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

J. Sargolzaei

Abstract— The power factor of wind turbines are estimated using artificial neural networks (ANNs) based on experimental that are collected over seven prototype vertical Savonius rotors. 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 quantity for the estimation in neural network is tip speed ratio (TSR). Rotor's power factor was simulated in TSR 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 estimations 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.

Keywords— Vertical Savonius rotors, Neural networks, Wind tunnel, Power factor, Tip speed ratio.

I. 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].

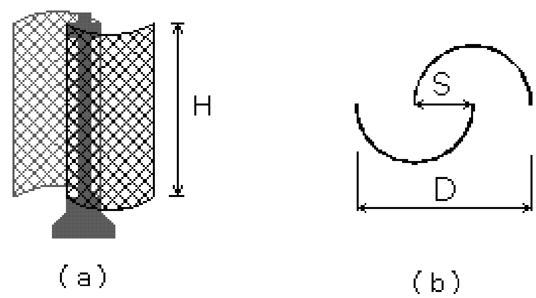

Figure 1: Schematic of a Savonius rotor. (a) Front view; (b) Semicircle shape

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. 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.

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Artificial neural networks are becoming useful as modeling of wind turbine. Two experimental data sets were used as the training data for Savonius rotor of wind turbine. Radial basis function (RBF) network good provide predictions because of it is able to handle noisy and noise filtering. It is clearly illustrated that the computation of optimal isotopic spread is crucial for proper performance of the RBF network. In this research, the modeling is done using MATLAB toolbox. The model accuracy is evaluated by comparing the simulated results with the actual measured values at the wind tunnel and is found to be in good agreement.

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 estimations for the maximum power of rotors and maximizing the efficiency of Savonius wind turbines.

II. 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.

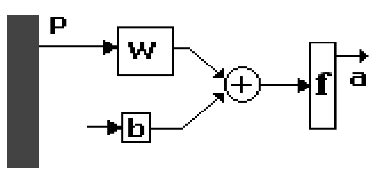

Fig. 2: The architecture of the neural network

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. Therefore, a set of data was produced describing the whole operating range of the system. The knowledge of the neural network is encoded in the values of its weights.

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:

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

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:

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

The term back-propagation refers to the manner in which the gradient is computed for non-linear multiple-layer networks. 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:

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

Where α is the momentum coefficient that between 0.1 to 0.9 values. This and other training functions gave good results in earlier neural network modeling of wind turbine [7, 11, 12]

III. Methods and materials

A. Calculating power of wind force

Kinetic energy of air is calculated by following equation:

$$P_W = \frac{1}{2}\mathring{m}V^2 \quad (4)$$

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

$$P_W = \frac{1}{2}\rho V^3 A \quad (5)$$

$P_W(watt)$ 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:

$$P_t(\theta) = F(\theta).v(\theta) = T(\theta)\omega(\theta) \quad (6)$$

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:

$$C_P = \frac{P_t}{P_W} \quad (7)$$

Product of dot multiply in equation 7 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.

B.Produced Samples

Savonius rotor has been tested with six different blade's curves in a square section wind tunnel to dimension $0.4\times 0.4\times 14$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.

These gap distance change amount of drag force on back and front of blade in different angles in proportion to blowing wind. The blade's curve in rotor "VI" is Savonius curve which is similar to rotor "IV" in dimensions. 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.

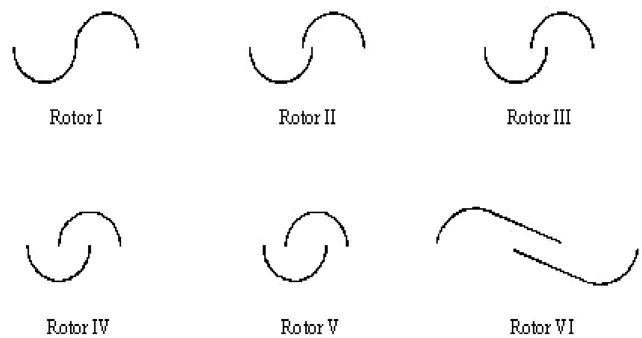

Fig. 3: Shapes of experimented rotor's blades

C.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. When the increase of hidden neurons did not improve the model anymore, the model with the smallest amount and maximum performance was chosen as the best model. 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.

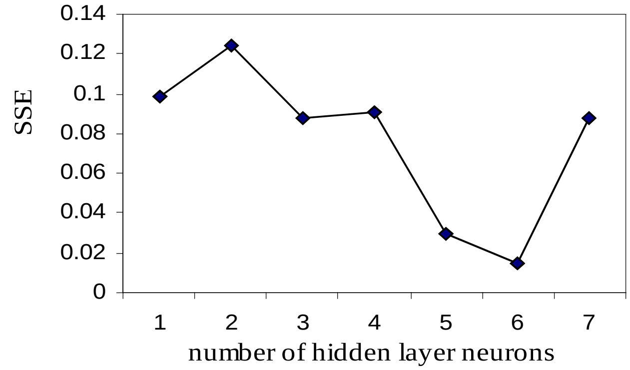

Fig. 4: The effect of number of neurons in hidden layer

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:

$$y_J = f(x_J) = \frac{1}{1+e^{-x_J}} \tag{8}$$

This sigmoid function maps input into output in a range between 0 and 1, distributed as an S-shaped curve, so the input and output data should be scaled to the same range as the transfer function used. The software used for the ANNs modeling was Matlab Toolbox version 7.0.

IV. 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 Figs. 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 "IV" and "V" 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.

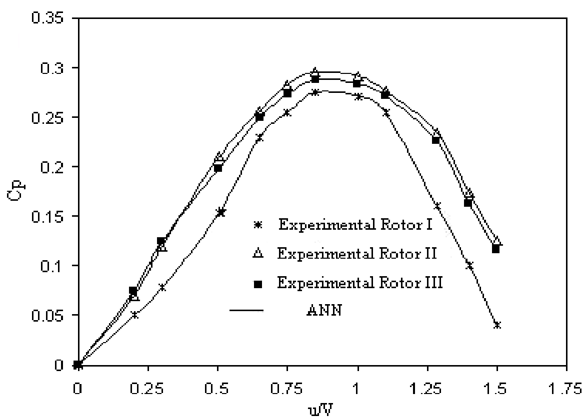

Fig. 5: Comparison between power factor of rotors "I" to "III"

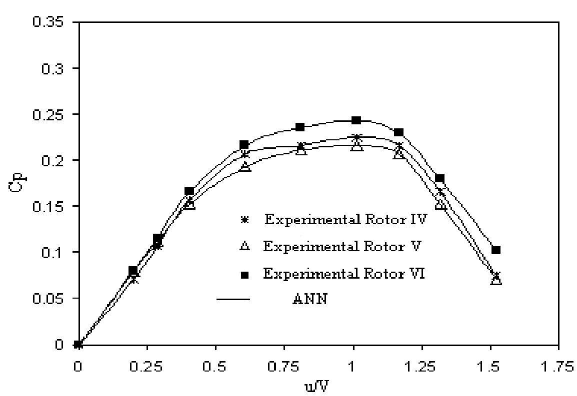

Fig. 6: Comparison between power factors of rotors "IV" to "VI"

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.

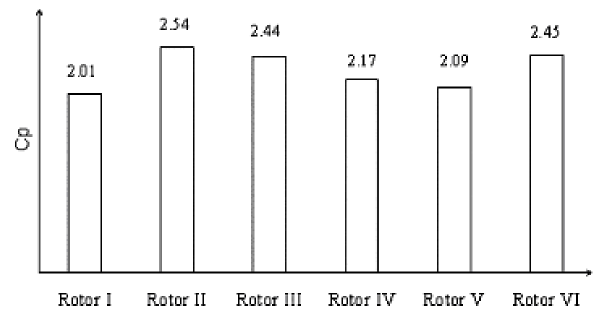

Fig. 7: Comparison between power factor in rotors "I" to "VI"

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 Figs. 8 and 9.

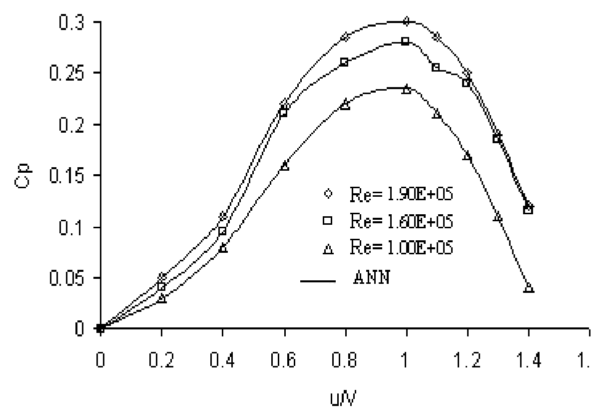

Fig. 8: Rotor's power factor in different Reynolds numbers

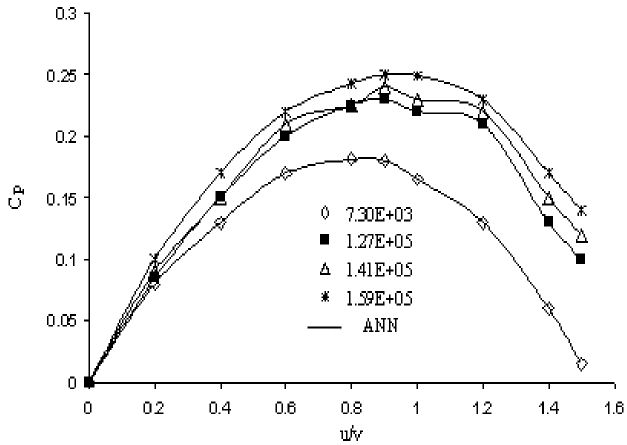

Fig. 9: Power factor in rotor "IV" in different Reynolds numbers

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 Fig. 10, 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.

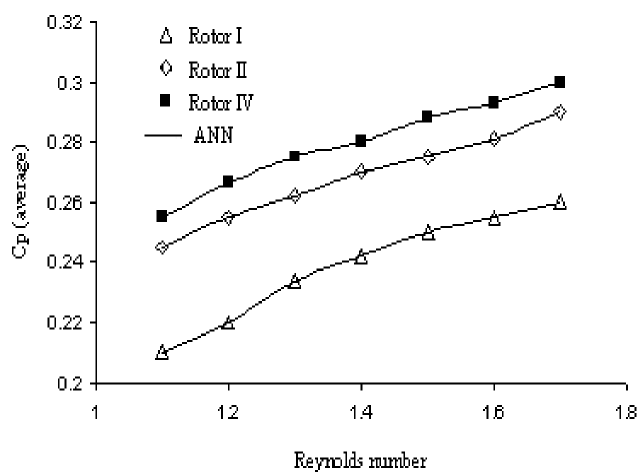

Fig. 10: Comparison of average power factor of different rotors by Reynolds numbers

V. Conclusion

In this paper, an ANN approach is presented to estimation of power factor 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. According to results of numeric solution and experiments, the best blade's curve is the curve of rotor "II". Other results prove that, increase of wind speed leads to serious increase of output power (is related to third exponent of speed).

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