Maximum Power Point Tracking of a Wind Turbine Based on Artificial Neural Networks and Fuzzy Logic Controllers

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Abstract. In this research paper, a maximum power point tracking (MPPT) has been achieved using controllers based on artificial intelligence techniques, such as fuzzy logic (FLC), and artificial neural networks (ANN) controllers, since PI and PID classical controllers cannot give good performances in many applications that include strong nonlinearity caused by wind turbines aerodynamics, power converters of the conversion system, and the nature of wind flow. For this reason, we have proposed to use three MPPT control strategies; classical PI controller, fuzzy logic controller (FLC), and artificial neural network (ANN) controller. To avoid wind turbine catastrophes in high winds, the technique of pitch control has been investigated in parallel. Using MATLAB/Simulink, the proposed technique has been validated on a variable speed wind turbine with five-phase permanents magnets synchronous generator (PMSG) connected to a grid. The simulation results show the effectiveness of the proposed FLC and ANN controllers to achieve high tracking performance in the variable speed wind energy conversion systems (WECS).

Keywords: Maximum power tracking (MPPT), five-phase PMSG, wind turbine system, artificial neural networks, fuzzy logic, pitch control.

1 Introduction

Wind energy is one of the potential sources of alternative energy for the future. It considered being the most competitive renewable energy as it is a clean energy source with an inexhaustible and endless supply. A variable speed wind turbines have many advantages over fixed-speed generation such as, operation at maximum power point, higher efficiency, increased energy capability and power quality. However, as the wind owns a random nature and its speed varies depending on the conditions, the power of wind turbine is still fluctuating. Therefore, the maximum power point tracking (MPPT) technique is important for wind energy conversion systems. In the literature, various methods have been presented such as: Tip speed ration control (TSR), Optimal torque control (OT), Power signal feedback control (PSF), and Perturbation and observation control (P&O) or Hill-climb searching method (HCS) [1,2]. The problem with this strategy is that larger power variations are frequently caused by wind changes, which can be misinterpreted by the MPPT strategy. This can drive the system off, resulting in a poor MPPT. Nowadays, soft computing algorithms are an essential solution for wind energy conversion systems applications. Among these methods, fuzzy logic and neural networks techniques are widely extended for MPPT methods [3,4]. The problem associated with conventional PI and PID controllers is that these cannot perform practical control for some complex processes for highly non-linear systems. The fuzzy logic control has the advantages of rapid convergence, parameter insensibility, and acceptance of noisy and inaccurate signals. Neural networks algorithms regulate the optimal condition of different control variables.

Multiphase machines are used to minimize torque pulsations, current per phase without influence on voltage per phase and to enhance the fault tolerant capability. Permanent magnet synchronous generators (PMSGs) are distinguished by high power density, high efficiency, low maintenance cost particularly at high power capacities as offshore systems [5].

2 WECS Modeling

According to wind speed range, wind turbine has three operation modes and control objectives, as shown in Figure 1, an understanding of each of these operating regions is essential for the analysis of each WT control technique. Fig. 2 shows the wind system configuration for variable speed WECS. It contains: a three-blade rotor with a pitch angle controller, a maximum power point tracking controller (PI, FLC and ANN), a five-phase PMSG with 1.5 MW and 40 poles pairs, a back-to-back converter control connected to grid.

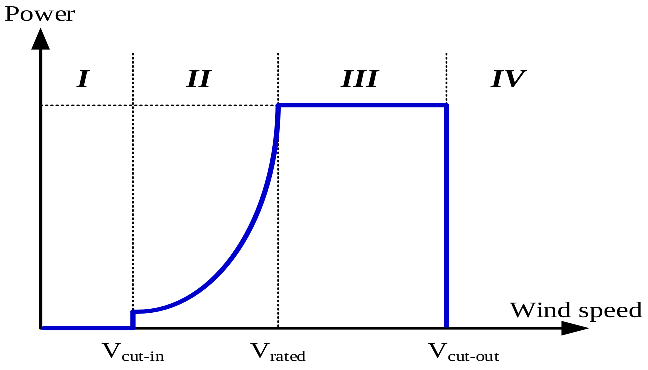


Fig. 1. Wind turbine operation regions.

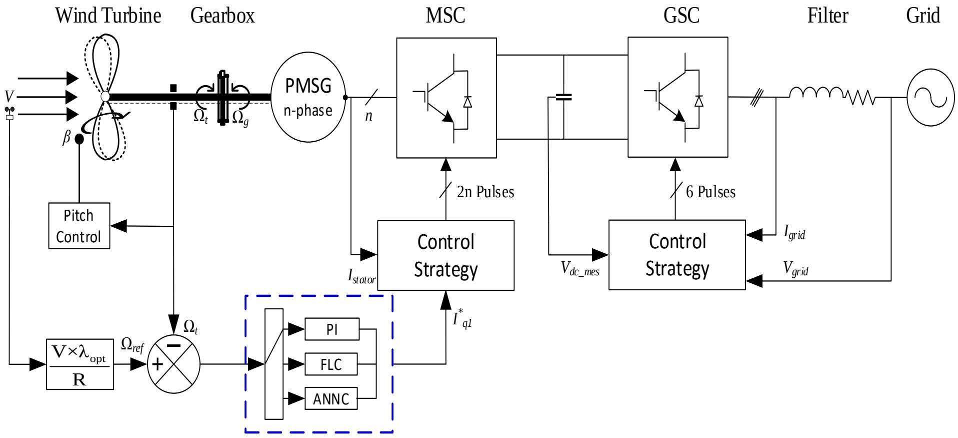


Fig. 2. Configuration of the variable speed WECS.

2.1 Wind turbine

The purpose of a wind turbine is to convert the wind power given by equation (1) to a mechanical power (2)

$$P_W = \frac{1}{2}\rho\pi R^2 V^3 \tag{1}$$

Where ρ is the air density (kg/m^3), R is the radius of the turbine blade (m) and V is the wind speed (m/s).

$$P_t = C_p P_w = \frac{1}{2}\rho\pi R^2 V^3 C_p(\lambda,\beta) \tag{2}$$

Where C_p is the Power Coefficient represents the efficiency of the wind turbine which never exceeds 59.26% according to the law of Betz, it depends on the tip-speed ratioλ andthe blade pitch angleβ.

The turbine studied it has the following characteristics

$$\begin{cases} C_p(\lambda,\beta) = 0.5176(\dfrac{116}{\lambda_i} - 0.4\beta - 5)e^{-\frac{21}{\lambda_i}} + 0.0068\lambda \\ \dfrac{1}{\lambda_i} = \dfrac{1}{\lambda + 0.08\beta} - \dfrac{0.035}{\beta^3 + 1} \end{cases} \tag{3}$$

The tip-speed ratio is given by:

$$\lambda = \frac{R\Omega_t}{V} \tag{4}$$

The aerodynamic torque of the turbine is defined as follows:

$$C_t = \frac{P_t}{\Omega_t} = \frac{1}{2\Omega_t}\rho\pi R^2 V^3 C_p(\lambda,\beta) \tag{5}$$

According to the characteristic of the wind turbine, the power coefficient C_p changes as a function of lambda and beta as shown in Fig. 3

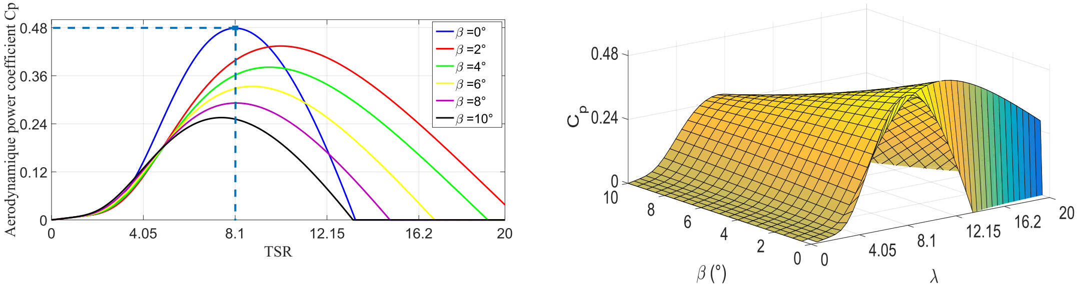


Fig. 3. Power coefficient as function of λ and β.

According to Fig. 3 the turbine used gives a maximum C_{pmax} of 0.48 corresponding to a tip-speed ratio which called optimal value λ_{opt}=8.1 when β=0.

2.2 MPPT strategy control

The power point trackingcontrol strategy is applied for adjusting the electromagnetic torque of the generator, so as to force the mechanical speed to track a reference value Ω_{ref}, in order to maximize the power extracted from the turbine. for that, a speed control of the generator must be performed. The maximum mechanical power can be achieved if the system is operating at its corresponding maximum power coefficient value C_p and the optimum tip-speed ratio λ_{opt}. Hence, the desired speed of the generator Ω^*_g is obtained by the following equation:

$$\Omega_g^* = \frac{\lambda_{opt} V}{R} \tag{6}$$

2.3 Five phase PMSG

The dynamic model of the five-phase PMSG in the synchronous reference frame can be expressed by the following equations when using Park's transformation

$$\begin{cases} V_{d1} = -R_s i_{d1} - L_{d1}\dfrac{di_{d1}}{dt} + \omega_r \psi_{q1} \\ V_{q1} = -R_s i_{q1} - L_{q1}\dfrac{di_{q1}}{dt} - \omega_r \psi_{d1} \\ V_{d3} = -R_s i_{d3} - L_{d3}\dfrac{di_{d3}}{dt} + 3\omega_r \psi_{q3} \\ V_{q3} = -R_s i_{q3} - L_{q3}\dfrac{di_{q3}}{dt} - 3\omega_r \psi_{d3} \end{cases} \tag{7}$$

Where: R_s is the stator resistance and ω_r is the electric angular of rotor speed. L_{d1}, L_{d3}, L_{q1} and L_{q3} are d-q stator inductance components, i_{d1}, i_{d3}, i_{q1} and i_{q3} are d-q stator current components.

The stator flux linkages components of the five-phase PMSG are given by the following equations [6]:

$$\begin{cases}\psi_{d1} = L_{d1} i_{d1} + \psi_f \\ \psi_{q1} = L_{q1} i_{q1} \\ \psi_{d3} = L_{d3} i_{d3} \\ \psi_{q3} = L_{q3} i_{q3}\end{cases} \tag{8}$$

ψ_f is the amplitude of the fundamental component of the permanent magnet flux linkage.

The electromagnetic torque of the five-phase PMSG is formulated as:

$$T_{em} = \frac{5}{2} P(\psi_{d1} i_{q1} - \psi_{q1} i_{d1} + 3\psi_{d3} i_{q3} - 3\psi_{q3} i_{d3}) \tag{9}$$

Where P is the number of pole pairs.

Because Ld1= Lq1= Ld3= Lq3 and Joule losses are eliminated by imposing i_{d1}, i_{d3} and i_{q3} equal to zero, the electromagnetic torque becomes:

$$T_{em} = \frac{5}{2} P \psi_f i_{q1} \tag{10}$$

The mechanical equation of the wind turbine coupled to the generator isgiven by:

$$J \frac{d\Omega_g}{dt} = T_g - T_{em} - f\Omega_g \tag{11}$$

Where f is the friction coefficient and J is the total moment of inertia.

2.4 Pitch control

Fig. 4 shows the pitch angle control, it is used to keep the wind turbine operating zone in the safe one (zone III figure. 1). So, when the wind speed is higher than the nominal speed this command is triggered and the pitch angle β increases, consequently, according to Fig. 3 the C_p decreases. Finally, the power turbine does not exceed its nominal power value. Many control structures are presented in literature [7-9]. A conventional PI controller is used in this work.

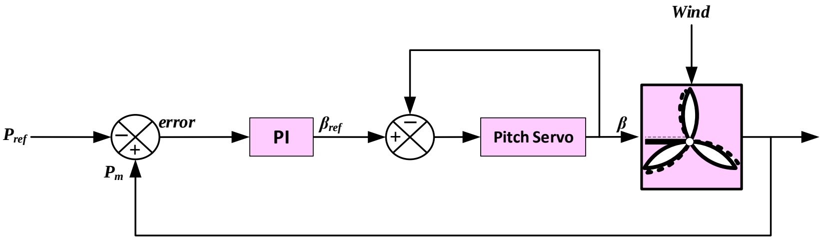


Fig. 4. Pitch angle control using a PI controller.

3 PI controller

The speed control loop shown in Fig. 5 is established from the dynamics of rotating bodies. The reference electromagnetic torque T_{em_ref} provides to obtain a generator mechanical speed equal to the reference speed Ω_g^* by the following relation:

$$T_{em\_ref} = \left(\frac{K_i + K_p s}{s} \right) . (\Omega_g^* - \Omega_g) \tag{12}$$

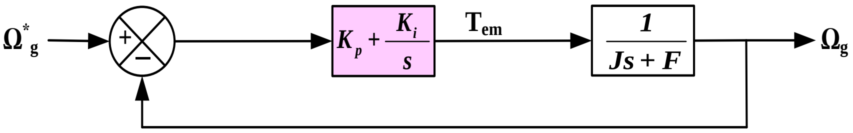


Fig. 5. Structure of PI controller.

The closed-loop transfer function is written as:

$$\frac{\Omega_g(s)}{\Omega_g^*(s)} = \frac{2\xi\omega_n s + \omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2} = \frac{\dfrac{K_i + K_p s}{J}}{s^2 + \dfrac{K_p f}{J} s + \dfrac{K_i}{J}} \tag{13}$$

The system transfer function is the second order; the expressions of the regulator parameters obtained by identification are given by:

$$\begin{cases} K_p = 2\xi\omega_n J - f \\ K_i = J\omega_n^2 \end{cases} \tag{14}$$

4 Fuzzy logic controller (FLC)

Many applications of fuzzy logic have experienced rapid growth in recent years in the industries, a controller based on fuzzy logic is known as a robust and adaptive tool for nonlinear and complex systems [10,11]. In this study, a Fuzzy Logic controller is proposed to control the mechanical speed of a WECS, in order to ensure the maximization of power extraction during wind speed variations. The system architecture based on the FLC controller is shown in Fig. 6.

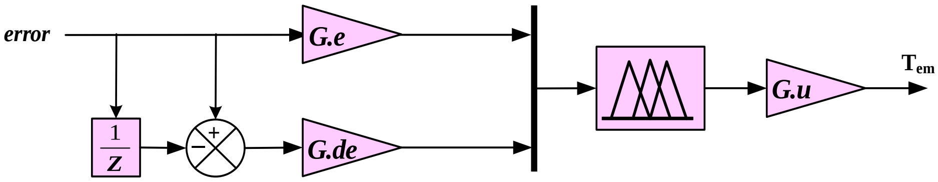


Fig. 6. Structure of FLC controller.

As shown, the controller has two variable inputs the speed error *(e)* and the shift error (de), The FLC output is the electromagnetic torque T_{em}.*(e)* and *(de)* are calculated for any sample time (k) by equation (14) and (15):

$$e(k) = \Omega_g^*(k) - \Omega_g(k) \tag{15}$$

$$de(k) = e(k) - e(k-1) \tag{16}$$

The two inputs of FLC are multiplied by two scaling factors *(G.e)* and *(G.de)*, respectively. The output is multiplied by another scaling factor *(G.u)*. Five fuzzy sets are chosen for *(e)*, *(de)* and T_{em} BN, N, Z, P, BP indicates Negative Big, Negative, Zero, Positive and Positive Big respectively (see Table 1 and Fig. 7).

Table 1. Rules of FLC.

Output		**de(t)**				
		BN	**N**	**Z**	**P**	**BP**
e(t)	**BN**	BN	BN	N	N	Z
	N	BN	N	N	Z	P
	Z	BN	N	Z	P	P
	P	N	Z	P	P	BP
	BP	Z	P	P	BP	BP

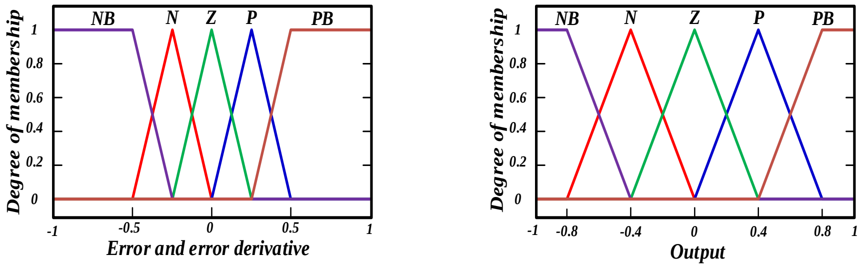


Fig. 7. Membership of the functions error, error derivative and output.

5 Neural network controller (ANNC)

The structure of the proposed neural network controller is shown in Fig. 8. It has 2 input nodes Ω_g^* and Ω_g , ten nodes in the hidden layer and one node in the output layer T_{em}.

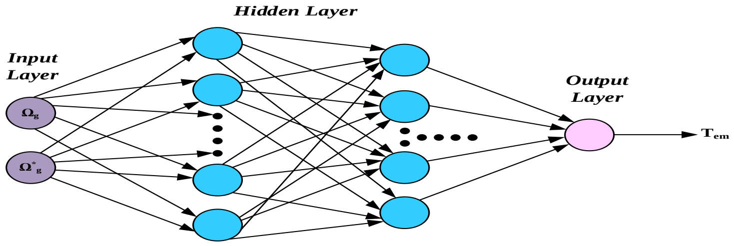
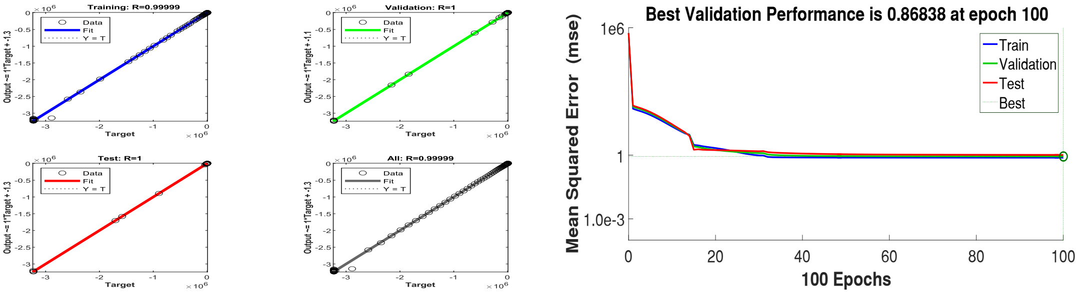


Fig. 8. ANNC proposed scheme.

The most appropriate number of hidden layers and their neurons is decided to base on an empirical basis to achieve the required precision of the proposed approach [12, 13]. 70% of the setpoints were used for training, 15% for the test and 15% for validation (Fig. 9 (b)). After that, a regression analysis non-linear network has been applied for the further checking the performance of ANNC (Fig. 9 (a)).



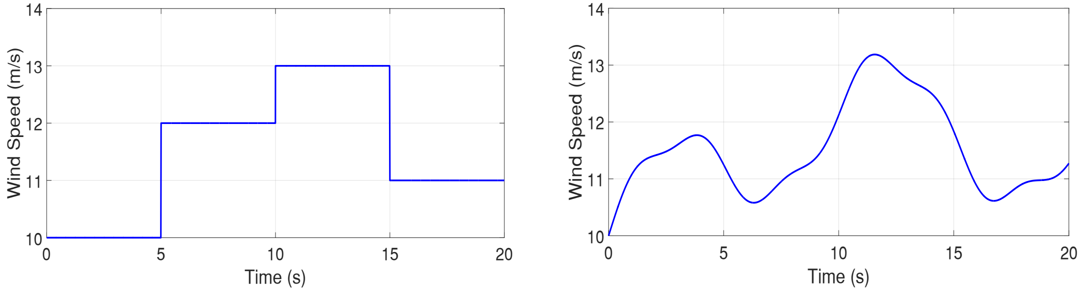
(a) (b)

Fig. 9. (a) Output and target fitting correlations. (b)The Performance curve of training.

6 Results and Discussions

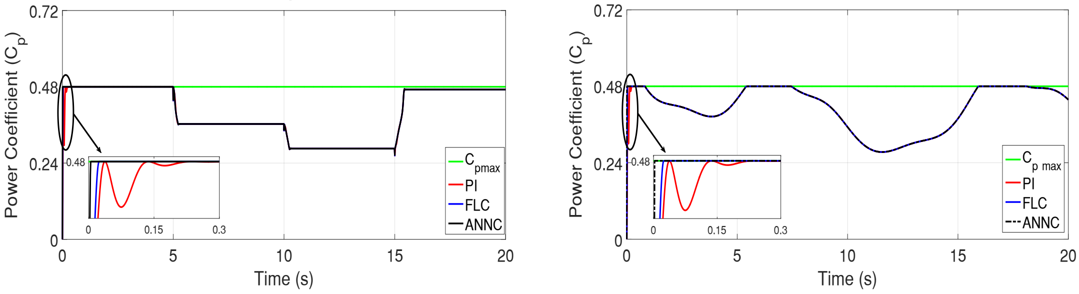
The performances of the selected controllers (PI, FLC and ANNC) are tested in our system on two wind profiles: the first is a step change in the wind speed which variated between 10 and 13 m/s (see Fig. 10 (a)). the second is a variable wind speed that changes between 10 and 13.3 m/s (see Fig. 10 (b)). The objective is to study the characteristics of the proposed controllers, dynamic responses, and efficiency.

In the rest of this section, Figs. 11-14 (a) show the results of the system when applying a step change in the wind speed, and Figs. 11-14(b) show the results of the system under a variable wind speed.



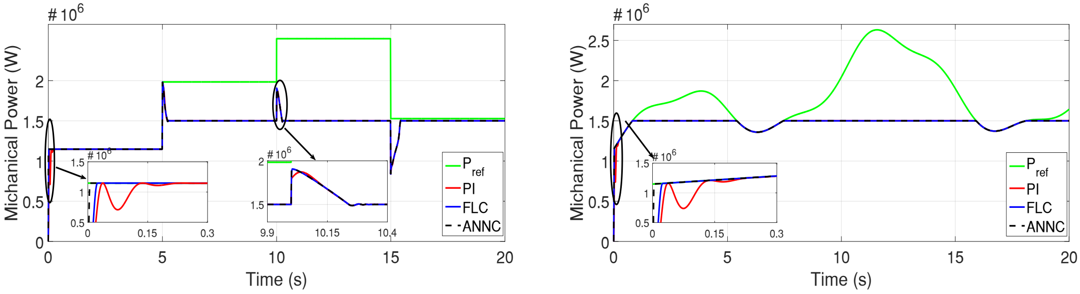
(a) (b)

Fig. 10. Wind Speed profile: (a) step change (b) variable.



(a) (b)

Fig. 11. Power Coefficient C_p: (a) step change (b) variable.



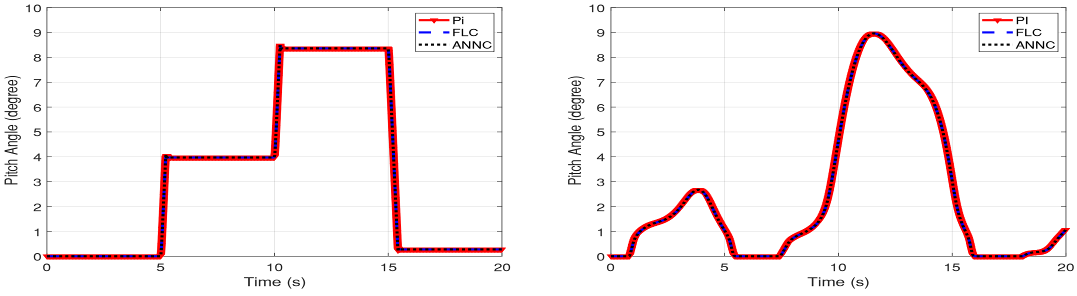
(a) (b)

Fig. 12. Mechanical Power: (a) step change (b) variable.

Figs. 11 and 12 show the three controllers (PI, FLC and ANNC) are followed the set-point perfectly, it is noted that the regulator based on neural network achieves the setpoint faster compared to the others with a response time = 4.5 ms, the FLC has a response time = 23 ms, so it is faster than the conventional PI controller which has a response time = 222 ms.

If the wind speed is lower than the nominal wind speed V_{rated}, so the power is less than the nominal power P_{rated}. Therefore, the power coefficient C_p takes the maximum value C_p=C_{pmax}, the power equals to its reference value, and the pitch angle β = 0 °. However, when the wind speed is higher than the nominal speed V_{rated}, the power coefficient C_p decreases, with respect to the increase of pitch control β and when the wind speed is higher than V_{rated} (See Fig. 13), the power remains constant equal to its nominal value P_{rated} = 1.5MW.

It can be seen from the figures of mechanical power and the power coefficient C_p that they take a time to return to its reference values when the wind speed exceeds V_{rated}.

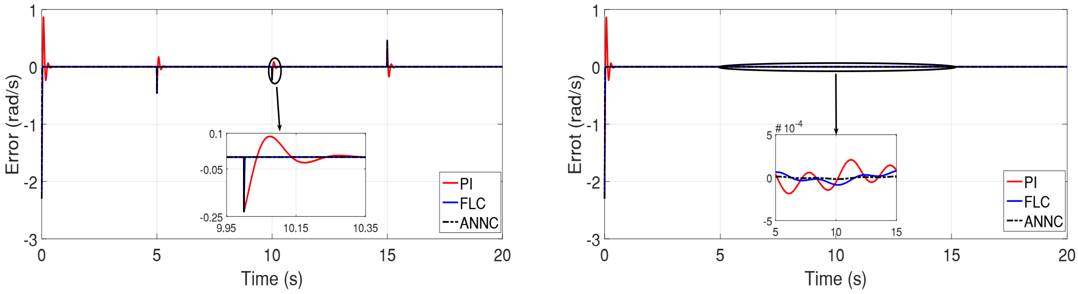


(a) (b)

Fig. 13. Pitch Angle β: (a) step change (b) variable.

We also notice in the case of the wind speed step change, some mechanical power peaks. Moreover, these peaks are still apparent even in Fig. 14(a) which gives the speed error. On the other hand, these peaks have never appeared by applying a variable wind profile.

For the speed error, the controller based on neural network (ANNC) gives the smallest static error which never exceeds 0.06%, so he has given the best performance compared to the controller based on fuzzy logic that has given an error of 0.2% and 6.2% for the conventional controller PI.



(a) (b)

Fig. 14. Speed Error: (a) step change (b) variable.

Table 2 below represents the comparison between all proposed controllers (PI, FLC and ANNC) in terms of response time, static error, and Set-point tracking. This table shows that the results obtained when applying the FLC controller are better than the PI, more that it gives remarkable improvements achieved by the Artificial Neural Network Controller (ANNC).

Table 2. COMPARATIVE RESULT BETWEEN THE PI, FLC AND THE ANNC.

Performance	PI	FLC	ANNC
Response time (ms)	222	23	4.5
Static errors (%)	6.2	0.2	0.06
Set-point tracking	Good	Very good	Excellent

7 Conclusion

In this work, a study of the performance of 3 types of controllers applied at the MPPT control for a WECS was performed; a conventional PI controller and two artificial intelligence controllers, fuzzy logic FLC and neural network ANNC. Our study has shown that the performances of controllers based on artificial intelligence are better than the conventional PI controller. Moreover, the ANNC controller gives the best performance for response time, set-point tracking and static error. In perspective, we propose to use the artificial intelligence techniques to replace the PI controller in the pitch angle control. This allows improving generator side converter performance in WECS before implementing the proposed techniques by using a dSPACE card1104.

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