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Literature review on the control of brushless doubly-fed induction machines

Ulrich Ngnassi Nguelcheu [1, *], Ngasop Ndjiya [2], Eric Duckler Kenmoe Fankem [1], Aslain Brisco Ngnassi Djami [3], Golam Guidkaya [1] and Alix Tioffo Dountio [1]

[1] *Department of Physics, Faculty of science, University of Ngaoundere, Ngaoundere, Cameroon.*

[2] *Department of Electrical Engineering, Energy and Automation, National Advanced School of Agro-Industrial Sciences, University of Ngaoundere, Ngaoundere, Cameroon.*

[3] *Department of Fundamental Sciences and Techniques of Engineer, Chemical Engineering and Mineral Industries School, University of Ngaoundere, Ngaoundere, Cameroon.*

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Abstract

In recent years, dual-fed brushless asynchronous generators (BDFIG) have attracted considerable attention in variable-speed drive applications due to their simple and robust structure, good operating characteristics, and low maintenance requirements. The purpose of controlling dual-fed brushless induction generators is to achieve better performance. However, various control techniques applied to this machine have shown their limits in case of sudden fluctuations in rotor speed, relatively long response time, poor stability and high performance sensitivity to parameter fluctuations. Given its difficulty, research has focused on the most advanced technology in the world: artificial intelligence (AI). The main objective of this article is to list all the control techniques that have been applied to the BDFIG. It appears from our study that genetic algorithms as well as the multilayer perceptron have not yet been applied for the control of BDFIG.

Keywords: BDFIG; Artificial intelligence; Control techniques; Performance

1. Introduction

Over the past two decades, wind power generation has grown rapidly [1, 2]. Because wind energy does not emit any greenhouse gases. Currently, the conversion of wind energy to electricity relies heavily on dual-fed induction generators (DFIG) [3, 4] for variable speed applications. This is due to the benefits such as variable speed operation and on-grid reactive power capability provided by DFIG [2]. However, the use of dual-fed generators leads to an increase in the cost and complexity of the power-generating unit [4]. The main problem with this setup is the need for a wound rotor and brushes/slip rings to transfer power to and from the rotor windings [2]. These aspects increase the maintenance workload, which is a particular problem for offshore systems [5]. An alternative to DFIG that can alleviate these issues is the dual-Fed Brushless Induction Generator (BDFIG). The BDFIG has two three phase stator windings, a power winding (PW) and a control winding (CW) [6]. Many articles describe different control schemes for the BDFIG.

Artificial intelligence (AI) refers to the development of computer systems capable of performing tasks that normally require human intelligence, such as visual perception, speech recognition, decision making, and language translation [7]. AI systems use algorithms and statistical models to analyze and learn from data, then apply that knowledge to perform specific tasks.

* Corresponding author: Ulrich Ngnassi Nguelcheu

The rise of artificial intelligence is due to the interaction of two main factors, in particular the digitization of microprocessors, which allows the creation of massive volumes of data; and increasing the computing power and storage capacity of IT tools.

In this article, we present the description and modeling of the BDFIG; We then introduce the most important classical control techniques and advanced control techniques using artificial intelligence. Finally, we present the main previous works on the advanced control of dual-feed machines using artificial intelligence in order to give an overview of the current state of research.

2. Machine description and modeling

2.1. Description

Invented in the mid-1980s at Oregon State University, the brushless doubly-fed induction motor (BDFIM) is a twin-stator wound motor that has been extensively studied [8,9]. The BDFIM is an induction motor that can work in both asynchronous and synchronous modes, the latter being the best [10].

2.2. Machine Modelling

Of the two stator windings of the BDFIG, the power winding (PW) is directly connected to the grid, while the control winding (CW) is connected to the grid through a partially rated bidirectional power electronic converter [11]. In order to avoid direct coupling between the two windings, the two windings preferably have different numbers of pole pairs [12]. A specially designed rotor is capable of coupling to both windings, creating a cross-coupling effect between PW and CW. In order to achieve the ideal cross-coupling effect with a simple rotor structure, the number of rotor loops should be selected as follows [13]:

$$N_r = p_p + p_c \tag{1}$$

It is also desirable to prevent direct transformer coupling between the two stator windings. This can be achieved by satisfying the following constraint [14, 5]:

$$p_p \neq p_c \tag{2}$$

To achieve the desired cross-coupling effect, both PW and CW must induce currents in the rotor bars with the same frequency [15].The synchronous rotor speed, ω_r, determined by the excitation frequencies of the two stator windings, is expressed as:

$$\omega_r = \frac{\omega_p + \omega_c}{P_p + P_c} \tag{3}$$

The above relationship can be satisfied by using a synchronous approach in the startup phase [16]. The BDFIG exhibits a stable behavior after reaching a synchronous operating mode, and then the rotor speed can be easily controlled by controlling the frequency of the windings [17, 18]. The rotor speed at which the CW angular frequency is zero is defined as the natural angular frequency ω_n, and expressed as

$$\omega_n = \frac{\omega_p}{P_p + P_c} \tag{4}$$

For the system studied in this paper, the grid frequency is taken to be 50 Hz and the number of pole-pairs of PW and CW are selected to be one and three, respectively, in accordance with [17, 12]. The corresponding natural synchronous speed is then 750 rpm. BDFIG can be modeled in the Park reference frame by the following electrical equations [20, 12]:

$$V_{sp}^q = R_{sp} i_{sp}^q + \frac{d\Psi_{sp}^q}{dt} + \omega_p \Psi_{sp}^d \tag{5}$$

$$V_{sp}^d = R_{sp} i_{sp}^d + \frac{d\Psi_{sp}^d}{dt} - \omega_p \Psi_{sp}^q \tag{6}$$

$$0 = R_r i_r^q + \frac{d\Psi_r^q}{dt} - (\omega_p - p_p\omega_r)\,\Psi_r^d \tag{7}$$

$$0 = R_r i_r^d + \frac{d\Psi_r^d}{dt} - (\omega_p - p_p\omega_r)\,\Psi_r^q \tag{8}$$

$$V_{sc}^q = R_{sc} i_{sc}^q + \frac{d\Psi_{sc}^q}{dt} + (\omega_p - (p_p + p_c)\omega_r)\,\Psi_{sc}^d \tag{9}$$

$$V_{sc}^d = R_{sc} i_{sc}^d + \frac{d\Psi_{sc}^d}{dt} - (\omega_p - (p_p + p_c)\omega_r)\,\Psi_{sc}^q \tag{10}$$

Expressions for the flux linkages of the two stator windings and the rotor are (Figure 1) [21]:

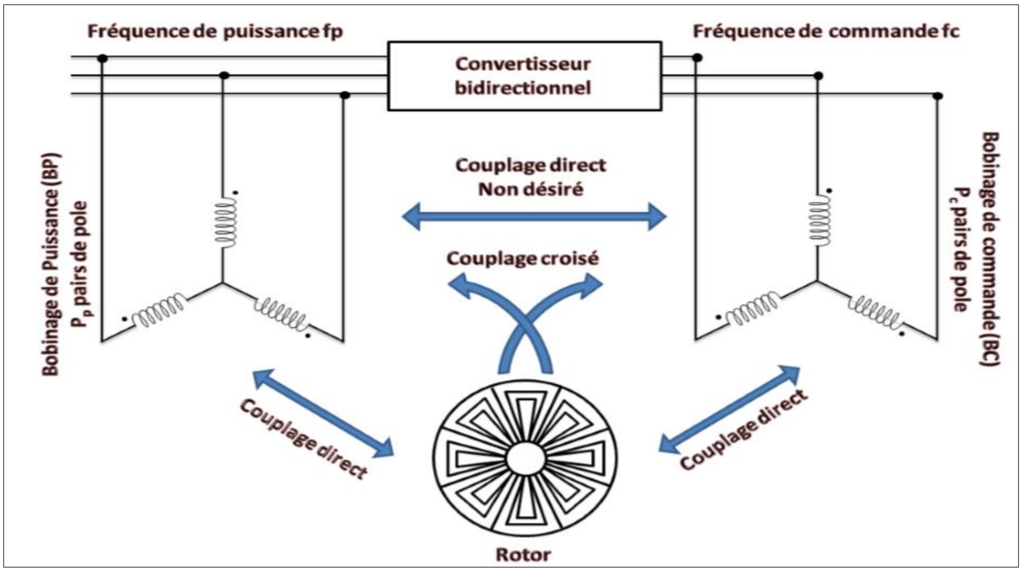


Figure 1 Basic structure of BDFIG [17, 22].

$$\Psi_{sp}^q = L_{sp} i_{sp}^q + L_{mp} i_r^q \tag{11}$$

$$\Psi_{sp}^d = L_{sp} i_{sp}^d + L_{mp} i_r^d \tag{12}$$

$$\Psi_{sc}^q = L_{sc} i_{sc}^q + L_{mc} i_r^q \tag{13}$$

$$\Psi_{sc}^d = L_{sc} i_{sc}^d + L_{mc} i_r^d \tag{14}$$

$$\Psi_r^q = L_{mp} i_{sp}^q + L_r i_r^q + L_{mc} i_{sc}^q \tag{15}$$

$$\Psi_r^d = L_{mp} i_{sp}^d + L_r i_r^d + L_{mc} i_{sc}^d \tag{16}$$

The electromagnetic torque is given by:

$$T_{em} = \frac{3}{2}\left(p_p\left(\Psi_{sp}^d i_{sp}^q - \Psi_{sp}^q i_{sp}^d\right) + p_c L_{mc}\left(i_{sc}^d i_r^q - i_{sc}^q i_r^d\right)\right) \tag{17}$$

Also, the mechanical dynamic equation of BDFIG can be written as:

$$J\,\frac{d\omega_m}{dt} = T_{em} - f\omega_m - T_g \tag{18}$$

The active and reactive powers of the PW and CW are respectively given by [19, 23]:

$$P_p = \frac{3}{2}\left(V_{sp}^q i_{sp}^q + V_{sp}^d i_{sp}^d\right) \tag{19}$$

$$Q_p = \frac{3}{2}\left(V_{sp}^{q} i_{sp}^{d} + V_{sp}^{d} i_{sp}^{q}\right) \quad (20)$$

$$P_c = \frac{3}{2}\left(V_{sc}^{q} i_{sc}^{q} + V_{sc}^{d} i_{sc}^{d}\right) \quad (21)$$

$$Q_c = \frac{3}{2}\left(V_{sc}^{q} i_{sc}^{d} + V_{sc}^{d} i_{sc}^{q}\right) \quad (22)$$

The total active and reactive powers provided for the grid neglecting losses in the back-to-back converters will then be [24, 6]:

$$P_T = P_p + P_c \quad (23)$$

$$Q_T = Q_p + Q_c \quad (24)$$

3. Classic control strategies

There are several control strategies that can be used for BDFM, including:

3.1. Vector Control

The Vector control is a widely used strategy for BDFM. The machine's stator and rotor currents as well as torque and speed are controlled according to a mathematical model of the machine [25,1,26]. This control strategy has the advantage of high precision and good performance, but requires a high level of computing power and is more complex to implement than other control strategies (figure 2) [27, 28].

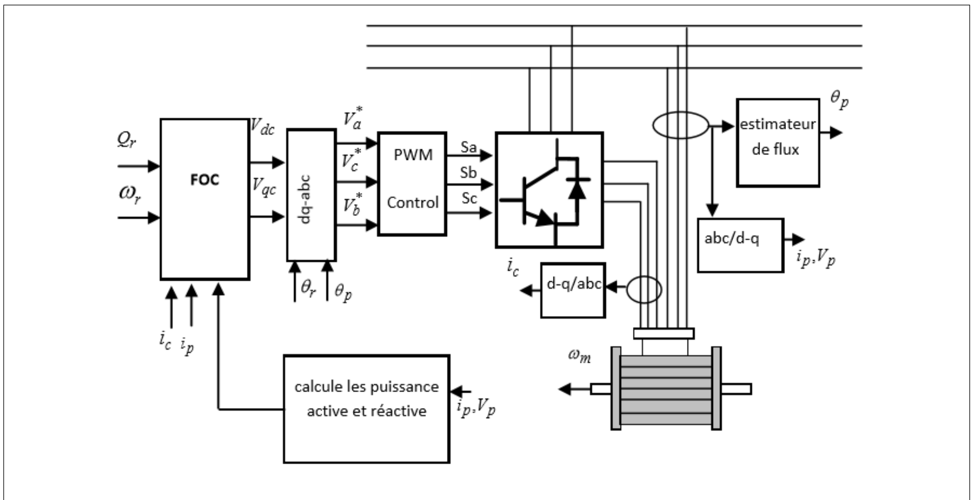


Figure 2 Block diagram of vector control [29, 30].

3.2. Direct Torque Control

Compared with vector control, direct torque control is a simpler control strategy because it does not require a mathematical model of the machine [17]. Instead, it controls the machine's torque directly based on stator and rotor currents. The advantage of this control strategy is that it is easier to implement and requires less computing power, but it may not provide the same precision as vector control (Figure 3).

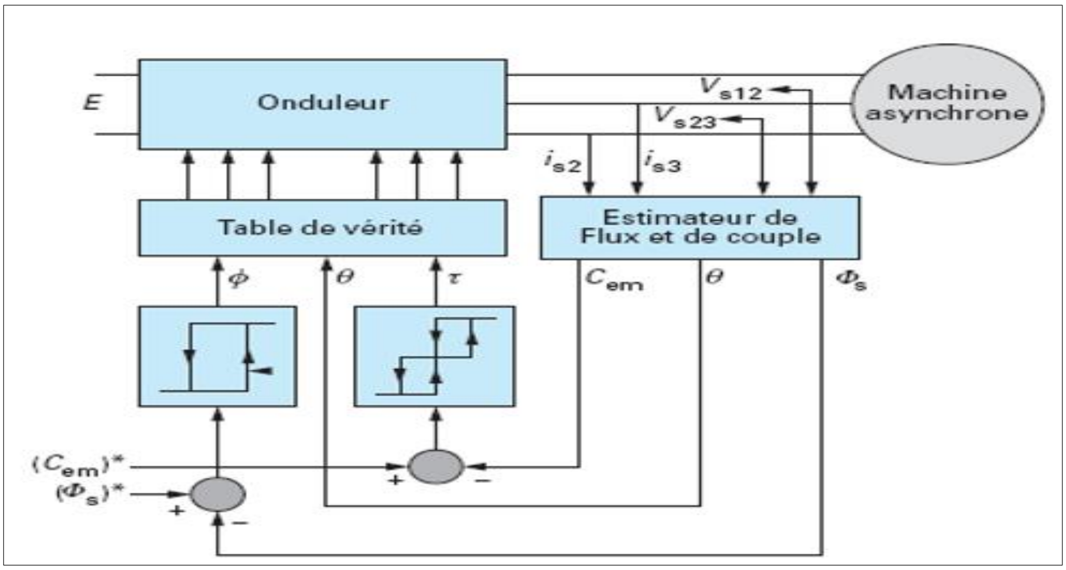


Figure 3 Block diagram of DTC [22].

3.3. Field-oriented Control

Field Oriented Control is a control strategy that converts three-phase stator currents into two-phase currents that match the rotor flux. This allows for more precise control of the machine's torque and speed. This control strategy has the advantage of providing good performance and is relatively easy to implement, but it may be more sensitive to parameter changes and may require additional sensors to estimate the rotor position [31].

3.4. Sliding Mode Control

Sliding mode control is a robust control strategy that can handle disturbances and uncertainties in the system. During this process, a planing surface is created for the machine's behavior to follow, and control inputs are adjusted to keep the system on the planing surface. This control strategy has the advantage of being robust to uncertainties and disturbances, but may require more complex control algorithms and may result in higher noise and vibration levels [32].

4. control techniques using Artificial intelligence (AI)

Artificial intelligence is one of the most advanced technologies in the field of machine control. In the field of artificial intelligence, we have several control techniques.

4.1. Reinforcement Learning (RL)

Reinforcement learning is a form of machine learning in which an agent learns to take actions in an environment to maximize a reward signal. In control applications, reinforcement learning can be used to learn optimal control strategies for a given system. Reinforcement learning has shown promising results in controlling robotic systems and autonomous vehicles. Reinforcement learning can be used to learn control policies for systems whose dynamics are not well understood or whose optimal control policy is not easily determined [33].

4.2. Deep Reinforcement Learning (DRL)

DRL is an extension of RL that uses deep neural networks to represent policy functions. DRL has been used to solve complex control problems in robotic systems, such as grasping and manipulation. DRL can handle high-dimensional state and action spaces and learn complex control policies that are difficult to manually design [33].

4.3. Evolutionary Algorithms (EA)

EA is a population-based optimization technique that mimics the process of natural selection. In control applications, EA can be used to optimize the control parameters of the system [34, 35]. EA has been used to optimize the control parameters of industrial automation systems and drones. EAs can handle nonlinear and non-convex optimization problems and find optimal solutions in complex search spaces [36, 37].

4.4. Fuzzy Logic Control (FLC)

FLC is a control strategy that uses fuzzy logic to map input variables to output variables [38, 39]. FLC can handle nonlinear and uncertain systems and is used in various control applications such as HVAC (heating, ventilation and air conditioning) systems and robotics. FLC is particularly useful for systems where the control rules are not well defined or where there is significant uncertainty in the system dynamics. [40, 41, 42].

4.5. Model Predictive Control (MPC)

MPC is an advanced control strategy that uses a mathematical model of a machine to predict its behavior and optimize its performance. The goal is to solve the optimization problem at each time step to determine the optimal control inputs. This control strategy has the advantage of being able to handle nonlinearities and uncertainties in the system, but it requires a high level of computing power and is more complex to implement than other control strategies [43].

4.6. Artificial Neural Networks (ANNs)

Artificial neural networks are computational models inspired by the structure and function of the brain. Artificial neural networks can be used to learn control policies for systems and have been used in various control applications such as robotic systems and process control [44]. Artificial neural networks can learn complex mappings between input and output variables and process high-dimensional state and action spaces. [45].

4.7. Probabilistic Approaches

Probabilistic methods such as Bayesian networks and Markov decision processes can be used to model and control unsafe systems. These methods have been used in various control applications such as robotics and autonomous vehicles. Probabilistic methods can deal with uncertainties in system dynamics and provide probabilistic estimates of system behavior [46].

5. Scientific articles using AI for DFIM and BDFIG Control

In 2010 A. Meroufel and his collaborators published an article titled « Vector control by artificial Neural Network based control of a DFIM». This work is dedicated to active and reactive energy vector control via neural networks for doubly-fed induction motors (DFIM) integrated into wind power systems. The power transmission between the stator and the grid takes place via a bidirectional converter acting on the rotor signal. For comparative studies, the independent control of active and reactive power is ensured by a traditional controller (PI) in the first step and by a neural controller (RN) in the second step.

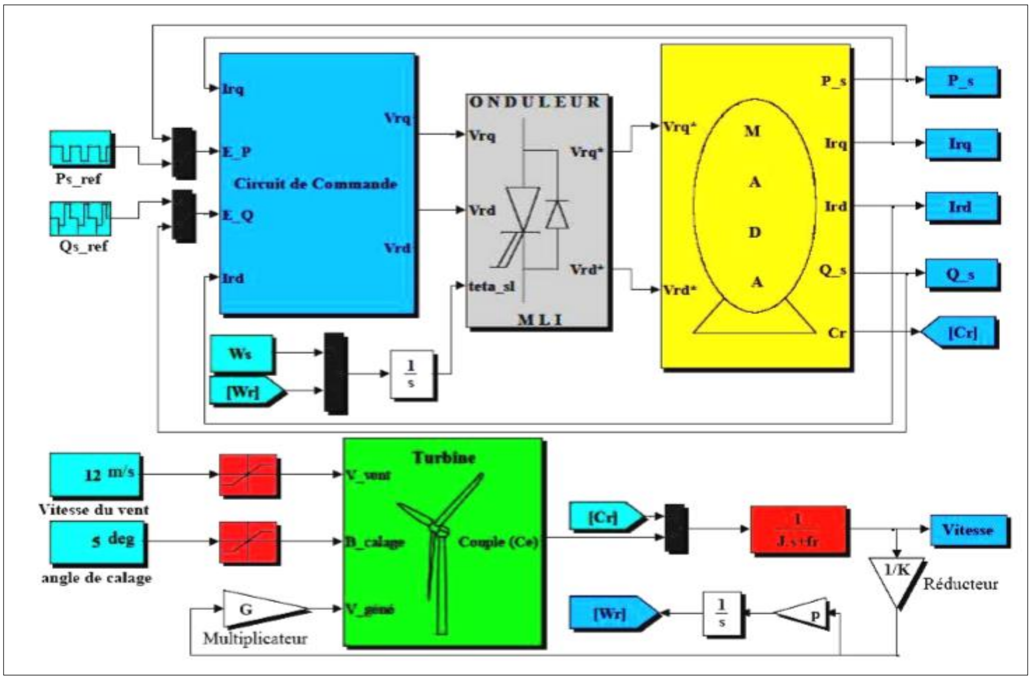


Figure 4 Block diagram of the indirect control of the DFIM with PI controller [47].

They used a multilayer perceptron with 2 neurons in the input layer, 3 neurons in the hidden layer, and 1 neuron in the output layer (Figure 5).

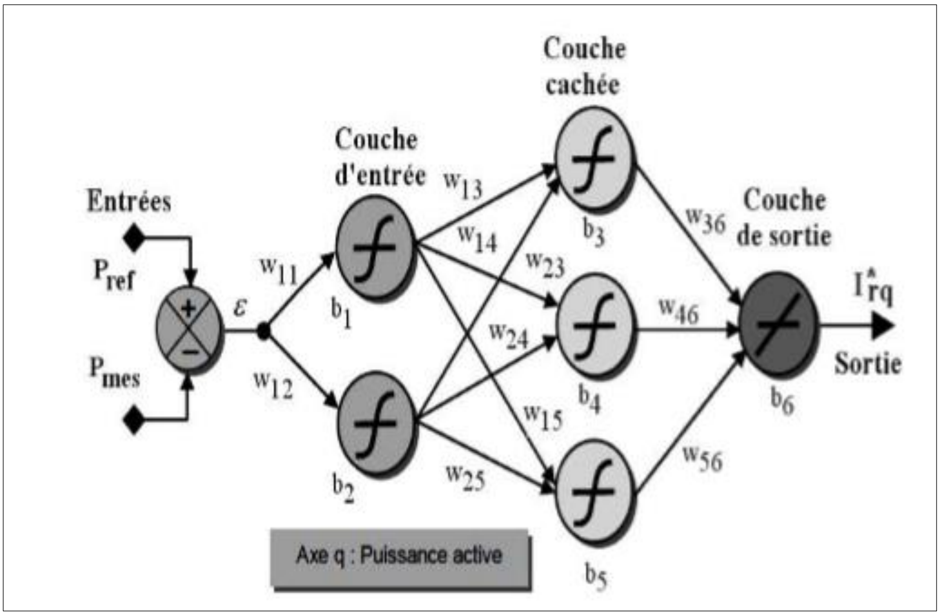
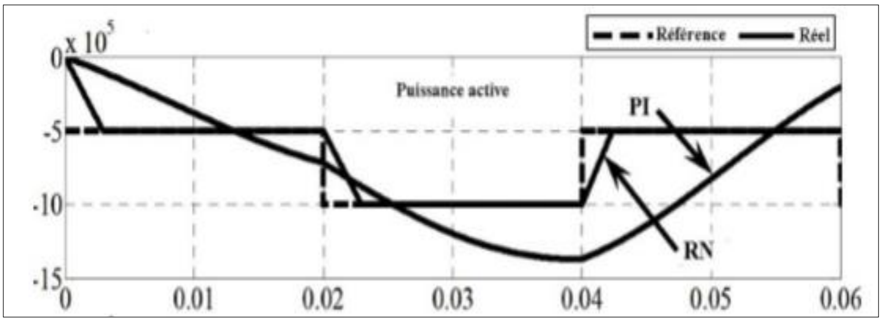
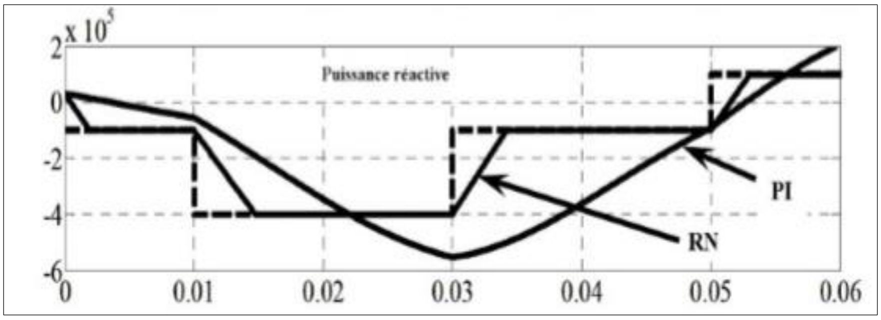


Figure 5 Multi-layered perceptron (2-3-1) [47].



a)



b)

Figure 6 Active and reactive power [47].

It was shown that neural controllers can improve the dynamic and statistical performance of DFIM on the one hand and ensure the robustness of the machine to parameter changes on the other hand (Figure 6) [47].

In 2012 Prabha kasliwal and his collaborators published an article titled « Neural Network based control of Doubly-Fed Induction Generator in Wind power generator. » In this work, the phasor model of DFIM is used. His thesis presents research on a doubly-fed induction generator driven by a grid-connected wind turbine and controlled by an ANN artificial neural network controller. The behavior of the system is represented by PI control and then by ANN control. Compare the effectiveness of an artificial neural network controller with that of a PI controller. SIMULINK/MATLAB simulates the doubly-fed induction generator and displays the corresponding results and waveforms.

The Artificial Neural Network (ANN) controller consists of 6 inputs and 1 hidden layer using linear functions at the input and output levels (Figures 7 and 8).

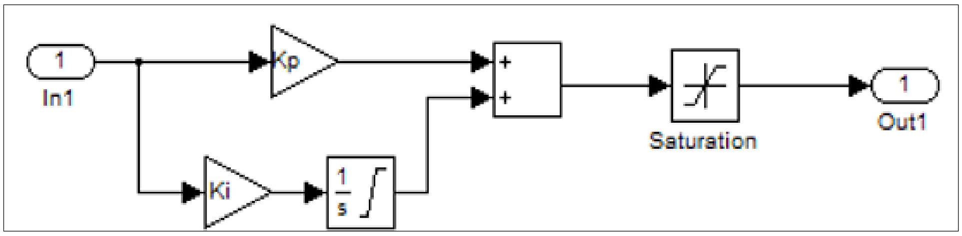


Figure 7 PI controller [48].

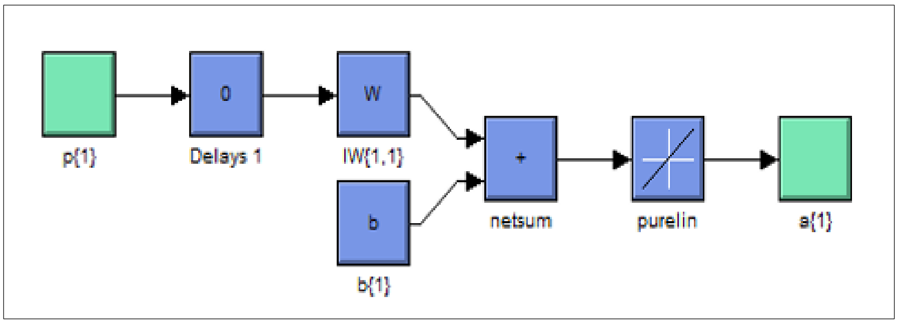


Figure 8 ANN layer model [48].

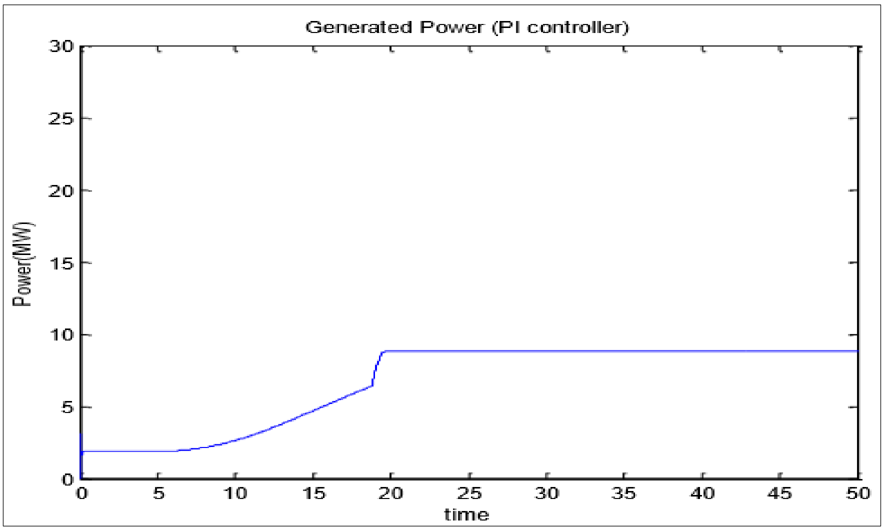


Figure 9 System Response with PI controller [48].

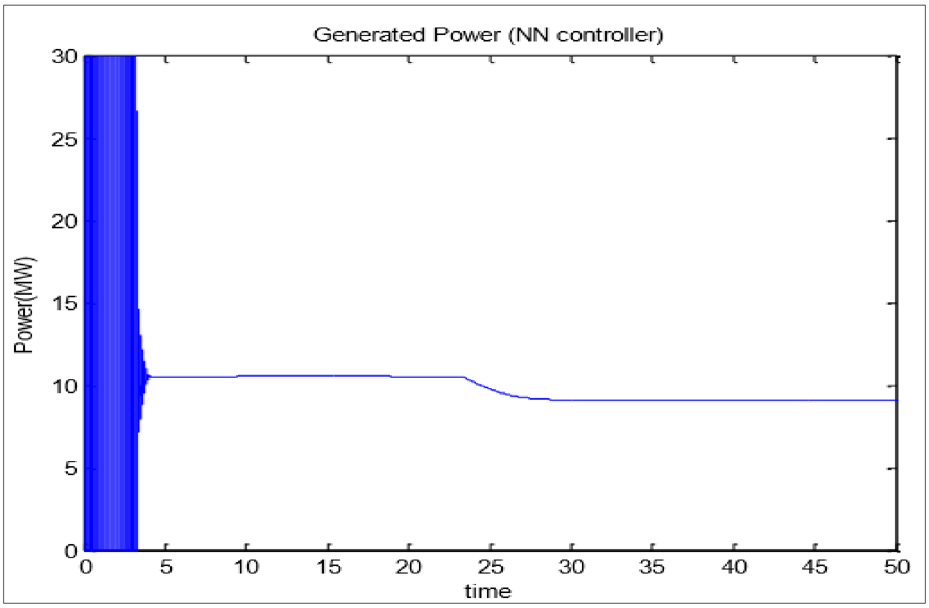


Figure 10 System Response with Neural network controller [48].

A comparative study between the two controllers shows that ANN is very effective in helping to stabilize the system. The processing becomes simpler and the computational complexity is reduced (Figures 9 and 10) [48]. The main advantage of ANN is that it has no mathematical model, which reduces computation time [48].

In 2014, Youcef Djeriri and his collaborators published an article entitled « Direct Torque Control of Doubly-fed Induction Generator Based on Artificial Neural Network. » This paper presents an improved DTC strategy using intelligent artificial techniques such as artificial neural networks (ANNs) applied to switch selected voltage vectors. In this way, the pulsation of current and torque can be reduced [7]. The Levenberg-Marquardt backpropagation algorithm is used to train the neural network, the network structure is simple, and the training and processing time is short (Figure 11).

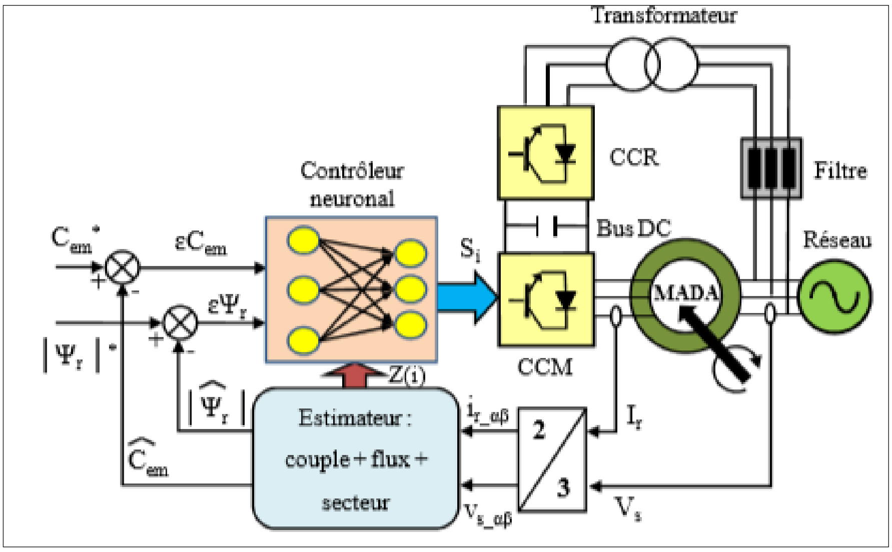


Figure 11 ANN-DTC [7].

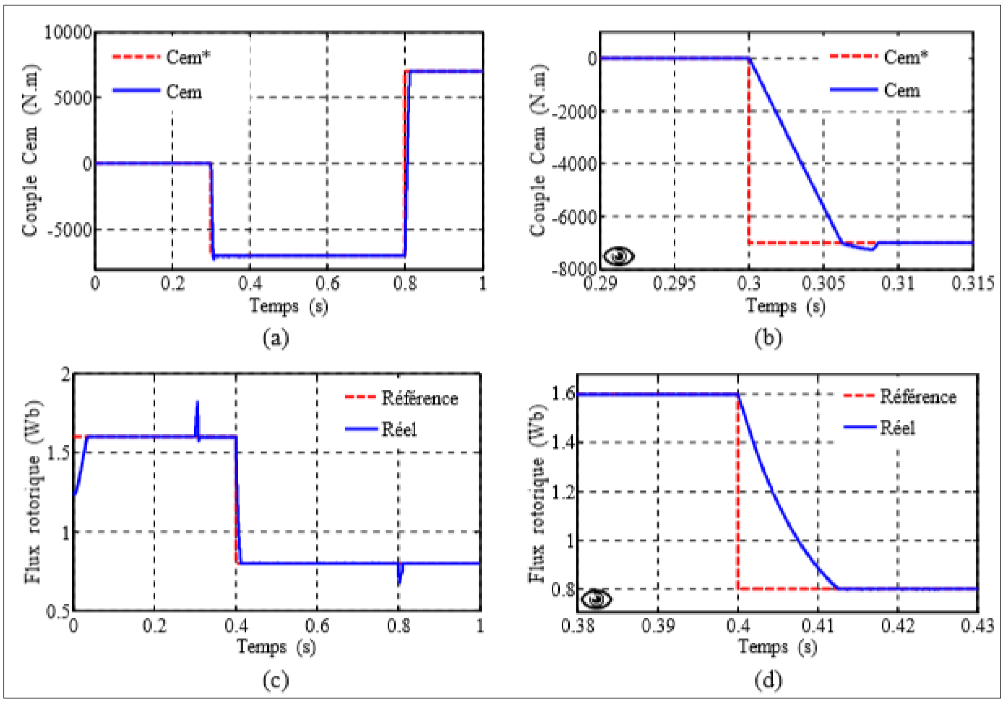


Figure 12 Torque and flux response [7].

Finally, simulation results show that the proposed ANN-DTC strategy effectively reduces the torque and flux ripples at low switching frequency, even under variable speed operation conditions (Figure 12) [7].

In 2016 Abderrahim and his collaborators published an article titled « Innovative improved Direct Torque Control of Doubly Fed Induction Machine (DFIM) using Artificial Neural Network (ANN-DTC) ». They proposed a control scheme consisting of two neural network architectures: a neural selector with a feed-forward based multilayer neural network architecture with four hidden layers saving 4, 14, 16 and 3 neurons per layer ; an output layer with 3 neurons, providing a voltage vector using the activation functions "logsig" and "tansig" [50].

The second RNA controller replaces the classic PI speed controller and is based on a multilayer neural network with three hidden layers of 10, 14 and 1 neuron each, with the "purelin" activation functions used in the first and second layers and the "logsig" function for the third layer (Figure 13) [50].

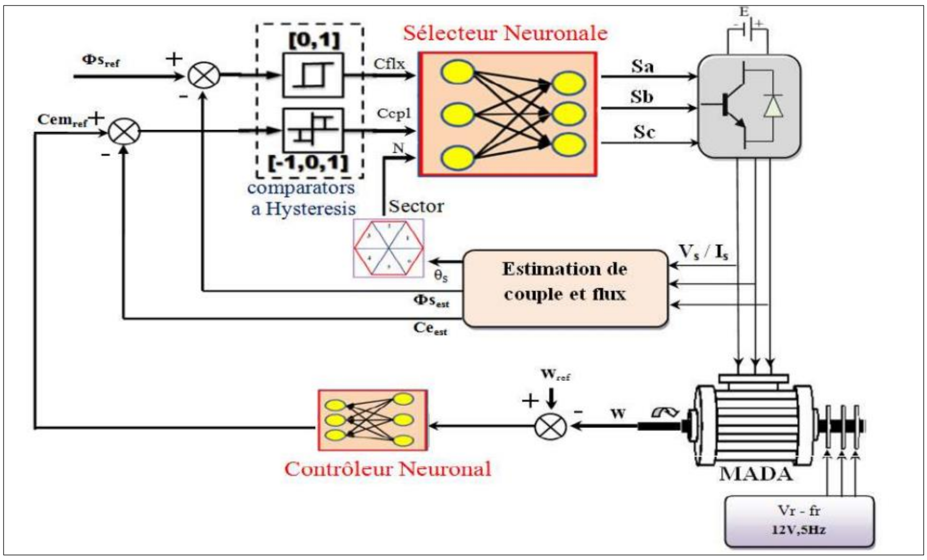


Figure 13 Direct torque control of DFIM based on ANN [51].

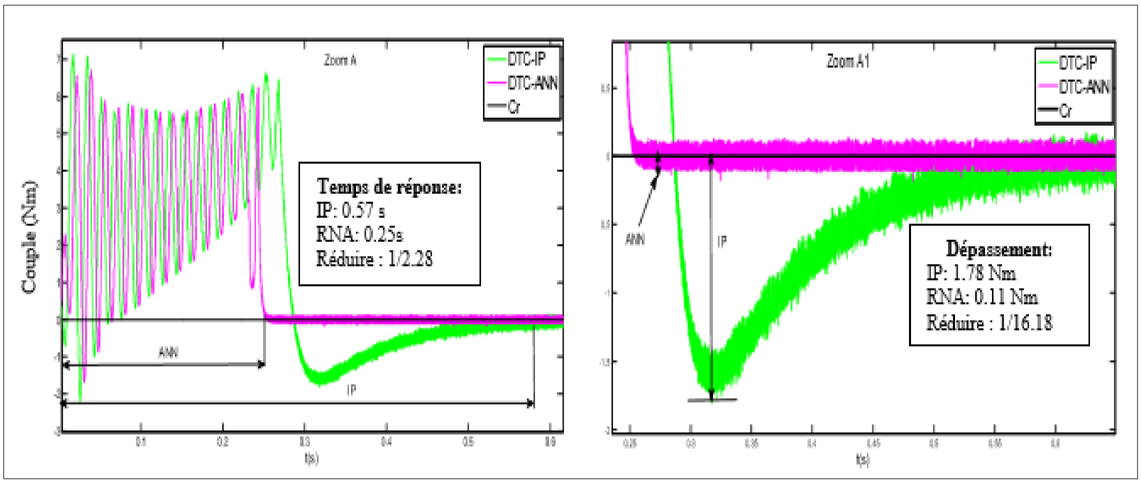


Figure 14 Torque response for a load varying from 3N.m and 5Nm [50].

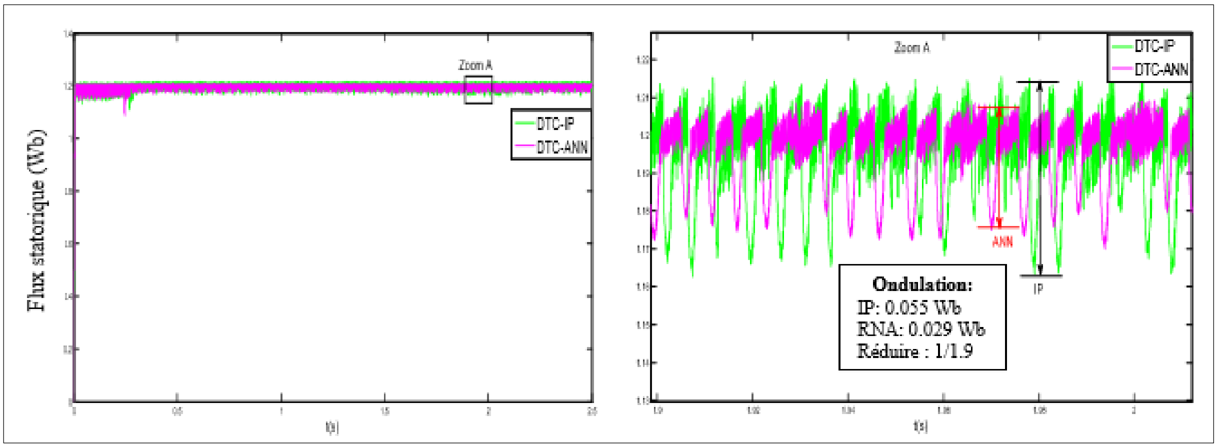


Figure 15 Stator flux of DFIM [50].

The results of their work showed that applying DTC-RNA technology provided good torque and flow response. The ripple or torque and flux levels are reduced compared to conventional technologies, which is reflected in the improved control performance of the ANN-DTC (Figures 14 and 15).

In 2018, Larbi Djilali and his collaborators published an article entitled « Neural Sliding Mode Control of a DFIG Based Wind Turbine with Measurement Delay ». This paper proposes a robust predictive sliding mode neural control algorithm for wind turbines based on doubly-fed induction generators. To improve the robustness of the proposed controller under parameter fluctuations and disturbances, a recurrent high-order neural network identifier is proposed, which is trained online using an extended Kalman filter. Furthermore, to compensate for the measurement delay of the stator and rotor currents, a predictor-based robust controller is integrated in the control scheme (Figures 16 and 17) [52]. In order to clarify the importance of the proposed control scheme, various experiments such as B. ideal state, measurement delay and the presence of parameter fluctuations were carried out.

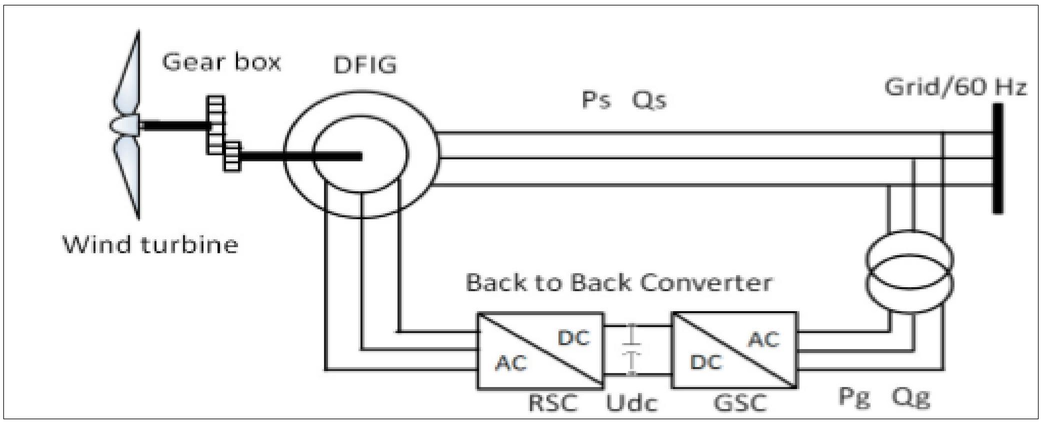


Figure 16 Scheme of DFIG connected to the electrical grid [52].

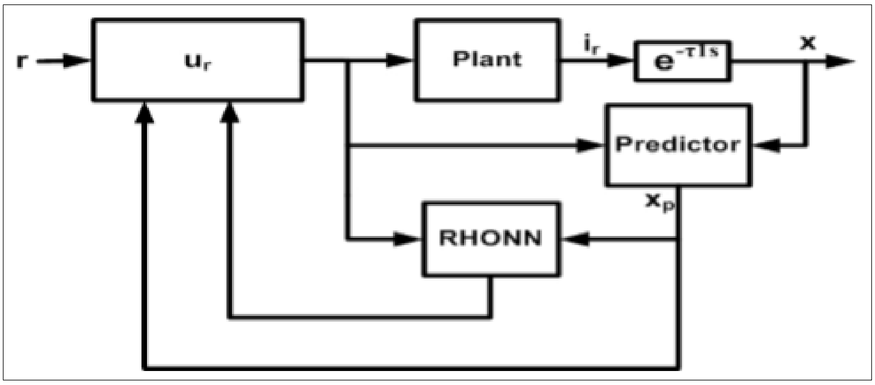


Figure 17 DFIG control scheme with measurement delay [52].

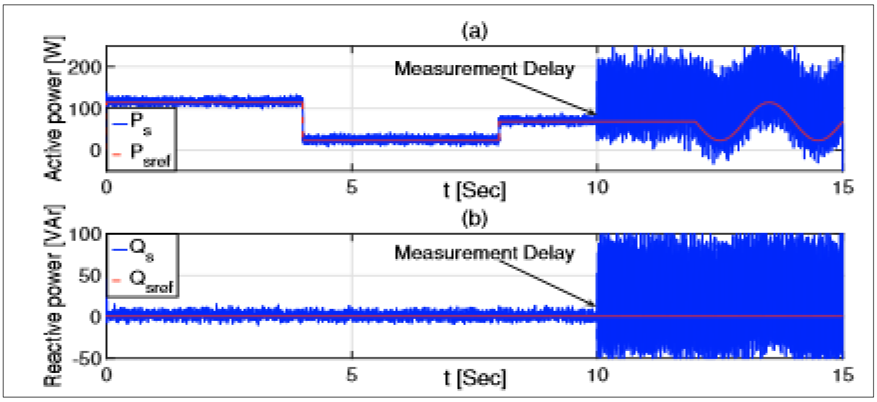


Figure 18 Stator powers with measurement delay [52].

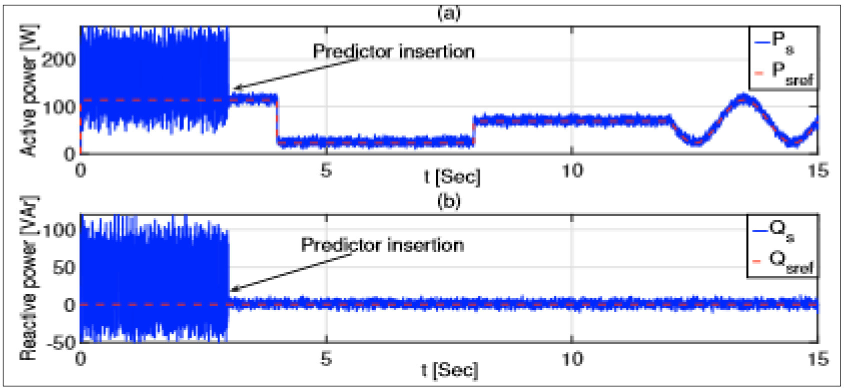


Figure 19 Stator powers with predictor [52].

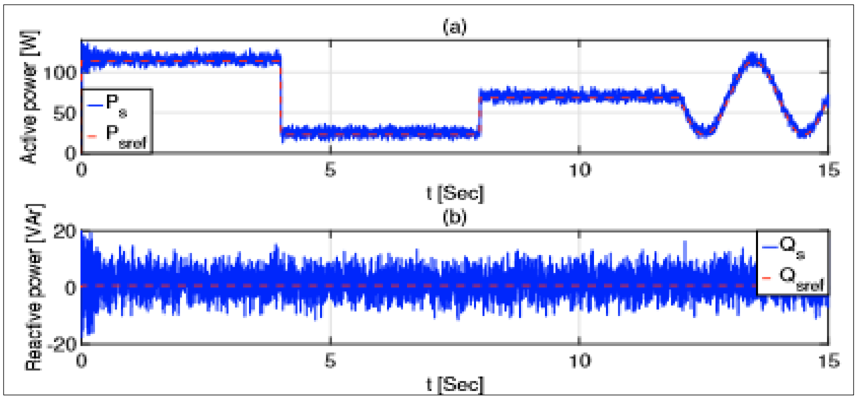


Figure 20 Stator powers dynamics with Lm variations [52].

Simulation results show a good estimation for real rotor currents of the Doubly Fed Induction Generator and illustrate the effectiveness of the proposed control scheme even in presence of reference changing, parameter variations and measurement delays. In addition, the stability, decoupling and convergence are achieved (Figures 18, 19 and 20). [52].

In 2019 Zoheir Tir and his collaborators published an article titled « Intelligent control of a brushless doubly-fed induction generator ». This article present Control of a BDFIG with back-to-back PWM converters using an artificial intelligence approach, fuzzy PID controller (Figures 21 and 22).

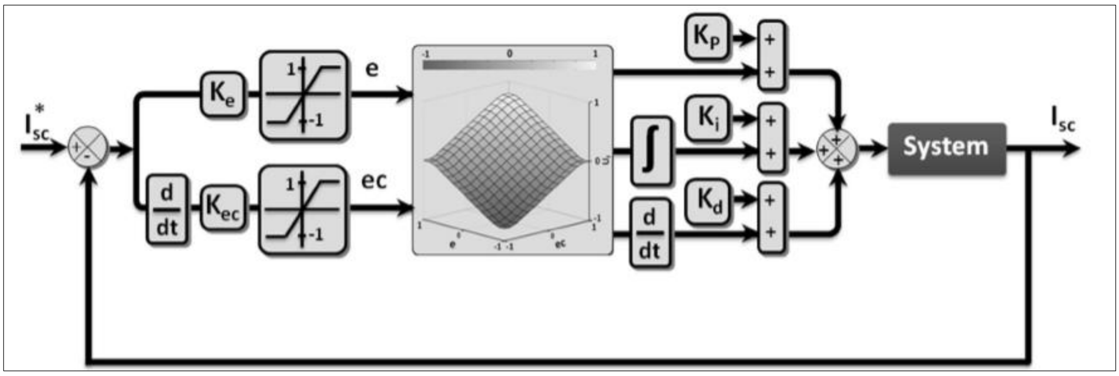


Figure 21 Block diagram of the proposed fuzzy PID type controller [17].

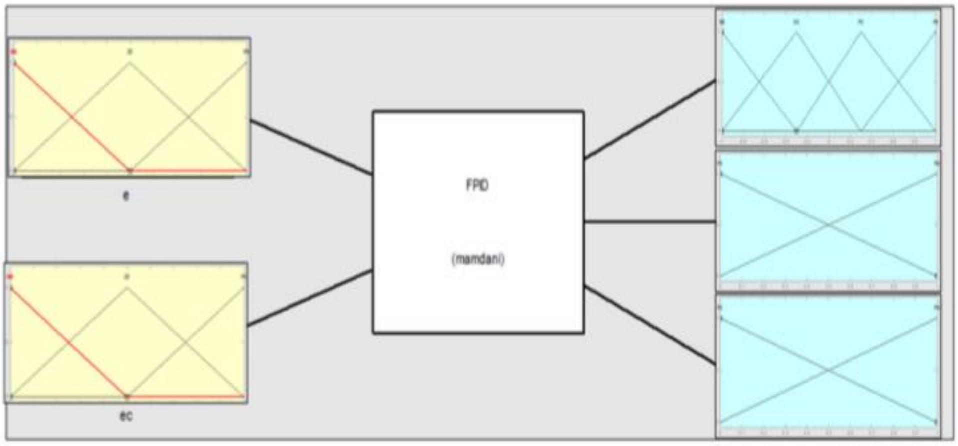


Figure 22 The membership functions used for the input and output fuzzy sets using Mamdani approach [17, 53, 54].

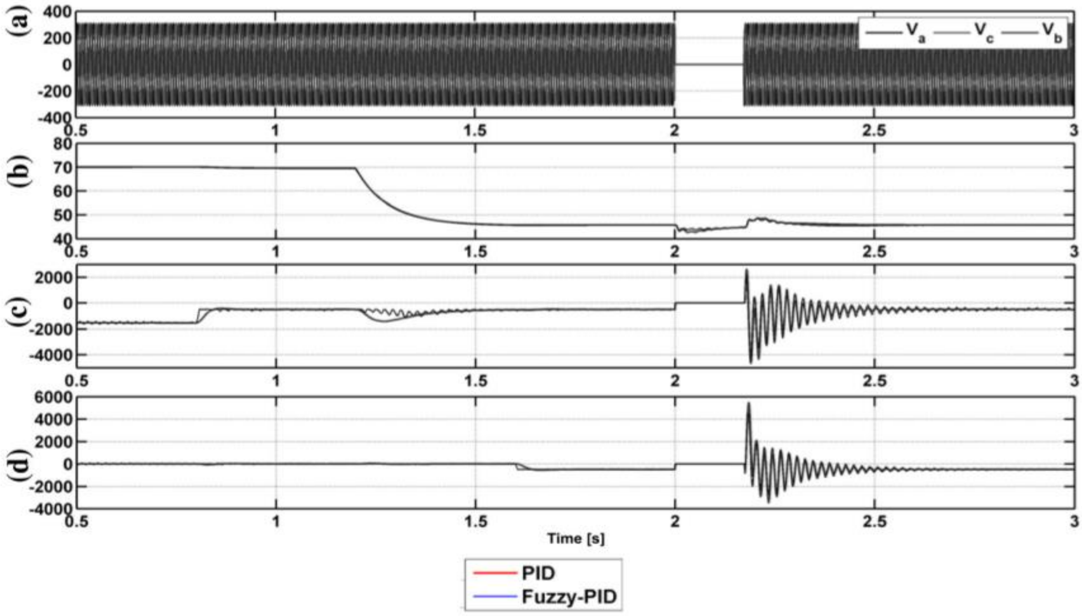


Figure 23 Performance of the BDFIG under various speeds, stator reactive power steps and 100% voltage dip: a) Network voltage, V. b) Rotor speed, rad/s. c) Stator active power of PW, W. d) Stator reactive power of PW, VAr [17].

The results of their work show that a fuzzy PID controller can provide a very attractive solution for wind energy conversion systems using the BDFIG (Figure 23). Although most BDFIG control schemes described in the literature use a classical PID controller, the findings reported in this paper show that the limitations of this controller can negatively affect the quality and quantity of energy generated. Using the proposed fuzzy PID controller can improve the performance of the system [17, 55, 56].

In 2020, L. Ouada and his collaborators published an article entitled « Neuro-fuzzy sliding-mode controller based on brushless doubly-fed induction generator ». Combinations of neural networks and fuzzy controllers are considered to be the most effective methods for approximating various functions and have shown their ability to control nonlinear dynamic systems [45, 57]. This paper presents a hybrid control strategy based on a brushless doubly-fed induction generator (BDFIG), called neuro-fuzzy sliding mode control (NFSMC). Instead of the sliding surface of the controller, chattering caused by discontinuous control action is eliminated (Figures 24, 25, and 26) [58].

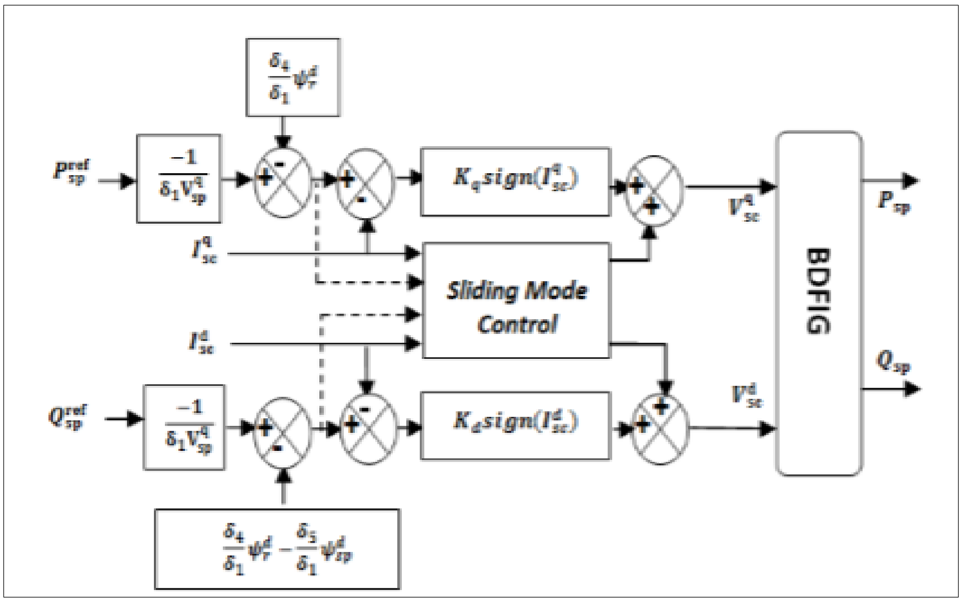


Figure 24 Block diagram of BDFIG sliding mode control [58].

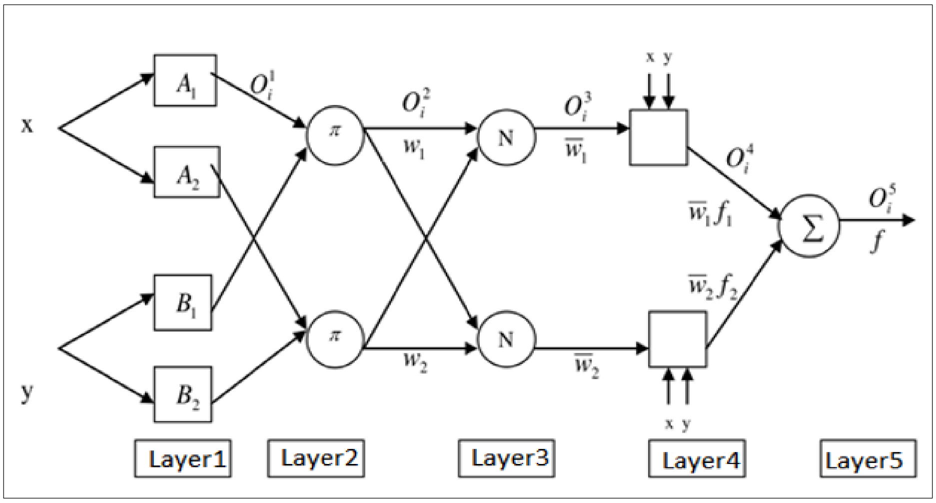


Figure 25 ANFIS architecture [58].

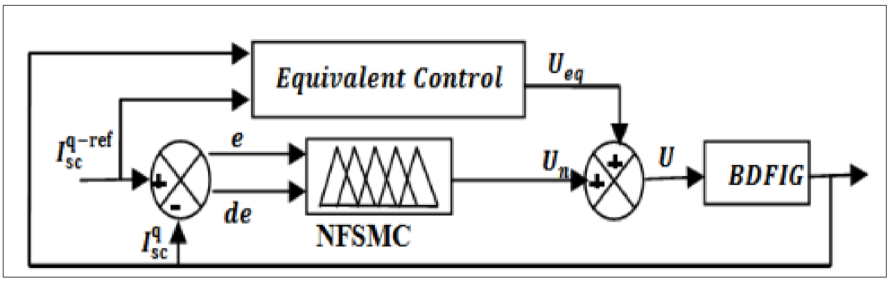


Figure 26 Neuro-Fuzzy-Sliding Mode Control [58].

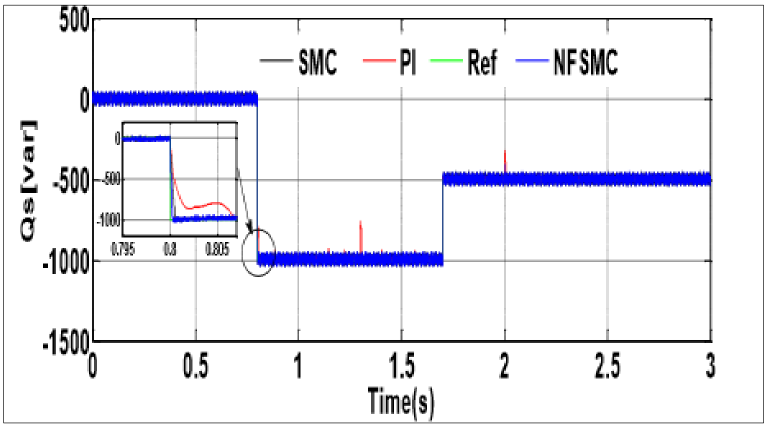


Figure 27 Reactive power response [58].

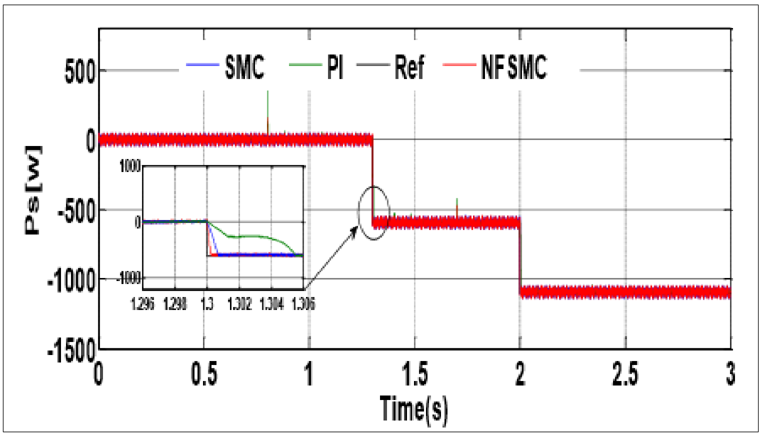


Figure 28 Active power response under VC, SMC and NFSMC strategies [58].

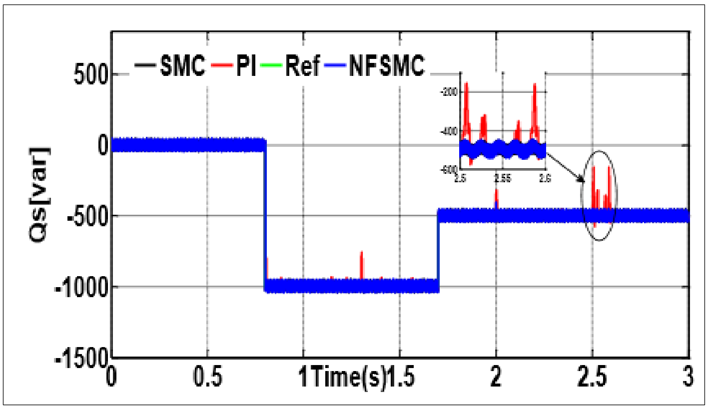


Figure 29 Reactive power under stator resistance variation [58].

Simulation results show that the power supply ripple in NFSMC is lower compared to other controllers. The efficiency of the proposed NFSMC is verified by simulation tests performed on a 2.5 KW BDFIG system. Furthermore, to verify the effect of BDFIG parameter variation on the performance of the proposed NFSMC, the sensitivity of the stator resistance parameters of the three schemes was tested against +100% stator resistance variation (Figures 27, 28 and 29). The proposed method has been shown to be robust and capable of suppressing the effects of system parameter uncertainties [58, 59].

6. Conclusion

In this article, we started with the description and modeling of the BDFIG. We then presented the main classic and advanced control techniques using AI. Finally, we presented previous work on advanced control of BDFIG and DFIG using AI. It appears from this study that the choice of strategy depends on the specific requirements of the application and the performance criteria. Artificial intelligence has therefore made it possible to improve the control of machines. However, genetic algorithms and the multilayer perceptron have not yet been used for the control of the BDFIG integrated in a wind turbine. Artificial intelligence has therefore made it possible to optimize the response time and the stability of the powers during parametric variations.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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