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Research paper

Application of combined mathematical modeling/optimization methods coupled pitch controller in wind turbine using hybrid MLP neural network and firefly algorithm

Ehsanolah Assareh[a, *], Iman Poultangari[b] and Afshin Ghanbarzadeh[c]

[a]*Department of Mechanical Engineering, Islamic Azad University Dezful Branch, Dezful, Khouzestan, Iran*
[b]*Department of Electrical Engineering, on, Islamic Azad University Dezful Branch, Dezful, Khouzestan, Iran*
[c]*Department of Mechanical Engineering, Shahid Chamran University, Ahvaz, Khouzestan, Iran*

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[*]Corresponding author:
e.assareh@gmail.com

Abstract

With pitch angle control, wind turbines can retain power generated at high speeds of wind and avoid severe mechanical stress. By varying the angle of the blades of the wind turbines, they can keep the power generated up near the maximum amount. A controller based on PI is suggested due to control angle of the pitch of the wind turbine blades in the present study. Therefore, PI controller gains are tuned via hybridization of firefly evolutionary algorithm and MLP artificial neural network so that the controller at its output sends a suitable control signal to the pitch actuator and thus varies the blades pitch angle appropriately to preserve power of the generator at a nominal amount even at high wind speeds. Simulating and analyzing the results was done by employing a five MW wind turbine made by National Renewable Energy Laboratory based on FAST software code. The simulation of the method showed that its performance is good.

1. Introduction

Nowadays, a very common way to produce electricity is the utilize of renewable energies and through the development of technology and reasonable cost of using these type of energy investment for the constructing power plants according to renewable energies is enhancing. The utilizing wind energy has remarkably enhanced to generate electricity. Wind turbines are devices to supply wind energy, and diverse control methods are utilized for their optimal application. Control approach in wind turbines is generally taken according to the fixed speed of the wind that is named the nominal wind speed. This is a speed of the wind which in the maximum value of wind turbine generator power is achieved. When the speed of the wind is less than the nominal wind speed, a method named torque control is usually utilized. Though pitch angle control is often employed in speeds of wind higher than nominal speed. In this method, the aerodynamic power and so the produced generator power are held around their nominal values by varying the angles of the blades about their axis and consequently the value of mechanical stress on wind turbine at high wind speeds is minimized. In current study, a PI controller-based method is suggested to control pitch angle when wind turbines operating at higher speeds of wind than their nominal wind speed. Also, a hybrid procedure of FA evolutionary algorithm and MLP artificial neural network is utilized to regulate the gains of the PI controller. Thus, when the speed of the wind is upper than the nominal speed, PI controller tunes the angle of the pitch of the blades so that the powerof the generator is kept about the nominal amount. A wind turbine 5MW made by National Renewable Energy Laboratory (NREL) simulated and analyzed using FAST code. The results of the simulation show the good efficiency for the suggested method.

Different methods and procedures are used to achieve the purpose of setting the pitch angle in wind turbines. As an example, Yilmas and Ozer done optimal control of the angle of the pitch for wind turbines in over nominal speed of the wind by using the RBF and MLP neural networks. In current study, a pitch angle control method using ANN (Artificial Neural Networks) was presented [1]. Oguz and Guney [2] used an adaptive neuro-fuzzy model to improve the quality of power of variable-speed WPGS (wind power generation systems). In a study conducted by Zhang *et al.* [3], a pitch control method was designed for wind turbines based on quasi-sliding mode control. The results show that the proposed controller has a good performance rather than the PI controller. In a study conducted by Yao *et al.*, a pitch adjusted LQG controller is design for wind turbines. In this study, LQG controllers was designed for regulated pitch angle of the wind turbines.

A comparison between the performance of control and a PID controller is done by using the wind model and SUT-1MW wind turbine. The result of this comparison showed that LQG controller have a better [4]. In the study of Yao *et al.* [5], the RBF neural network based on adaptive PID pitch control method is studied for WPGS. Yao *et al.* [6] used the pitch angle control for wind turbines under the PID controller based on neural network. This method enhances accuracy of control of the whole pitch-controlled system. In a research conducted by Yao *et al.* [7], the LQG controllers is designed for pitch wind turbines. Moreover, in order to consider the system non linearities and evaluate the control objectives, the control structure based on a linear model method is utilized.

Gao *et al.* [8] proposed a pitch angle control for commercial wind turbines according to feed forward fuzzy-PI. Minh Quan *et al.* used Pitch angle control by employing the combined controller for all operating areas of SCIG wind turbine system. In order to develop the quality of power and keeping the permanent energy output generated by SCIG wind farm, a combined controller based on fuzzy methods and PI for the purpose of pitch angle control is a very common method for smoothing energy production differences. All of the controllers and models that are explained in current study were based on Simulink and Matlab modelling [9].

Seyed Abbas Taher *et al.* [10] designed an optimum gain scheduling power controller for a variable-speed variable-pitch wind energy conversion system. Therefore, by considering differential evolution (DE) optimization algorithm, a group of LQG controllers are optimally suggested. Bindi Chen *et al.* [11] used the wind turbine pitch faults prognosis by utilizing a-priori knowledge-based Adaptive Neuro-Fuzzy Inference System (ANFIS). In their study, a new fault prognosis method was designed by applying ANFIS. Their purpose was to achieve an automatic detection of notable pitch faults that are considered to be significant failure modes. The suggested system has developed ability to translate the formerly undetected situations by considering the privilege of a-priori knowledge incorporation and so diagnoses of fault are corrected.

Musyafa *et al.* [12] studied control of the pitch angle of wind turbine by employing the Fuzzy Logic Control (FLC). Then, they made a sample of wind turbine using control the pitch angle based on fuzzy logic to enhance the energy output in a maximum level. Current study describes a PI controller-based method to control the pitch angle in wind turbines at higher wind speeds compared with the nominal wind speed. This paper makes the following contributions:

• For the first time, the optimization process in such studies has been based on a hybrid method (MLP artificial neural network– firefly (FA) evolutionary algorithm. A major advantage of the suggested hybrid method is its freedom of model and its preparation that the factors of the model are uncertain and cannot be resolved by analytical approaches, making the suggested method helpful and beneficial. Furthermore, by utilizing FA for optimization, we have successfully prepared the necessary data for training the neural network. However, in previous studies, most algorithms and methods did not make use of this helpful feature.

• In current study, the software FAST made is utilized by NREL (National Renewable Energy Laboratory), which is a powerful tool for modeling and validating the simulated results. For the first time, the authors have utilized this tool for modeling and validating the results by considering other methods utilized in the previous studies. The main advantage of FAST software is that various degrees of freedom are given to scientists for modeling the wind turbine. This makes it possible for modeling the wind turbine which explains the behavior of real wind turbine well. Lastly, the results have been validated well by utilizing this software.

2. The wind turbine under study

In current study, the wind turbine under study is a five MW variable pitch HAWT (horizontal axis wind turbine). The wind turbine mathematical model can be explained due to this turbine specifications that are presented in [13]. Fig. 1 shows a wind turbine model that illustrates its general structure. The aerodynamics system, the drive-train, the generator, and the actuator of the pitch angle are the key compartments for the wind turbine model. The following sub-sections describe each of these components.

2.1. Aerodynamic modeling

An explanation for the aerodynamic wind turbine power is as follows:

$$P_a = \frac{1}{2}\rho\pi R^2 C_p(\lambda\ \beta)v^3 \tag{1}$$

In Eq. (1), R represents the rotor radius, v is considered as the wind speed and ρ shows the air's density. The coefficient of the power depends on the angle of the pitch β and TSR (Tip Speed Ratio) λ. Following is an explanation of the TSR:

$$\lambda = \frac{\omega_r R}{v} \tag{2}$$

where, ω_r is the speed of rotor. Fig. 2 shows the power coefficient curve $C_p(\lambda,\beta)$ from the suggested wind turbine that is based on a table given in the [14].

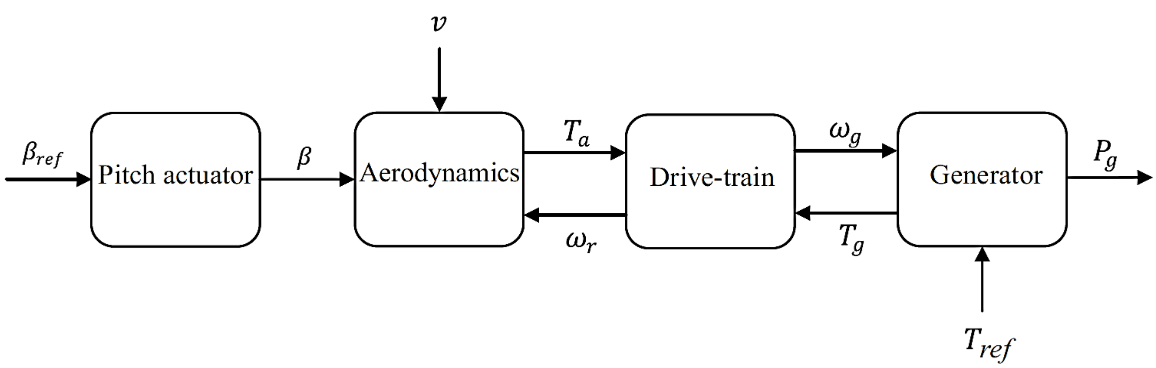

Fig. 1. Overall structure the model of wind turbine.

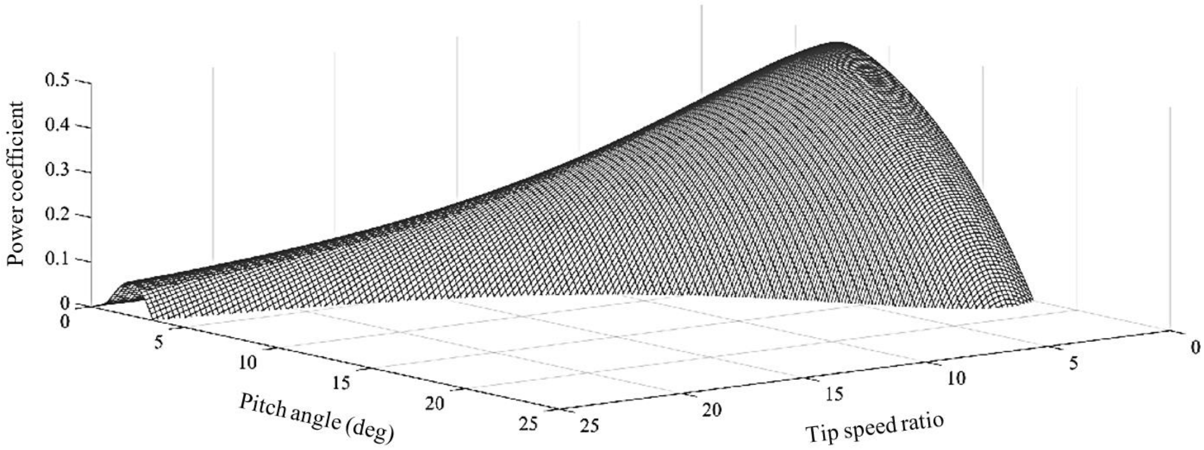

Fig. 2. The coefficient of the power curve [14].

The aerodynamic torque that is marked via T_a, it can also be explained as follows:

$$T_a = \frac{1}{2}\rho\pi R^3 C_q(\lambda, \beta)v^2 \quad (3)$$

where,

$$C_q(\lambda\ \beta) = \frac{C_p(\lambda\ \beta)}{\lambda} \quad (4)$$

Shows the torque coefficient.

Due to the Eqs. (1-4) and Fig. 2, the aerodynamic torque T_a demonstrates a nonlinr reaction owing to the coefficient of the power (C_p). Moreover, the equation of C_p is naturally in a nonlinear form [13]. Therefore, it can be found that in terms of aerodynamic torque (T_a) explained in Eq. (3), there is uncertainty.

2.2. The generator's model

In this study, the simple 1st order generator's model is employed. The generator's torque (T_g) is showed based on Eq. (5) [13]:

$$\dot{T}_g = \frac{1}{\tau_{gen}}(T_{ref} - T_g) \quad (5)$$

In Eq. (5), τ_{gen} represents the generator's time constant and T_{ref} shows torque reference of the generator. The power of the generator P_g is determined by the Eq. (6):

$$P_g = T_g\omega_g \quad (6)$$

where ω_g is the speed of the generator. T_{ref} is a control signal to adapt the torque of the generator T_g and a suitable controller can predict its value.

2.3. The model of the Drive-train

The power transfers from the axis of the rotor to axis of the generator by utilizing a part named drive-train. In current study, according to a description given in [15] as can be observed in Fig. 3, a 2 mass model is used for modeling and designing the drive-train. As it is obvious, based on the Eq. (3), the aerodynamic torque (T_a) causes the speed of the rotor ω_r that provides the dynamics as fallowing:

$$J_r\dot{\omega}_r = T_a - T_{ls} - K_r\omega_r \quad (7)$$

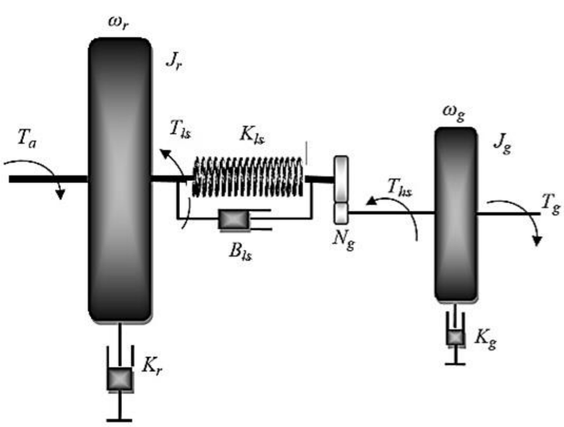

Fig. 3. The dynamics of the wind turbine drive-train.

In Eq. (7), J_r shows the inertia of the rotor and K_r represents the outside damping of the rotor. It can consider which Low-speed shaft torque T_{ls} acts on the rotor as a braking torque, and it can be predicted based on the Eq. (8) [15]:

$$T_{ls} = K_{ls}(\psi_r - \psi_{ls}) + B_{ls}(\omega_r - \omega_{ls}) \tag{8}$$

In Eq. (8), ψ_r represents the angular deviation of the rotor-side and ψ_{ls} shows the angular deviation of the gearbox-side.
ω_{ls} is utilized as the speed of low-speed shaft. Additionally, B_{ls} and K_{ls} represent low-speed shaft stiffness and low-speed shaft damping, respectively.
The generator's inertia J_g is driven by the high-speed shaft T_{hs} and is braked by the torque of the generator T_g. These dynamics can be stated based on the Eq. (9):

$$J_g\dot{\omega}_g = T_{hs} - T_g - K_g\omega_g \tag{9}$$

where, K_g represents external damping of the generator.
The velocity and torque of high-speed shaft could be transmitted by employing a gearbox with N_g ratio. As an ideal gearbox, the following equation can be used:

$$N_g = \frac{T_{ls}}{T_{hs}} = \frac{\omega_g}{\omega_{ls}} \tag{10}$$

2.4. The model of the pitch actuator

The part of pitch actuator can be utilized for rotating the wind turbine blades about their longitudinal axis. Its model that is utilized to design the suggested wind turbine in current study is a model of order 2. It defined as follows [13]:

$$\ddot{\beta} = \frac{1}{\tau_\beta}\left(\left[K_\beta\left(\beta_{ref} - \beta\right)\right]^\gamma - \dot{\beta}\right) \tag{11}$$

where τ_β and γ are constant of the time and timing of the delay of the pitch-actuator's model respectively. Moreover, K_β is considered as a proportional tuner by a fixed amount. β_{ref} represents the reference of the angle of the pitch and is a control signal to modify the angle of the pitch β. The β_{ref} amount is often predicts using a suitable pitch controller.

3. Operating areas

In the Fig. 4, as can be observed the wind turbine operating Areas are divided into 4 regions. In this division, the speeds of the wind are considered as boundaries that are cut-in speed of the wind v_{cut-in}, nominal (rated) speed of the wind v_n and cut-out speed of the wind $v_{cut-out}$.
For the suggested five MW wind turbine in current study, the amounts of v_{cut-in}, $v_{cut-out}$ and v_n are 3 m/s, 25 m/s and 11.4 m/s respectively. In the region I, the wind has a lower speed compared to v_{cut-in} and this has caused the wind turbine to go into stop mode. Due to this, wind turbine generator cannot generate power since their torque is zero. Normally considers the pitch angle to be 90 degrees in this region.
In the partially load region (region II) that is referred to as the second region, the wind speed has higher value compared to the v_{cut-in} however this value is lower than v_{rated}. In this region, the main control purpose is to enhance the power generated by the wind device until a maximum amount is reached. The coefficient of the power C_p should be set to the maximum value $C_{p,\,max}$ to receive the maximum power. $C_{p,\,max}$ happens when the amounts of TSR (λ) and the angle of the pitch β are adjusted into the optimal amounts. It can be expressed mathematically as follows:

$$C_{p\ max} = C_p\Big|_{\lambda=\lambda_{opt}}^{\beta=\beta_{opt}} \tag{12}$$

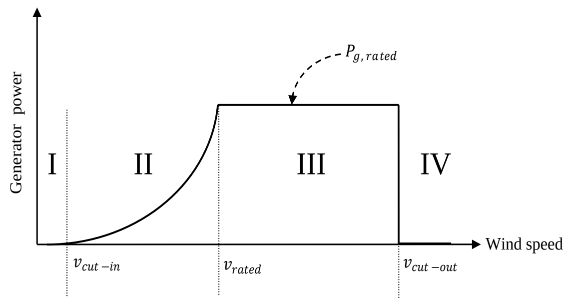

Fig. 4. Operating Areas of the wind turbine.

In Eq. (12), β_{opt} and λ_{opt} are considered as an optimal angle of the pitch and an optimal TSR, respectively. For the five MW wind turbine considered in current paper [13] and due to the Fig. 2, the amounts of $C_{p\,max}$, λ_{opt} and β_{opt} are 0.482, 7.55 and zero, respectively. Based on Eqs. (2, 5), the maximum energy is receivable in region II by considering a suitable T_{ref}.

The higher wind speed than normal wind speed but is less than the $v_{cut-out}$ in the full load region (region III). In this area, the Initial control aim is to preserve the power of the generator P_g about the nominal power of the generator $P_{g\ rated}$. To accomplish this goal, the control law for T_{ref} can be determined based on Eq. (13):

$$T_{ref} = \frac{P_{g\ n}}{\omega_g} \tag{13}$$

According to the Eqs. (5, 6, 13), when ω_g be set around the rated generator speed $\omega_{g\ rated}$, so P_g remains around $P_{g\ rated}$. In full load area, the pitch control can be utilized to keep ω_g around $\omega_{g\ rated}$.

In the next region (region IV), the speed of the wind has higher value compared to the cut-out speed of the wind. In this region, the wind turbine should be turned off to prevent of fatigue and destructive stresses. In this area, the angle of the pitch is normally adjusted to be 90° and production of power is stopped.

The purpose of current study is the modeling and designing an optimum PI pitch controller by focusing on the full load region (region III).

4. MLP neural network and firefly algorithm (FA)

Evolutionary algorithms and artificial neural networks are widely utilized to design control systems. Multi-layer perceptron (MLP) neural network [16] and firefly algorithm (FA) [17] evolutionary algorithm are utilized for the suggested method.

5. Suggested method

In this section, a method is suggested for the wind turbine pitch control that is showed in Fig. 5. As can be found in Fig. 5, the difference between nominal and real generator's speed is reduced to a minimum amount via using an optimal PI controller. To reach this goal, the PI should provide a sufficient reference of the pitch angle β_{ref} (which is described in sub-section 2.4) in its output. Ttherefore β_{ref} is determined by the below subsequent relation:

$$\beta_{ref}(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau \tag{14}$$

In Eq. (14), K_i and K_p represents integral and proportional gains of the PI controller, respectively and $e(t)$ can be stated based on the Eq. (15) as follows:

$$e(t) = \omega_{g\ n} - \omega_g(t) \tag{15}$$

where, $\omega_{g\ rated}$ and $\omega_g(t)$ are nominal and real generator speed, respectively.

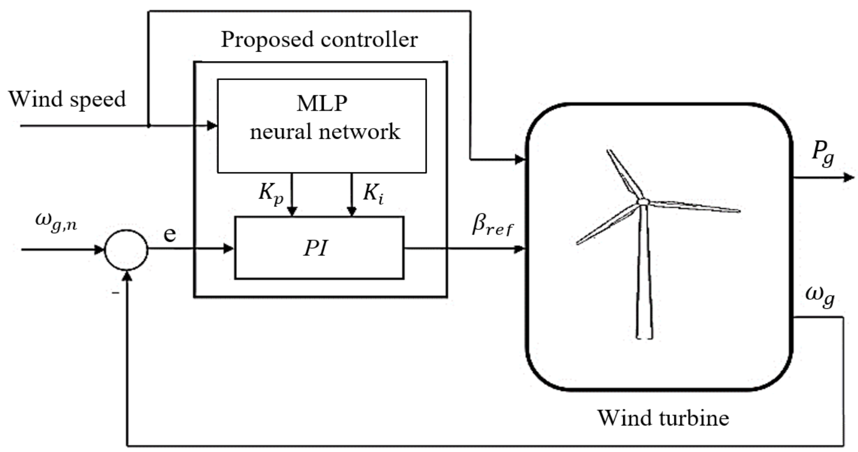

Fig. 5. Structure of the proposed pitch controller.

MLP artificial neural network is employed to set the gains of the PI controller. The MLP considers the wind speed as input and provides the gains of the PI controller as its output.
According to the Eq. (11) the suggest pitch controller generates a proper pitch angle β by turning the reference of the pitch angle β_{ref}. Based on Eqs. (3-10), by varying the angle of pitch β, speed of the rotor ω_r and accordingly, speed of the generator ω_g are changed. Consequently, if the suggest controller does sufficiently, speed of the generator ω_g is held about nominal generator speed $\omega_{g\ rated}$ and due to the Eqs. (5, 6, 13), the generator's power P_g and the generator's torque T_g are held about their nominal values.
The MLP should be trained with optimal data to provide an optimal PI pitch angle controller. Then, this neural network offers the optimal gains of the PI controller. firefly algorithm (FA) is used to determine an optimal data for training MLP. By considering the FA and for many fixed speeds of the wind over the nominal speed, the PI controller optimal gains are determined for the related fixed speed of the wind. Fig. 6 shows this process by a block diagram. The PI gains could be determined for the fixed speed of the wind over the nominal speed of thew wind by using the FA method so that the subsequent IAE (Integral Absolute Error) is reduced to a minimum amount as a cost function:

$$IAE = \int_0^{t_s} |e(t)|dt \tag{16}$$

The $e(t)$ could be obtained by Eq. (15). As pitch controller starts to run, the integrating act starts and will continue till the angle of the pitch controller will be nullified. The lower and upper bounds of the Eq. (16) are zero and simulation time (t_s) respectively.

Note 1. The firefly algorithm (FA) outperforms its counterparts; that is why this algorithm was preferred to be employed in the method of the present study. Table 1 demonstrates the results obtained from FA as used for the purpose of minimizing IAE in Eq. (16), and compares the results with those of PSO, GA and ICA evolutionary algorithms.

6. Simulation results

A model of 5MW wind turbine explained in Section 2 has been used based on FAST code to consider the performance of the suggested optimal pitch controller [18]. Fig. 7 shows the FAST wind turbine model in Simulink and Matlab that is used for simulation in this study. Table 2 demonstrates the values of the model's specifications [13].

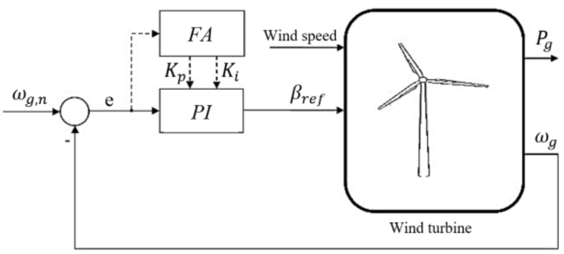

Fig. 6. Method based on FA to obtain the optimal data for the MLP training operation.

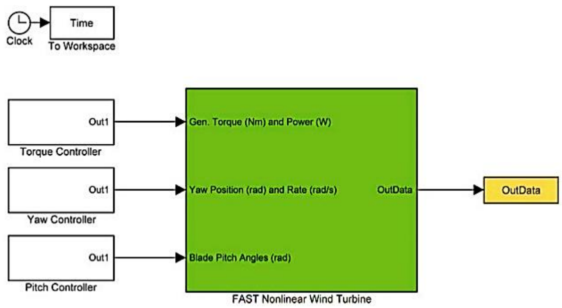

Fig. 7. FAST simulator block in Simulink.

Table 1. IAE values related to FA, ICA, GA and PSO.

Wind speed (m/sec)		4.5	5.3	6.25	7.5	8.75	9.5	10	10.75
IAE	FA	41.67	39.83	34.36	56.72	39.06	41.99	41.33	41.27
	PSO	91.61	84.67	85.34	90.08	90.32	91.71	83.88	93.11
	ICA	80.55	78.26	69.45	83.22	76.88	65.33	70.33	80.29
	GA	100.44	102.77	104.55	107.19	100.32	101.11	99.07	100.28
Simulation time (sec)		500	500	500	500	500	500	500	500

Table 2. Parameters of NREL 5MW wind turbine.

Parameter	Values
Power capacity	5MW
Cut-in wind speed	3 m/s
Cut-out wind speed	25 m/s
Nominal wind speed	11.4 m/s
Rotor radius	63 m
Nominal generator speed	122.9 rad/s
Nominal generator torque	43093.55 N·m
Gearbox ratio	97:1
Maximum power coefficient	0.482

In the suggested controller, for training the MLP, the optimal data for 48 fixed wind speeds acquired through FA is utilized that 8 of them are presented in Table 3. This table demonstration the PI controller optimal gains and the related IAEs of 8 of optimal data obtained from FA for the five MW wind turbine explained in Section 2. For evaluation of the performance of the suggested Method, the proposed controller is compared to a PI controller. Fig. 8 demonstrations the structure of the PI controller for tune the pitch angle of the blades. The PI gains are ($K_p = -1{,}03 \;\; K_i = -19{,}46$) which are chosen according to 15 m/s mean wind speed and are obtained via FA algorithm explained in Section 4. The profile of the wind speed presented in Fig. 9 is utilized for providing favorable conditions to compare both controllers.

Table 4. Specifications of MLP's trained neural network.

Parameter	Values
Input neurons	1
Hidden neurons	6
Output neurons	2
Learning rate	0.5
Basis width (spread)	0.75
Training data	0.65

This profile of the wind speed is acquired according to wind speed model that presented by kaimal [19].

Fig. 10 demonstrations that angle of the pitch changes in suggested controller has smaller oscillations compared to PI controller and so to change the pitch angle, the pitch actuator uses fewer energy. Fig. 11 demonstrations that each of the controllers can keep the generator output power around the nominal power (that is five MW) but the oscillations of the power of the generator about the nominal value in suggested controller is noticeably fewer compared to the PI controller and so, the output power in suggested controller is more desirable.

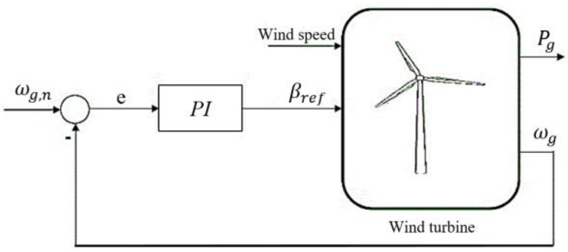

Fig. 8. Structure of the PI pitch controller

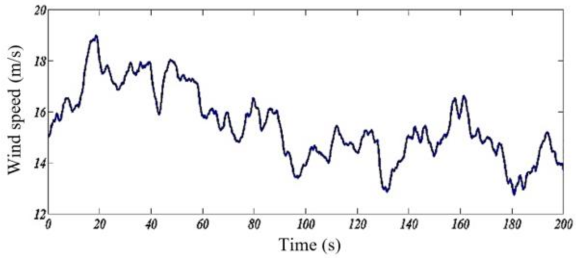

Fig. 9. The profile of the wind speed.

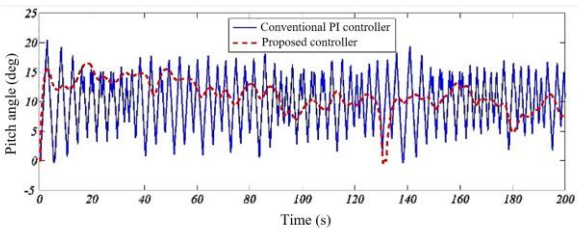

Fig. 10. Angle of the pitch.

Table 3. A part of optimal data determined via FA.

Wind speed (m/s)	12	13.5	15	17.5	19	21.5	23	24.5
K_p	-5.86	-1.85	-1.03	8.125	-4.52	-7.65	-2.63	-0.92
K_i	12.65	8.11	-19.4	34.2	0.89	11.87	-3.69	18.11
IAE	19.33	21.08	25.32	18.66	17.33	21.34	23.54	20.93
Computations time(s)	400	400	400	400	400	400	400	400

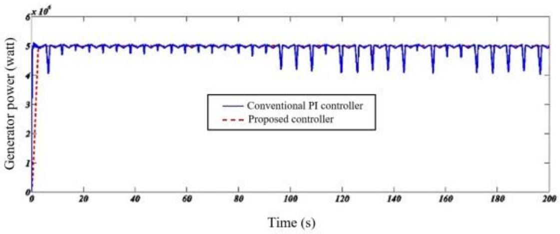

Fig. 11. Power of the generator.

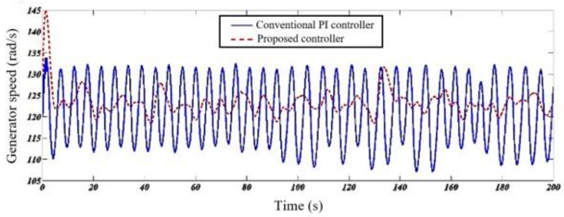

Fig. 12. Speed of the generator.

Fig. 12 demonstrations that the suggested controller keeps speed of generator around the generator nominal speed (that is 122.9 rad/s) with less oscillations than the PI controller. Therefore, based on the results of the simulation, the suggested controller compared with the PI pitch controller in has better performance.

7. Conclusions

In current research, a method has been suggested for pitch angle control using PI controller in wind turbines. Therefore, difference between the nominal and real generator speed is minimized by PI controller, and so power generated from the generator remains around the nominal value. MLP artificial neural network is utilized to determine appropriate gains of PI controller at different speeds of the wind higher than the nominal speed of the wind. FA evolutionary algorithm is utilized for determining suitable data collection to train MLP neural network. Therefore, the neural network trained by optimal data collection determines suitable gains at different wind speeds (higher than nominal wind speed) for PI. Due to change the angle of the pitch, the PI controller generates a suitable control signal to actuator of the pitch at its output. For evaluation of the results, a 5MW wind turbine is made by NREL according to FAST software code. The results of simulation demonstrate that the suggested method has a good efficiency.

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