

PREDICTION OF PERFORMANCE FOR SAVONIUS-DARRIEUS WIND ROTOR BY HYBRID NEURO-FUZZY CONTROLLER

Agnimitra Biswas^{1*} and Rajat Gupta²

¹Department of Mechanical Engineering, National Institute of Technology Silchar, India

²Professor & Director, National Institute of Technology Silchar, India

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Abstract:

Vertical Axis Wind Turbine (VAWT) is a viable proposition for small-scale uses like, rural electrification, pumping, desalinating, household applications etc in many developing countries including India. In this paper, a hybrid neuro-fuzzy controller has been developed using gradient-based training algorithm to evaluate the performance of a combined three-bladed Savonius-Darrieus rotor. The objective of the study is to design a controller that causes more uniform loading on the generator by minimizing fluctuations in output parameters with change of input and also that improves rotor performance. A two-input-single-output controller has been designed. The tip speed ratio and overlap have been taken as input parameters, and output parameters are power coefficients and torque coefficients. At the first step, the input data are fuzzified by assigning fuzzy levels to the input data sets, and then trained outputs are obtained by back propagation learning algorithm. The controller results are in good agreement with the experimental results both qualitatively and quantitatively. For power coefficient (C_p), the agreement is within $\pm 4.5\%$, and for torque coefficient (C_t) it is within $\pm 2\%$. Moreover, the performance of the hybrid neuro-fuzzy controller has also been compared with Fuzzy Logic Controller (FLC) & ANN controller. The present controller predicts smoother values of performance parameters compared with other controllers.

Keywords: Hybrid neuro-fuzzy controller; power coefficient; torque coefficient; tip speed ratio; overlap; uniform controller output.

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* Correspondence to: Agnimitra Biswas, Tel.: +91 3842 242273; Fax: +91 3842 224797.
E-mail: agnibis@yahoo.co.in

INTRODUCTION

Renewable energy sources like wind energy can help in reducing the dependency on fossil fuels. Countries like China, USA, Germany, Spain, India, etc are leading producers of wind-generated energy to date (GWEC, 2017). The most important part of a wind power plant is the wind turbine, which transforms the wind kinetic energy into mechanical or electric energy. Wind turbine of vertical axis type has been studied in this paper. The vertical axis wind turbines have many advantages over horizontal axis wind turbines such as, simple in construction, self-starting, inexpensive, acceptance of wind from any direction without orientation (Sharma *et al.*, 2005). These are of mainly three types: Savonius, Darrieus & H-Darrieus wind turbines. Savonius rotor was developed initially by S.J. Savonius (1929) with an efficiency of 31%. The Darrieus wind turbine was originally invented and patented by G.J.M. Darrieus in 1931 (Shankar, 1979). It has two or three curved blades with airfoil cross-section of constant chord length. Both ends of the blades are attached to a vertical shaft. Darrieus wind rotor is never used alone; rather it can be used in conjunction with a high starting torque rotor like, Savonius rotor. And this concept leads to the essence of combined Savonius-Darrieus rotor. Various researchers (Bach, 1931; MacPherson, 1972; Newman, 1974; Khan, 1975; Modi *et al.*, 1984; Sivasegaram, 1978; Khan, 1988; Ushima & Nagai, 1988; Sheldahl *et al.*, 1978) had performed experimental works to determine maximum obtainable power coefficients. There are only a few available literatures on experimental investigations of combined Savonius-Darrieus rotor. Gupta *et al.*, 2006 studied experimentally the performance of a combined Savonius-Darrieus wind rotor in a sub-sonic wind tunnel with provisions for overlap variations in the upper Savonius rotor. Wakui *et al.*, 2005 performed comparative analysis of the performances of two different hybrid configurations of Savonius-Darrieus wind machine. Gupta *et al.*, 2008 compared the performances of a combined three-bladed Savonius-Darrieus rotor and a three-bucket Savonius rotor within overlap range of 16.2%-35%. The maximum power coefficient of the combined rotor was higher of 0.51 than the Savonius rotor. Ali, 2009 measured the performance of a combined two-bladed Savonius rotor mounted inside a three-bladed Darrieus rotor both experimentally and computationally.

A maximum power coefficient of around 0.34 was reported for without overlap condition. Savino *et al.*, 2012 made a PIV investigation on the instantaneous and average velocity fields to optimize the performance of a combined Savonius and Darrieus rotor in medium to low wind regimes. Sharma *et al.*, 2013 analyzed the

performance of a combined three-bladed Darrieus and three-bladed Savonius rotor under steady state condition to improve the power coefficient of the rotor.

Artificial Neural Network (ANN) has recently been applied for simulating wind power, wind speed pattern of places, and also for simulating the performance of non-linear systems like that of renewable energy system including wind and solar systems. Kalogirou, 2001 utilized ANN technique for predicting wind speed of a small wind generator in addition to his works on solar steam generator, solar water heating systems, photovoltaic systems etc (Kalogirou *et al.*, 1996; Kalogirou *et al.*, 1997; Kalogirou *et al.*, 2000). ANN was also used as a classification tool for determining average wind speed and power in several regions of Turkey (Cam *et al.*, 2005). Yurdusev *et al.*, 2004 formulated one algorithm based on ANN through its generalization and adaptability capabilities to assess optimum tip speed ratio and the power factor of wind turbine for different blade profiles. Other important parameters in wind turbine design are overlap, power and torque coefficients. ANN has also been successfully applied to predict the power and torque coefficients of VAWT rotors (Debnath *et al.*, 2009; Biswas & Gupta, 2010; Sargolzaei, 2007; Debnath & Das, 2010; Sargolzaei & Kianifar, 2009). There are only few applications of ANN as a control algorithm for wind speed prediction and active power generation (Flores *et al.*, 2005).

Hybrid neuro-fuzzy controller is an improvement over individual controller based ANN as the latter suffers a problem of output fluctuation over the input function. Hybrid controller can be a good option when smoothness in the values of performance parameters requirement is prime consideration though it may sometimes generate little lower output compared to other controllers. Deshmukh and Moorthy, 2010 applied genetic algorithm controller to neural network model for estimation of wind power potential. Sargolzaei and Kianifar, 2010 used neuro-fuzzy modeling tools for estimation of aerodynamic torque of a two-bucket Savonius type VAWT rotor. The problem facing the VAWT rotors is the non-uniform loading on the generator as the output fluctuates with change of input parameters. It is imperative to estimate the input parameters such as tip speed ratio, overlap etc so that the fluctuations of performance coefficients like power coefficient and torque coefficient are minimized as these directly affect the cost of the generator and rotor power output. In this paper, an attempt has been made to develop a hybrid neuro-fuzzy controller for the combined three-bladed Savonius-Darrieus VAWT rotor that causes more uniform loading on the generator by minimizing fluctuations in output parameters with change of overlap and tip speed ratio and also that

improves rotor performance. Gradient-based training algorithm is used, which simulates the real time wind tunnel performances of such rotor.

DESIGN OF COMBINED SAVONIUS-DARRIEUS ROTOR AND EXPERIMENTATION

A three-bladed combined Savonius-Darrieus rotor was designed and fabricated for the present study. In the upper part of the combined rotor, there is Savonius rotor that consists of three blades each having diameter of 8 cm and height of 10 cm as shown in Fig. 1. In the lower part of the combined rotor, the Darrieus rotor is connected. The Darrieus rotor consists of three semi-circular curved blades spaced 120° apart with a height of 10 cm, radius of 5 cm and width of 12 mm, as shown in Fig. 1. There is a provision for variations of overlap in the upper part of the Savonius-Darrieus machine. The overlap may be defined as the distance from the axis of rotation to the end of the bucket arc assuming the arc is carried to the full hemi-circle. And overlap ratio is the ratio between this overlap to the overall rotor diameter. The total height of the three-bladed combined Savonius-Darrieus rotor is 20 cm. The rotor is mounted on a flat base of diameter 9.2 cm and height 2.8 cm as shown in Fig. 1.

The material used for the rotor is aluminium. The shaft is made up of mild-steel of 15 mm diameter. The rotor is fixed to the shaft-using nut & bolt arrangement. The overlap variations are made in the range of 0 - 35%. The models are tested in an open circuit sub-sonic wind tunnel available in the department, as shown in Fig. 2. The brief description of wind tunnel can be found in the paper (Gupta *et al.*, 2006). From the experiments, values of rotor tip speed ratios, power coefficients and torque coefficients at various overlap conditions are evaluated. The blockage effects (Blackwell *et al.*, 1978) are also taken into consideration. The experimental values are taken as training samples i.e. target data that have been applied as input to the hybrid neuro-fuzzy controller.

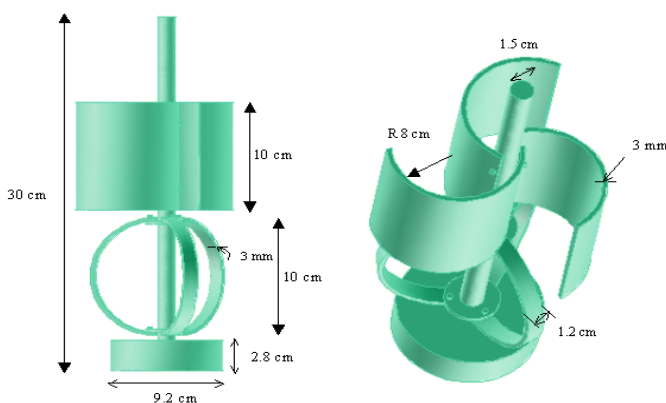


Fig. 1 Combined Savonius-Darrieus rotor with provision for overlap variation.

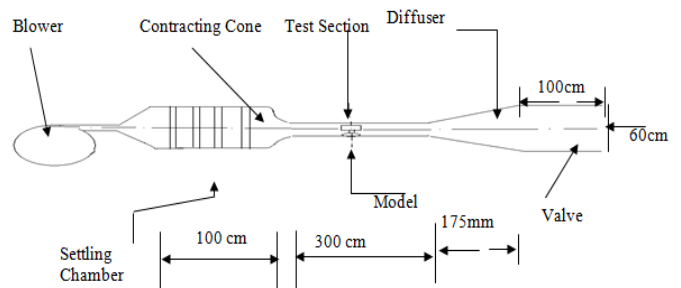


Fig. 2 Schematic Layout of a Sub-Sonic Wind Tunnel.

HYBRID NEURO-FUZZY CONTROLLER DESIGN

Neuro-Fuzzy hybridization is done first by incorporating fuzziness into neural network framework. This is done by assigning fuzzy labels to the training samples. Then, applying back propagation learning procedure, the neural network outputs are obtained in terms of fuzzy sets. The outputs are properly trained based on the sample given as input to the controller. In the present study, using the gradient based training algorithm, a hybrid neuro-fuzzy controller has been developed. The neuro-fuzzy controller is of two-input-two-output system. The tip speed ratio & overlap ratio are taken as the inputs whereas power coefficient & torque coefficient are taken as the outputs. The outputs are trained and matched with their training samples.

Fuzzification of Parameters

First, the inputs to the controller are fuzzified by defining various fuzzy sets, which are represented in the forms of membership functions. For input tip speed ratio (TSR), five membership functions have been defined, namely min ($0.12 \leq \text{min} \leq 0.27$), low ($0.23 \leq \text{low} \leq 0.37$), average ($0.33 \leq \text{average} \leq 0.47$), high ($0.43 \leq \text{high} \leq 0.57$), and upperhigh ($0.53 \leq \text{upperhigh} \leq 0.57$). These are depicted in Fig. 3. For input overlap, another three functions are defined in the form of small ($0.06 \leq \text{small} \leq 0.28$), medium ($0.18 \leq \text{medium} \leq 0.32$) and big ($0.27 \leq \text{big} \leq 0.35$), as depicted in Fig. 4. The membership range of the variables is selected in such a way that there is a small overlapping in their membership values. In wind energy conversion system, the output varies for discrete change of input parameters and in the overlapping zone there will be mutual effect of the membership values on the output parameters. For output power coefficient, three, namely low ($0.05 \leq \text{low} \leq 0.25$), average ($0.21 \leq \text{average} \leq 0.43$), high ($0.35 \leq \text{high} \leq 0.45$) are defined as shown in Fig. 5. Similarly for output torque coefficient also, three are defined, namely low

($0.85 \leq low \leq 0.92$), average ($0.91 \leq average \leq 0.99$) and high ($0.96 \leq high \leq 1.0$), as depicted in Fig. 6. Gaussian type membership functions would be the best fit for the operating parameters of wind energy conversion system (Iqbal *et al.*, 1993). Further Gaussian functions generate smooth and continuously differentiable hyper surfaces of fuzzy model. These are required for modeling characteristic rotor parameters, like power coefficients and torque coefficients that normally vary as a second degree polynomial with the input parameters like tip speed ratio & overlap. Therefore, Gaussian distributions are considered for the present study. Neuro-Fuzzy hybridization starts with fuzzyfying the training samples i.e. the input and output parameters using their membership values. Then, applying back propagation learning procedure, the neural network outputs are obtained in terms of fuzzy sets.

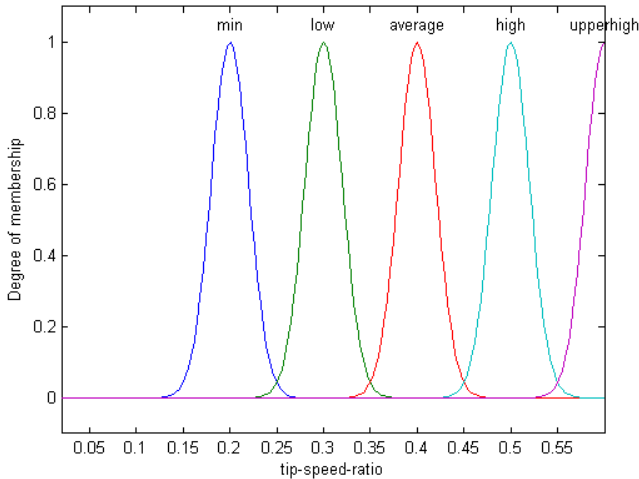


Fig. 3 Membership functions of input: tip speed ratio.

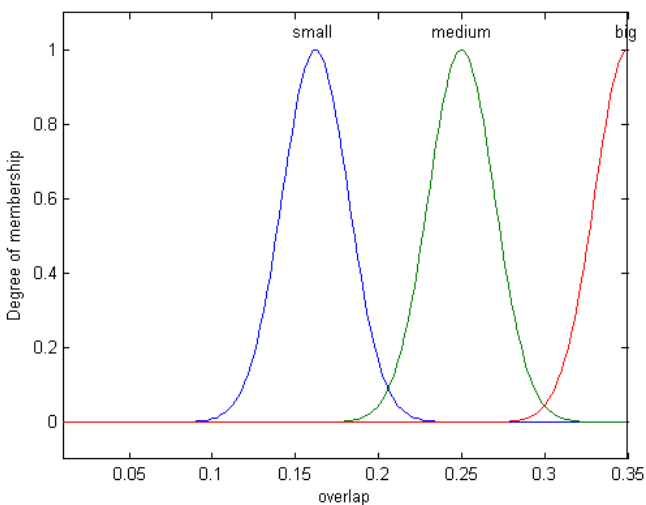


Fig. 4 Membership functions of input: overlap.

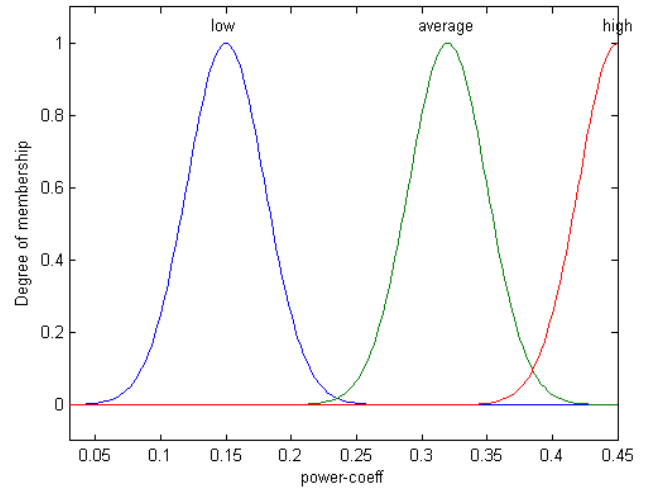


Fig. 5 Membership functions of output: power coefficient.

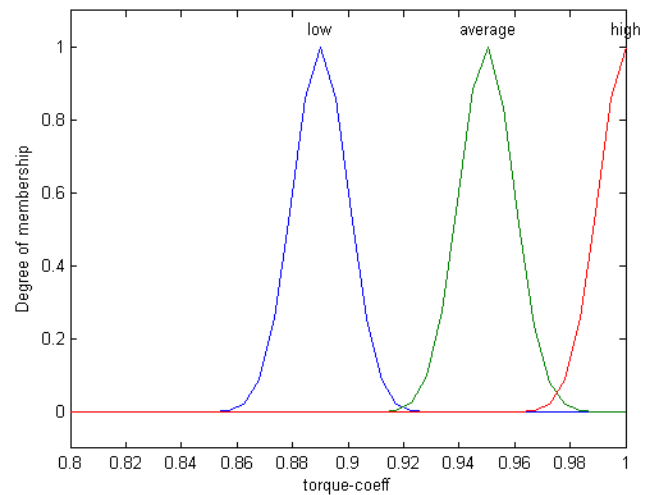


Fig. 6 Membership functions of output: torque coefficient.

The rule base of the fuzzy system for modeling the hybrid controller is nine in numbers for both power and torque coefficients predictions. This rule base for power coefficient and torque coefficient predictions are given in Table 1. Both ‘and’ and ‘or’ operators have been considered only to consider all probable interactions among the membership functions. The architecture of the hybrid neuro-fuzzy controller is depicted in Fig. 7. The complete rule base of Table 1 of the fuzzy system is interpreted as neural network. Fuzzy sets are regarded as weights whereas the input and output variables and the rules are modeled as neurons. The input layer comprises of two neurons to designate the two input variables of overlap and tip speed ratio on which the rule base is integrated to generate the output. The controlled output designates the fuzzy knowledge base, which is compared with the original rule base. And the weights are modified to improve the system as the error is determined. In this way the neurons of the hidden layer would be included or deleted in the learning step as the rules are fired.

Table 1. Rule base for power and torque coefficients predictions

Rule No.	TSR	Overlap	C _t	C _p	Operator type
1.	minimum	big	low	low	and
2.	low	big	high	high	or
3.	average	small	low	low	and
4.	average	medium	average	average	and
5.	average	big	high	high	and
6.	high	small	average	Average	and
7.	high	medium	average	average	or
8.	upperhigh	small	average	Average	or
9.	upperhigh	medium	average	Average	and

Fuzzy system using Back propagation

Fuzzy systems can be trained using various training algorithms based on numerical data. Back-propagation learning method can be applied to any type of feed-forward networks, which is also considered in the present study. Given the training data sets on input (x^l_i) and output (d^p), the task is to find the fuzzy system output such that the back propagation error is minimized.

$$e^p = \frac{1}{2} [f(x) - d^p]^2 \tag{1}$$

The functional output of the fuzzy system, f(x^l_i) can be obtained by training the input and output data sets for the ‘l’ input fuzzy sets i.e. x^l_i and y^l_i respectively. The standard deviations of the input values over the membership sets, σ^l_i are also determined for the ‘l’ input fuzzy sets to evaluate weight correction factor, z^l_i (equation. 3), which is utilized in the back propagation period to train the network. The standard deviation (Song, 2002) for each membership set during training period, k can be expressed as:

$$\sigma_i^l = \frac{\max(x_i^l) - \min(x_i^l)}{2 * M} \tag{2}$$

The weight correction (defined in the process) factor may be expressed as

$$z_i^l = \prod_{i=1}^M \exp\left(-\left(\frac{x_i - x_i^l}{\sigma_i^l}\right)^2\right) \tag{3}$$

By using the above forms of equations, the weight parameters are updated during back propagation, which utilize the following equations (Song, 2002).

$$y^l(i+1) = y_i^l - \gamma \frac{f - d^p}{b} z_i^l \tag{4}$$

$$x^l(i+1) = x_i^l - \gamma(f - d^p) \frac{y_i^l - f}{b} z_i^{l^2} \frac{(x_i^p - x_i^l)}{\sigma_i^{l^2}} \tag{5}$$

$$\sigma_i^l(i+1) = \sigma_i^l - \gamma(f - d^p) \frac{y_i^l - f}{b} z_i^{l^2} \frac{(x_i^p - x_i^l)}{\sigma_i^{l^3}} \tag{6}$$

where, l = 1,2,3...M and i = 0, 1, 2,...k. Then the functional output of the fuzzy system on power and torque coefficients, f(x^l_i), obtained from the training process, can be expressed as $f(x_i^l) = \frac{a}{b}$, such that

$$a = \sum_{l=1}^M y^l z^l \tag{7}$$

$$b = \sum_{l=1}^M z^l \tag{8}$$

Suitable Matlab codes have been written for obtaining the outputs of power and torque coefficients, f(x^l_i), for the combined Savonius-Darrieus rotor. The selection of learning rate has got important influence on the performance of the controller. The best learning rate of 100% (Zhang, 1993) has been taken to obtain the results.

RESULTS ANALYSIS AND DISCUSSION

After applying back propagation learning procedure, the neural network outputs are obtained in terms of fuzzy sets, which are analyzed in this section. **Figure 8** shows the training result of the hybrid neuro-fuzzy controller on the variations of power coefficient (C_p) of the Savonius-Darrieus rotor. The red curve marks the training data set of the power coefficient taken from the membership values, and the blue curve indicates to the variation of trained C_p produced by the hybrid controller with respect to time in seconds.

While comparing between the target data and the trained data, it is observed from **Fig. 8** that the trained data follow the similar trend to that of the target data. The controller has responded in less than 0.1 second, reached to the maximum within 0.2 second. The maximum power coefficient of 0.42 is obtained from the controller, whereas the maximum value of target data is 0.44. Thus it can be concluded that there is a fairly good match between the trained data and the target data with a variation of ± 4.5%. **Figure 9** shows

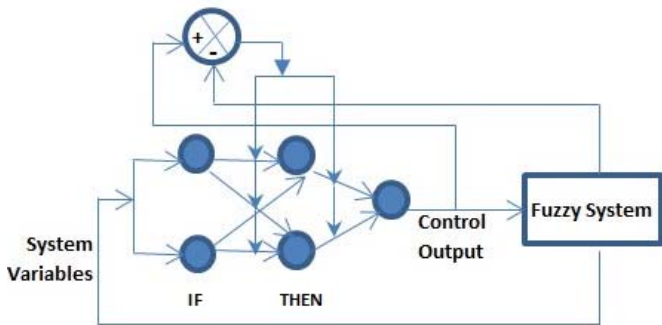


Fig. 7 Architecture of hybrid neuro-fuzzy controller.

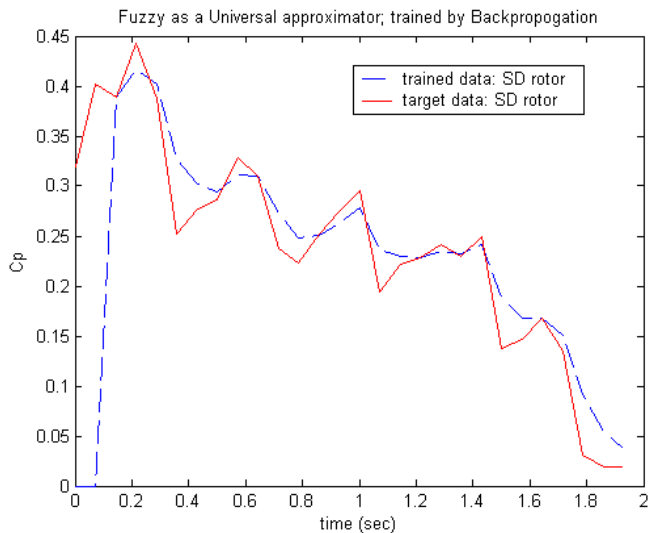


Fig. 8 Variations of target and trained power coefficients with time of combined Savonius-Darrieus rotor for different overlaps & TSRs

the training result of the hybrid neuro-fuzzy controller on the torque coefficient (C_t) of the rotor. Similar trend is also observed for the torque coefficient, which is depicted in Fig. 9. The agreement between the trained and target data is within the range of $\pm 2\%$.

The responses of the trained data of power and torque coefficients are little sluggish initially to start with, for which the values are not trained to the target data set in the beginning. The time taken to respond depends on the number of fuzzy membership sets. The simulation results show that the trends in the variations of power and torque coefficients match fairly well with that of experimental outputs.

Figure 10 shows the comparison of the variation of power coefficient versus overlap whereas Fig. 11 shows the comparison of the variation of torque coefficient versus overlap for both the target experimental data and trained controller data. It is observed from Fig. 10 that the power coefficient of the neuro-fuzzy controller matches the experimental output qualitatively.

A second order polynomial curve is also fitted in the same Fig. 10. It is selected because the response pattern of performance coefficients of vertical axis wind turbines with respect to input parameters like overlap or

tip speed ratio are parabolic in nature. Figure 10 shows that the output points of the hybrid controller are more nearer to the polynomial curve than the experimental readings meaning better performance of the hybrid controller. The maximum C_p , both of the controller and experimental output, is obtained at an overlap of 0%. Though the maximum C_p obtained experimentally is about 0.44 and the hybrid controller produces a lower

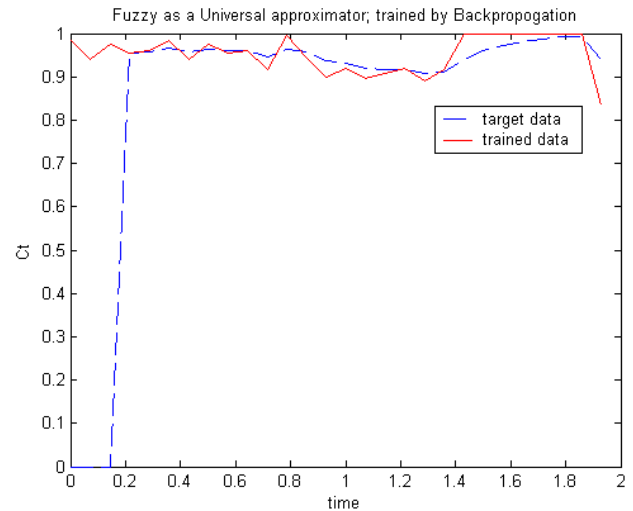


Fig. 9 Variations of target and trained torque coefficients with time for combined Savonius-Darrieus rotor for different overlaps & TSRs

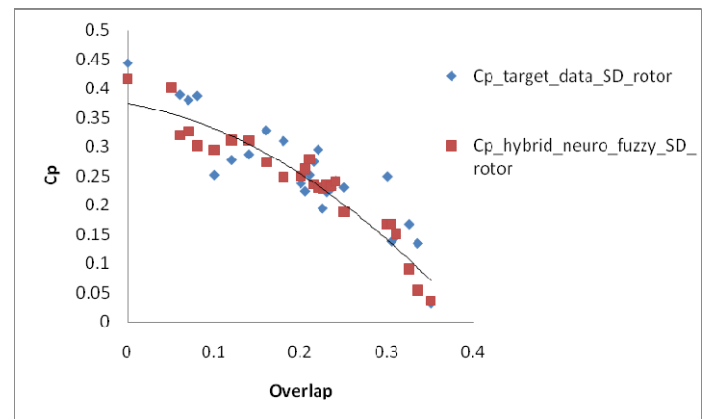


Fig. 10 Comparisons of power coefficients with respect to overlap

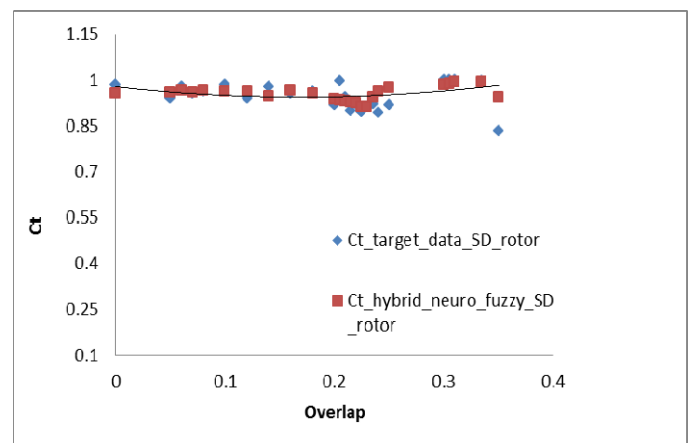


Fig. 11 Comparisons of torque coefficients with respect to overlap

maximum C_p of 0.42, but the variations with overlap for the hybrid controller is more uniform than the former. **Figure 11** show that the torque coefficient of the neuro-fuzzy controller follows similar trend to that of experimental output. The maximum C_t for both of the controller and experimental outputs are obtained at an overlap of 0.31 and the agreement is in the range of $\pm 2\%$. Further, the C_t readings are closely associated with the fitted second order polynomial curve.

Figure 12 shows the comparison of the variation of power coefficients versus tip speed ratio whereas **Fig. 13** shows the comparison of the variation of torque coefficients versus tip speed ratio for both the target experimental data and the controller data. It is observed from the above two figures that the predicted results are in good agreement with the experimental results. **Figure 12** shows that the C_p values, both of the experimental and the controller output, are in good agreement. The maximum C_p of the controller output is 0.42 obtained at the tip speed ratio of 0.55. And the maximum C_p of the experimental output is 0.44 obtained at the tip speed ratio of 0.59. **Figure 13** shows that the cluster of C_t points, both of experimental and controller outputs, match with each other at almost all tip speed ratios.

Figures 14–15 show the comparison of the variations of power coefficient and torque coefficient respectively with respect to overlap (0-35%), each obtained from experimentation, Fuzzy Logic Controller (FLC), ANN controller and hybrid neuro-fuzzy controller for the combined rotor. As can be seen from **Fig. 14**, for the combined rotor, the maximum C_p values from each case are obtained at overlap of 0%. Out of the four cases, the maximum C_p is obtained for experimental condition, which is 0.44. The maximum C_p for ANN and FLC controller are close to the highest C_p only barring hybrid controller, which produces slightly lower value of highest C_p (0.42). However, the variation patterns by the respective methods are more or less abrupt, only barring the hybrid controller which gives smooth trend in the variations. Moreover, the performance coefficients obtained from the hybrid controller become higher as overlap increases to a higher level (after 16.2%), which can also be observed from **Fig. 14**. Moreover, the output points of the hybrid controller are very closely associated with the fitted second order polynomial curve. In **Fig. 15**, the maximum C_t of about 1.15 is obtained at an overlap of 0.31 from the experimental output out of the four cases. The maximum C_t for the hybrid controller is close to 1.12 obtained at the same overlap while for the other two cases, it is between these two values. The variation pattern of C_t for the ANN controller is the most abrupt while the hybrid neuro-fuzzy controller produces smoother trend of variation of C_t than any other case. Further, the torque coefficients obtained from the hybrid

controller are better than any other controllers for most of the overlap conditions. Moreover most of the output points directly fall on the fitted second order polynomial curve. Thus, the present controller predicts smoother values of performance parameters (both C_p & C_t) compared with other controllers. Thus the present controller will cause more uniform loading on the

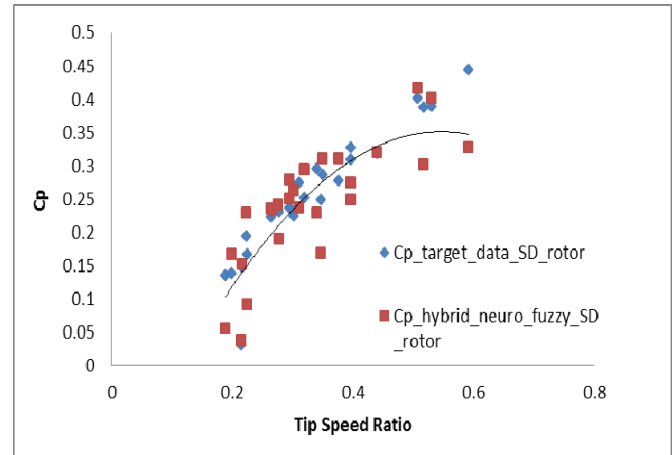


Fig. 12 Comparisons of power coefficients with respect to TSR

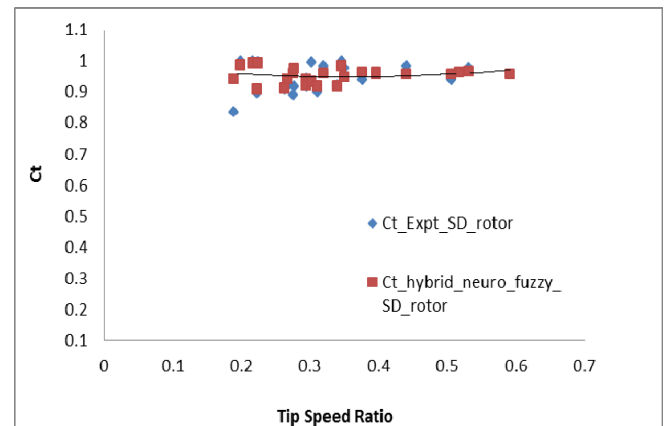


Fig. 13 Comparisons of torque coefficients with respect to TSR

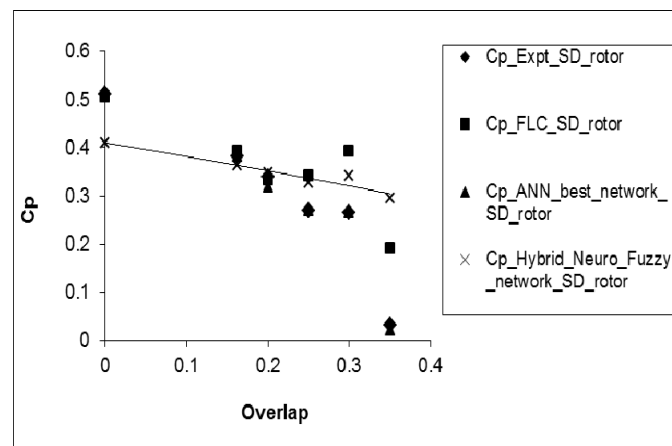


Fig. 14 Comparison of power coefficients with respect to overlap obtained from experimentation and three different controllers.

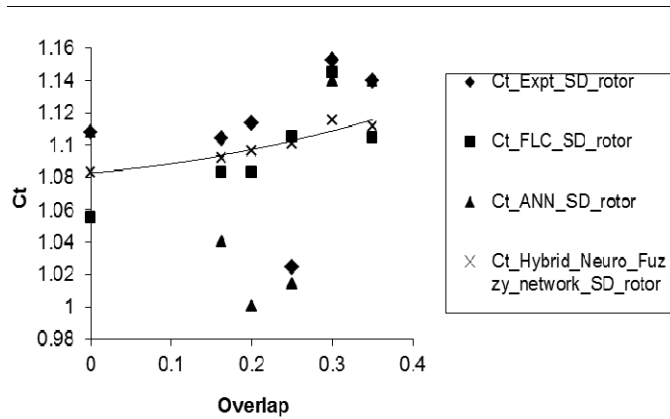


Fig. 15 Comparison of torque coefficients with respect to overlap obtained from experimentation and three different controllers.

generator as fluctuations in output parameters with change of input parameters are minimized. And simultaneously overall power coefficients, i.e. the efficiency of the rotor is also improved by the present controller design for higher values of overlap conditions compared with experimental or any other controller designs.

CONCLUSIONS

From, the study the conclusions are summarized below:

(a) The controller results are in good agreement with the experimental results both qualitatively and quantitatively. For power coefficient (C_p), the agreement is within $\pm 4.5\%$, and for torque coefficient (C_t) it is within $\pm 2\%$.

(b) The FLC and ANN controllers predicts as high C_p as that of experimental result whereas the highest C_p obtained from the present controller is little lower than those. The maximum C_p of the controller output is 0.42 obtained at tip speed ratio of 0.55. The maximum C_p of the experimental output or other controllers output is 0.44 obtained at tip speed ratio of 0.59 and all of these obtained at an overlap of 0%.

(c) Though the highest C_p obtained from the hybrid controller is lower, but the present controller predicts smoother values of performance parameters (both C_p & C_t) compared with other controllers. Thus the present controller will cause more uniform loading on the generator as fluctuations in output parameters with change of input parameters are minimized.

(d) The overall power coefficients, i.e. the efficiency of the rotor is also improved by the present controller design for higher values of overlap conditions (beyond 16.2%) compared with experimental or any other controller designs.

REFERENCES

- Global wind energy market as of 2017. Press release of Global Wind Energy Council (GWEC)
- Sharma, K.K., Gupta, R., Singh, S.K. & Singh, S.R. (2005) Experimental investigation of the characteristics of a Savonius wind turbine. *J. Wind Engg.*, **29**(1), 77-82.
- Savonius, S.J. (1931) The S-rotor and its application. *J. Mech. Engg.*, **53** (5), 333-338.
- Shankar, P.N. (1979) Development of vertical axis wind turbine. *Proc. Indian Academic Science*, **C2** (1), 49-66.
- Bach, G (1931) Investigation Concerning Savonius rotors and related Machines. Translated into English, Brace Research Institute., Quebec, Canada.
- Macpherson, R.B. (1972) Design, Development and testing of Low Head High Efficiency Kinetic Energy Machine. MSc Thesis, University of Massachusetts, Amherst, M.A.
- Newman, B.G. (1974) Measurement on a Savonius rotor with variable gap. *Proc. Sherbrook University Symposium on wind energy*, 116.
- Khan, M.H. (1975) Improvement of Savonius Rotor-windmill. MS thesis, University of the Philippines, Lasbonas.
- Modi, V.J., Roth, N.J. & Fernando M.S.U.K. (1984) Optimal configuration studies and prototype design of a wind energy operated irrigation system. *J. Wind Engg & Industrial Aerodynamics*, **16**, 85-96.
- Sivasegaram, S. (1978) Secondary parameters affecting the performance of resistance type vertical axis wind rotors. *J. Wind Engg*, **2**, 49-58.
- Khan, M.H. (1988) Model & prototype performance characteristics of S-rotor wind mills. *J. Wind Engg.*, **12**, 59-75.
- Ushiyama, I & Nagai, H. (1988) Optimum design configurations & performance of S-rotors. *J. Wind Engg.*, **12**, 59- 76.
- Sheldahl, R.E., Feltz, L.V. & Blackwell, B.F. (1978) Wind tunnel performance data for two- & three- bucket Savonius rotor. *J. Energy*, **2**(3), 160-164.
- Gupta, R., Das, R. & Sharma, K.K. (2006) Experimental study of a Savonius-Darrieus wind machine. *Proc. International Conference on Renewable Energy for Developing Countries*, University of Columbia, Washington DC.
- Wakui, T., Yoshiaki, T., Takumi, H. & Toshio, N. (2005) Hybrid configuration of Darrieus and Savonius turbines for stand-alone wind turbine-generator system. *J. Elect. Engg. in Japan.*, **150** (4), 13-22.
- Gupta, R., Biswas, A. & Sharma, K.K. (2008) Comparative study of three bucket Savonius turbine with combined three-bucket Savonius - three-bladed-Darrieus turbine. *J. Renewable Energy*, **33**, 1974–1981.
- Ali, M.E. (2009) Estimation of the Performance of the Darrieus-Savonius combined machine. *Proc. Ecologic Vehicles and Renewable Energies*, Monaco, Germany.
- Savino, G., Pietrogiaconi, D. & Romano, G.P. (2012) Experimental investigation on the flow field and performances of a Savonius-Darrieus wind turbine. *Proc. Seventh International Symposium on Turbulence, Heat and Mass Transfer*, Palermo, Italy.
- Sharma, K.K., Biswas, A. & Gupta, R. (2013) Performance Measurement of a Three-Bladed Combined Darrieus-Savonius Rotor. *J. Renewable Energy Research*, **3**(4), 885-891.
- Kalogirou, S.A. (2001) Artificial neural networks in renewable energy systems applications: a review. *J. Renewable Sustain. Energy*, **5** (4), 373-401.
- Kalogirou, S.A., Neocleous, C.C. & Schizas, C.N. (1996). *Proc. International Conference EANN '96*, London, UK, p. 5–8.
- Kalogirou, S.A., C. C. Neocleous, C.C. & Schizas, C.N. (1997). *Proc. the International Conference EANN '97*, Stockholm, Sweden.

- Kalogirou, S.A., Neocleous, C.C. & Schizas, C.N. (2000). *Proc. CLIMA*, Brussels, Belgium.
- Cam, E., Arcaklioglu, E. Cavusoglu, A. & Akbiyik, B.A. (2005) Classification mechanism for determining average wind speed and power in several regions of Turkey using artificial neural networks. *J. Renewable Energy*, **30** (2), 227-239.
- Yurdusev, M.A., Rasit, A. & Cetin, N. (2004) Assessment of optimum tip speed ratio in wind turbines using artificial neural networks. *J. Energy*, **31**, 2153–2161.
- Debnath, B., Biswas, A. & Gupta, R. (2009) Computational fluid dynamics analysis of a combined three-bucket Savonius and three-bladed Darrieus rotor at various overlap conditions. *J. Renewable and Sustainable Energy*, **1**, 033110.
- Biswas, A. & Gupta, R. (2010) Performance Measurement of a twisted three-bladed airfoil-shaped H-rotor. *J. Renewable Energy Technology*, **1**(3), 279-300.
- Sargolzaei, J. (2007) Prediction of the power ratio in wind turbine Savonius rotors using artificial neural networks. *J. energy & environment*, **1**(2), 51-55.
- Debnath, B.K. & Das, R. (2010) Prediction of performance coefficients of a three-bucket Savonius rotor using artificial neural network. *J. Renewable and Sustainable Energy*, **2**, 043107.
- Sargolzaei, J. & Kianifar, A. (2009) Modeling and simulation of wind turbine Savonius rotors using artificial neural networks for estimation of the power ratio and torque. *J. Simulation Modeling Practice and Theory*, **17**, 1290-1298.
- Flores, P., Tapia, A., Tapia, G. (2005) Application of a control algorithm for wind speed prediction and active power generation. *J. Renewable Energy*, **30**(4), 5523–36.
- Deshmukh, M.K. & Moorthy, C.B. (2010) Application of genetic algorithm to neural network model for estimation of wind power potential. *J. Engineering, Science and Management Education*, **2**, 42-48.
- Sargolzaei, J. & Kianifar, A. (2010) Neuro-fuzzy modeling tools for estimation of torque in Savonius rotor wind turbine. *J. Advances in Engineering Software*, **41**, 619–626.
- Song, I. (2002) Fuzzy logic and neural network controller. SD558 Fuzzy logic and neural network, University of Waterloo, Ontario.
- Zhang, Y. (1993) Updating learning rates for back propagation network. *Proc. International Joint Conference on Neural Networks*, Nagoya, Japan.
- Iqbal, M.T., Coonick, A.H. & Freris, L.L. (1993) Some control aspects of a wind turbine. *IEE Colloquium on Two Decades of Fuzzy Control - Part 1*.