A Novel Control Strategy Study for DFIG-Based Wind Turbine

Reza Sedaghati

Young Researchers Club, Beyza Branch, Islamic Azad University, Beyza, Iran
reza_sedaghati@yahoo.com

Abstract

In recent years the use of renewable energy including wind energy has risen dramatically. Because of the increasing development of wind power production, improvement of the control of wind turbines using classical or intelligent methods is necessary. In this paper, in order to control the power of wind turbine equipped with DFIG, a novel intelligent controller based on the human mind's emotional learning is designed. The performance of proposed controller is confirmed by simulation results. Some outstanding properties of this new controller are online implementation capability, structural simplicity and its robustness against any changes in wind speed and system parameters variations.

Keywords: Double Fed Induction Generator(DFIG), Emotional learning, Wind turbine, Intelligent controller.

1. Introduction

One of the common controllers in industrial systems is the classical PI controller that despite its simple construction enjoys an acceptable performance (especially in the areas of linear systems) [1]. In [2,3] two samples of the application of this controller is given for controlling wind turbines. However, in systems such as wind turbine, which enjoys non-linear and undefined factors, in principle using a simple PI controller will not follow a desired response. This is due to the fact that the control system parameters with wind speed change (and therefore changing the system work point) and system parameters change need to be adjusted again.

This defect may be overcome in two ways: the use of classical linear control methods (adaptive /resistant) or the use of neural - fuzzy intelligent control methods (having adaptive-extension power and the possibility of on – line implementation). In [4,5] the classical control method of sliding mode (which is the oldest and still most popular method of resistant nonlinear control) is used to control the wind turbine system. Also in [6-8] the neural - fuzzy intelligent methods are used to achieve better solutions in the design of wind turbine control system.

Wind turbines equipped with double fed induction generator of coiling rotor due to their advantages (including: production capacity in a range of wind speed, good performance, no need for capacitor banks for producing required reactive power of generator and lower-cost of power electronic converters) have widely been used. Therefore, analysis of wind turbines equipped with double fed induction generators and methods for controlling it, is one of the main analyses in producing wind power. In [9,10] for the implementation of the proposed control strategies for controlling wind turbines equipped with DFIG, PI controllers have been used. In this paper, the proposed control strategy for controlling active and reactive power of wind turbine equipped with DFIG has been implemented with the help of emotional intelligence controllers.

2. Model of Wind Turbine Equipped With DFIG

2.1 Model of Rotor Aerodynamic

Mechanical power of wind turbine that in fact is a percentage of the total wind energy, is calculated as follows:

$$P_r = \frac{\rho}{2} A C_P(\lambda, \beta) V^3 \tag{1}$$

In which ρ is the air density, C_P is power efficiency, λ is the edge speed, β is the step-angle, A is the surface swept by the rotor and finally V is the wind speed. Parameter λ is also defined as following:

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

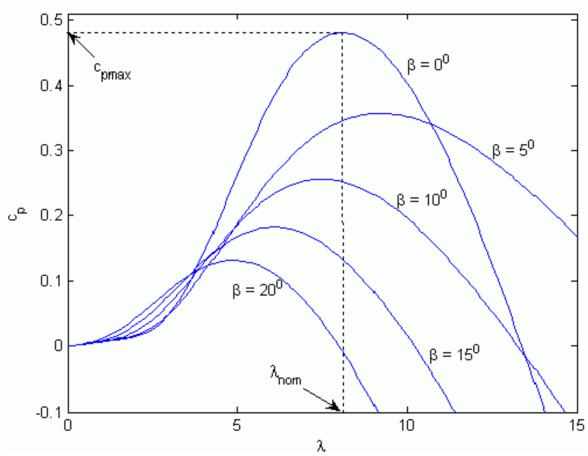
In which R is the radius of the rotor and ω_r is the rotor angular speed. Due to the constant parameters ρ and A and also the wind speed is not at our disposal, from (1) it is implied that by adjusting C_P (which is a function of two parameters λ and β), P_r can be controlled to a desired manner. It should be explained that in wind speeds higher than rated speed , C_P tuning is done by parameter β and in wind speeds lower than rated speed (of course in turbines with variable speed) C_P tuning is done by parameter λ . In [11], using numerical approximation methods, the relation between C_P and parameters λ and β is obtained as following:

$$C_P(\lambda, \beta) = c_1\left(\frac{c_2}{\lambda_i} - c_3\beta - c_4\right)e^{\frac{-c_5}{\lambda_i}} + c_6\lambda \tag{3}$$

$$\lambda_i = \left(\frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1}\right)^{-1} \tag{4}$$

In Figure 1, C_P specification has been drawn based on λ and by different values of β .

Fig.1. *Specification of power efficiency in terms of edge speed and different values of pitch-angle [11].*



2.2 The Generator Model

Relations for DFIG model in synchronous coordinates are as follows [12]:

$$\bar{I}_s R_s + \bar{V}_s = -\frac{d\overline{\psi_s}}{dt} - j\omega\overline{\psi_s} \quad (5)$$

$$\overline{\psi_s} = L_s \bar{I}_s + L_m \bar{I}_r \quad (6)$$

$$\bar{I}_r R_r + \bar{V}_r = -\frac{d\overline{\psi_r}}{dt} - j(\omega_1 - \omega_r)\overline{\psi_r} \quad (7)$$

$$\overline{\psi_r} = L_r \bar{I}_r + L_m \bar{I}_s \quad (8)$$

Paralleling the coordinate system to the stator flux causes the stator flux $\overline{\psi_s}$ becomes almost constant, so the stator voltage amplitude, frequency and phase are fixed.

$$\psi_q = 0;\ \overline{\psi_s} = \psi_s = \psi_d;\ \frac{d\psi_q}{dt} = 0 \quad (9)$$

The equation of the stator base is broken into two axes and is as follows:

$$I_d R_s + V_d = -\frac{d\psi_d}{dt} \quad (10)$$

$$I_q R_s + V_q = -\omega_r \psi_q \quad (11)$$

does not change very much $\frac{d\psi_d}{dt} \approx 0$ and consideri

Since the stator flux ψ_d does not change very much $\frac{d\psi_d}{dt} \approx 0$ and considering $R_s = 0$ we have:

$$V_d = 0, V_q = -\omega_r \psi_q \quad (12)$$

Stator active and reactive power can now be stated as follows:

$$P_s = \frac{3}{2}(V_d I_d + V_q I_q) \approx \frac{3}{2} V_q I_q = \frac{3}{2}\omega_1 \psi_d \frac{L_m I_{qr}}{L_s};\ \omega_1 = \omega_r \quad (13)$$

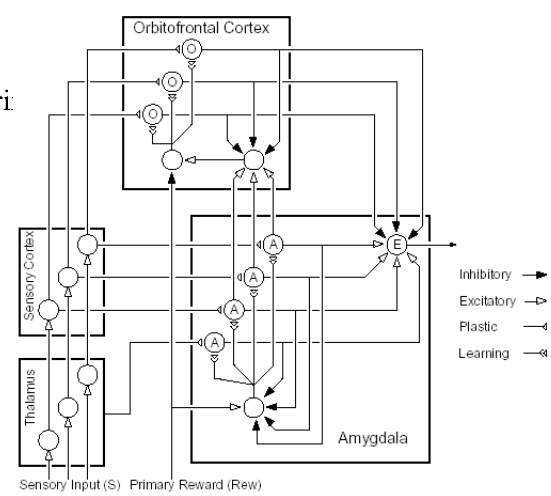
$$Q_s = \frac{3}{2}(V_d I_q - V_q I_d) \approx \frac{3}{2}\omega_1 \psi_d I_d = \frac{3}{2}\omega_1 \frac{\psi_d}{L_s}(\psi_d - L_\omega I_{dr}) \quad (14)$$

The above equation clearly shows that in vector control of the stator flux, active power delivered or absorbed by the stator can be controlled through the rotor I_{qr} flow, while the reactive power for $\psi_s = \psi_d$ can be controlled through the rotor I_{dr} flow.

3. Designing Intelligent Controller Based on Human Brain Mechanisms of Emotional Learning

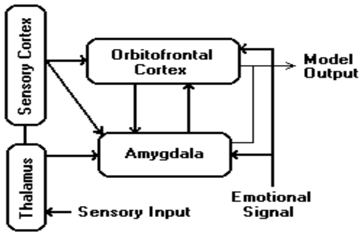
In recent years, the development of computational models of the function of parts of the brain that are responsible for emotional processing task is of interest to researchers. In [13], a new computational model of the function of brain emotional processing unit, including units: the amygdala, orbitofrontal cortex, thalamous and finally the sensory cortex are presented (Figure 2). According to the above model and based on new theories the amygdala - orbitofrontal cortex system performs learning process in two steps. At first, the input stimulation signals are evaluated and then the assessment is used as the multiplier coefficients in response affected by stimulation. Amygdala is one of the primary structures of the brain which exists relatively uniform in the form of large scale structures among different species of animals. Amygdala is a small network in temporal lobe, which has the task of emotional assessment of stimuli that these assessments, are used on: moods, emotional reactions, attention signals and also long-term memory. A number of intrinsic stimuli such as hunger, pain, some smells *etc.,* can stimulate the amygdala and the amygdala response to these stimulations is used in learning. Research conducted by scientists show that animals that have suffered damage from the amygdala have difficulty in learning and evidence of this is that the learning is done in the amygdala. On the other hand, orbitofrantal cortex plays the role of correcting responses and adverse reactions of amygdale. Experiments done on patients with damaged orbitofrantal cortex show that these patients are not able to adapt themselves to new conditions (in other words, previous learning prevent understanding; subsequently an appropriate response to new conditions).

Fig.2. *Graphical description of the detailed computational model of emotional learning system of the brain [13].*



In this paper, according to the model presented in [13] from human brain mechanisms of emotional learning, an intelligent control strategy has been presented for controlling blocks which have the same performance with a self-regulatory PID controller. Regardless of the details, schematic of brain emotional learning system has been shown in Figure 3 that following in order to illustrate the proposed computational model of emotional learning, the amygdala- orbitofrontal is used.

Fig.3. *Block view of computational models of brain mechanisms of emotional learning [13].*



MO Computational model output (the emotional learning amygdala-orbitofrontal system's response to input stimuli and the emotional rewards / Composition *EC* signal) is equal to:

$$MO = AO - OCO \tag{15}$$

In which *AO* and *OCO* are respectively output units of amygdala and orbitofrontal and are equal to:

$$AO = G_a \,.\, SI \qquad OCO = G_{OC} \,.\, SI \tag{16}$$

In which G_a and G_{OC} are respectively equivalent gain of amygdala and orbitofrontal units. Learning low in the amygdala and orbitofrontal units, respectively, is:

$$\Delta G_a = k_1 \cdot \max(0, EC - AO) \geq 0 \qquad \Delta G_{oc} = k_2 \cdot (MO - EC) \tag{17}$$

In which k_1 and k_2 are respectively learning rate inamygdala and orbitofrontal units. Because of using max operator, unit gain of amygdala is subject to increased univocal changes. In other words, the desired working conditions (which will be reflected in the large amounts of emotional signals *EC*) gradually increase the gain of the amygdala unit to its physical limits. However, for unknown reasons, if conditions are unfavorable in the future (with a small amount of emotional signals *EC*) the amygdala unit will not be able to diagnose this problem and correct its answer and practically will respond the same as desired conditions. However, the orbitofrontal unit gain is allowed to positive / negative change so that the amygdala unit can properly carry out the reform against the unfavorable responses. By combining (15) and (16) we have:

$$MO = (G_a - G_{oc}) \cdot SI \equiv G(SI, EC, \ldots) \cdot SI \tag{18}$$

In other words, the output of amygdala-orbitofrontal system in emotional learning is the product of a variable G gain (dependent on several factors, including *EC* emotional signals, *SI* stimulation input, etc.) in the *SI* stimulus input. Citing the proven values of PID controller, most direct proposal for formulating *SI* stimulation signal, is a PID-like frame:

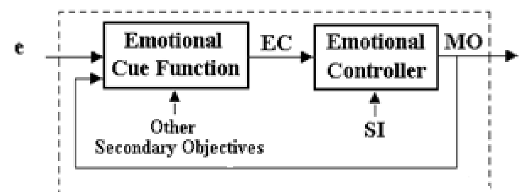
$$SI = k_P \cdot e + K_I \cdot \int_0^t e\,dt + K_D \cdot \dot{e} \tag{19}$$

In which e is the tracking error of closed-loop system. It should be explained that for various reasons including the noise of measurement devices, actually worse the operating system so at best, *PID* controller will not have better performance than *PI* controller. Therefore, the only two options *P* and *PI* will remain for *SI* stimulation signal. *EC* Emotional signals in general, should indicate the desirability of the performance of the controller and closed loop system. Therefore, without losing the whole, can be written based on a weighted combination of the primary / secondary areas of application (including tracking the desired output, trying to control the minimum or equivalent maximum efficiency, *etc.,*):

$$EC = a_{ec1} \cdot e + a_{ec2} \cdot MO + \textit{other terms} \tag{20}$$

From the above, the easiness of embedding the secondary goals in intelligent structures (including the obvious advantages of intelligent structures in comparison with the classical structures) is clearly implied. In figure 4 block display of the proposed intelligent controller based on human brain a mechanism of emotional learning has been shown.

Fig.4. *The block display of proposed intelligent controller based on the brain emotional learning.*



In Figure 5 diagram block of vector control (proposed) of wind turbine equipped with DFIG has been shown. Also, in Figure 6 details related to the control subsystem related to Figure 5 has been shown. Control strategy must be in the way that dual fed induction generator can track be in the maximum absorbable power of the wind turbine at any wind speed. Accordingly, the controller number 2 has been designed so that the active power produced by two fed induction generator can track the desired active power at any time through by injecting the desired voltage to the rotor Q component. The duty of controller No.1 is also production of desired active power (for controller No. 2) by tracking the reference speed of the rotor. Meanwhile, and amount of exchanges of reactive power between the DFIG and network is controlled by controlling the voltage of d component of rotor and this has been performed using the controller No. 3.

Fig.5. *Diagram block of vector control (proposed) of wind turbine equipped with DFIG*

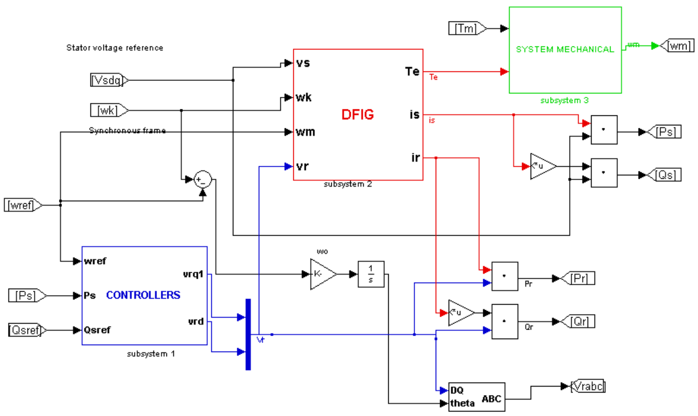
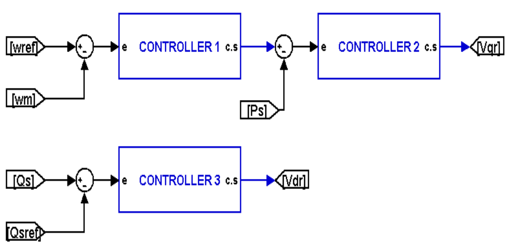


Fig.6. *Details related to the control subsystem related to Figure 5.*



4. Simulation

All simulations were done using MATLAB software for 18 seconds and in all of them, rated wind speed (to activate pitch-angle system) 12 m/s has been in order In Figure 7, wind speed profile (based on the model presented in Part 2) has been shown as a default. Figure 8 indicates the remarkable performance of the proposed intelligent controller in comparison with the classical PI controller for removing tuck and the responding rate. The simulation results of diagram block in Figure 7, for wind speed profile of Figure 7, are also given in Figures 8 to 11, respectively. It should be noted that all used controllers have been designed as intelligent and based on brain emotional learning Figures 10 and 11 shows active and reactive power produced by the DFIG, respectively. Figures 8 and 9, respectively, show the rotor speed and rotor voltage.

Fig.7. *Wind speed profile*

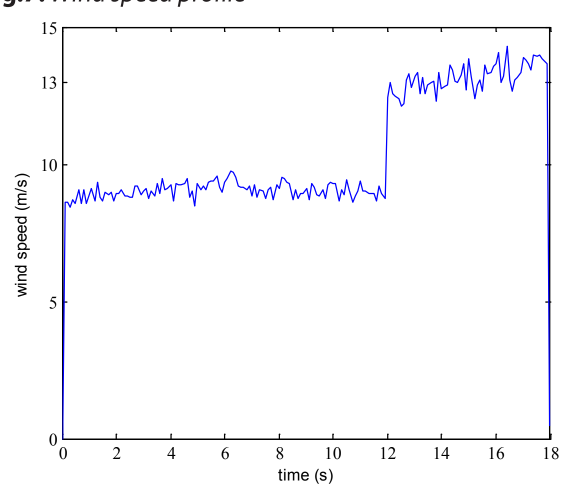


Fig.8. *Rotor speed*

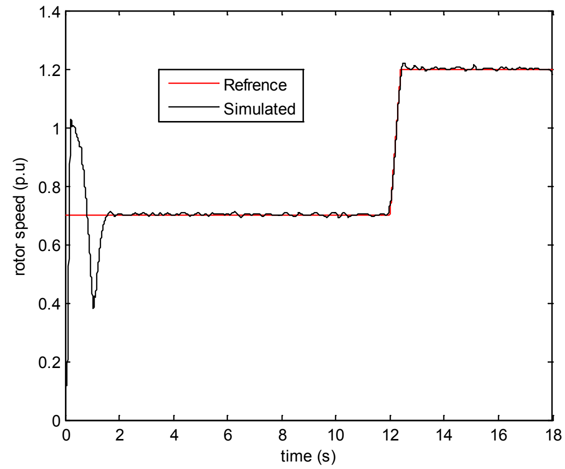


Fig.9. *Three-phase rotor voltage*

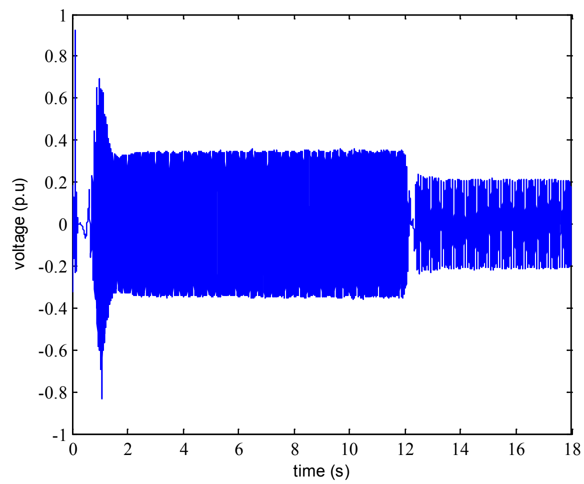


Fig.10. *Active power produced by the DFIG*

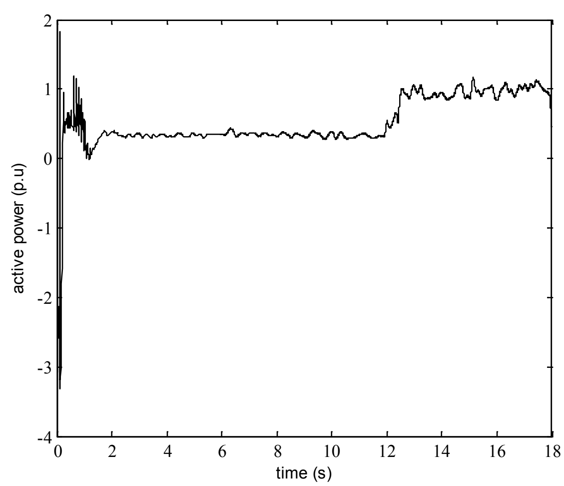
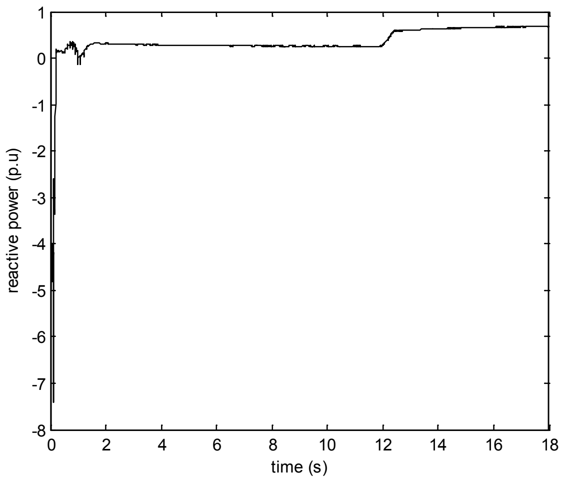


Fig.11. *Reactive power produced by the DFIG*



5. Conclusion

Analysis of wind turbines equipped with double-feed induction generators and their control methods is one of the main analyses in wind power generation. Regarding the improved capabilities of the intelligent controllers (include: high adaption and generalization ability, model-free capability, and also the ability of online implementation), these controllers can be used as wind turbine control systems to achieve more desirable responses and also to facilitate designing process. In this paper, an appropriate control strategy for active and reactive power control of wind turbines equipped with DFIG has been presented and implementing this control strategy has been done with the help of the new emotional intelligent controllers. According to simulation results, this control system meets the following objectives:

1. The desired quality from the perspective of transient and persistent behavioral indicators in the same simple structure (desired quality in terms of response rate, ripple response and lasting tracking error),
2. The remarkable consistency against work point changes (change in wind speed) and system parameters (by changing the work point and system parameters, they do not need to be redesigned but against these changes they are modified automatically to maintain their optimal performance).

6. Acknowledgment

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7. References

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