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Improving Modelling Accuracy of Aerodynamic Curve of a Wind Turbine Using Neural Networks

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

This paper addresses improved modelling of one of important aerodynamic curves of a wind turbine by means of artificial neural networks (ANNs). Aerodynamic curves play an important role in designing controller in wind turbines. Inherent nonlinearity of these curves and dependence of their current values to the operating conditions, make the wind turbine controller design a challenging problem. Currently, there are two major approaches for modelling these curves: 1- lookup tables and 2-polynomial approximation. Lookup tables are discrete and hence not suitable for continuous controller design and polynomial approximations are not accurate enough. These drawbacks impose inaccuracy to the controller design. To overcome this weakness, ANN is utilized to identify the aerodynamic curves. Specially, rotor power coefficient (Cp) is the focus of this paper as this curve has a direct effect on the controller's parameters both in below and above rated wind speed. As ANNs are universal approximators, they can model this curve with required accuracy. Using this approach in addition to identification of Cp and obtaining a high accuracy model for this curve, optimum critical parameters of this curve can be estimated. By employing these estimated values, a new controller gain is computed. This controller is used when the wind speed is below rated speed and the rotor speed should track a reference trajectory (named variable speed or region II). Simulation shows that with this new controller the overall power capture is improved at no cost.

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1. INTRODUCTION

Renewable energies have gained great focus nowadays. One of the most attractive sources of energy is the wind power. Although producing power from wind seems very simple, in the industrial scale, it is very costly and needs complex systems. As these expensive systems should work in the maximum efficiency, numerous engineering problem arises and should be addressed in appropriate manner.

One of these problems is controlling such huge structures. The goal of control is to maximize energy production while reducing structural load as much as possible.

Based on the wind speed, there are three regions of operation for a variable speed wind turbine. Region 1, is startup of a wind turbine. In this region, the wind speed is too low to generate power. Hence wind turbine is stopped or rotates freely without producing power. In region 2, the goal is to maximize the power capture from the wind. In this region, the wind speed is below the rated speed of wind turbine. The goal of the controller is to change the rotor speed to capture maximum power. In region 3, as the wind speed is above the wind turbine rated speed, and in order to save electrical and mechanical equipment from exceeded loads, turbine should limit the capture of power by changing its blade pitch angles. In this region controller tries to maintain the rotor speed at predefined value and reduce undesired mechanical torques by changing blade pitch angels.

In this paper, the goal is to improve the accuracy of modeling the rotor power coefficient curve. Specifically, the focus is on enhancing the estimation accuracy of the curve's critical parameters such as its maximum and the parameters at which this maximum occurs. This curve plays an important role in controller design. For simplicity, only region II is considered in this paper. This region is responsible for more than 50% of power capture for a wind turbine in a year [1].

This paper is organized as follows. In sections 2 and 3, a brief introduction to rotor power coefficient is presented. Section 4, is devoted to artificial neural networks and their capability of modelling and estimation. The outcome of the proposed method is reported in Section 5. And finally some concluding remarks are given in section 6.

2. MATHEMATICAL THEORY

The standard control scheme which is used in region 2 is called variable-speed control law [2] and basically it is a simple gain (k) multiplied by square of angular speed of the rotor [1-3]:

$$\tau_c = k\omega^2 \tag{1}$$

$$k = \frac{1}{2}\rho A R^3 \frac{C_{p_{\max}}}{\lambda_*^3} \tag{2}$$

In the abovementioned equations, the parameters are defined as follows: τ_c is computed controller torque, ω is the rotor angular speed in rad/s, $C_{p_{\max}}$ is the maximum rotor power max coefficient, λ_* is the optimal tip speed ratio (TSR) corresponding to $C_{p_{\max}}$ and TSR is max defined as $\lambda = \frac{\omega R}{v}$ and v is the wind speed.

The goal of this control law is to keep the turbine operating at the peak of Cp - TSR – Blade Pitch angle (BPA) surface [1]. Fig. 1 is an example of such surface.

Although this scheme seems to be very simple, there are two significant problems with this control scheme:

1. As blade aerodynamics could change over time, determination of k (the controller gain) is not accurate.
2. Wind speed fluctuations, causes the turbine to operate off the peak of its optimal curve, causing reduction of energy capture.

It can be seen from (1) and (2) that the controller relies on two critical parameters: $C_{p_{\max}}$ and λ_*. In [2], sensitivity of energy loss to errors in these two critical parameters is considered and it is showed that [3]:

> *"a 5% error in the optimal tip-speed ratio λ can cause a significant energy loss of 1–3% in region 2"*

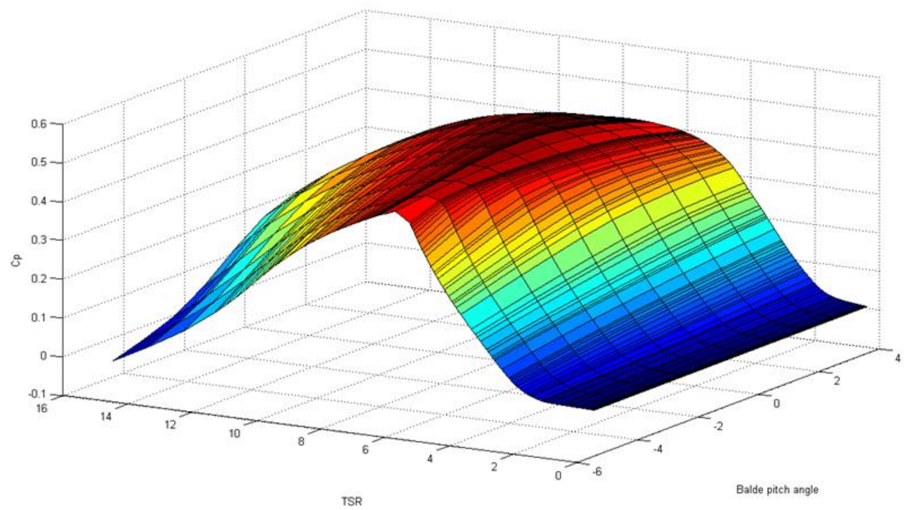

Fig. 1. Cp curve

There are some papers dealing with these issues. [1, 3], have proposed adaptive controllers to overcome both issues and showed that maximum power capture in the presence of parameter uncertainty is reachable. [2], modifies above mentioned simple controller and this new controller leads the rotor to approach the desired operating point more rapidly. With such controller, it is shown that improving overall energy capture by 5% is feasible.

As determination of controller gain is heavily based on maximum rotor power coefficient $(C_{P_{\max}})$ and optimum tip speed ratio (λ_*); and these parameters should be determined via $P_{\max}$ modelling tools, there is an inherent inaccuracy in them, because the modelling software used to determine the Cp-TSR-Pitch surface is not perfectly accurate [1]. In fact in [3] it is stated that:

> *"Unfortunately, modeling tools such as PROP are of questionable accuracy; in fact, an NREL study [4] comparing wind turbine modeling codes reports large discrepancies and an unknown level of uncertainty. Therefore, computer models are unreliable for fixed-gain controller synthesis."*

It should be noted that, in literature, the reported $(C_{P_{\max}})$ is 0.482 which occurred at zero BPA and optimum TSR = 7.55 for a benchmark 5-MW wind turbine model [5]. But these parameters lead to a suboptimum controller because the modelling software used to determine the Cp-TSR-Pitch surface is not perfectly accurate [1].

This paper addresses the first issue by an intuitive way: instead of relying just on inaccurate modeling tools, an ANN is utilized to model the rotor power coefficient (C_p) as a nonlinear function and its critical parameters have been estimated using this network, which is trained specially for this purpose. To this end, an ANN has been trained by using available data on Cp-TSR-Pitch which can be accessed at [6].

Simulation results show that the new optimum values for $(C_{P_{\max}})$ and (λ_*) the controller which will improve the efficiency of entire system.

3. ROTOR POWER COEFFICIENT

The ratio of turbine power to the available power in the wind is called rotor power coefficient (C_p)

$$C_p = \frac{P}{P_{wind}} \tag{3}$$

where

$$P_{wind} = \frac{1}{2}\rho A v^3.$$

It is obvious that the rotor power (P) is proportional to C_P, so it is desired that the turbine works at $(C_{P_{\max}})$.

As mentioned earlier, C_p varies by two parameters: BPA and tip speed ratio (TSR). Fig. 1, shows the surface which is produced by changing these two parameters for NREL 5-MW wind turbine benchmark model.

For producing Fig. 1, a lot of simulation should be conducted. In each simulation, the values of TSRs and BPAs should have been fixed to produce a point in this surface. Next, another pair of TSR and BPA should be chosen and the entire simulation should be repeated. This procedure should be iterated until desired points in the surface are produced. It should be noted that a simple controller must be designed to control the system to a steady state condition.

So this surface is produced in a discrete fashion. Also the value for C_p in each simulation has a transient part and a steady state part. The reported C_p is the mean value for the steady state part. Fig. 2, shows the behavior of this parameter during a simulation.

By fixing BPA at zero, Fig. 3 is produced which shows how C_p varies with TSR. In region II, it is common to fix BPA to a constant value (e.g. 0 degree, which is supposed to have maximum C_p).

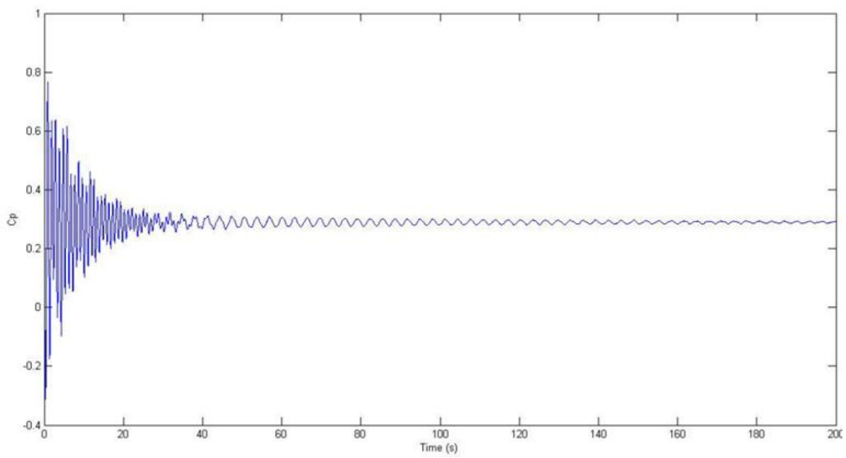

Fig. 2. Time evolve of Cp during one of simulations

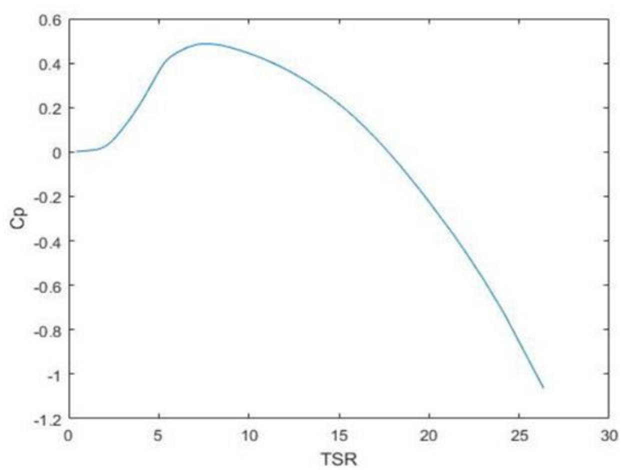

Fig. 3. Cp-TSR curve at BPA=0

As mentioned earlier, aerodynamic curves play an important role in wind turbine systems. Among them, rotor power coefficient (C_p) attracted more attention since it is directly related to controller design. There are some researches that have tried to model this curve.

Reference [7], proposes an exponential relation. The author simplifies the dependency of C_p to BPA and TSR by fixing BPA at a constant value. The resulting model is:

$$C_p = 0.44\left(\frac{125}{\lambda_i} - 6.94\right)e^{-\frac{16.5}{\lambda_i}};\lambda_i = \frac{1}{\frac{1}{\lambda} + 0.002}$$

Reference [8] tries to model aerodynamic curves of wind turbine, with polynomial/exponential equations. Resulting models are relations with 10 to 12 coefficients.

The proposed model in [9-10] for rotor power coefficient is:

$$C_p(\lambda,\beta) = c_1\left(\frac{c_2}{\lambda_i} - c_3\beta - c_4\right)e^{-\frac{c_5}{\lambda_i}} + c_6\lambda;\ \frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3+1}$$

Reference [11], has tried to estimate TSRs under wind speed variations, based on a perturbation and observation (P&O) method.

In [12], ANFIS and ANN methods for predicting tip speed ratio and power factor for data set of blade profile types (LS-1 and NACA 4415) are proposed. In this reference, the focus is on designing the wind turbine blades, not on the controller.

In theory, the maximum efficiency of a wind turbine is given by the Betz limit and for any real wind turbine, it is equal to C_p = 16 / 27 [3] Typically wind turbines operate below this limit [13].

Any inaccuracy in the $C_{p_{\max}}$ or λ_* has a direct effect on the controller gain and results in less efficient power capture. This inaccuracy is the motivation for improving modeling accuracy of C_p curve and estimation of $C_{p_{\max}}$ and λ_* by means of neural network.

In the next section, a brief overview of artificial neural network and their modelling and estimation capability is presented.

4. ARTIFICAIL NEURAL NETWORKS [14]

Curve fitting is a well-known problem in engineering. It consists of fitting parameterized functional forms to the sets of input-output pairs of data.

Neural networks are computational systems which are inspired by human brain. Many different structures of these networks exist, each of them specially developed to tackle a specific problem. Interested reader can refer to [15] for an introductory review of neural networks.

A multilayer perceptron (MLP) consists of a network of neurons as illustrated in Fig. 4

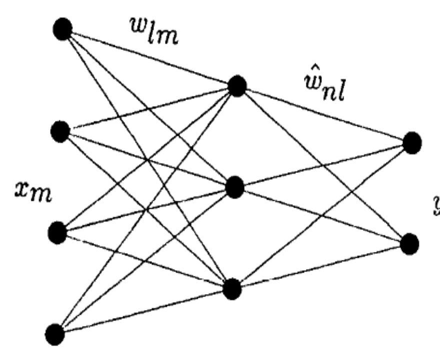

Fig. 4. A MLP with one hidden layer [14]

Each circle in the diagram is a node or neuron and the lines connecting the nodes are called weights.

This network is an analytical mapping between input x_m ($m = 1,\ldots, M$) and output z_n ($n = 1,\ldots, N$) where M and N are the number of inputs and outputs respectively.

The inputs are fed into the input layer (the first layer in the diagram), then multiplied by a weight matrix $W = [w_{lm}]$ $(l = 1,\ldots, L;\ m = 1,\ldots,M)$ where L is the number of neurons in the hidden layer (the second layer in the diagram). The results then transformed by a nonlinear function $f(.)$ and multiplied by another weight matrix $\hat{W}$ = $[\hat{w}_{nl}]$ to produce outputs. The function $f(.)$ is generally a sigmoid or hyperbolic tangent function.

The entire network could be summarized as following analytical function:

$$z_n\left(x_1,\ldots,x_M\right)=\sum_{l=1}^{L}\hat{w}_{nl}\times f\left(\sum_{m=1}^{M}w_{lm}x_m+b_l\right)+\hat{b}_n \quad (4)$$

Where b_l and $\hat{b}$ are bias inputs to the network's layers.

Determining weights to optimize the accuracy of the mapping is called training. To this end a large number of input-output pairs are required.

The error between the output vector y of the network (for given input vector x^p) and the corresponding target vector z^p, summed over all exemplars p is defined as:

$$E_{net}=\sum_{p=1}^{P}\sum_{n=1}^{N}\left[z_n(x^p)-z_n^p\right]^2$$

Minimizing this error function is used to determine network's weights. Back-propagation is the most widely used technique to minimize the E_{net} A detailed information for the back-propagation procedure can be found in [16]. More powerful optimization algorithms exist, and in this article, Levenberg-Marquardt [15] is used for training the network.

5. ESTIMATION OF C_P CURVE

As mentioned previously, C_p is an important parameter for tuning the gain of controller for a wind turbine. So knowledge of its behavior and the way it varies is vital for controller design. Fig. 1, depicts the way this parameter varies with TSR and BPA.

It is obvious that there are at least two sources of uncertainty and inaccuracy to obtain $C_{p_{\max}}$ Conducting simulations in discrete steps and Time varying behavior of C_p during each simulation.

The first problem could easily resolve as ANNs has the ability of estimating a continuous function from discrete samples. To overcome the second problem, mean value of steady state condition for each simulation is used. So the goal is to train an artificial neural network to model the relationship between C_p, TSR and BPA accurately.

The data which is used for training this network is freely available in the NREL website [6]. This data contains various simulation scenarios for BPAs from -5 degree to 9 degree with 1 degree step, and TSR between 0.4120 and 26.3640. All these scenarios assume steady wind condition (v=8 m/s). The maximum C_p in this data is 0.48546 which is occurred at TSR=8 and pitch angle=0, which its difference with reported $C_{p_{\max}}$ and optimum TSR by [5], proves the imperfection of modelling tools.

The network which is used in this paper has 2 inputs (TSR and pitch angle) and 1 output (C_p). In total, 2730 input-output pairs are available for training, validating and testing.

As the aim of neural network in this paper is to find the maximum of C_p curve and the point in which this maximum is occurred, without loss of generality and to increase the accuracy of overall network, negative values of C_p can be removed from data. Also for getting better performance and to give equal importance to the inputs, it is advised to normalize the inputs and output of the network [15].

With this modification 2474 normalized input-output pairs are utilized. 70 percent of this data is used for training while 15 and 15 percent of randomly selected data are chosen for validating and testing. Levenberg-Marquardt optimization technique is used for training function and mean square error (MSE) is selected for performance function. 10 neurons are placed in the hidden layer. Also MATLAB neural networks toolbox is used for training.

Fig. 5 shows regression plot and Fig. 6 depicts output of NN after training. These two plots confirm that training procedure is accomplished successfully.

It should be noted that, because of the nonlinear nature of data and sensitivity of neural network training algorithms to initial weights, the training of the network is repeated several times to obtain optimum performance. This repetition causes to reinitialize the weights and helps the network to escape from local minima.

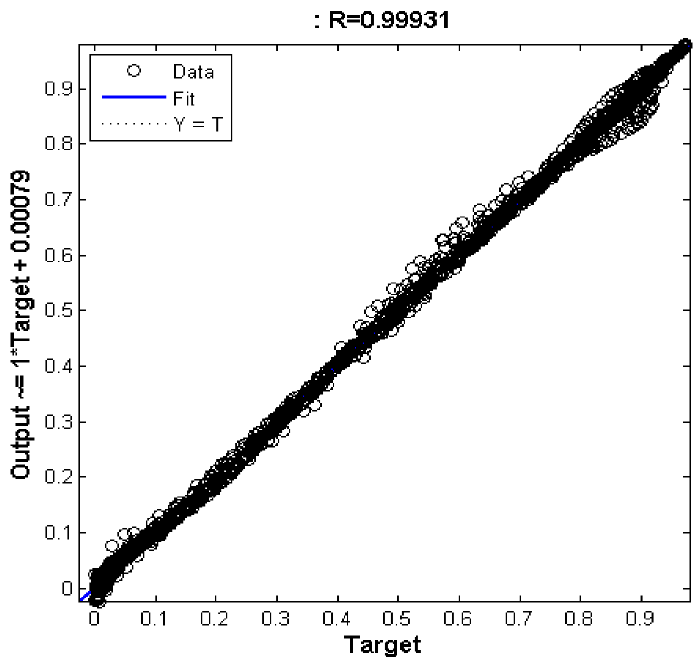

Fig. 5. Regression plot for training phase of ANN

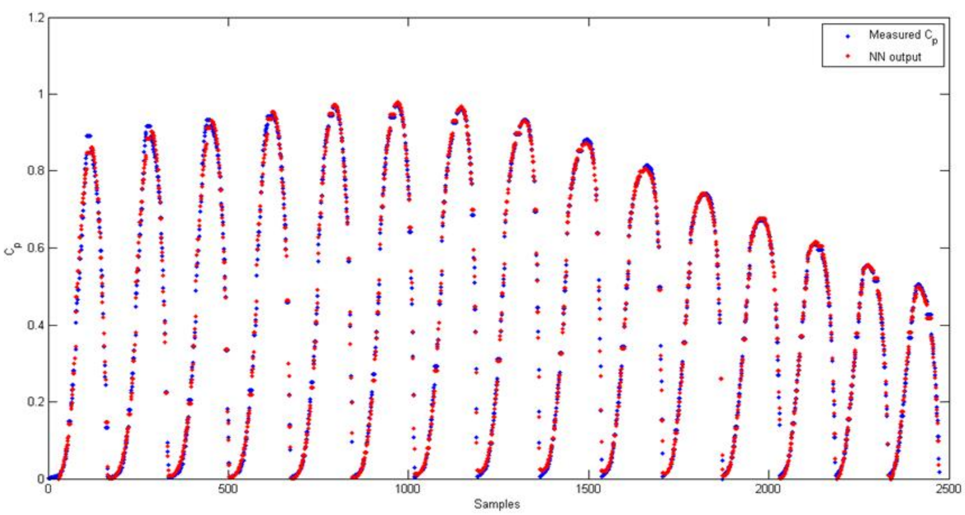

Fig. 6. Comparison of normalized output of NN and training data

After training phase, finding the maximum of resulting model should be triggered. To this end, because of the nature of data a direct search with arbitrary step size could be employed. In this research a step size of 0.01 is chosen.

The resulting $C_{p_{\max}}$ obtained with this method is 0.48955 at BPA= -0.11 and TSR= 7.63.

Recall that in [3] these optimum parameters are $C_{p_{\max}}$ =0.482, BPA= 0 and TSR=7.55.

By replacing the old optimum values by new ones in eq. (2) the new gain can be computed: $K_{new} = 0.0252\left(Nm/\mathrm{rpm}^2\right)$. Compared to the old gain ($K_{old} = 0.0255764\left(Nm/\mathrm{rpm}^2\right)$) it could be seen that the new gain is reduced by a factor of 0.9841.

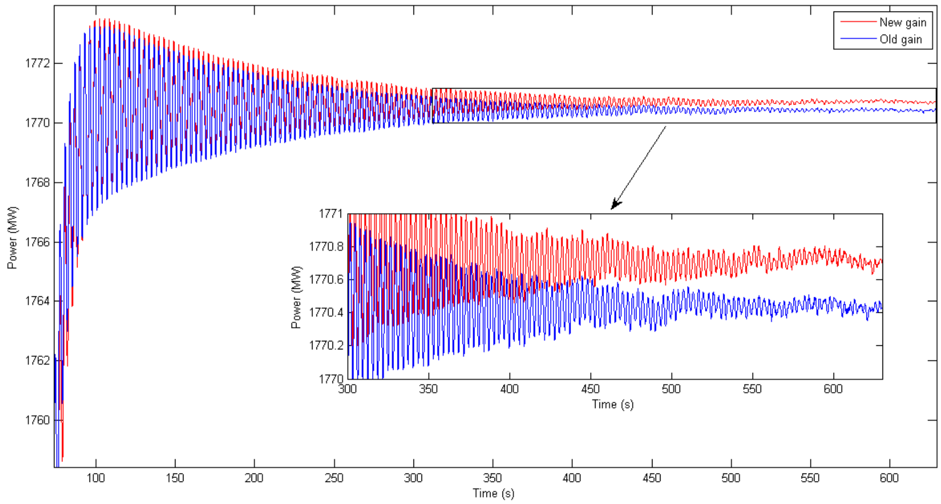

Fig. 7. Generated power

The reason of reduction in controller gain is that, although the new $C_{p_{max}}$ is higher than old $C_{p_{max}}$,the new optimum TSR, is also higher than old optimum TSR. As this parameter has an inverse cubic form in eq. (1), this parameter, cancels out improvement of new $C_{p_{max}}$.

But, with this new controller gain and under steady wind condition, simulation shows that, in spite of reduction in control gain, the overall energy capture is improved.

Fig. 7, compares the generated power with old and new controller gains. This figure shows generated power of benchmark 5 MW wind turbine model for steady wind (8 m/s).

It is clear that with the new controller gain, the power capture of wind turbine is increased.

Recall that, region II is responsible for 50% of power generation in a year. So this new controller gain can improve the power generation capability of a wind turbine system at no cost.

6. CONCLUSION

In this paper, using neural network modelling capability and based on simulated data, an accurate model for one of the most important aerodynamic curves of wind turbine, namely rotor power coefficient (C_p) is identified.

The proposed method, addressed the problem of sub-optimality of controller gain in the region II. Because the reason for this inaccuracy lies in uncertainty of C_p curve, accuracy of this curve could enhance the efficiency of the entire wind turbine and improves the power capture, especially in region II.

Based on this model, the maximum of this curve is estimated. This maximum, together with blade pitch angle and tip speed ratio at which this maximum occurs, result in a new controller gain which cause improvement in the overall power capture.

Using the outcome of this paper, it is planned to design more advanced controllers using adaptive and nonlinear control theory. Also the C_p curves varies slightly with wind speed. In this research, only constant wind is considered. So modelling C_p in variable wind speed could be the topic of future research.

Simulations, showed the effectiveness of proposed method.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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