Robust power control of DFIG using artificial neural networks for a wind energy conversion system based energy storage unit

H . Mesai Ahmed , Y. Djeriri , A. Bentaallah
Electrical Department, Faculty of Electrical Engineering,
ICEPS Laboratory, Djillali Liabes University
Sidi Bel Abbes, Algeria
hamza.mesai_ahmed@univ-sba.dz

Abstract— *This paper presents the control of the dual fed induction generator (DFIG) using the Artificial Neural Networks (ANN), used in a variable speed wind energy conversion system. After having presented the simplified model of the DFIG, we approached its indirect vector control by stator field orientation. We focused on PI controllers for the control of active and reactive stator powers and the impact of its replacement by other neural controllers; which have a high robustness against parameters variations of DFIG. Simulation results on a 1.5 MW DFIG system are provided to demonstrate the robustness of the ANN controllers and the large interest of energy storage unit in such wind energy conversion systems.*

Keywords— ***Wind energy; DFIG; Artificial neural networks; Robustness; Storage system.***

I. INTRODUCTION

The latest generation wind turbines operate at variable speed. This type of operation makes it possible to increase the energy efficiency, to lower the mechanical loads and to improve the quality of the electrical energy produced. Compared to fixed speed wind turbines. These wind turbines often use the dual fed Induction machine (DFIM) as a generator because of its advantages. In fact, the most typical connection diagram of this machine is to connect the stator directly to the network, while the rotor is fed through two static converters in back-to-back mode (one MSC machine side and the other side GSC network). This last configuration allows operation of the variable speed wind turbine which gives the possibility of producing the maximum possible power over a wide range of speed variation (± 30% around the speed of synchronism). In addition, the static converters used for the control of this machine can be sized to pass only a fraction of the total power (which represents the power of the slip). This implies fewer commutative losses, a lower converter production cost and a reduction in the size of the passive filters, thus reducing costs and additional losses.

Indirect vector control based on classical PI (Proportional-Integral) controllers has traditionally been used to control the active and reactive power of the DFIG [1, 2]. This technique decouples the rotor current into active and reactive components and is obtained indirectly by controlling the input currents.

The techniques of artificial intelligence are currently known for their great potential to be able to solve problems related to industrial processes [3]. Among these techniques, we find genetic algorithms, neural networks, fuzzy logic, ... etc. which apply more and more in the control of the induction machine and the adaptation of its vector control. In our study, we looked at neural networks to synthesize robust controllers for parametric DFIG variations to replace the four classical PI controllers used in vector control, so we will examine the use of an energy storage system to preserve active power constant to the electrical network. Simulation results are presented to show the effectiveness of these controllers in solving the problem of robustness and compare their performance with conventional controllers.

II. SIMPLIFIED MODEL OF DFIG

The DFIG is represented by its Park model (d,q) whose equations are established in a reference linked to the rotating field as follows:

Stator voltages

$$\begin{cases} V_{sd} = R_s i_{sd} + \frac{d}{dt}\phi_{sd} - \omega_s \phi_{sq} \\ V_{sq} = R_s i_{sq} + \frac{d}{dt}\phi_{sq} + \omega_s \phi_{sd} \end{cases} \quad (1)$$

Rotor voltages

$$\begin{cases} V_{rd} = R_r i_{rd} + \frac{d}{dt}\phi_{rd} - (\omega_s - \omega_r)\phi_{rq} \\ V_{rq} = R_r i_{rq} + \frac{d}{dt}\phi_{rq} + (\omega_s - \omega_r)\phi_{rd} \end{cases} \quad (2)$$

The active and reactive stator and rotor powers are expressed by

$$\begin{cases} P_s = \frac{3}{2}\left(v_{sd}i_{sd} + v_{sq}i_{sq}\right) \\ Q_s = \frac{3}{2}\left(v_{sq}i_{sd} - v_{sd}i_{sq}\right) \end{cases} \tag{3}$$

The electromagnetic Torque

$$T_{em} = \frac{3}{2}p\frac{L_m}{L_s}(\phi_{sq}i_{rd} - \phi_{sd}i_{sq}) \tag{4}$$

With: p is the number of pole pairs of the DFIG.

In view of the vector control of the GADA, it is better to choose the d-q mark linked to the stator rotating field, which is relative to the frequency of 50 Hz (mains frequency). Therefore, the Park mark will be synchronized with the stator flux (Figure 1).

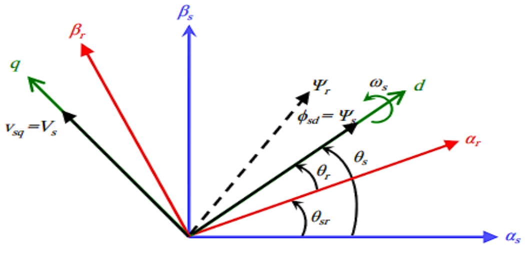

Fig. 1. *Orientation of the stator flux of the DFIG.*

Often in the case of a medium and high power DFIG, the stator resistance Rs is neglected during the synthesis of its model under the stator flow orientation hypothesis [4, 5].

By assuming the hypothesis that the stator resistance Rs is negligible and that the stator flux is constant and oriented along the axis d, we deduce:

$$\begin{cases} V_{rd} = R_r i_{rd} - g\omega_s\sigma L_r i_{rq} \\ V_{rq} = R_r i_{rq} + g\omega_s\sigma L_r i_{rd} + g\frac{L_m V_s}{L_s} \end{cases} \tag{5}$$

The adaptation of the power equations (3) to the selected system of axes and to the simplifying hypotheses carried out in our case (Vsd = 0) gives:

$$\begin{cases} P_s = -\frac{3}{2}V_s\frac{L_m}{L_s}i_{rq} \\ Q_s = \frac{3}{2}\left(V_s\frac{\Psi_s}{L_s} - V_s\frac{L_m}{L_s}i_{rd}\right) \end{cases} \tag{6}$$

$$T_{em} = -\frac{3}{2}p\frac{L_m}{L_s}\Psi_s i_{rq} = -\frac{3}{2}p\frac{L_m V_S}{L_s\omega_s}i_{rq} \tag{7}$$

III. INDIRECT VECTOR CONTROL

This method consists of taking into account the coupling terms (Cd and Cq) and compensating for them by using a system comprising two loops making it possible to control the rotor powers and currents. In this method, the decoupling is done at the output of the regulators in rotor current with a return of the system, which allows the adjustment of the powers (figure 2).

IV. CONTROL BY ARTIFICIAL NEURAL NETWORKS

A "formal neuron" (artificial) is a nonlinear and bounded algebraic function whose value depends on parameters called coefficients or weights. The variables of this function are usually called "inputs" of the neuron, and the value of the function is called its "output" [6].

A neuron is therefore above all a mathematical operator, whose numerical value can be calculated by a few lines of software. It has become customary to graphically represent a neuron as shown in Figure 3.

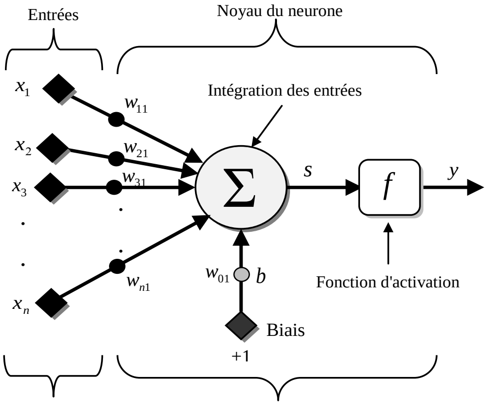

Fig 2. *Model of an artificial neuron.*

From biological neuron observations, follows the model of the formal neuron proposed by W. M. Culloch and W. Pitts in 1943:

- The represent the input vectors, they come either from the outputs of other neurons, or from sensory stimuli (visual sensor, sound ...);
- The are the synaptic weights of the neuron. They correspond to synaptic efficiency in biological neurons (excitatory synapse, inhibitory synapse). These weights weights the inputs and can be modified by learning;
- Bias: input often takes the values -1 or +1 which allows to add flexibility to the network by allowing to vary the threshold of trigger of the neuron by the adjustment of the weights and the bias during learning;
- Core: integrates all inputs and bias and calculates neuron output according to an activation function that is often nonlinear to give greater learning flexibility.

In our work, the multilayer static network used as a neural controller of active and reactive power has a single neuron input layer, a hidden layer of 5 neurons and an output layer to a neuron. For the controllers of the rotor currents only 3 neurons are used in the hidden layer. The activation functions of the first two layers are respectively the "logsig" function and the "tansig" function, while the "linear" function is used for the output layer. Its learning is carried out using the error-based gradient propagation algorithm [7].

The architecture of this neural network is shown in Figure 4, the choice of this structure was made by simulation [8]:

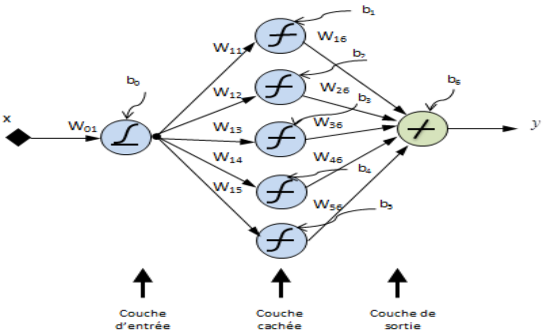

Fig 3. *Neural architecture proposed for the implementation of the controller.*

The update of the weights and the Bias of this network is realized by an algorithm of backpropagation called the Levenberg-Marquardt algorithm [9, 10].

gorithm changes the weight of a network whose architecture is set by the operator, whenever an example is presented. This change is made of such a fate to minimize the error between the desired output and the response of the network to an input. This is achieved through the gradient descent method. At each iteration, the input signal propagates in the network in the input-output direction, an output is thus obtained, the error between this output and the desired output is calculated and then by backpropagation "error back-propagation", errors intermediates corresponding to the hidden layer are thus calculated and allow the weight of the hidden layer to be adjusted [7, 11].

The gradient retropropagation algorithm therefore comprises two phases:

1- Propagation: at each stage, the network is presented with an input example. This input is propagated to the output layer.

2- Correction: for sure, the network will not provide exactly what was expected. An error (usually the mean squared sum of errors for all output neurons) that is back-propagated in the network is therefore calculated. This process is interrupted as soon as the overall error is estimated will be sufficient.

V. SIMULATION RESULTS AND DISCUSSION

The indirect control strategy in power of the DFIG by the neural networks has been validated by numerical simulation using the MATLAB / SIMULINK software for the wind speed profile and power coefficient max. The overall control scheme is summarized in FIG 4. All of its blocks are first programmed separately using the expressions detailed in the text. Only the basic elements of the Simulink library are used with fixed step size of sampling frequency 10^{+5} Hz. The DFIG used in this work is of 1.5 MW, whose nominal parameters are indicated in appendix.

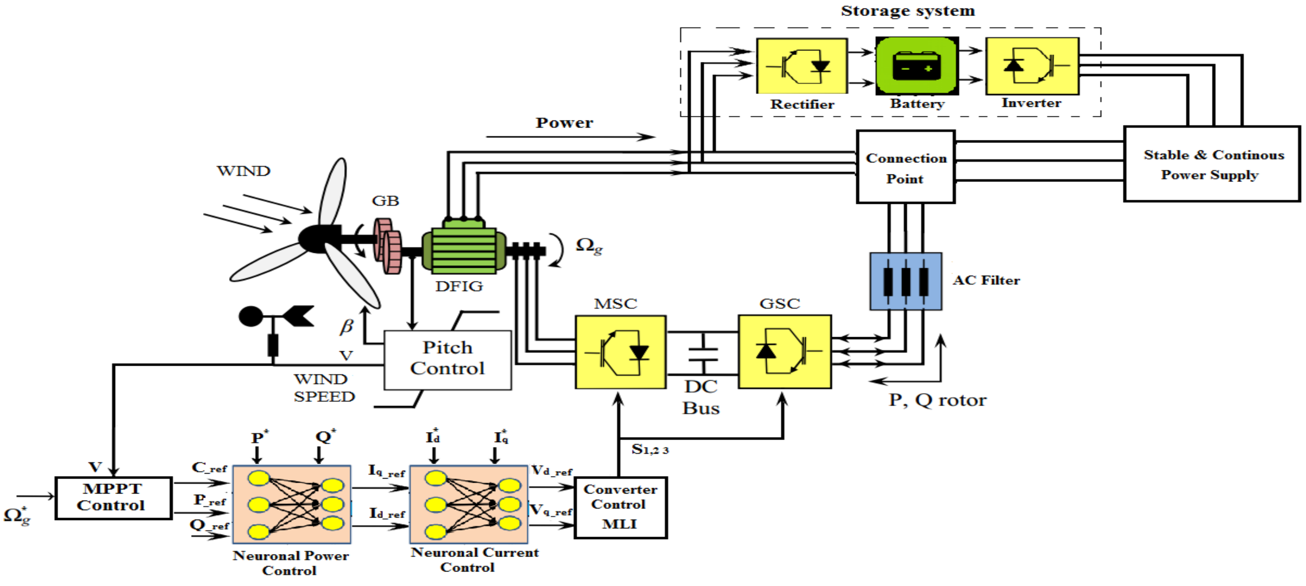

Fig 4. *Bloc diagram of the global wind conversion system based on DFIG*

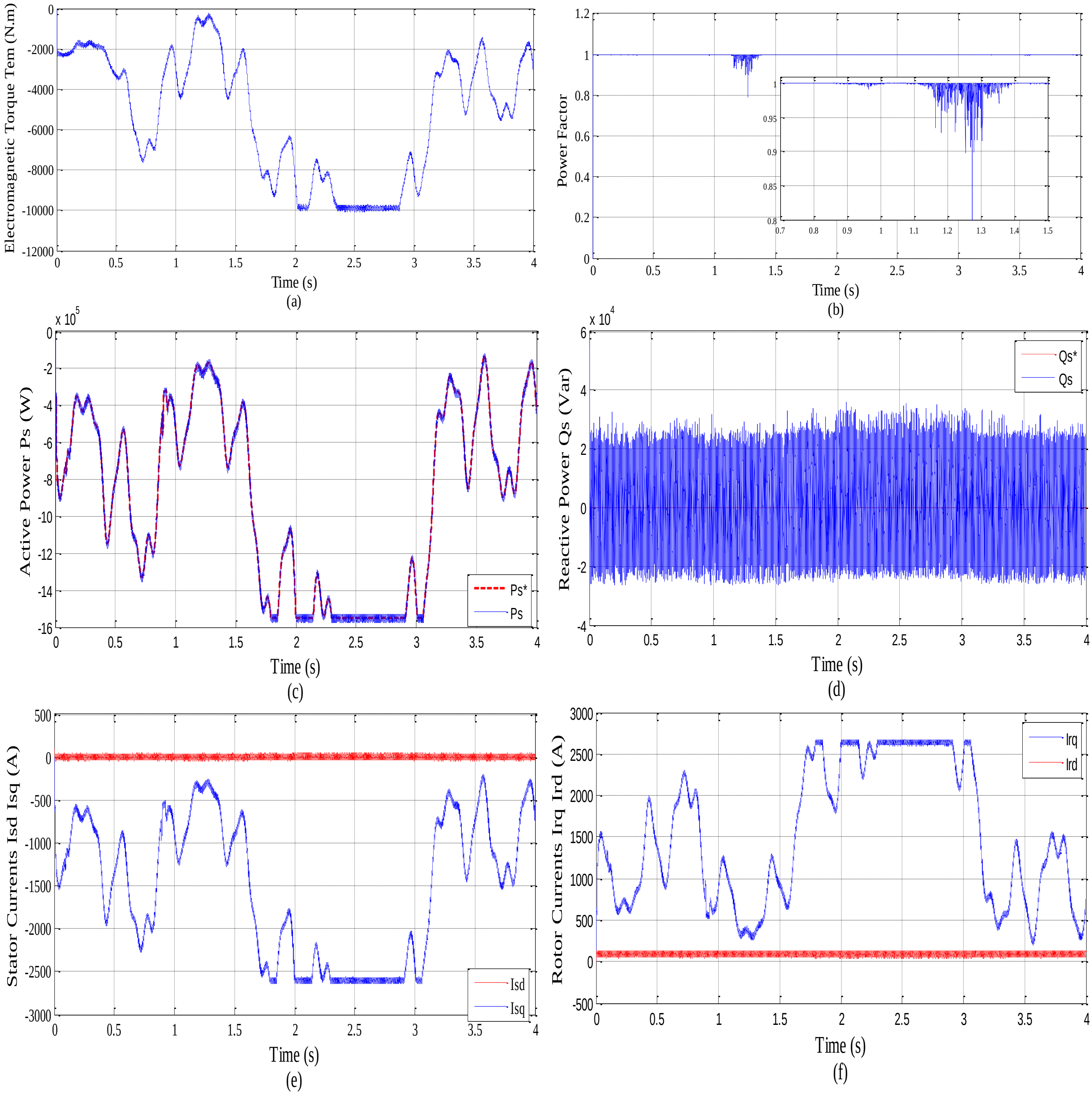

Fig 5. *Simulation results of indirect control by neural networks.*

It is clear from Fig 5.a that the electromagnetic torque generator follows its reference resulting from the MPPT control. We can see from Fig 5.e that The current of the stator depending on the imposed wind profile also because it is image of the active power, since we considered that the stator of the DFIG connected to a source of perfect tension (398V, 50Hz). In order to get a unit power-factor in network side (figure 5.b) , the reactive power reference is fixed at zero value (is shown in Fig 5.d).

An essential characteristic of the wind being the discontinuity in time, for this, during periods of high wind speeds, the generator will provide 750 kW to the grid and recharge the storage unit with the excess of available power. The power to be stored is the difference between the power extracted from the wind and the power supplied to the grid:

$$P_{stock} = P_t - P_{grid}$$

Or just :

$$P_{stock} = P_t^* - 750\,kW$$

We can now choose the power of the storage unit which will be 750 kW; (See Figure 6)

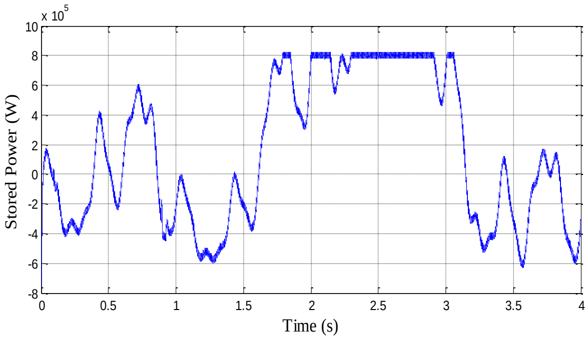

Fig 6. *Stored Power*.

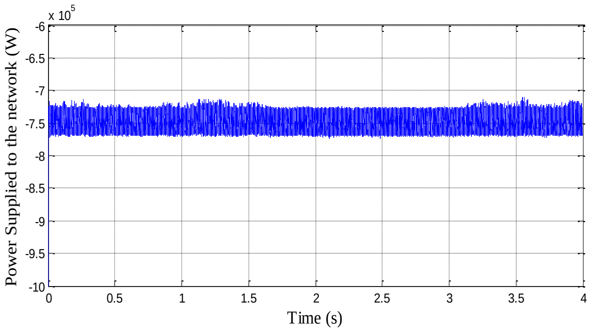

Fig 7. *Power Supplied to the network.*

- **Robustness test**

The purpose of this test is to test the robustness of the two regulators (PI-ANN) with respect to the variations of the parameters of the DFIG. We will perform a decrease of the mutual inductance (30% of Lm), which corresponds to a saturation effect of the magnetic circuit of the machine.

From the results obtained in FIG. 7, it can be seen that the artificial neural network (ANN) -based regulator offers a great deal of robustness in view of the variation in mutual inductance. On the other hand, the PI regulator is very fragile in the face of changes in the DFIG parameters, where the dynamic and static performance of the control are degraded.

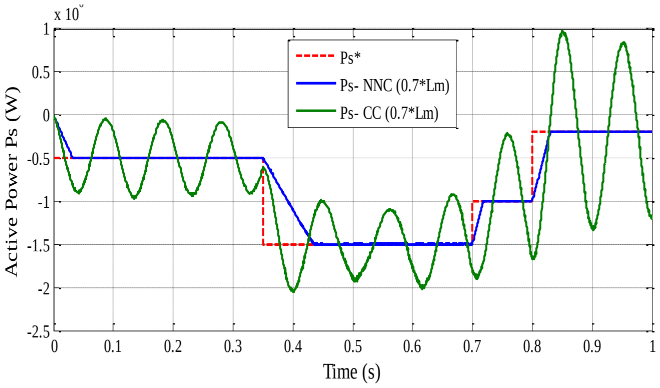

Fig 7. *Neural and classical PI controllers face parametric variations of DFIG.*

We can summarize the dynamic and static performances obtained by the two regulators in the normal state of operation (without parametric change) by the following comparative table:

TABLE I. Comparison of the performances of the two regulators

		Regulators	
Performances		**PI**	**NNC**
Response time (ms)		6	0.97
Exceeding (%)		6	4.4
Static error	(%)	0.6	0.77
	(W)	9000	11600
Robustness vis-a-vis variation parametric		Bad	Strong
THD I_s (%)		1.44	12.15

VI. CONCLUSION

In this paper, the vector control of DFIG based on artificial neural networks has been exposed, which we have synthesized a neural controller. To train this type of network the backpropagation method is the learning algorithm that remains the most used in this field. We can say that offline learning leads to a much more efficient control because it allows the neural controller to refine throughout the ordering process.

The incorporation of a storage battery or other energy storage device in the wind system allows a temporary storage of energy and therefore the ability to provide a constant active power injected into the network, both deterministic and resistant to fluctuations the speed of the wind.

The results of the simulation showed, on the one hand, the effectiveness of neural regulators in improving the robustness of the vector control vis-a-vis the parametric changes of the DFIG, compared to conventional PI-type regulators. On the other hand, they have proved the great interest of the energy storage system in such wind energy conversion systems.

- *Abbreviations and Acronyms*

L_m	Magnetizing inductance
R_r	Rotor resistance
R_s	Stator resistance
L_r	Rotor inductance
L_s	Stator inductance
g	Sliding
ω_s	Synchronous reference Speed
ω_r	Rotor electrical angular speed
V_{ds} V_{qs}	d-q stator voltages
V_{dr} V_{qr}	d-q rotor voltages
$Ø_{ds}$ $Ø_{qs}$	d-q stator flux
$Ø_{dr}$ $Ø_{qr}$	d-q rotor flux
I_{ds} I_{qs}	d-q stator currents
I_{dr} I_{qr}	d-q rotor currents
P_s Q_s	Active and réactive Power
T_{em}	Electromagnetic Torque
DFIG	Dual Fed Induction Generator
MPPT	Maximum Power Pointe Tracking
ANN	Artificial Neural Network
GSC	Grid Side Converter
MSC	Machine Side Converter
NNC	Neural Network Controler
CC	Classical Controler

TABLE II. Appendix parameters

Turbine				
R (m)	Number of blades	G	C_{pmax}	λ_{opt}
35.25	3	90	0.48	8.01

DFIG						
P_n (MW)	U_s (V)	F (Hz)	Pair poles	I_n (A)	U_r (V)	L_m (H)
1.5	398/690	50	2	1900	225/389	0.0045
R_s (Ω)	R_r (Ω)	L_s (H)	L_r (H)	L_m (H)	U_{dc} (V)	J (kg.m^2)
0.012	0.021	0.0137	0.0136	0.0135	1200	1000

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