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Performance enhancement of small-scale wind turbine based on artificial neural network

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ABSTRACT

Small-scale wind turbine is typically designed to resisted extreme wind; this work aims to adjust their pitch angle based on simulations that use standardization codes for wind turbines. Proportional integral derivative (PID) and artificial neural network (ANN) controllers are used to control the speed of wind turbines. The ideal action for controlling the blade pitch angle can be attained by providing the controller with speed information ahead of time, allowing the controller to provide the best action for blade pitch angle control. The results of this work represent the relationship between the turbine speed with respect to time at different pitch angle. It has been concluded that the ANN controller produced the best time response as compared with the PID controller.

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1. INTRODUCTION

The adjustment of pitch angle can be handled using conventional methods, such as creating a controller after linearizing equipment working locations. However, wind turbines are non-linear of equipment. This type of method needs careful calculation and a lot of design work. To simplify and make the control system realistic, the system can be trained to use an offline-learnable mathematical model [1]. Wind energy is now the most competitive kind of renewable energy due to its rapid growth over the previous few decades. Modern wind energy systems depend heavily on control. By controlling the wind turbine, the load that it produces due to aerodynamics and mechanicals may be reduced and the turbine's capacity can be used more effectively [2]. There are two main operating zones for variable-speed wind turbines: below-rated power and above-rated power. The turbine runs at a varied speed of rotation to harness the most amount of wind energy when power output is below the rated power [3], [4]. In the region of higher power, the major objective is to maintain the power output consistent. This is often achieved by reducing the quantity of wind energy captured, which is done by varying the blades pitch angle. This work suggests a new method for controlling the pitch angle of the blade that makes use of neural networks. Nonlinear control systems have been designed using neural networks. In the region of above-rated power, this neural network pitch controller is employed to maintain a consistent power [5].

The manufacturers of wind turbines produce this turbine without control of its power. Due to the over speeding of the turbine rotor, small wind turbines cannot withstand strong winds velocity. The tiny WT system becomes more difficult and costs more as a result of the addition of pitch control [6]. Figure 1 shows depicts the wind turbines (WT's) construction. The main parts of the WT are the main controller, nacelle, tower, and blades [7]. A gearbox, generator, transformer, and power converter are all inside the nacelle. The turbine and generator shafts connected by a gear box because the wind rotates the blades [8]. A transformer transmits the generator's power to the grid [9]. The mechanical stress and load on the drive system of a wind turbine are affected by loads that do not involve torque, which are mainly applied to the blades and generator. These non-torque loads act as input and output on both sides of the WT, and can impact its overall mechanical load and stress [10]. Additionally, the mechanical load is impacted by the rotating load, which stresses the WTs. Unexpected loads are also produced by wind on the input shaft, including rapid changes in wind speed and direction, unequal blade loading, and wind disturbance [11].

From the previous studies, the comparison between small-scale and large-scale wind turbines can be led to the conclusion that the small-scale wind turbine is designed to spin at a high speed compared to slow wind turbines, which may give it many more revolutions over a period of time compared to large wind turbines. This will continue to produce electrical energy within a narrow band of wind speed.

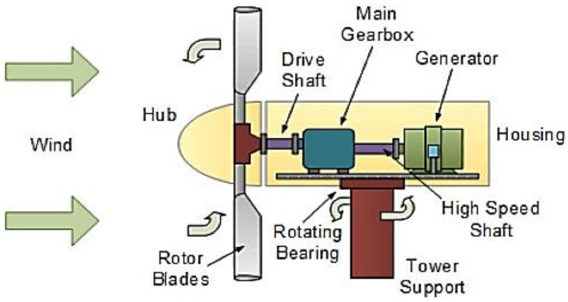

Figure 1. Main parts of WT

2. LITERATURE REVIEW

Salem *et al*. [6] research focused on how to provide a good pitch angle controlling action for wind turbines in order to achieve the desired speed curve. It has been concluded the neural net (NN) fitting provided an accordant pitch angle control exertion, which made the response of the wind turbine follow the desired speed and gave an unavoidable change between pitch angle and speed. Najd *et al.* [12] studied the control strategy in wind turbine due to the effect of pitch angle using neural networks, then focused on increasing wind turbine speed and power by controlling the blades pitch angle. Simulation results showed that the suggested neural network controller was very operant for correcting the pitch angle. It has been concluded that changes in system parameters that may occur over time have no effect on the operation of the control system.

A study was conducted by Yan *et al*. [13] on the potential of small wind turbines for power generation based on rotor speed. The study found that installing small wind turbines on platforms is a good alternative to solar panels because they take up less space. However, it was determined that small wind turbines were not feasible for harnessing wind power in certain areas due to low wind speeds throughout the year. The minimum cut-in speed for the selected models of small wind turbines was 2.5 m/s.

3. WIND TURBINE BASED ON PID CONTROLLER

In a digitally controlled system, analog input channels are used to convert analog quantities into digital quantities after first sampling the process parameters. When dealing with these analog values in accordance with certain control algorithms, the results of the calculations are being appeared through an output channel and control the objects using a mover [14]. The most fundamental and popular industrial control technique is PID control, which is also commonly employed on wind turbines [15]. In Laplace notation, a PID controller is:

$$y = \left(\frac{k_I}{s} + k_p + \frac{k_D}{1+s_\tau}\right) x \quad (1)$$

K_I, K_P and K_D represent the proportional, integral and differential gains, while, x is used to correct the signal and y is a signal that give an indication about control behavior, τ represents the time constant. It can be modelled the whole wind turbine generator by a one-order inertia link, and the objects controlled by out-put have been kept constant under outboard external circumstances using a PID organizer. The transfer function of the regulator's is given as:

$$D(s) = \frac{U(s)}{E(s)}$$
$$D(s) = K_P \frac{1+K_I s+T_D K_I s}{K_I s} \quad (2)$$

while, K_P is a system of proportional gain, T_I is time integral constant, T_D is the differential time constant. The form of increment used to represent PID control algorithms:

$$u(n) = u(\text{n-1}) + K_P[e(n) - e(n-1)] + \frac{T}{T_I}\text{e(n)} + \frac{T_D}{T}[e(n) - 2e(n-1) + e(n-2)] \quad (3)$$

while, $u(n)$ is control action, u(n-1) is last control action, $e(n)$is deviation, $e(n-1)$is last deviation and T is sampling period.

4. NEURAL NETWORK

The cascade feed forward approach, which is a three-layers feed forward network with one single layer hidden was used [16]. Figure 2 shows the internal structure of the proposed artificial neural network (ANN). The input layer node as shown in Figure 3, cascade feed forward transfers input signals to the hidden layer. The hidden nodes are constructed from radiation effect functions such as the Gaussian function, but the output nodes are constructed from basic linear functions. The primary function of the hidden layers responds to incoming signals in a local area. That is, when an input signal approaches the basic function’s center scope, hidden nodes increase the output [17], [18].

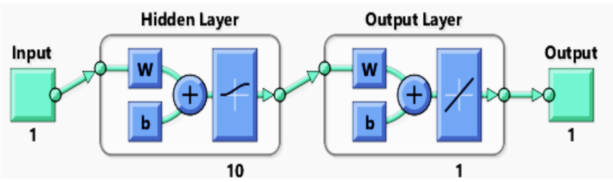

Figure 2. Internal structure of the proposed ANN

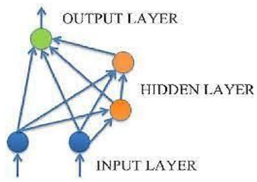

Figure 3. Structure of cascade feed forward neural network

Cascade feed forwarded way has been chosen from ANN, this is comparable to a weight link from the input layer succeeding layers, which are analogous to feed-forward networks. Feed-forward networks with further layers may learn complex relationships further quickly, even if two-layer feed-forward networks have the potential to learn almost any input-output relationship [19]. Networks with cascade-forward are built using the newly created function as an illustration, a three-layers network has engagements between layers 1 and 2, layers 2 and 3, and layers 1 and 3. Additionally, the input is connected to all three layers of the three-layer network. It’s possible that the extra connections will hasten the network’s learning of the intended relationship [20]. CF artificial intelligence model is similar to the basic characteristic of the feedforward backpropagation neural is which each neuron in the current layer is linked to every neuron in the previous layer. The backpropagation method is used by this network to update its weights [10]. To achieve the optimal state, all three types of transfer functions log-sigmoid, tan-sigmoid were used, as well as pure linear threshold functions [21].

$$MSE = \left[\sum_1^v \left(\frac{Q_{exp}-Q_{cal}}{n}\right)^2\right] \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\left[\sum_1^v \left(\frac{Q_{exp}-Q_{cal}}{Q_{exp}}\right)^2\right]} \quad (5)$$

$$R^2 = 1 - \left[\sum_1^v \left(\frac{Q_{exp}-Q_{cal}}{Q_{exp}}\right)^2\right] \quad (6)$$

Where, MSE mean squire error Qexp = value as observed; Qcal = value predicted; Qexp = mean predicted value; n = the dataset's number of observations. RMSE =root mean square and R2 = normalized version, were utilized to constant the prediction performance of the advanced models. The best score for R2 outcome is 1 and for latest measures is zero. Figure 4 show the trained ANN's performance and state plot. The regression performance plot is depicted in Figure 5.

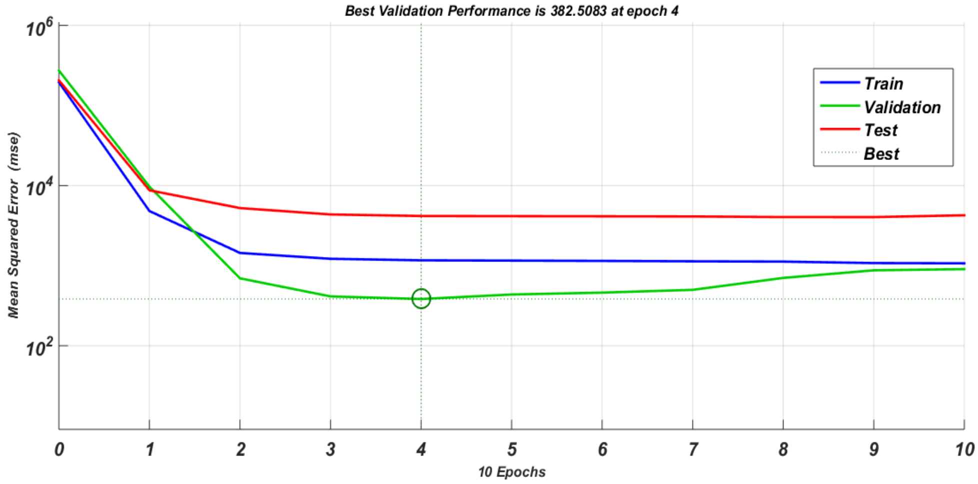

Figure 4. The effectiveness plot of the trained ANN

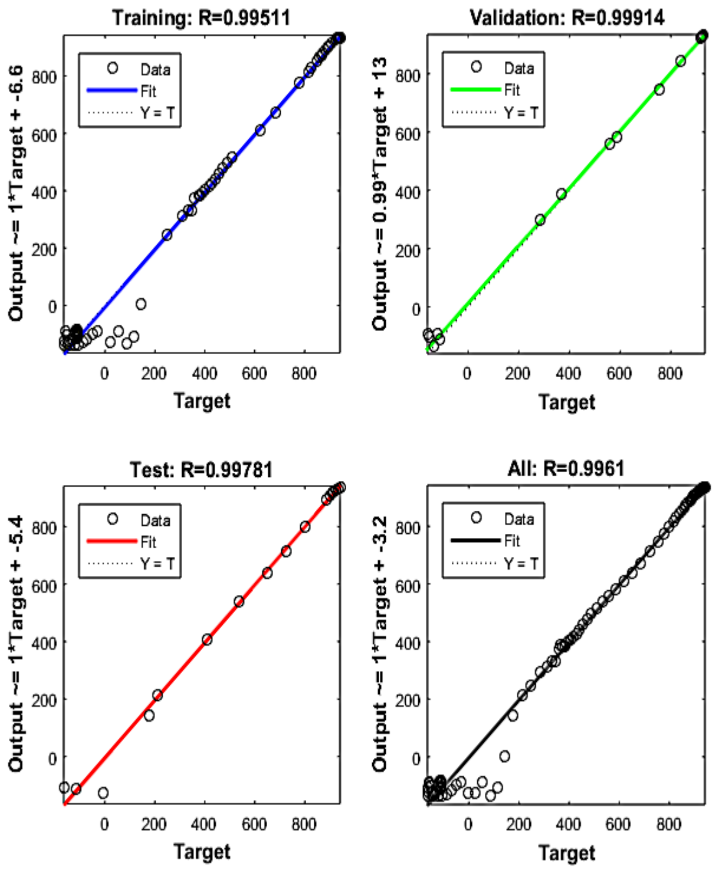

Figure 5. Regression performance plot

5. NEURAL NETWORK BASED PITCH CONTROLLER ALGORITHM

The flowchart of the NN pitch controller algorithm is shown in Figure 6. The initial phase of startup is split into three situations based on whether the present generator speed is more, equal, or less than the rated generator speed [22]. Furthermore, the varying rate of generator speed is taken into account when deciding whether to raise or reduce pitch angle β [23]. When the current rotor speed exceeds the rated speed, the changing rate of the rotor speed is taken into account once more to increase the pitch angle. If the rate of change of the rotor speed increases, the pitch angle is decided to increase. Otherwise, no changes are made to the pitch angle [24], [25]. When the current rotor speed is lower than the ordained speed, the same process is used to decrease pitch angle. When the present rotor speed equals the ordained speed, the pitch angle changes proportionately to the rate at which the rotor speed changes. When the changing rate of the rotor speed is positive, the pitch angle increases [1], [26].

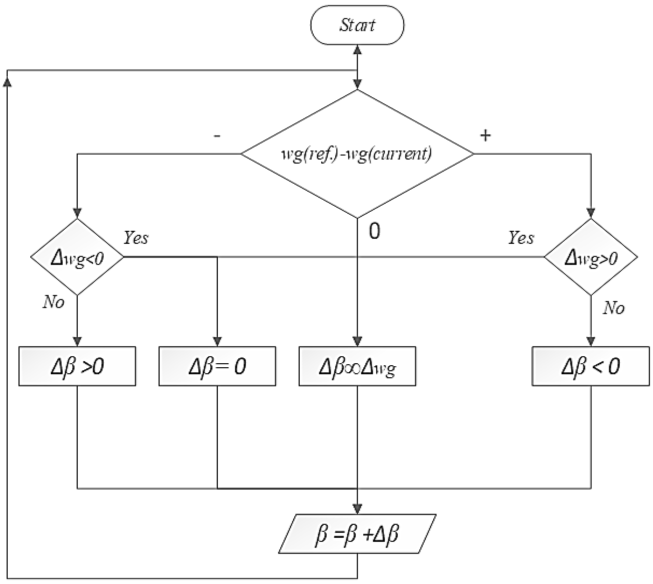

Figure 6. Flowchart of the neural pitch controller

6. MODELLING OF WIND TURBINE BASED ON PID CONTROLLER

The modeling of a 1 kW self-excitation induction generator (SEIG) wind turbine is utilized for simulation. The speed control of the shaft is adjusted by the pitch angle of the blade. Figure 7 represents the block diagram model of this wind turbine.

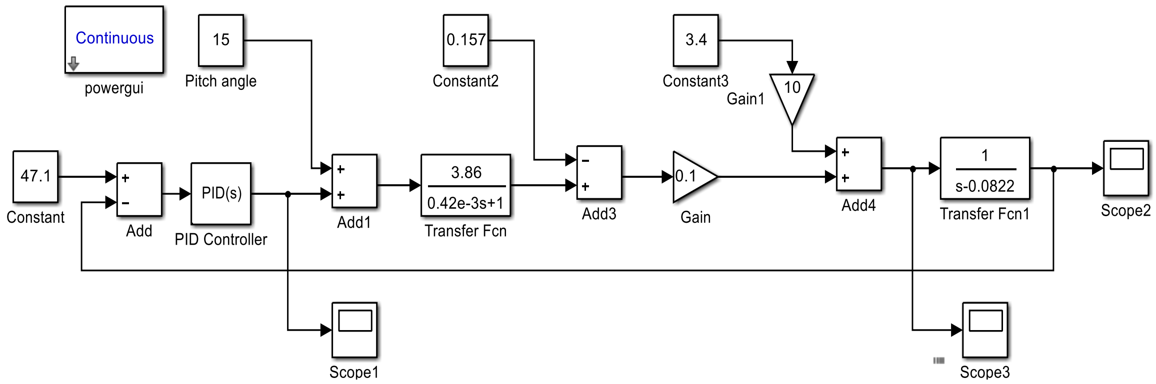

Figure 7. Speed control of wind turbine based on PID controller

7. MODELLING OF WIND TURBINE BASED ON ANN CONTROLLER

The use of an ANN controller was employed to test the efficiency of a wind turbine. MATLAB was chosen for its vast collection of algorithms capable of solving various mathematical problems such as differential equations, matrix algebra, and linear and nonlinear systems. The findings suggest that small wind turbines mounted on platforms could be a feasible alternative to solar panels due to their smaller size. However, certain areas with low wind speeds made it unfeasible to harness wind power using small turbines with a minimum cut-in speed of 2.5 m/s. MATLAB provides a fascinating environment with numerous built-in algorithms that are efficient and dependable. These functions can assist in solving a wide range of mathematical problems, including linear systems, nonlinear systems, differential equations, matrix algebra, and many other technical solutions. Figure 8 gives the modeling of wind turbine based on NN controller.

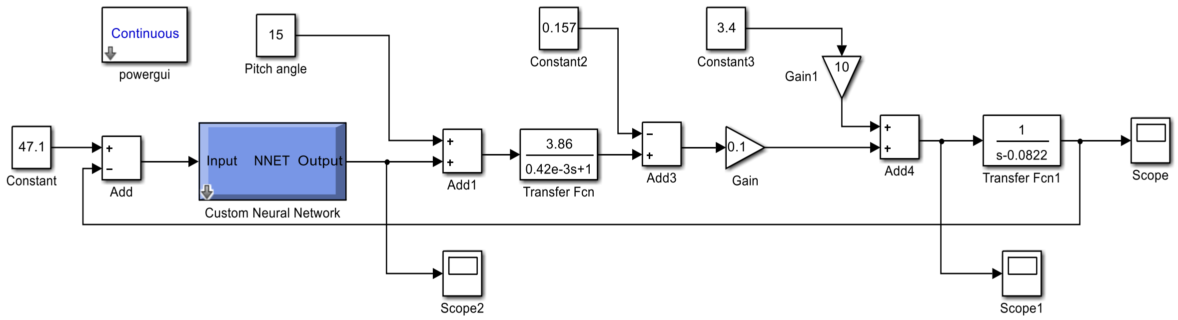

Figure 8. Speed control of wind turbine based on ANN controller at reference pitch angle 15°

8. SIMULATION RESULTS

For PID controller case, at reference pitch angle, the behaviour of speed response of wind turbine is given in Figure 9. At reference pitch angle the behaviour of peed response curve of wind turbine with respect to time is given in Figure 10. For ANN controller case, the behaviour of speed response of wind turbine with respect to time is shown in Figure 11. At reference pitch angle, the behaviour of speed response of wind turbine with respect to time is given in Figure 12. The transient response of rotor speed for wind turbine-based PSD controller with respect to time are listed in Table 1.

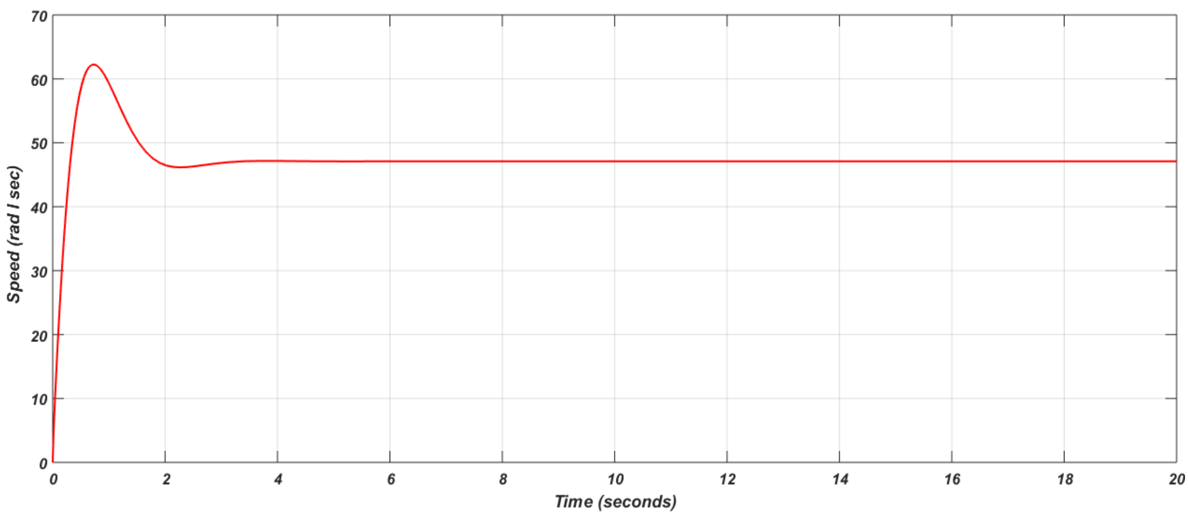

Figure 9. Speed response of wind turbine at pitch angle 15°

Table 1. Time response parameters of 1 kW wind turbine

Controller	Pitch Angle	Peak over shoot %	Peak time tp (sec)	Rise time tr (sec)	Setting time (sec)
PID-controller	15°	15.15	0.749	0.238	1.727
	35°	16.145	0.72	0.246	1.718
ANN-controller	15°	0.1113	0.782	0.2565	0.4
	35°	0.12	0.76	0.26	0.42

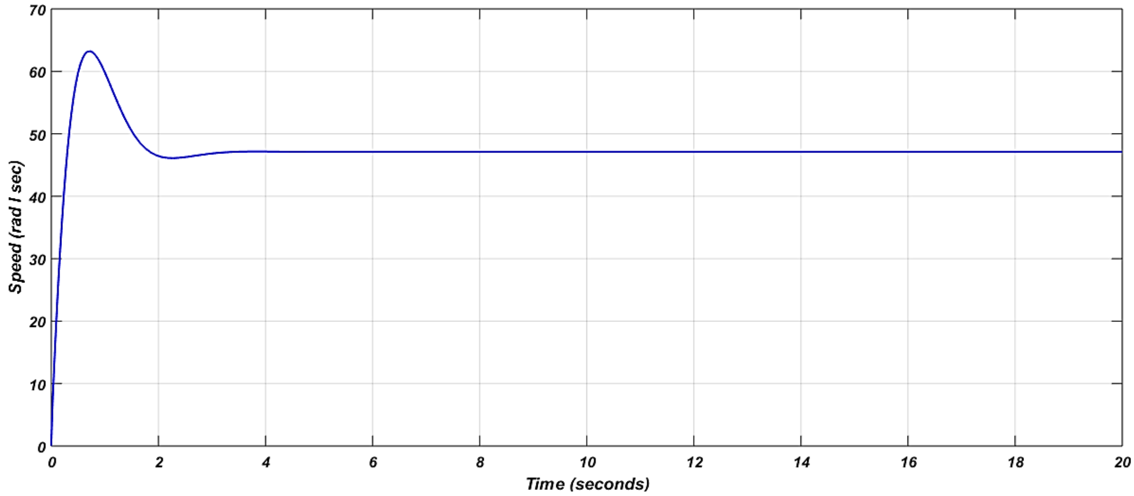

Figure 10. Speed response of wind turbine at pitch angle 35°

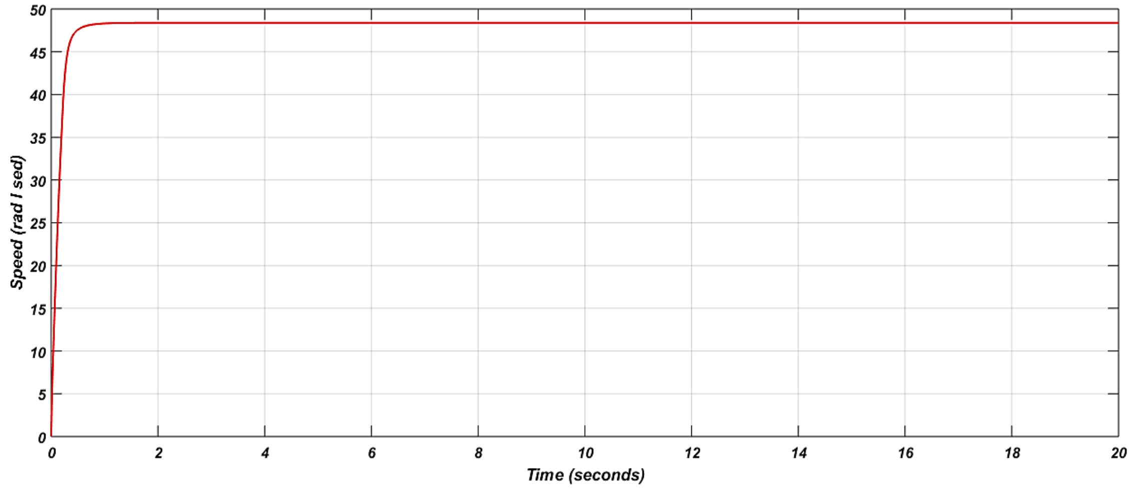

Figure 11. Speed response of wind turbine at pitch angle 15°

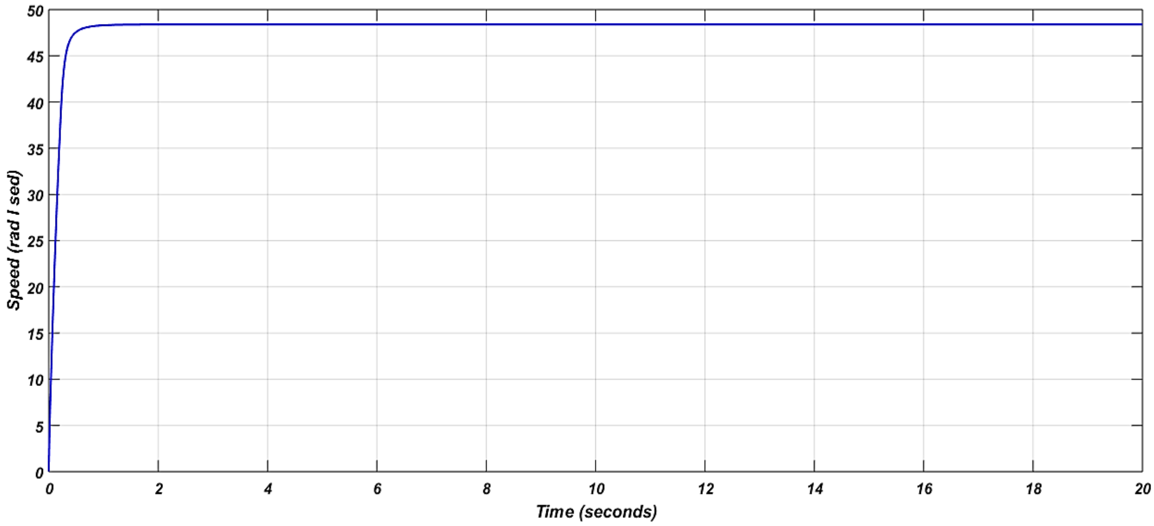

Figure 12. Speed response of wind turbine at pitch angle 35°

9. CONCLUSION

The performance of pitch angle behavior with small wind turbine could provide quick action and an effective wind turbine blades The ANN technique provides a good and suitable control action to control pitch angle. At a pitch angle of 15° ANN, the controller made an enhancement in percentage peak overshoot and setting time by reducing these parameters by 15.038% and 1.327 sec, respectively as compared by the PID controller, at a pitch angle of 35°, the ANN controller made an enhancement in percentage peak overshoot and setting time by reducing these parameters by 16.025% and 1.258 sec, respectively as compared to the PID controller. The ANN controller at pitch angle 35° enhancement the peak over shoot by 0.987 % and the settling time by 0.065 sec as compared with pitch angle 15°. Finally, the ANN controller provided a continuous relationship between Pitch angle and variations in wind speed.

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