Journal of Advanced Research in Science and Technology
ISSN: 2352-9989

Artificial neural network-based robust tracking control for doubly fed induction generator used in wind energy conversion systems

Youcef Djeriri [1*], Abdelkader Meroufel [1] and Mohamed Allam [2]

[1] ICEPS (Intelligent Control & Electrical Power Systems) laboratory
[2] IRECOM (Interaction REseau COnvertisseur Machines) laboratory

Abstract. This paper deals with a variable speed device to produce electrical energy on the power network, based on a doubly fed induction generator (DFIG). This machine is intended to equip nacelles of wind turbines. First, a mathematical model of the machine written in an appropriate d-q reference frame is established to investigate simulations. In order to control the power flowing between the stator of the DFIG and the power network, a control law is synthesized by using two types of controllers: Proportional-Integral (PI) controller and Neural Networks (NN) based controller. Their respective performances are compared by simulation in terms of power reference tracking and robustness against machine parameters variations.

Keywords: *Wind Energy, DFIG, PI Controller, Artificial Neural Networks.*

1. Introduction

During the last decade, the concept of the variable speed wind turbine (VSWT) equipped with a doubly fed induction generator (DFIG) has received increasing attention due to its noticeable advantages over other wind turbine concepts [1, 2]. In the DFIG concept, the stator is usually connected to the three-phase grid directly; the rotor is also connected to the grid but via a transformer and two back-to-back pulse width modulation (PWM) [3] or space vector modulation (SVM) [4] inverters (Fig.1).

This arrangement provides flexibility of operation in subsynchronous and supersynchronous speeds in both generating and motoring modes (± 30 % around the synchronous speed). The power inverter needs to handle a fraction (25-30 %) of the total power to achieve full control of the generator, the fraction depending on the permissible sub and supersynchronous speed range. Therefore, it is possible to use a high-frequency switching PWM converter to achieve high performance, such as fast dynamic response, low harmonic distortion and high efficiency without cost penalty.

The control of DFIG wind turbine systems is traditionally based on either stator flux oriented control (FOC) [5] or stator voltage oriented control (VOC) [6], These techniques decouple the rotor current into active and reactive power components; controlling of the active and reactive power is achieved indirectly by controlling the input currents. Some investigations using PI controllers by using FOC that generates reference currents from active and reactive power errors to the inverter or a cascade PI controllers that generate a rotor voltage which has been presented by [7, 8].

[*] Corresponding author.
E-mail: ydjeriri@yahoo.fr (Y. Djeriri).
Address: BP 89, Sidi Bel-Abbes, Algeria.

Therefore, the conventional PI controllers, because of their simple structures, are still the most commonly used control techniques in power systems, as can be seen in the control of the wind turbines equipped with DFIGs [6, 7, 8 and 9]. Unfortunately, tuning the PI controller is tedious and it might be difficult to tune the PI gains properly due to the nonlinearity and the high complexity of the system. Another main drawback of this controller is that its performance depends greatly on accurate machine parameters pertaining to the resistances (by warming-up) and inductances (by saturation).

The Artificial neural networks (ANNs) have been proven to be universal approximators of non-linear dynamic systems, their learning to examples leads to robust generalization capabilities by using an appropriate multilayer neural network [10]. In our study we learning the ANN to the PI controllers to design the NN controllers witch replace the all PI controllers used in the regulation of DFIG.

2. Modeling of the DFIG

In the rotating field reference frame of Park, the model of the DFIG is given by the following equations:

Equations of stator voltage components:

$$\begin{cases} V_{ds} = R_s.I_{ds} + \frac{d}{dt}\phi_{ds} - \omega_s.\phi_{qs} \\ V_{qs} = R_s.I_{qs} + \frac{d}{dt}\phi_{qs} + \omega_s.\phi_{ds} \end{cases} \quad (1)$$

Equations of rotor voltage components:

$$\begin{cases} V_{dr} = R_r.I_{dr} + \frac{d}{dt}\phi_{dr} - (\omega_s - \omega_r).\phi_{qr} \\ V_{qr} = R_r.I_{qr} + \frac{d}{dt}\phi_{qr} + (\omega_s - \omega_r).\phi_{dr} \end{cases} \quad (2)$$

Equations of stator flux components:

$$\begin{cases} \phi_{ds} = L_s.I_{ds} + L_m.I_{dr} \\ \phi_{qs} = L_s.I_{qs} + L_m.I_{qr} \end{cases} \quad (3)$$

Equations of rotor flux components

$$\begin{cases} \phi_{dr} = L_r.I_{dr} + L_m.I_{ds} \\ \phi_{qr} = L_r.I_{qr} + L_m.I_{qs} \end{cases} \quad (4)$$

Equation of DFIG electromagnetic torque:

$$T_{em} = -\frac{3}{2}.p.\frac{L_m}{L_r}.\left(\phi_{ds}.I_{qr} - \phi_{qs}.I_{dr}\right) \quad (5)$$

Generator active and reactive powers at the stator side are:

$$\begin{cases} P_s = \frac{3}{2}.(V_{ds}.I_{ds} + V_{qs}.I_{qs}) \\ Q_s = \frac{3}{2}.(V_{qs}.I_{ds} - V_{ds}.I_{qs}) \end{cases} \tag{6}$$

3. Field oriented control (FOC) strategy

To achieve a stator active and reactive power vector control, we choose a (d-q) reference frame synchronized with the stator flux. By setting the stator flux vector aligned with d-axis, we have: $\phi_{ds} = \phi_s$ and $\phi_{qs} = 0$.

Assuming that the resistance of the stator windings R_s is neglected (that's the case for medium and high power machines used in wind energy conversion systems [7, 11]), the voltage equations and flux equations of the stator windings can be simplified in study state as:

$$\begin{cases} V_{ds} = 0 \\ V_{qs} = V_s = \omega_s.\phi_s \end{cases} \tag{7}$$

$$\begin{cases} \phi_s = L_s I_{ds} + L_m I_{dr} \\ 0 = L_s I_{qs} + L_m I_{qr} \end{cases} \tag{8}$$

From (8), the equations linking the stator currents to the rotor currents are deduced below:

$$\begin{cases} I_{ds} = \frac{\phi_s}{L_s} - \frac{L_m}{L_r}.I_{dr} \\ I_{qs} = -\frac{L_m}{L_s}.I_{qr} \end{cases} \tag{9}$$

Taking into consideration the chosen reference frame, the active and reactive powers in (6) can be written as follows:

$$\begin{cases} P_s = \frac{3}{2}.V_s.I_{qs} \\ Q_s = \frac{3}{2}.V_s.I_{ds} \end{cases} \tag{10}$$

Replacing (9) in (10), the active and reactive powers at the stator side can expressed by:

$$\begin{cases} P_s = -\frac{3}{2}.\frac{L_m}{L_s}.V_s.I_{qr} \\ Q_s = \frac{3}{2}.V_s.\left(\frac{V_s}{L_s.\omega_s} - \frac{L_m}{L_s}.I_{dr}\right) \end{cases} \tag{11}$$

The electromagnetic torque is as follows:

$$T_{em} = -\frac{3}{2}.p.\frac{L_m}{L_s}.\phi_s.I_{qr} \tag{12}$$

Due to the constant stator voltage, the stator active and reactive powers are controlled by means of I_{qr} and I_{dr} respectively.

We could express the rotor voltages according to the rotor currents, thus we obtain:

$$\begin{cases} V_{dr} = R_r.I_{dr} - g.\omega_s.\left(L_r - \dfrac{L_m^{\ 2}}{L_s}\right).I_{qr} \\ V_{qr} = R_r.I_{qr} + g.\omega_s.\left(L_r - \dfrac{L_m^{\ 2}}{L_s}\right).I_{dr} + g.\dfrac{L_m.V_s}{L_s} \end{cases} \tag{13}$$

By using the simplified model of the DFIG and by establishing the FOC strategy, we can establish the global block diagram of the controlled system (Fig. 2).

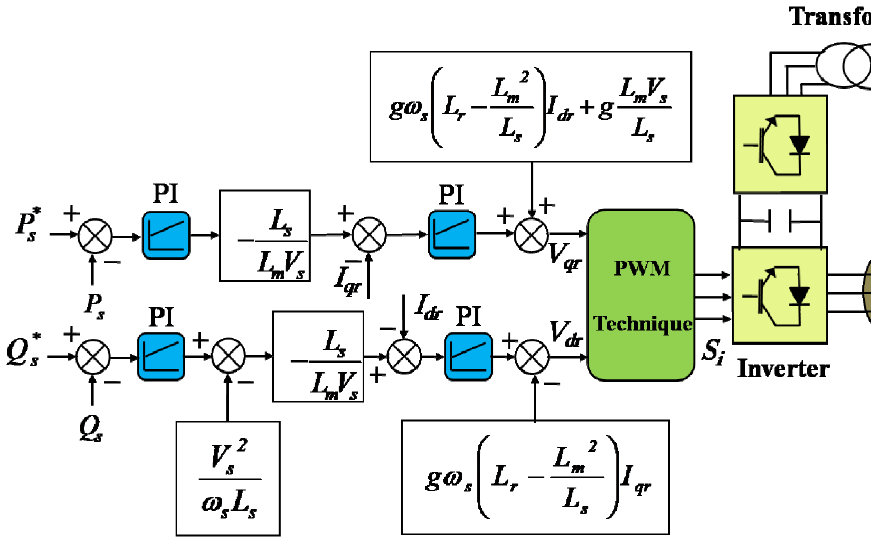

Fig. 2: Global block diagram of indirect field oriented control technique

4. Neural controller design

The dimension of the neural network making it possible to obtain a better result is impossible to fix. It was established that a neural network with only one hidden layer can make the approximation of any function, some parameters of ANNs cannot be determined from an analytical analysis of the process under investigation. This is the case of the number of hidden layers and the number of neurons belonging to them. By taking all these concepts in consideration, we can note that it is especially the experiment and the number of tests which direct us in the search of the number of neurons, and more exactly on optimal architecture by a given problem.

The optimal architecture of Multilayer Perceptron (MLP) in our case is to take one hidden layer containing three neurons for designing the numerical controllers, which replace the four PI controllers of powers and currents presented in the Fig. 2, in order to maintain high dynamic performances even when detuning occurs. At first, we are learning the MLP to the PI controller by presenting 15001 examples to the network with a maximal error of 10^{-20}, the number of epochs count maximum 10^3 with an iteration step of five. Then, the MLP must be trained in order to adjust and to find the adequate weights. The backpropagation algorithm named *Levenberg–Marquardt (LM)* [12, 13 and 14] is used to train the networks.

This method, which is an approximation of Newton's method, has been shown to be one of the fastest algorithms for training moderate size MLPs and ensures best convergence towards a minimum of the quadratic error; it's much more efficient than other techniques, such as conjugate gradient algorithm and variable learning rate algorithm, for the network with a few hundred weights [13].

5. Simulation results

In this part, simulations are investigated with a 1.5 MW generator connected to a 398V/50 Hz grid (Appendix), by using the MATLAB/SIMULINK software.

So as to really evaluate the performances of the tow controllers, we test and compare the responses of the tow last ones in tow cases:

In the first case, we initial simulation with various active and reactive power steps in nominal regime of DFIG; this last one is driven at supersynchronous speed $\Omega_t = 1700\ rmp$ (or g=-0.13). The active power step is changed from -0.6 MW to -1.2 MW between the instants t=0.5s and t=1s and again from -1.2 MW to -0.3 MW between t=1s and t=1.5s; while the reactive power step is changed from -0.3 MVAR to 0.3 MVAR at the instant t=0.7s. (The negative sign "-" refers to the generation of active power and to the absorption of reactive power). The active power, reactive power, stator current and rotor current responses are show in Fig. 3 for the PI controller and in Fig. 4 for the NN controller.

In the second case, we increase the rotor resistance of 100% (case of warming-up of rotor windings) and decrease all inductances of 10% (case of inductances saturation); we keep the same conditions as the precedent case such as the rotor speed and powers steps. Fig. 5 and 6 show the simulation results.

The results steps responses in Fig. 3 and 4 show that the NN controller has a faster time response than the PI controller. The PI controller is sensitive to the changes in the parameters of the DFIG especially to the inductance variations. The Fig. 5 and 6 prove the robustness of the NN controller; this does not depend on the parameter variations of DFIG and shows robust performance than the PI controller.

We notice that for the NN controller, the response time is almost degraded but the regulator nevertheless arrive to keep the powers responses to their references, and ensure a stable current delivered from the DFIG stator to the public network, contrary to the PI controller.

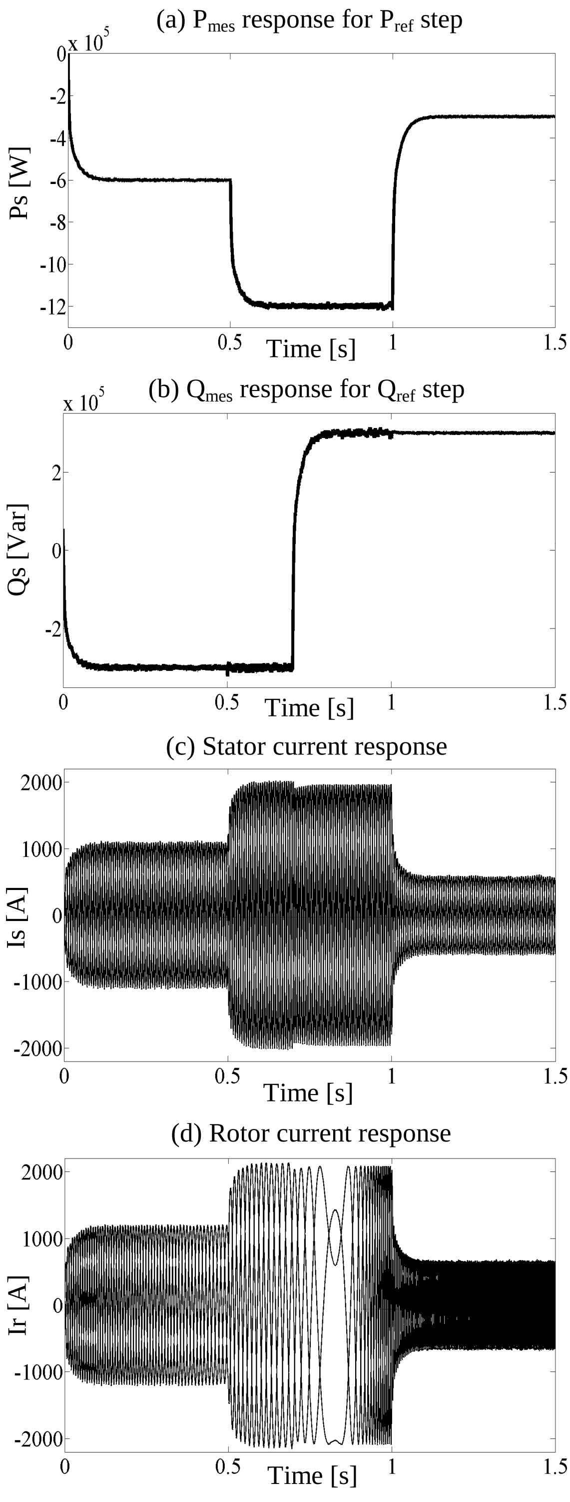

Fig. 3: PI controller responses in nominal regime of DFIG

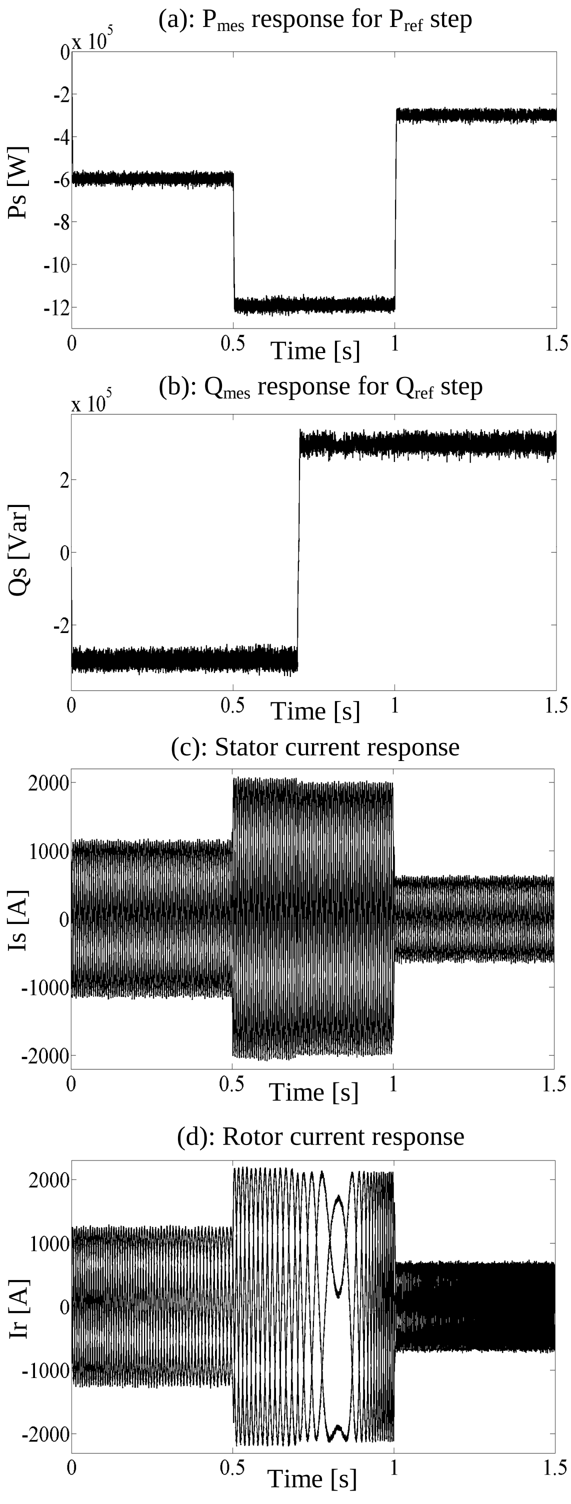

Fig. 4: NN controller responses in nominal regime of DFIG

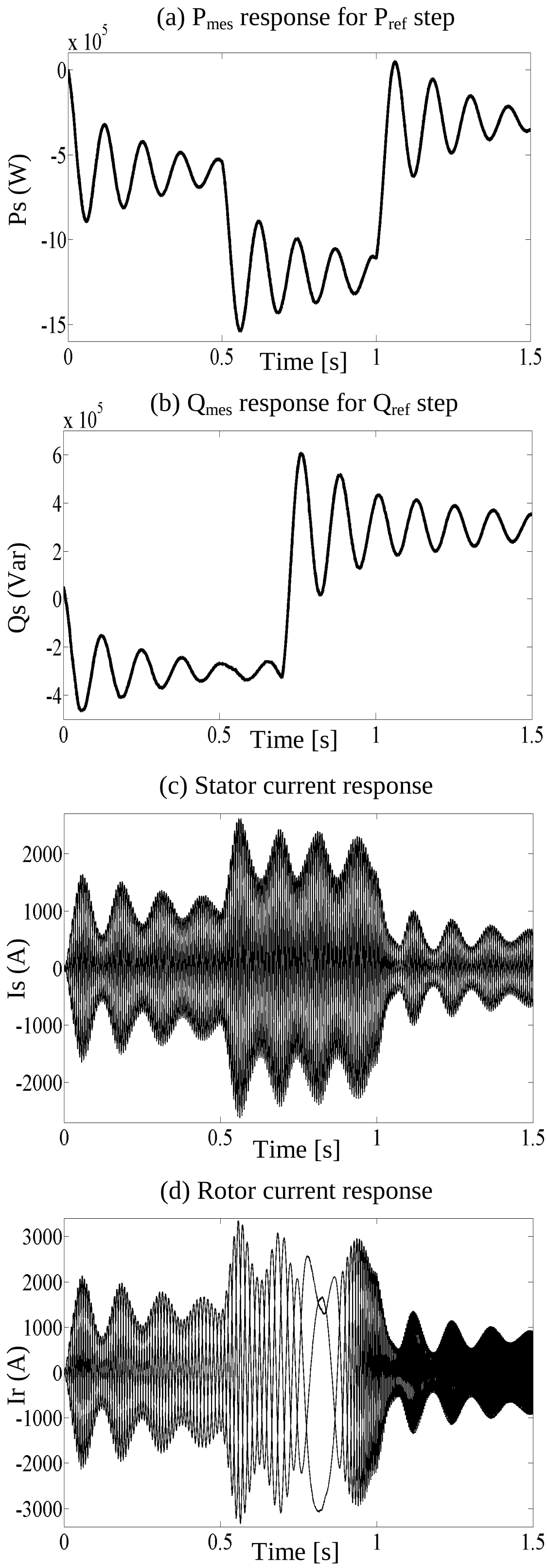

Fig. 5: PI controller responses against parameter variations

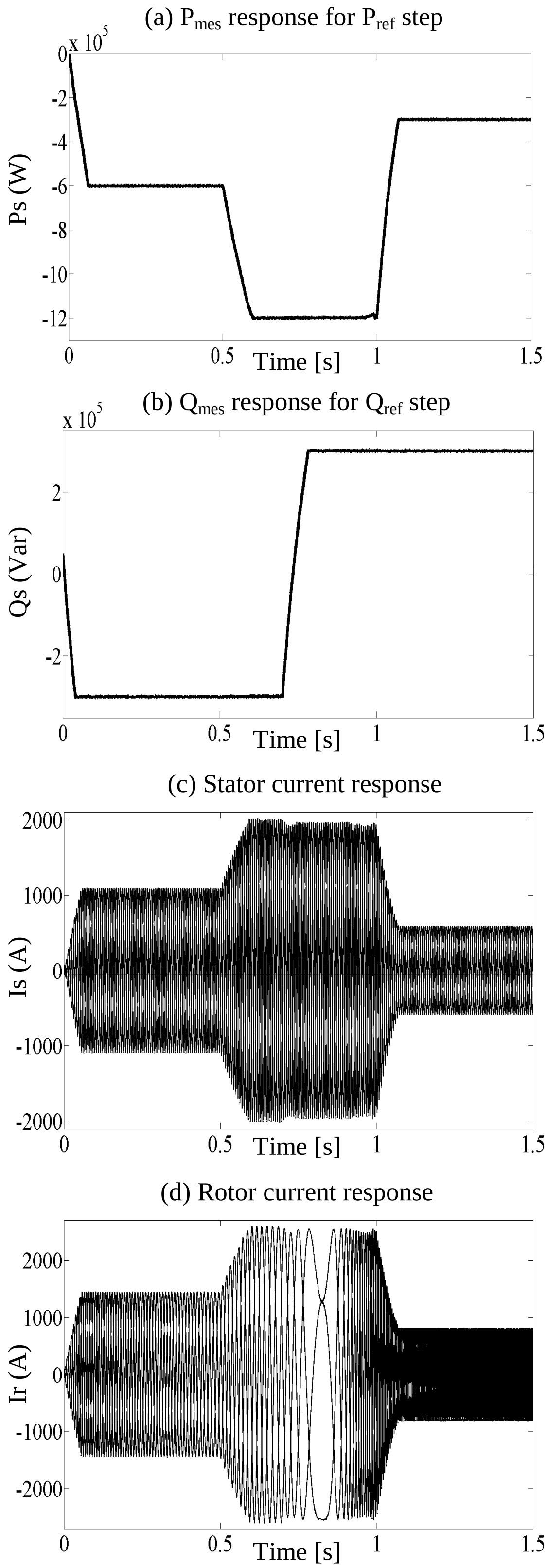

Fig. 6: NN controller responses against parameter variations

6. Conclusion

In this paper we introduced the mathematical model of the doubly fed induction generator dedicated for the variable speed wind turbines; with aim to controlling the stator active and reactive power of the DFIG connected to the public network, we have applied the stator field oriented control strategy. This last one is based on two types of controllers in our study: the first one is the PI controller and the second one is the NN based controller.

Simulation results show that the NN controller gives the best time response, and it's more robust against parameter variations of the DFIG than the PI controller. The big criterion to engineers and researches is to choose between both controllers mainly the requirements of the application in terms of high performances in ideal conditions and robustness in the case of parameter variations, involved in the field of the doubly fed induction generator based wind energy conversion systems.

7. References

[1] A. Petersson, Analysis, modeling and control of doubly fed induction generators for wind turbines, Ph.d.thesis, Champers University of Technology, Sweden, 2005.

[2] S. EL Aimani, B. François, F. Minne and B. Robyns, Modelling and simulation of doubly fed induction generators for variable speed wind turbines integrated in a distribution network, 10th European conference on power electronics and applications, Toulouse, France, 2-4 September 2003.

[3] R. Pena, J. C. Clare and G. M. Asher, Doubly fed induction generator using back-to-back PWM converters and its application to variable speed wind energy generation, IEE Proceedings – Electric Power Applications, vol. 143, no. 3, May 1996, pp. 231-241.

[4] K. C. Wong, S. L. Ho and K. W. E. Cheng, Direct torque control of a doubly fed induction generator with space vector modulation, Electric Power Components and Systems, vol. 36, no. 12, 2008, pp. 1337-1350.

[5] B. Hopfensperger, D. J. Atkinson and R. Lakin, Stator-flux-oriented control of a doubly-fed induction machine with and without position encoder, IEE Proc.-Electr. Power Applications, vol. 147, no. 4, July 2000, pp. 241–250.

[6] Y. Zhou, P. Bauer, J.A. Ferreira and J. Pierik, Control of DFIG Under Unsymmetrical Voltage Dip, IEEE Power Electronics Specialists Conference, 2007, pp. 933-938.

[7] A. Tapia, G. Tapia, J. X. Ostolaza, and J. R. Sáenz, Modeling and control of a wind turbine driven doubly fed induction generator, IEEE Trans. on Energy Conversion, vol. 18, no. 2, June 2003, pp. 194-204.

[8] F. Poitiers, Study and control of asynchronous generators for the wind energy utilization, Ph.d.thesis in electrical engineering, Polytechnic school of the University of Nantes, France, 19 December 2003.

[9] M. Yamamoto, O. Motoyoshi, Active and reactive power control for doubly-fed wound rotor induction generator, IEEE Transactions on Power Electronics, vol. 6, no. 4, October 1991, pp. 624-629.

[10] K. Hornik, M. Stinchcombe and H. White, Multilayer feed forward networks are universal approximators, Neural Networks, vol. 2, pp. 359-366, 1989.

[11] G. Tapia, A. Tapia and J. X. Ostolaza, Proportional–integral regulator based approach to wind farm reactive power management for secondary voltage control, IEEE Trans. Energy Conversion, vol. 22, no. 2, June 2007, pp 488-498.

[12] J. J. Moré, The Levenberg-Marquardt Algorithm: Implementation and Theory, Numerical Analysis, ed. G. A. Watson, Lecture Notes in Mathematics 630, 1977, Springer Verlag, pp. 105-116.

M. T. Hagan, M. Menhaj, Training feedforward networks with the Marquardt algorithm, IEEE Trans, Neural Networks 5 (6), 1994, pp. 989-993.

8. Appendix

Table I. Wind turbine parameters

Blade radius, R	35.25 m
Number of blades	3
Gearbox ratio, G	90
Moment of inertia, J	1000 $Kg.m^2$
Viscous friction coefficient, f_r	0.0024 $N.m.s^{-1}$
Cut-in wind speed	4 m/s
Cut-out wind speed	25 m/s
Nominal wind speed, v	16 m/s

Table II. Doubly fed induction generator parameters

Rated power, P_n	1.5 MW
Stator rated voltage, V_s Rated current, I_n	398/690 V 1900 A
Stator rated frequency, f	50 Hz
Stator inductance, L_s	0.0137 H
Rotor inductance, L_r	0.0136 H
Mutual inductance, L_m	0.0135 H
Stator inductance, R_s	0.012 Ω
Rotor inductance, R_r	0.021 Ω
Number of pair of poles, p	2