Optimization by Gaussian Radial Basis Function Neural Networks of the Performance of Doubly Fed Induction Machine System based on Wind Energy

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ABSTRACT

The present paper introduces Gaussian Radial Basis Function Neural Networks (GRBFNN) into the power control scheme of a wind turbine connected to a Doubly Fed Induction Machine (DFIG). These GRBFNN will replace the existing four PI controllers. The new controllers regulate power flow between the DFIG stator and the power network, reduce chattering, and enhance overall performance. We tested the performance of the GRBFNN controllers against a traditional PI controller through simulations in the Matlab/Simulink environment. Results indicate that the proposed controllers offer improved settling time, reduced overshoot, greater robustness to parameter variations, and effective tracking of references.

key words

Wind Turbine; Doubly Fed Induction Machine; Vector Control; Power Control; PI Controller; Gaussian Radial Basis Function Neural Network Controller.

1. INTRODUCTION

Currently, the doubly-fed induction generator is one of the most widely used variable speed wind turbines, thanks to its advantages, including improved reliability, efficient energy distribution, high energy efficiency, power control capability, low maintenance costs, and comprehensive power management capabilities [1-3].

Additionally, many researchers have suggested indirect vector control techniques, typically utilizing classical controllers, to regulate the active and reactive power of the DFIG [3-4]. The main objective of these techniques is to decouple the rotor current into its active and reactive components by managing the (d-q) components of the stator input current.

Classical control systems for wind turbines linked to doubly-fed induction machine drives, including PI, PD, and PID controllers, offer benefits such as robustness and a wide stability margin. However, these controllers also have drawbacks, including high sensitivity to parameter changes and a significant response sensitivity to nonlinear dynamic systems [5, 6].

To address these issues and enhance the performance of vector control, several robust control techniques and nonlinear feedback controls based on differential geometric theory for induction motor control have been proposed in the literature in recent years. These methods have been applied in various applications, including sliding mode control, predictive control, adaptive control, H∞ control approaches, and fractional control, among others [5-7].

On the other hand, artificial intelligence methods have been integrated into these systems and have demonstrated their ability to achieve superior performance compared to the previously mentioned techniques. These include the Takagi-Sugeno fuzzy method, fuzzy logic, artificial neural networks, genetic algorithms, among others. These advanced intelligent techniques have shown to be particularly effective for control systems characterized by varying parameters, ensuring optimal performance as noted in various studies [8-11].

Indeed, in various applications, the Gaussian Radial Basis Function Neural Network (GRBFNN) has demonstrated that this approach provides greater robustness against parameter variations and external disturbances during the operation of the process [12-15].

Regarding the previously mentioned literature, the issue of designing a robust tracking controller based on GRBFNN techniques appears to have not been addressed until now. Consequently, this study focuses on introducing the GRBFNN approach to develop a new robust control strategy. Furthermore, to assess the performance of the proposed GRBFNN control system, the authors will compare the results obtained with those achieved using traditional PI controllers as well as other control methods presented in previous works [12-15].

2. MODELLING OF SYSTEM UNDER STUDY

As illustrated in Fig. 1, the overall grid-connected wind turbine consists of a doubly-fed induction generator that is connected directly to the utility grid through its stator, while the rotor is connected indirectly via a rotor side converter (RSC) and a grid side converter (GSC).

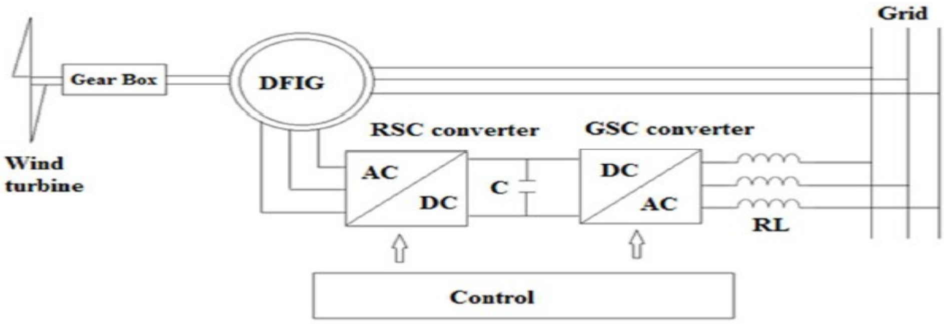

Figure 1. Block scheme of the studied system.

2.1 The Wind-Turbine model

The wind turbine model is given by the following system of equations [1-3]:

$$P_{ex} = \frac{1}{2}\rho S_u C_p(\lambda,\beta)V_w^3 \tag{1}$$

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

$$\Omega_t = \frac{\Omega_{mec}}{G} \tag{3}$$

$$C_p(\lambda,\beta) = 0.5176\left(\frac{116}{\lambda_i} - 0.4\beta - 5\right)\exp\left(\frac{-21}{\lambda_i}\right) + 0.0068\lambda \tag{4}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \tag{5}$$

Where: Pex: is the extracted power from the wind and the following parameters ρ: describes the air density, R represents the rotor blade radius, Su: is the area swept by the pales of the turbine, Vw is the wind speed, λ: the specific speed, β: the angle of orientation of the blades, Cp: is the power coefficient f the turbine, Ωt is the blade angular velocity [rad/s], Ωmec is the mechanical speed of DFIG.

Fig. 2 shows the Cp-λ characteristics for different values of angle β.

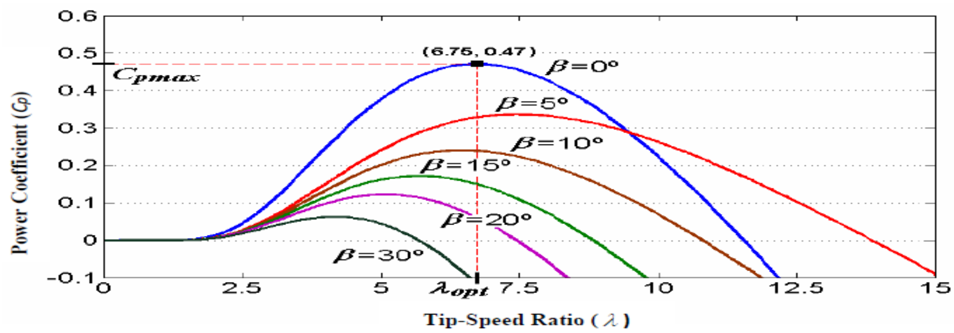

Figure 2. The Cp-λ characteristics, for different values of the pitch angle β, in MATLAB/Simulink.

The optimal values are extracted from Fig. 2 as; λ opt =6.75 and Cpmax =0.47.

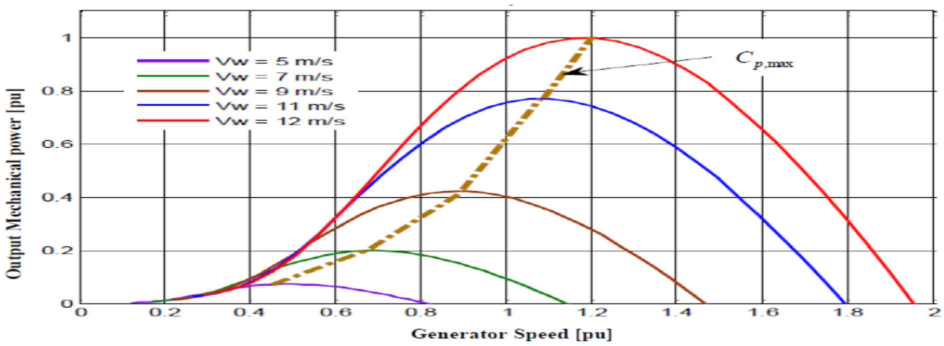

Figure 3. Mechanical power versus rotor speed curves.

Fig. 3 shows the mechanical power versus the rotating speed of the generator with no blade pitch angle control (β=0°) at various wind speeds. It is observed that the operation of the wind generator must follow a specific point of the rotor speed for each wind speed to maximize the mechanical power to get the maximum value of the wind power coefficient (Cpmax) [1]. Thus, the maximum mechanical power that can be ontinuously extracted from the low and the medium wind could be achieved by controlling the rotation speed of the generator to track the maximum power point (MPPT) for each wind speed as depicted by the dotted line in Fig. 3.

2.2 The DFIG model

The DFIG can be modelled by the following equations [2] in the direct (d) and quadrature (q) axis reference frame, which is rotating at synchronous speed. So, the stator voltage and rotor voltage are expressed as:

$$\begin{cases} V_{ds} = R_s i_{ds} + \dfrac{d\phi_{ds}}{dt} - \omega_s \phi_{qs} \\ V_{qs} = R_s i_{qs} + \dfrac{d\phi_{qs}}{dt} + \omega_s \phi_{ds} \\ V_{dr} = R_r i_{dr} + \dfrac{d\phi_{dr}}{dt} - \omega_r \phi_{qr} \\ V_{qr} = R_r i_{qr} + \dfrac{d\phi_{qr}}{dt} + \omega_r \phi_{dr} \end{cases} \tag{6}$$

The stator and rotor flux are given by:

$$\begin{cases} \phi_{ds} = L_s i_{ds} + L_m i_{dr} \\ \phi_{qs} = L_s i_{qs} + L_m i_{qr} \\ \phi_{dr} = L_r i_{dr} + L_m i_{ds} \\ \phi_{qr} = L_r i_{qr} + L_m i_{qs} \end{cases} \tag{7}$$

The stator power could be written as:

$$\begin{cases} P_s = v_{ds} i_{ds} + v_{qs} i_{qs} \\ Q_s = v_{qs} i_{ds} - v_{ds} i_{qs} \end{cases} \tag{8}$$

The rotor and stator angular velocities are expressed by the following relationship:

$$\omega_r = \omega_s - P\,\Omega_{mec} \tag{9}$$

The electromagnetic torque can be obtained by using the power budget and is given hereby:

$$C_{em} = p \frac{L_m}{L_s} (\phi_{qs} i_{dr} - \phi_{ds} i_{qr}) \tag{10}$$

3. FIELD ORIENTED CONTROL OF DFIG

Induction generators can be controlled using several approaches, including Direct Torque Control (DTC) and Field Oriented Control (FOC) [3, 4]. Of these techniques, FOC is the most widely used in the industrial sector due to its straight forward design and superior performance.

Field Oriented Control (FOC) allows for natural decoupling of flux and torque, similar to the operation of a separately excited DC machine.

Assuming that the resistance of the stator windings (Rs) is neglected, the voltage and the flux equations of the stator winding can be simplified as follows:

$$V_{ds} = 0, \quad V_{qs} = V_s = w_s \phi_{ds}, \quad \phi_{ds} = \phi_s, \quad \phi_{qs} = 0 \tag{11}$$

The active and reactive power equations at the stator side of a DFIG can be expressed as:

$$\begin{cases} P_s = -\dfrac{L_m V_s}{L_s} i_{qr} \\[2ex] Q_s = \dfrac{V_s^{\,2}}{\omega_s L_s} - \dfrac{V_s L_m}{L_s} i_{dr} \end{cases} \tag{12}$$

As can be seen from Eq. (12), Ps and Qs are proportional to the rotor currents, Idr and Iqr, respectively. The quadrature (q) current of the RSC (Iqr) is used for controlling the real power output; while the direct (d) current (Idr) is used for controlling the reactive power output.

By exploiting Eqs. (6), (7), (11) and (12), we can get the ollowing rotor voltages coordinates:

$$\begin{cases} V_{dr} = R_r I_{dr} + \sigma L_r \dfrac{\mathrm{d}I_{dr}}{\mathrm{d}t} - g\ \omega_s \sigma L_r I_{qr} \\[2ex] V_{qr} = R_r I_{qr} + \sigma L_r \dfrac{\mathrm{d}I_{qr}}{\mathrm{d}t} + g\ \omega_s \sigma L_r I_{dr} - g\dfrac{L_m V_s}{L_s} \end{cases} \tag{13}$$

From the above equations, we can conceive the block diagram of the DFIG represented in Fig. 4. As it is shown the DFIG model becomes approximately decomposed in two decoupled subsystems.

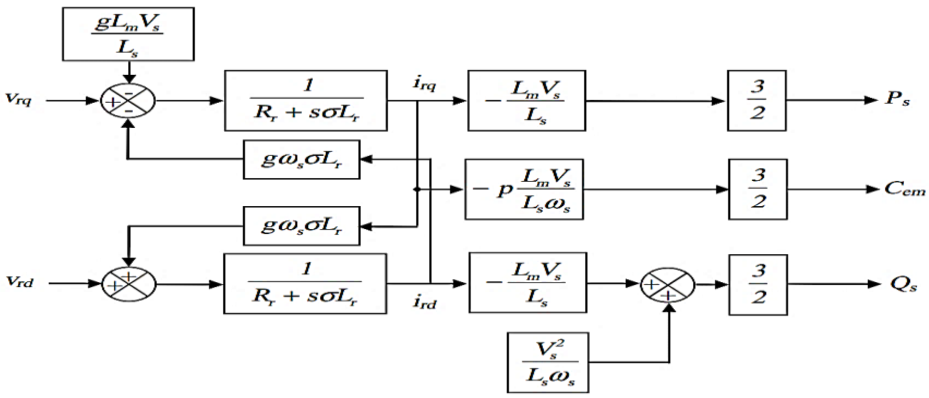

Figure 4. Block diagram of the simplified model of the DFIG.

4. CONTROLLER SYNTHESIS

To date, research has shown that artificial neural networks leverage non-linear learning, generalization abilities, and parallel processing for advanced intelligent control applications [10, 11]. This inherent capability of neural networks for general non-linear approximation provides significant potential for nonlinear control.

In the literature, the Gaussian Radial Basis Function Neural Network (GRBFNN) is often viewed as a smooth integration of neural networks and fuzzy logic. Structurally, the GRBFNN consists of receptive units (neurons) that serve as operators, providing information about the class to which the input signal belongs. When the aggregation method, the number of receptive units in the hidden layer, and the constant terms match those of a fuzzy inference system, a functional equivalence exists between GRBFNN and FIS [12-15]. The structure of the GRBFNN utilized in this paper is illustrated in Fig. 5.

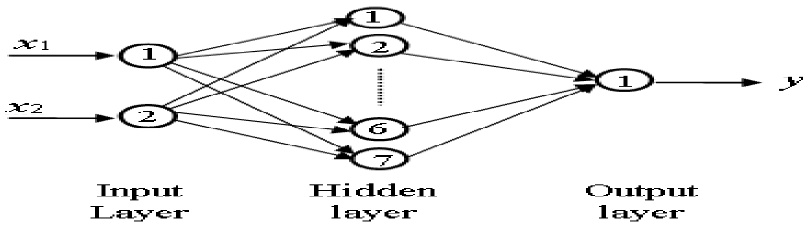

Figure 5. Architecture of the GRBFNN.

In this architecture, each neuron in the hidden layer assigns a degree of membership value to the input pattern based on its corresponding basis vector. The output layer consists of linear neurons. The neural network framework allows the GRBFNN to achieve mathematical tractability, particularly in terms of backpropagating errors through the network. Meanwhile, the fuzzy system perspective facilitates the integration of expert knowledge into the training process. This can be particularly important for initializing the network's adjustable parameter vector closer to its optimal values, leading to faster convergence in parameter space, provided that the system dynamics are well understood [12, 13].

It is important to note that the output of each neuron is calculated based on the multiplication of the individual Gaussian outputs corresponding to each input. The overall response is determined by multiplying the hidden layer output vector by a matrix/vector of suitable dimensions. In fuzzy terms, this can be described as employing the product inference rule in conjunction with a weighted sum defuzzifier.

If the network output and hidden layer output vectors are denoted by F and $\underline{o}$ respectively, the activation level of the ith receptive unit (or firing strength of each rule) and the overall realization performed by the network could be described by (14) and (15) respectively [14].

$$o_i = \prod_{j}^{inputs} \exp\left\{ -\left(\frac{u_j - c_{ij}}{ij} \right)^2 \right\} \tag{14}$$

$$F = W_{outputsx\ \ hiddeneuronso} \cdot \underline{o} \tag{15}$$

According to the error back-propagation rule, the parameter update law can be summarized as follows:

$$\begin{aligned} &{}_{-output} = \underline{d} - f \\ &{}_{-hidden} = w^T{}_{-output} \\ &\Delta W_{ij\,EBP} = N_{Wi} \\ &\Delta c_{ij\,EBP} = N_c \\ &\Delta_{ij\,EBP} = N_{ij} \end{aligned} \tag{16}$$

Where:

$$\begin{aligned} &N_{W_{ij}} ={}_{output}\ \ {}_i o_j \\ &N_{cij} ={}_{hidden}\ {}_i o_j\ 2\left(\frac{u_j - c_{ij}}{ij} \right)^2 \\ &N_{ij} ={}_{hidden}\ {}_i o_j\ 2\,\frac{(u_j - c_{ij})^2}{ij^3} \end{aligned} \tag{17}$$

5. REGULATORS PERFORMANCES

In this section, to illustrate the effectiveness of the proposed GRBFNN control strategy, we conducted a numerical simulation of the dynamics of the indirect vector control process with a DFIG connected to a wind system using Matlab/Simulink software. To achieve this, two scenarios were implemented.

5.1 Reference tracking scenario

The primary aim of this scenario is to analyze the behavior of various control strategies while the DFIG operates under ideal conditions, incorporating different steps for active and reactive power. Our objective is to fine-tune the architecture and corresponding parameters of the GRBFNN power regulator to achieve optimal reduction of chattering and ensure precise tracking of the reference values. The results of the simulations are presented in Figs. 6 and 7.

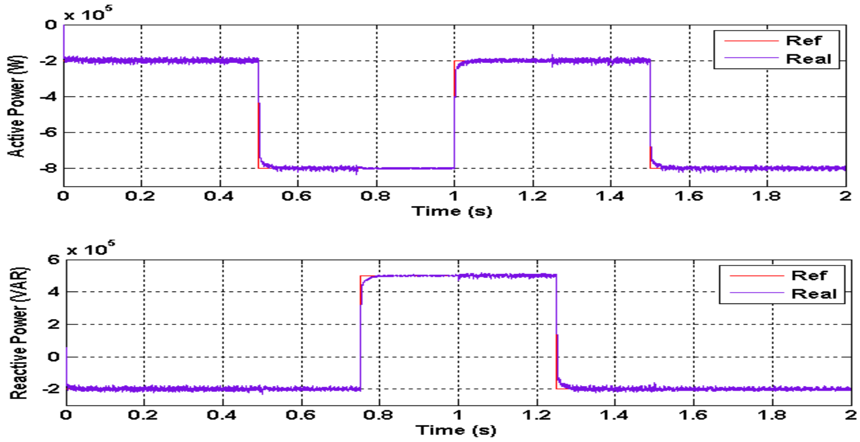

Figure 6. Simulation results to the active and a reactive power impact (PI controller).

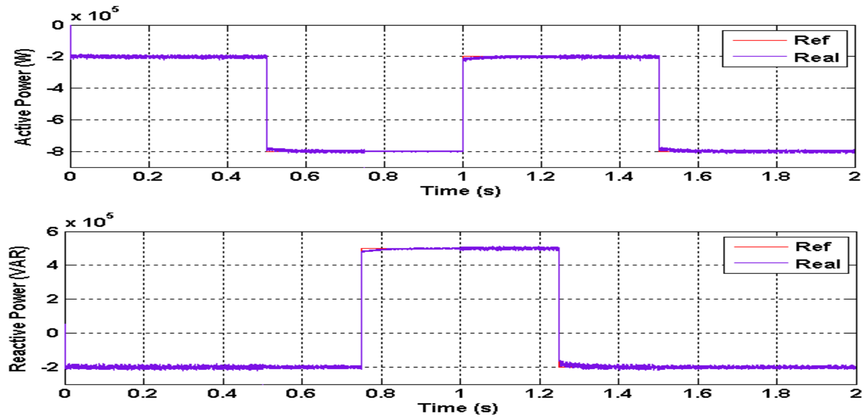

Figure 7. Simulation results to the active and a reactive power impact (GRBFNN controller).

As illustrated in Fig. 7, the GRBFNN regulator successfully tracks the reference values for both active and reactive power, demonstrating a significant reduction in chattering compared to the case with a PI controller, as shown in Fig. 6. This achievement aligns with our objective in this paper, showcasing the effectiveness of this technique.

5.2 Robustness scenario

To assess the robustness of the two controllers (PI and GRBFNN), the value of mutual inductance Lm was reduced by 10% and 20% of its nominal value. Figs. 8 and 9 illustrate the impact of these parameter variations on the active power responses for the two different controllers employed, as demonstrated in the figures.

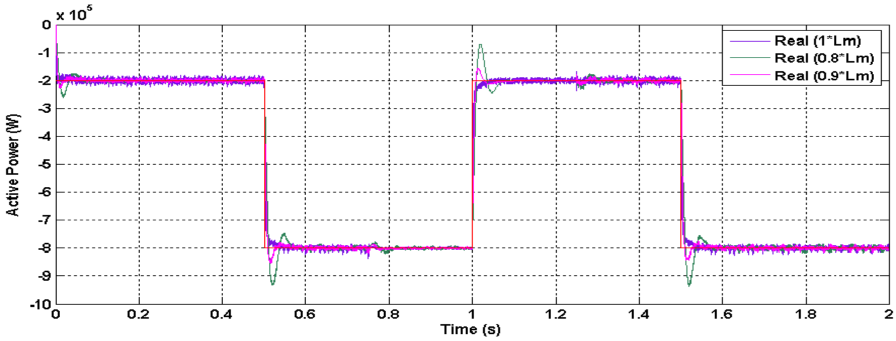

Figure 8. Simulation results of active power to parameters variations (PI controller).

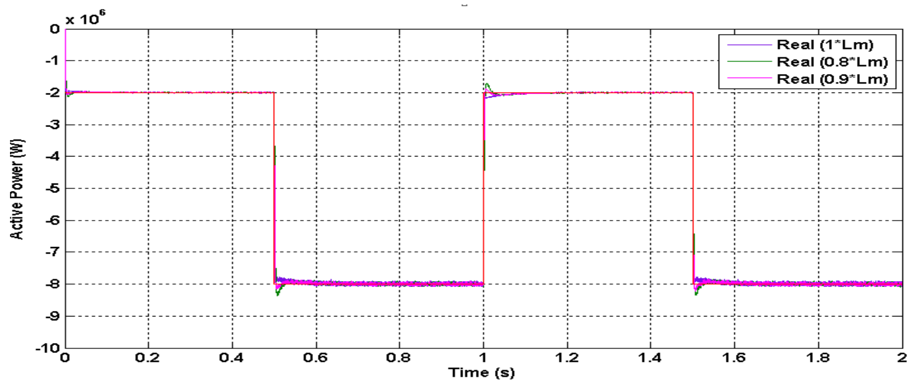

Figure 9. Simulation results of active power to parameters variations (GRBFNN controller).

The results presented in Fig. 9 indicate excellent dynamic and static performance, characterized by a very fast response time, okovershoot, minimal static error, and a significant reduction in chattering compared to the results shown in Fig. 8. Thus, we can conclude that the Gaussian Radial Basis Function Neural Networks (GRBFNN) controller offers substantial improvements in robustness against parameter variations and external disturbances, especially when compared to the PI regulator. This enhanced performance is attributed to the fact that our GRBFNN was designed with a fuzzy logic database in the training process. Consequently, we can assert that our GRBFNN control scheme is analogous to and could be regarded as a Neuro-Fuzzy system.

5.3 Comparison between the two controls

The analysis of the two system responses obtained using Proportional-Integral (PI) and Gaussian Radial Basis Function Neural Network (GRBFNN) controllers reveals the following observations, as summarized in Table 1:

Table 1. *Comparison between the two used different regulators performances*

	Regulators	
Performances	**PI**	**GRBFNN**
Static error (%)	*0.083593*	*0.0121*
Overshoot (%)	*1.0226*	*0.0231*
Response time (s)	*0.005132*	*0.001026*

From Table 1, we can conclude that the Gaussian Radial Basis Function Neural Network (GRBFNN) controller is more effective than the PI controller, offering a simpler design, a significantly faster response time, and minimal static error.

6. CONCLUSIONS

This paper presents a GRBFNN controller approach for designing a robust control system for DFIG-based wind energy conversion systems (WECS). The operating characteristics of the DFIG with the proposed GRBFNN controller are compared to those using a conventional PI controller. Additionally, numerical simulations were conducted using Matlab/Simulink under two different scenarios. The simulation results demonstrate that the process controlled by the GRBFNN approach exhibits greater robustness and insensitivity to parameter variations compared to traditional PI control. Furthermore, these findings indicate that this technique enhances the performance of the power control process for the DFIG in WECS, ensuring a fast and accurate dynamic response along with excellent steady-state performance. Thus, the objectives of this contribution have been successfully achieved.

Finally, it is important to note that the authors plan to include the experimental component of this proposed control technique in future work to validate the current simulation results and further advance the project.

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