig. 7 total power factor is presented. Rotor II as the most effective rotor in different speeds of blade’s tip could be seen in the Fig. 7.

Rotors VI and III also have good efficiency. Because the only difference between rotors I to V is the gap distance (S) between blades, the comparison between power factor of these rotors proves that increasing distance S in rotor II (S =3.2 cm) in proportion with rotor I (S =0), causes suddenly increase in power factor and intense decrease in resistance force against rotor movement. But this increase in rotors III (S =3.8cm) to rotor V (S =7.2 cm) causes decrease in power factor.

Therefore, the best gap distance (S) is in range 0 to 3.2 cm. Besides, power factor is at maximum level when linear speed of blade's rim is close to wind speed $(\lambda = 1)$.

The effect of gap distance (S) on power ratio could be examined by drawing speed vectors round the rotors. It is presented in results of numeric simulation. Power ratios in rotors I and IV in different Reynolds number are presented in Figures 8 and 9. According to figures, increasing Reynolds number (wind speed) leads to increase of power factor.

The reason is increase of wind energy. This increase is at maximum level when $\lambda = 1$. Getting away from this maximum point means decrease of power ratio.

Average power factor for rotors I, II and IV is compared in Fig. 10. According to the figure, increasing Reynolds number (wind speed) leads to increase in rotor's power factor. But the rate of this increase is decreasing. The reason is change in flow status and turbulence flow round the blades.

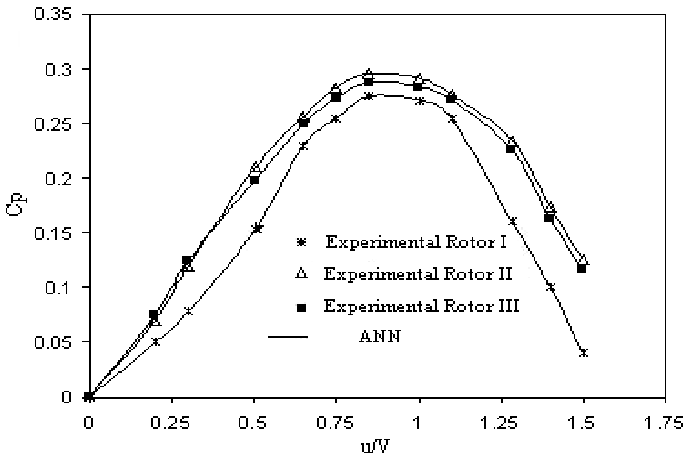

Fig. 5: Comparison between power factor of rotors I to III

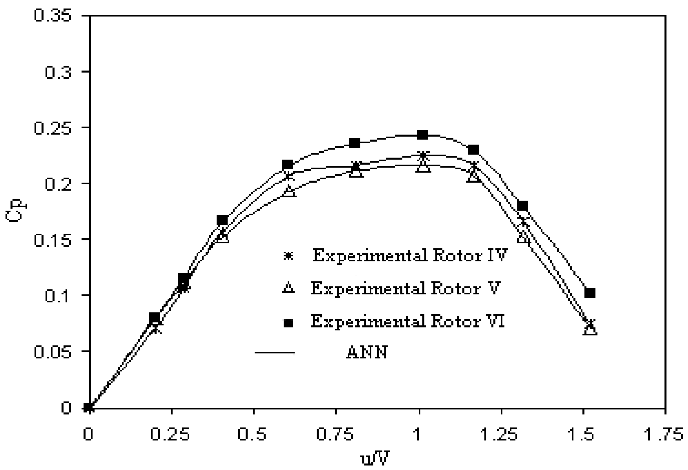

Fig. 6: Comparison between power factors of rotors IV to VI

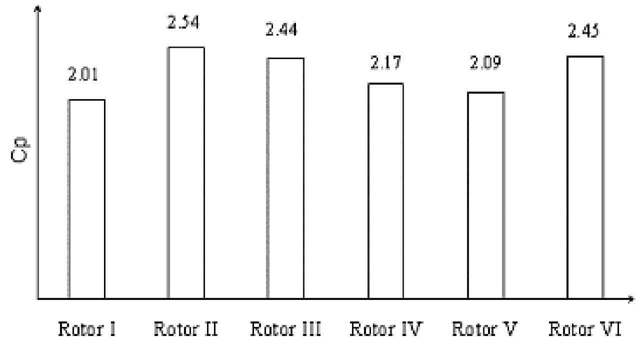

Fig. 7: Comparison between power factor in rotors I to VI

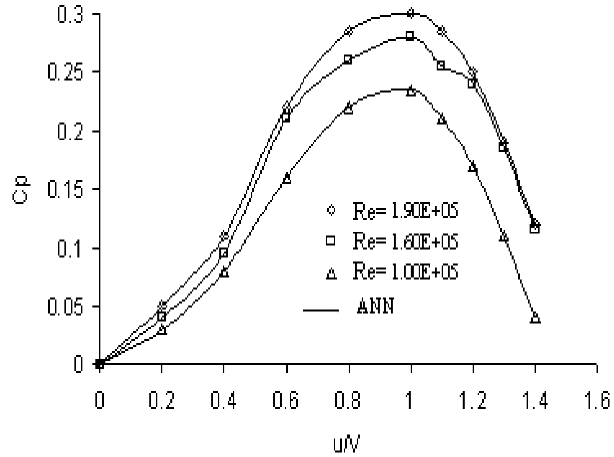

Fig. 8: Rotor's power factor in different Reynolds numbers

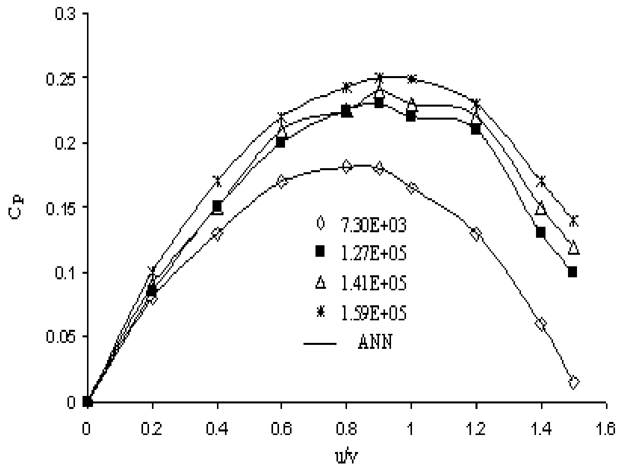

Fig. 9: Power factor in rotor IV in different Reynolds numbers

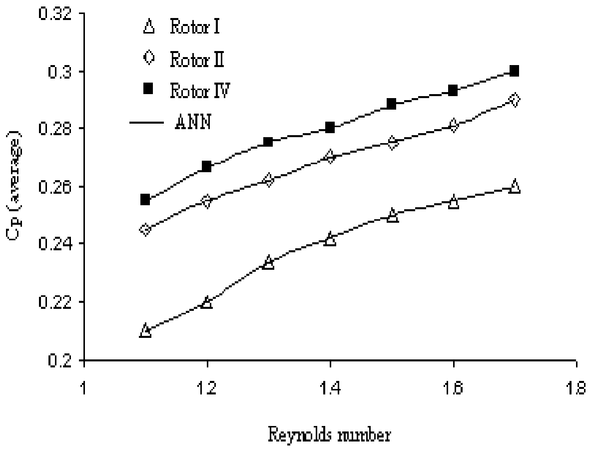

Fig. 10: Comparison of average power factor of different rotors by Reynolds numbers

Torque on turbine's blades in different wind speed and different angles of blade in proportion of wind speed which is simulated by ANN, is carried out. According to these results, increasing wind speed leads to increase of torque. For all examined rotors, maximum amount of torque happens in angle about 60° and minimum amount of torque happens in angle about 120°. Besides, in rotor I area of minimum torque is vast, however for other rotors it is not in this case.

5. Conclusion

In this paper, an ANN approach is presented to prediction of power factor and torque in wind turbine. Because of the capabilities of parallel information processing and generalization of the ANNs, the proposed algorithm is found to be fast and accurate. Results prove that curves for rotors II to IV have greater power factor than other rotors, because of the gap distance between blades. On the other hand, excess increase of gap distance, leads to decrease of power factor. In this research, the best ratio is defined as $\frac{S}{D} = 0.2$. Besides, according to results of numeric solution and experiments, the best blade's curve is the curve of turbine II. Other results prove that, increase of wind speed (Reynolds number) leads to serious increase of output power (is related to third exponent of speed).

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