
SIMULATION MODELLING PRACTICE AND THEORY
Volume 17, issue 7, August 2009
ISSN 1569-190X
ELSEVIER
International Journal of the Federation of European Simulation Societies
SIMULATION MODELLING PRACTICE AND THEORY
Available online at www.sciencedirect.com
ScienceDirect

Simulation Modelling Practice and Theory 17 (2009) 1290–1298

Contents lists available at ScienceDirect

Simulation Modelling Practice and Theory

journal homepage: www.elsevier.com/locate/simpat

Modeling and simulation of wind turbine Savonius rotors using artificial neural networks for estimation of the power ratio and torque

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ARTICLE INFO

Article history:
Received 26 August 2008
Received in revised form 5 April 2009
Accepted 8 May 2009
Available online 18 May 2009

Keywords:
Neural networks
Savonius rotors
Blade angles
TSR
Wind tunnel

ABSTRACT

The power factor and torque of wind turbines are predicted using artificial neural networks (ANNs) based on experimental data which have been collected for seven prototype vertical Savonius rotors tested in a wind tunnel. In this research, the rotors with different configurations were located in the wind tunnel and the tests were repeated 4–6 times in order to reduce errors. Since the Reynolds number has a negligible effect on power ratio, therefore tip speed ratio (TSR) is the main input parameter to be predicted in neural network. Also, the rotor's power factor and torque were simulated for different tip speed ratios and different blade angles. The simulated results show a strong capability for providing reasonable predictions and estimations of the maximum power of rotors and maximizing the efficiency of Savonius turbines. According to artificial neural nets simulations and the experimental results, increasing tip speed ratio leads to a higher power ratio and torque. For all the tested rotors, a maximum and minimum amount of torque has happened at angle of 60° and 120°, respectively.

1. Introduction

Wind turbine is a device to change wind energy into mechanical energy. These turbines are classified into two categories, horizontal and vertical axes. The horizontal axis wind turbines have complicated structures and are economically valuable only in areas where the permanent winds and high speeds are available and are mainly employed for generating electricity. The vertical axis wind turbines (VAWTs) such as Savonius turbines have a simple structure and are capable to operate at low wind speed [1,2]. Unlike horizontal axis turbines, in vertical axis turbines, the rotation speed is low and torque is high [3]. These turbines are independent of the wind direction [4].

In vertical axis wind turbines such as Savonius [5] rotating axis is perpendicular to the 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 for power ratio reduction. The Savonius rotor includes two half cylinder shape blades (nominal diameter D, height H), as shown in Fig. 1.

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].

One alternative method to predict wind turbine performances 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].

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doi:10.1016/j.simpat.2009.05.003

Nomenclature

A	swept area of the rotor (πR^2)
ANN	Artificial neural network
C_p	power factor
c_j	centre of the activation function
D	diameter of rotor (m)
H	height of rotor (m)
F_i	effect of external forces
N	number of data
P_w	power (W)
R^2	correlation coefficient index
Re	Reynolds number
RBF	radial basis function
RMSE	root mean square error
S.D.	standard deviation
SSE	standard sum error
S	gap distance (m)
T	torque of vertical force to blade's surface, (N m)
TSR	tip speed ratio
u	speed of blade's tip (m/s)
u_i	speed of airflow in specific direction (m/s)
V	wind speed (m/s)
y_{obs}	experimental values
y_{est}	estimated values
y_{pred}	predicted values
v	kinematics viscosity (kg/m/s)
λ	tip speed ratio
θ	angular position of turbine, radian
ρ	density (kg/m^3)
ω	rotation speed of rotor
σ_j	width of the activation function

ANNs have been utilized in energy systems. Comprehensive reviews of ANN applications in energy systems in general [8] and in renewable energy systems in particular [9] are available.

The experimental data are typically very complex to model due to the underlying correlation among several variables of different type. It is ordinary to have multivariate dependency with non-linear behavior. Furthermore, typical variables do not meet the common Gaussianity assumption. Standard statistical techniques may fail for adequate modeling complex non-linear phenomena. In contrast, neural networks (NNs) are becoming widely used because they have shown ability to model non-linear data and their non-reliance, on applied equations [8].

In this research, some of the data were employed in order to calculate the power ratio. Also the remaining data has employed for ANNs simulation of rotor's power ratio at different Reynolds number and blade angles for each complete rotation

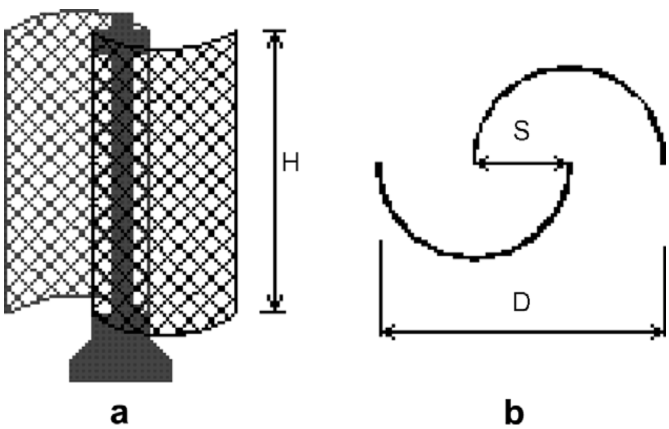

Fig. 1. Schematic of a Savonius rotor. (a) Front view; and (b) semicircle shape.

of wind turbines blades. Then, results were compared with the corresponding experimental data which show the simulation has the capability of providing reasonable predictions for the maximum power of rotors and maximum efficiency of Savonius wind turbines.

2. Theory

The model proposed in this work is based on a radial basis function (RBF) network. Since late 1980s, RBF networks have been a subject of study and have been employed with success in numerous fields [10], their main applications being time series forecasting and function approximation. In general, it can be said that a RBF network is a feed forward network that consists of three layers: the input layer, the hidden layer and the output layer, as it is shown in Fig. 2. The hidden layer is composed of a determined number of nodes or basis functions. These basis functions, also called kernel, which can be selected among several types of functions, but for most applications they are chosen to be Gaussian functions. These types of functions have the property of being local functions, which means that only they function with their centers close to the input patterns will give a response. So, the hidden layer is composed of a variable quantity of nodes, distributed over all the input space. Each node is a Gaussian function, characterized by a centre c and a width σ that produces a non-linear output. Let's assume that the inputs of the network are given in a vector of d components, $x = \{x_1, \ldots, x_d\}$,The activation function, $g_j(x)$, is of the form:

$$g_j(x) = \exp\left(-\frac{(x - c_j)^2}{\boldsymbol{\sigma}_j^2}\right); \quad j = 1, 2, \ldots, m \tag{1}$$

where c_j is the centre of the activation function and σ_j its width.

In this research, the centers are set using the well known K-means algorithm [11]. The parameter m corresponds to the number of nodes in the hidden layer. The design and training of RBF networks consist of the number of hidden nodes and their structure which must be determined, that is, the centers and widths of the basis functions, and the weights of the output layer. There are several methods for constructing and training a RBF network [12,13], and optimizing the design parameters [14], but the most common case is that the number of basis functions has to be given by complex specifications or by means of a trial and error process. In this case, an own algorithm is implemented to select the structure and number of the basis functions using the optimization routines from Matlab [15].

3. Neural network design

This step consists of designing the radial basis layer (number of neurons, centers and bias) as well as the calculus of the output layer weights. In order to do in theoretical part, many randomly selected patterns of each training test data (N 6 power ratio and N 10 torque) were used to design the net, constituting what it is called the training data set. The patterns corresponding to: maximum, minimum and median values of input and output variables of each training test (N 13 power ratio and N 27 torque) employed to measure the net model accuracy, constituting what it is called the checking data set. The reason for limiting the training data in design of the neural network is, on one hand, to limit the time consumed in setting up the model and, on the other hand, to avoid unnecessary information that can cause over fitting. If all the data are included in a single neural network model, it is very difficult to obtain a converged result. Hence, the data set for each rotor has been used in different models. The architecture of nets is different but the number of data is general for training and testing model.

Normalization of inputs leads to avoidance of numerical overflows due to very large or very small weights [16]. Therefore, Data were normalized between the upper limit $0 + \Delta_L$ and the lower limit $1 - \Delta_U$, where Δ_L and Δ_U are small margins used to

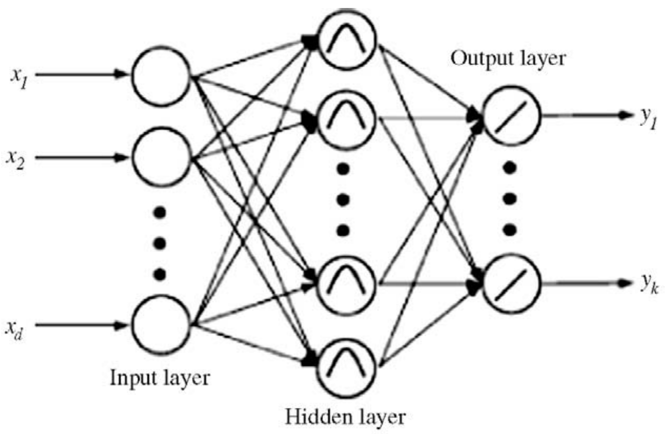

Fig. 2. RBF network structure (x_d = input to model: u/v, $\hat{y}_k$ = output from model: C_p or x_d = input to model: angle of rotor, $\hat{y}_k$ = output from model: torque).

give the network some extrapolation capability. The values for Δ_L and Δ_U used were 0.05 [17]. Data were normalized using the linear normalization method as follows:

$$V_n = (1 - \Delta_U - \Delta_L)\frac{V - V_{\min}}{V_{\max} - V_{\min}} + \Delta_L \tag{2}$$

where V_n is the normalized value of V. The $V_{\max}$ and $V_{\min}$ are the minimum and maximum values of V, respectively, $(1 - \Delta_U - \Delta_L)$ and Δ_L are positive constants. The magnitudes of $(1 - \Delta_U - \Delta_L)$ and Δ_L should be in range of: $\Delta_L \prec (1 - \Delta_U - \Delta_L) \prec 1$ and $(1 - \Delta_U) \prec 1$. The software utilized for the ANNs modeling was Matlab Toolbox version 7.0.

The performance of the neural network model evaluated using the root mean square error (RMSE). The determination coefficient (R^2) of the modeled output and the measured training data can be related as follows:

$$R^2 = 1 - \frac{\sum_P (y_{obs} - y_{est})^2}{\sum_P (y_{pred} - \bar{y}_{obs})^2} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_P (y_{obs} - y_{est})^2}{N}} \tag{4}$$

y_{obs}, y_{est} are experimental and estimated values, respectively, and N is the number of data. R^2 is computed as:

$$R^2 = \frac{\mathrm{SS}_{yy} - \mathrm{SSE}}{\mathrm{SS}_{yy}} = 1 - \frac{\mathrm{SSE}}{\mathrm{SS}_{yy}} \tag{5}$$

R^2 measures the relative sizes of SS_{yy} and SSE.

Actually, R^2 indicates that how well the prediction of y can be achieved using this model by computing $\bar{y}$ rather than just using the mean value of $\bar{y}$ as a predictor.

Note that when the $\hat{y}$ model is utilized, the prediction depends on x because $\hat{y} = b_0 + b_1 x$. Thus, x contains information about y. If we just use $\bar{y}$ to predict y, then x does not contribute information about y and thus the prediction of y does not depend on x.

More formally:

- SS_{yy} measures the deviations of the observations from their mean: $\mathrm{SS}_{yy} = \sum_P (y_i - \bar{y})^2$. If $\bar{y}$ is used to predict y, *then* SS_{yy} should be measured the variability of the y around the predicted value.
- SSE measures the deviations of observations from the predicted values: $\mathrm{SSE} = \sum_P (y_i - \hat{y}_i)^2$.

When the RMSE is at its minimum value and R^2 is high, $\geqslant 0.8$, a model can be judged as very good [7,18].

After this, the algorithm designs a group of neural networks using different spread values for the activation function in a wide range, from 0.05 to 25. Each of these neural networks, associated with a fixed spread, is designed with the training data set using the K-means algorithm increasing the number of neurons until the marginal prediction error is insignificant. The RMSE computed with the resulting neural network, net(s), using the checking data is fixed as the goal for the next neural network design. The final stage of the algorithm consists of selecting the neural network as the one with minimum RMSE computed using the checking data set.

4. Methods and materials

4.1. Produced samples

Savonius rotor has been tested with six different blade's curves in a wind tunnel. The test section had dimension $0.4 \times 0.4 \times 14$ m. In rotors I–V each blade had a semicircle shape with 16 cm diameter. The gap distance (S) were 0, 3.2, 3.8, 6.4, and 7.2 cm for rotors I–VI, respectively.

The distance gap changes the amount of drag force on back and front of blade for different angles with respect to the wind direction. The height (H) in all produced models was 30 cm, and the thickness of blade 1 mm, which was made of aluminum (Fig. 3).

4.2. Experimental methodology

Power coefficient was calculated by measuring rotor rotational speed and output torque, which were measured by two dynamometers which were attached to the tip of each blade. All the tests were conducted under identical conditions in the wind tunnel with a wind speed ranging from 8 to 14 m/s. First, the rotational speed and torque of each rotor were measured in one revolution of the rotor and the results were compared. Then, the same test was carried out for each blade at different Reynolds number. Results for rotors I and IV are presented here. Using the previous test results, the average power coefficient for one complete revolution of rotor at a particular speed were computed for each blade curve and then, the results were compared. With this comparison, optimum performance of the rotor was determined.

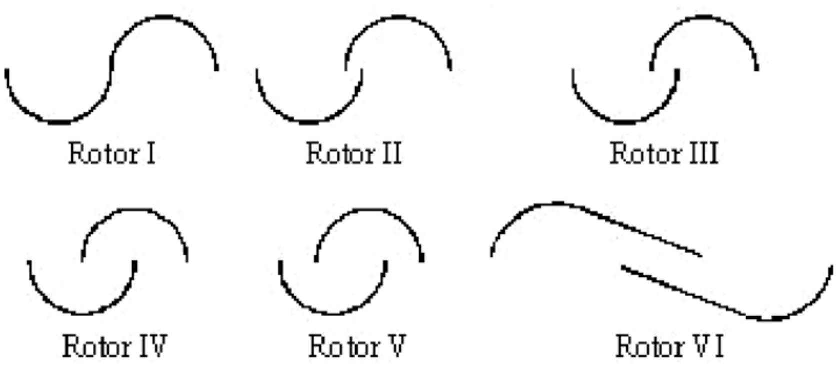

Fig. 3. Shapes of experimented rotor's blades.

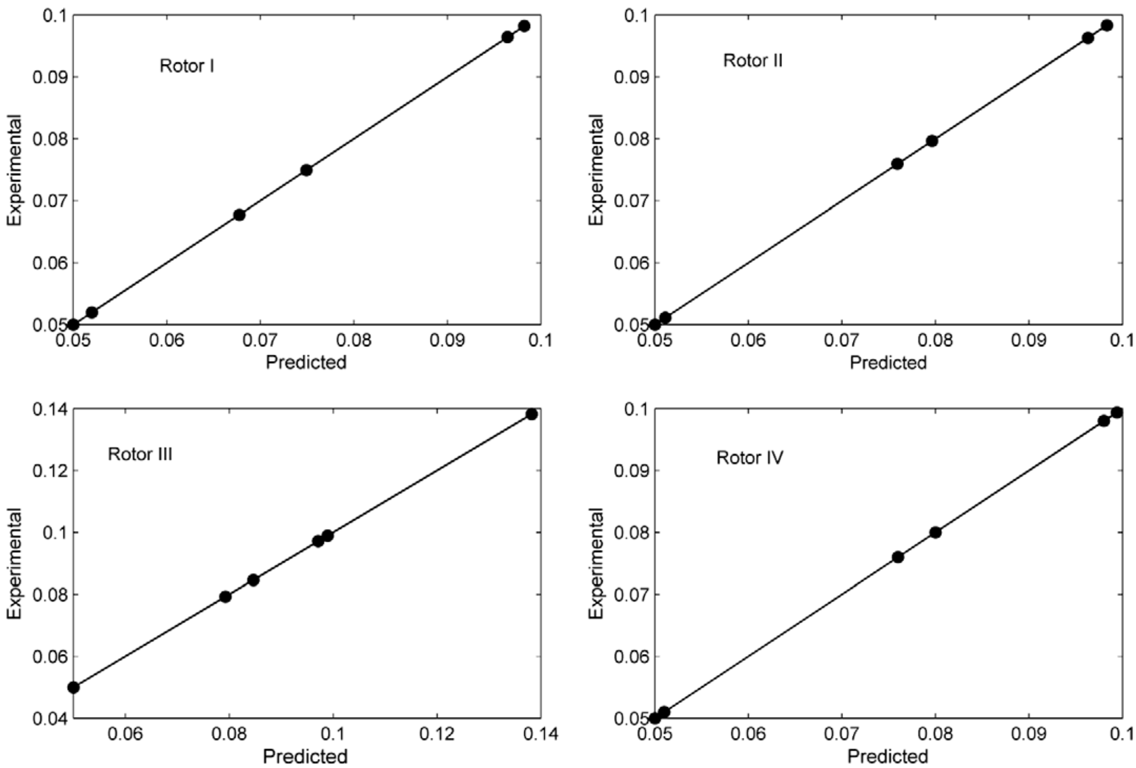

Fig. 4. Comparison between values of desired and the best RBF networks for all rotors with training data.

Table 1
Root mean square error (RSME) and correlation coefficient (R^2) for testing data in modeling with RBF network.

Spread	Rotor I		Rotor II		Rotor III		Rotor IV	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
0.05	0.002478	0.9857	**0.001624**	**0.993**	0.009033	0.9187	0.001835	0.9911
0.9	0.002274	0.9906	0.001889	0.9913	0.001854	0.993	0.001872	0.9909
1	0.002298	0.9918	0.001889	0.9913	0.001854	0.993	0.001872	0.9909
1.2	0.002274	0.9906	0.001889	0.9913	0.001854	0.993	0.001873	0.9909
5	**0.00178**	**0.9931**	0.001808	0.9914	**0.001267**	**0.9976**	**0.001764**	**0.9908**
10	0.001855	0.9913	0.001808	0.9914	0.001267	0.9976	0.001764	0.9908
25	0.001855	0.9913	0.001808	0.9914	0.001267	0.9976	0.001764	0.9908

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. Thus:

$$C_P = \frac{P_t}{P_w} \tag{6}$$

Variables tip speed ratio (λ), power factor (C_p) and Reynolds number (Re) can be defined using the following equations:

$$\lambda = \frac{u}{V} = \frac{\omega D}{2V} \tag{7}$$

$$C_p = \frac{2Fu}{\rho V^3 DH} \tag{8}$$

$$\mathrm{Re} = \frac{VD}{v} \tag{9}$$

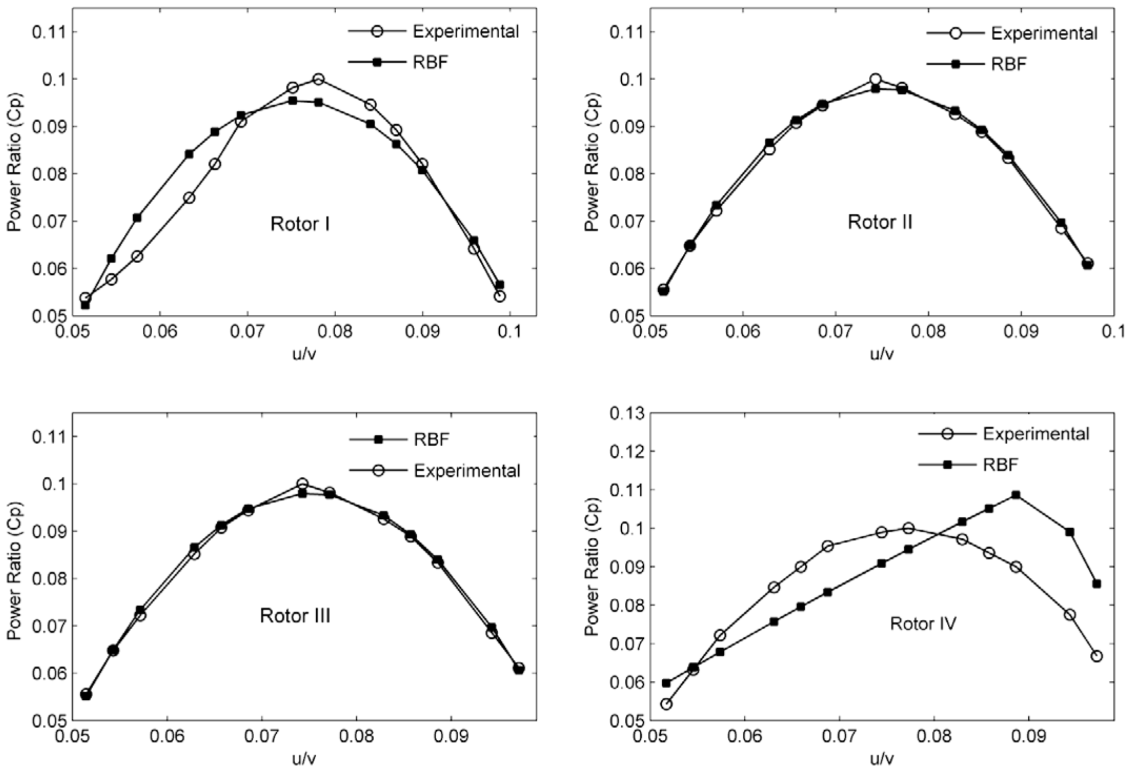

Fig. 5. Generalization performances of the best RBF networks for all rotors with testing data (rotor I: S.D. = 0.0151, rotor II: S.D. = 0.0148, rotor III: S.D. = 0.0159, rotor IV: S.D. = 0.015) (input to ANN: u/v, output from ANN: C_p).

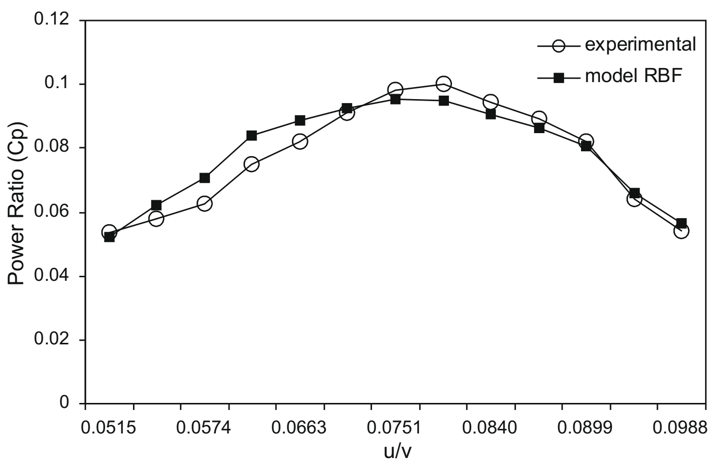

Fig. 6. Comparison experimental data and RBF model test data in rotor I for spread 5 (R^2 = 0.993, RMSE = 0.00178) (input to model: u/v, output from model: C_p).

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

5. Results and discussion

This section summarizes the results obtained using the neural network model to simulate the power ratio and torque of a vertical axis wind turbine. The aim is to check the effectiveness of the model and its generalization capability. In order to do this, the predicted power ratio of the model is compared with the measured power ratio in the following way.

The output values of the model are classified into two groups. The first group shows the predicted values when using input patterns belonging to train the network, that is, near the training data set. These results allow checking the effectiveness of the model closer to the data set used for model. The second group represents the predicted values that do not belong to the training data set. These values will allow testing the model.

Fig. 4 illustrates the best recall performances of RBF networks. Evidently, all plots generated by RBF networks pass through each and every training data point.

For each network, the optimum values of isotropic spread were attained by minimization of root mean square error (RMSE) and maximization of correlation coefficient (R^2). Table 1 shows the RMSE and R^2 results obtained for the designed model, where different models with various spreads are used.

It can be concluded that there is an optimum modeling using test data. Since it provides the minimum degrees of freedom sustained by testing data points.

The corresponding generalization performance of these networks is small but unrealistic oscillations as shown in Fig. 5. Also in this figure the results for rotor IV shows a significant error comparing the other rotors. The reason for such a substantial error is because the optimum spread of the ANN model has been employed only for rotor IV.

These fluctuations are due to the noise content of the training data and can be alleviated if the learning algorithm is equipped with some proper noise filtering facility (as in RBF networks).

Fig. 6 presents a comparison between the testing and predicted values for the rotors in optimum spread of RBF model. It can be seen that the predicted values for both groups, for the minimum RMSE from test data, are in very good agreement with experimental data.

The unregularized network clearly over-fits the data and requires large oscillations (as shown in Fig. 7 for rotor I) to pass through each and every noisy data point.

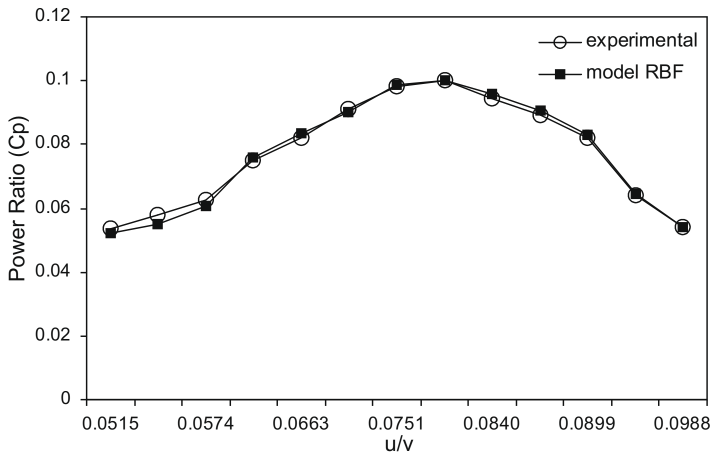

Fig. 7. Zero regularization (isotropic spread 1) of performance of the all noisy data of rotor I (R^2 = 0.985, RMSE 0.00247) (input to ANN: u/ν, output from ANN: C_p).

Table 2
The best isotropic spread for modeling with RBF net using testing data.

Spread	Rotor I			Rotor II			Rotor IV			Rotor IV		
	RMSE	R^2	S.D.	RMSE	R^2	S.D.	RMSE	R^2	S.D.	RMSE	R^2	S.D.
0.05	0.00499	0.931	0.0171	**0.00015**	**0.940**	**0.0153**	0.00217	0.981	0.0143	0.00203	0.984	0.0146
0.9	0.00093	0.997	0.0155	0.00068	0.997	0.0121	0.00078	0.991	0.0106	0.00084	0.995	0.0112
1	**0.00093**	**0.997**	**0.0155**	0.00068	0.997	0.0121	0.00078	0.995	0.0106	0.00084	0.995	0.0112
1.2	0.00093	0.997	0.0155	0.00068	0.997	0.0121	0.00078	0.995	0.0106	0.00084	0.995	0.0112
5	0.00188	0.906	0.0060	0.00031	0.998	0.0065	**0.00047**	**0.997**	**0.0082**	**0.00037**	**0.997**	**0.0069**
10	0.00188	0.907	0.0060	0.00031	0.998	0.0065	0.00047	0.997	0.0082	0.00037	0.997	0.0069

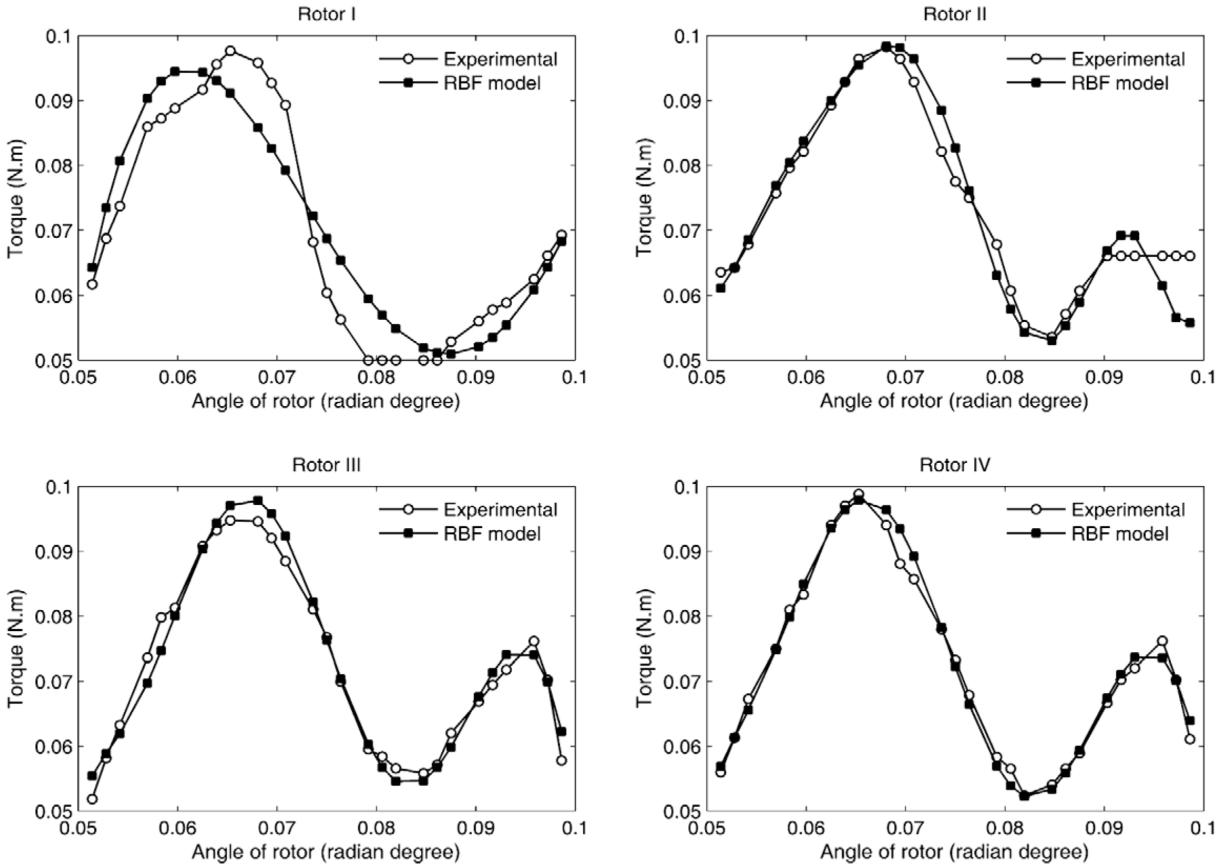

Fig. 8. Comparing different charts obtained from the best RBF nets with experiment data for torque (rotor I: S.D. = 0.0155, rotor II: S.D. = 0.0153, rotor III: S.D. = 0.0082, rotor IV: S.D. = 0.0069) (input to ANN: angle of rotor, output from ANN: torque).

The results of torque on different isotropic spreads are presented in Table 2. This Table is similar to the table of power ratio for different rotors. The 20% of set experimental data is selected patterns of each training test that are used to design the net, constituting which is called "the training data set". The patterns corresponding to maximum, minimum and median values of input and output variables of each training test (80% of set data) were used to measure the net model accuracy, constituting which is called "the checking data set". Table 2 shows the best model is the lower RMSE and S.D. in which is obtained from testing data.

The corresponding generalization performances of these networks are shown in Fig. 8. It can be seen that the predicted values are in good agreements with experimental results. Also, increasing wind speed leads to the torque improvement. For all tested rotors, the maximum amount of torque happens at angle of 60° and the minimum amount of torque happens at angle of about 120°. Besides that, in rotor I area of the minimum torque is vast, however for other rotors it is not.

Fig. 8 shows that rotor II has the greatest torque output. Therefore, an excellent agreement between experimental data and predicted values can be achieved by artificial neural networks and RBF model using the best isotropic spread.

6. Conclusion

In this paper, an ANN approach is presented to predict the power factor and torque in a Savonius wind turbine. The proposed algorithm is found to be fast and accurate. The results reveal that the prediction accuracy from the ANN method are quite high and a correlation coefficient of about one is obtained which shows an acceptable fitness through an appropriate training and test of the nets. In addition, the results show a simple alteration in the architecture of the nets can increase the scope of the vulnerability of the solution. Therefore, the findings of this study show that the artificial neural nets technique can be applied as a powerful tool and effective way in predicting and assessing the performance of the wind turbines (power ratio and torque). In addition, excellent agreement between experimental data and predicted values has been achieved by artificial neural networks and RBF model of training points. As a result, the amount of experimental tests that needed to be carried out on a pilot or large scale can be substantially reduced.

Acknowledgments

The authors would like to thank the Ferdowsi University for funding this research work and also the Electrical ministry of Razavi Khorasan for providing the laboratory facilities.

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