

Article

An ANN-Based MPPT and Power Control Strategy for DFIG Wind Energy Systems with Real-Time Validation

Hamid Chojaa ¹, Kawtar Tifidat ², Aziz Derouich ³, Mishari Metab Almalki ^{4,*} and Mahmoud A. Mossa ^{5,*}

¹ Higher School of Technology, Sidi Mohamed Ben Abdellah University, Fez 30000, Morocco; hamid.chojaa@usmba.ac.ma

² Laboratory of Materials, Signals, Systems and Physical Modeling, Department of Physics, Faculty of Sciences, Ibn Zohr University, B.P. 8106, Agadir 80000, Morocco; kawtar.tifidat@edu.uiz.ac.ma

³ Industrial Technologies and Services Laboratory, Higher School of Technology, Sidi Mohamed Ben Abdellah University, Fez 30000, Morocco; aziz.derouich@usmba.ac.ma

⁴ Department of Electrical Engineering, Faculty of Engineering, Al-Baha University, Alaqiq 65779-7738, Saudi Arabia

⁵ Electrical Engineering Department, Faculty of Engineering, Minia University, Minia 61111, Egypt

* Correspondence: mmalmalki@bu.edu.sa (M.M.A.); mahmoud_a_mossa@mu.edu.eg (M.A.M.)

Abstract

Doubly Fed Induction Generators (DFIGs) are widely employed in variable-speed wind turbine systems due to their high efficiency, enhanced controllability, and economic viability. This paper presents an intelligent neural-network-based control strategy aimed at maximizing wind energy extraction while ensuring accurate speed regulation of a DFIG by continuously tracking the maximum power point under fluctuating wind conditions. Two independent control schemes are developed for the decoupled regulation of active and reactive power in a grid-connected DFIG wind turbine. The first scheme is based on conventional field-oriented control using proportional integral regulators (FOC-PI), while the second employs an Artificial Neural Network Controller (ANNC). The effectiveness of both controllers is evaluated through MATLAB/Simulink 2020 Version simulations of a 1.5 MW DFIG-based wind energy conversion system and experimentally validated using a real wind profile implemented on an eZdsp TMS320F28335 digital signal processor. The proposed control approach achieves low output ripple, a steady-state error below 0.16%, total harmonic distortion of 0.38%, and a limited overshoot of 5%. The obtained results confirm the robustness and reliability of the implemented control strategies in enhancing power capture and improving overall system stability under variable wind conditions.

Keywords: Artificial Neural Network Controller (ANNC); MPPT algorithm; Wind Energy Conversion System (WECS); eZdsp TMS320F28335 card

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1. Introduction

Due to increasing energy consumption, limited fossil fuel availability, and critical environmental issues, several nations have expanded the incorporation of renewable energy resources, notably solar, wind, and biomass systems [1–3]. Wind energy, as a sustainable source, has gained substantial attention as a crucial factor in the transition towards cleaner and more efficient energy systems [4,5].

Generally, wind energy is characterized by its variability and the nonlinear behavior of power generation, which necessitates precise identification of the optimal operating point to achieve maximum efficiency [4,5]. Hence, to ensure maximum power capture under variable wind conditions, the inclusion of a controller capable of tracking the optimal power point is necessary. To overcome this challenge, a novel intelligent control technique grounded in neural network theory is presented in this investigation.

Doubly fed induction generators (DFIGs) have recently gained widespread adoption among the commonly used generators in WECS applications [6,7]. This common selection of DFIGs as a compelling choice for wind energy applications results from their durability, structural resilience, and capacity for reactive and active power regulation under variable-speed conditions [8–10].

To ensure high-quality electrical energy generation in a DFIG-based wind power system, appropriate control strategies must be applied to regulate the stator power output. This includes controlling the active power to track the turbine's reference power for improved efficiency, while maintaining the reactive power at zero to ensure a unity power factor on the stator side. Figure 1 illustrates the schematic overview of the DFIG-based wind energy system, in which the rotor circuit is interfaced with the grid through back-to-back power converters, whereas the stator is directly connected to the utility grid.

To enhance the performance of DFIGs, various strategies utilizing nonlinear control strategies have been introduced in recent years [11–13]. Among the various nonlinear control techniques for DFIGs, sliding mode control is widely adopted and valued for its robustness [14,15]. However, its primary limitation is the chattering effect caused by the discontinuous nature of the control signal. To mitigate the chattering effect, advanced sliding mode control (SMC) methods like Integral SMC [16], Second-Order SMC [17], and Super-Twisting SMC [18] have been introduced in research studies, offering superior dynamic characteristics such as finite-time convergence. The literature includes several investigations into methods such as scalar control [19], adaptive Fuzzy Logic control [20], backstepping control [21], Sliding mode control [22], and Direct power control (DPC) [23]. However, a notable limitation in these studies remains the absence of simulations using real wind profiles and the lack of comparative assessments of multiple control strategies under a common environment.

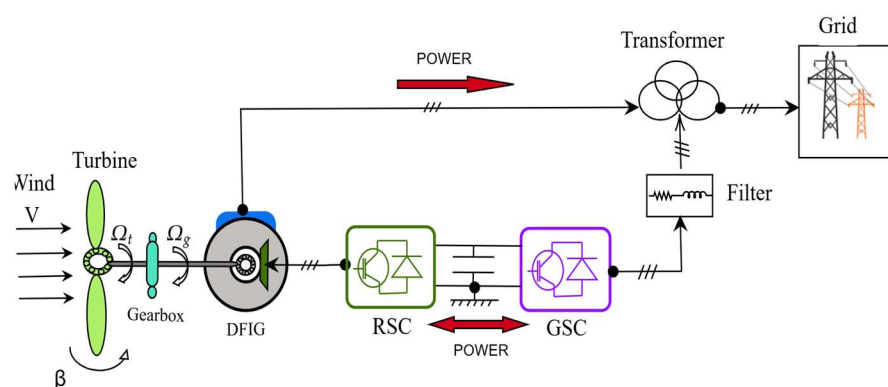


Figure 1. Design of a wind energy conversion system.

Motivated by the limitations observed in existing DFIG control strategies—particularly the lack of unified intelligent control frameworks, insufficient experimental validation, and limited comparative performance assessment—this paper proposes a comprehensive artificial neural network (ANN)-based control approach for DFIG-based wind energy conversion systems. The proposed strategy integrates an ANN-driven MPPT speed controller with ANN-based active and reactive power control, enabling optimal power

extraction, enhanced dynamic response, and improved power quality under realistic wind conditions.

Several experimental studies have been conducted on DFIGs to validate various control strategies, as summarized in Table 1. These works include both linear and nonlinear approaches implemented using different controllers, such as PI, sliding mode, and synergetic controllers, and are mainly applied to low-power DFIG systems ranging from 1 kW to 15 kW. Overall, the experimental results indicate that none of the reported methods completely eliminates active and reactive power ripples, and their dynamic performance varies significantly. In particular, conventional DPC-based approaches exhibit pronounced current and power ripples, leading to high current THD, which may negatively affect power quality, equipment lifetime, and grid stability.

Table 1. Experimentally validated control strategies for DFIGs.

Rating (Kw)	Technique	Controller	Reference Tracking *	Reference
15	FOC strategy	PI	++	[24]
2	DPC	SMC	+++	[25]
7.5	Direct FOC strategy	PI controller	++	[26]
7	Nonlinear control	Second-order sliding mode control	+++	[27]
1	Nonlinear control	Integral sliding mode controller	++	[28]
11	FOC strategy with a full-order adaptive observer	PI	++	[29]
3	FOC strategy with space vector modulation	PI	++	[30]
1.5	Predictive current control	-	++	[31]

* ++—high, and +++—very high.

In contrast to many previous studies that rely solely on numerical simulations, the effectiveness of the proposed control scheme is validated through both MATLAB/Simulink simulations and real-time implementation using an eZdsp TMS320F28335 platform. A detailed comparative evaluation with conventional field-oriented control using PI regulators is conducted to highlight the improvements in tracking accuracy, transient behavior, harmonic distortion, and robustness. Through this integrated design and validation framework, the present study aims to provide a practical, high-performance, and experimentally verified control solution for modern DFIG-based wind energy systems.

In summary, the key contributions of this work are:

- A unified intelligent control scheme integrating MPPT-based speed control with ANN-based active/reactive power control for the DFIG.
- A full real-time implementation using the eZdsp TMS320F28335 under a real wind profile, rarely reported in ANN-based DFIG studies.
- A consistent comparison between FOC-PI and ANN controllers, showing clear improvements (lower ripple, 0.16% steady-state error, 5% overshoot reduction, and 0.38% THD reduction).
- This combination and the real-time validation reinforce the originality and practical relevance of the contribution.

The work in this paper is organized into four main sections. Section 2 begins with the development of the turbine model, presents the neural network-based MPPT speed controller, details the dynamic DFIG modeling, and introduces and analyzes the proposed Artificial Neural Network Controller (ANNC). Section 3 presents the numerical results and describes the practical implementation of the proposed control strategy using the

eZdsp TMS320F28335 board, including experimental validation under varying wind speeds. Section 4 concludes the study by highlighting the main outcomes.

2. Materials and Methods

2.1. Wind Turbine Modeling

The basic element of wind energy conversion into electrical energy is the wind turbine, which generates electricity by driving an electrical generator. The airflow around the blades creates lift, producing a rotational force that turns a shaft within the nacelle, which is connected to a gearbox. By increasing the rotational speed, the gearbox enables the generator to function efficiently, utilizing magnetic fields to transform mechanical motion into electricity [1,5].

The wind turbine's power generation is governed by the expression given in Equation (1) below:

$$P_t = C_p(\beta, \lambda) \times \frac{\rho \pi V^3 R^2}{2} \quad (1)$$

In this context, the power coefficient is presented by $C_p(\beta, \lambda)$, and it is a function of β , the pitch angle, and λ , the tip speed ratio. R is set aside for the rotor radius, and ρ denotes the air density. The $C_p(\beta, \lambda)$, in this work, is presented by Equation (2) as follows:

$$\begin{cases} C_p(\beta, \lambda) = -\exp\left(\frac{-21}{\lambda_i}\right) \times \left(2.5 - \frac{116}{2\lambda_i} + 0.2\beta\right) + 0.0068\lambda \\ \frac{1}{\lambda_i} = \frac{-0.035}{\beta^3 + 1} + \frac{1}{0.08\beta + \lambda} \end{cases} \quad (2)$$

The formulation governing the tip speed ratio is expressed in Equation (3).

$$\lambda = \frac{\Omega_t}{V} \times R \quad (3)$$

Ω_t presents the wind turbine rotor's angular velocity.

The expression governing the relationship between the mechanical and the electromagnetic torques is presented in Equation (4) below:

$$C_{mec} = \frac{d\Omega_g}{dt} \times J = -C_f + C_g - C_{em} \quad (4)$$

In Figure 2a,b, the power coefficient dependency on λ for variable β values, in two and three dimensions, respectively. As depicted in the figures, the optimal $C_p(\beta, \lambda)$ value of 0.479 is attained for $\beta = 0^\circ$ and $\lambda_{opt} = 8.2$. Subsequently, an MPPT control is adopted to keep the power coefficient at its peak.

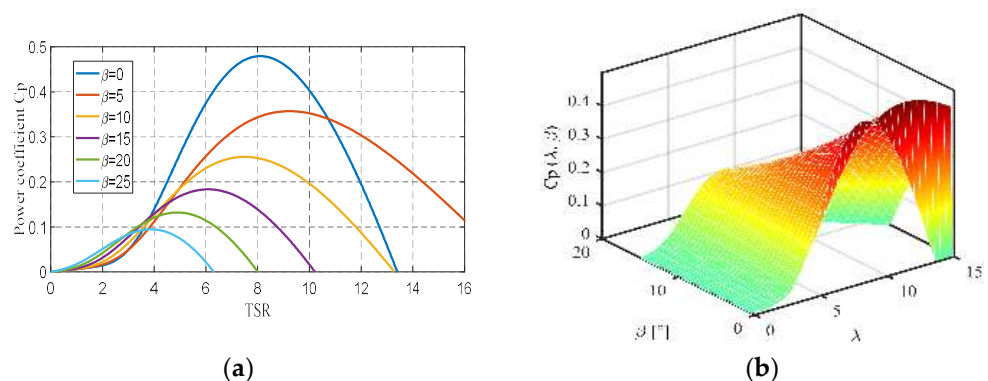


Figure 2. (a) Two-dimensional power coefficient (C_p) curves as a function of the tip-speed ratio (λ) for different pitch angles (β); (b) a three-dimensional representation of C_p variations with respect to β and λ .

- MPPT-based speed regulation

The MPPT approach (Figure 3) seeks to boost the effectiveness of energy harvesting from wind within WECS. By adjusting the generator's electrical power according to λ_{opt} , the speed controller ensures that the reference torque T_{em-ref} is effectively tracked by the electromagnetic torque. This approach guarantees that the rotational speed remains aligned with the desired reference Ω_{ref} , derived from the speed control strategy.

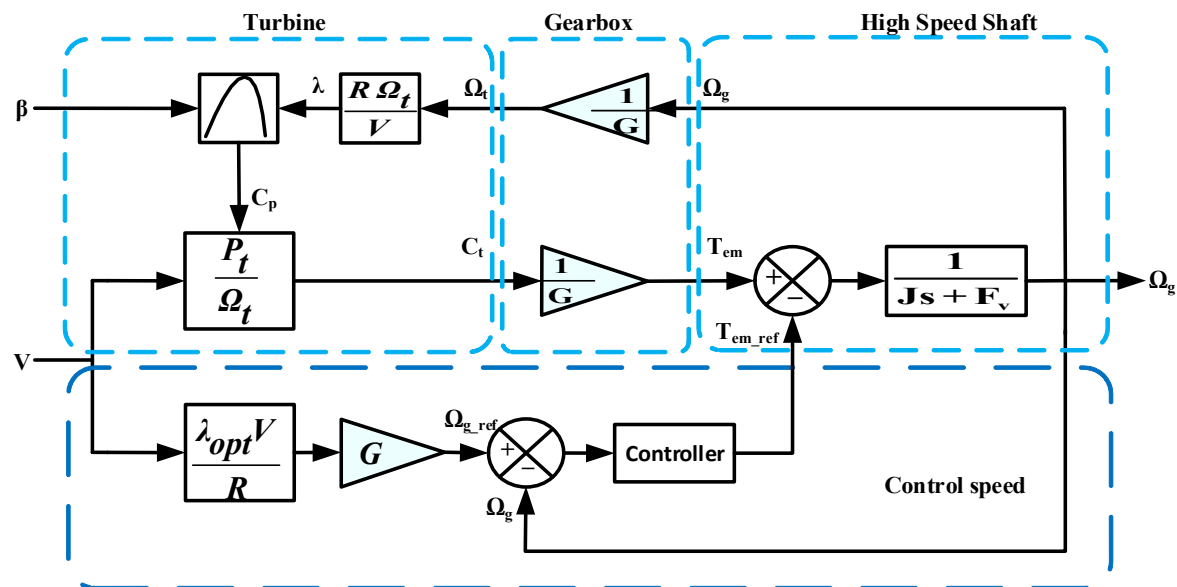


Figure 3. Speed control strategy with MPPT implementation.

- Artificial neural networks

Due to the nonlinear dynamics of wind power generation, this paper employs the artificial neural network (ANN) control approach. ANN-based control techniques are among the most recent and advanced strategies, providing high-performance solutions for modeling complex nonlinear systems [16,23,32].

The internal arrangement of the ANN is displayed in Figure 4.

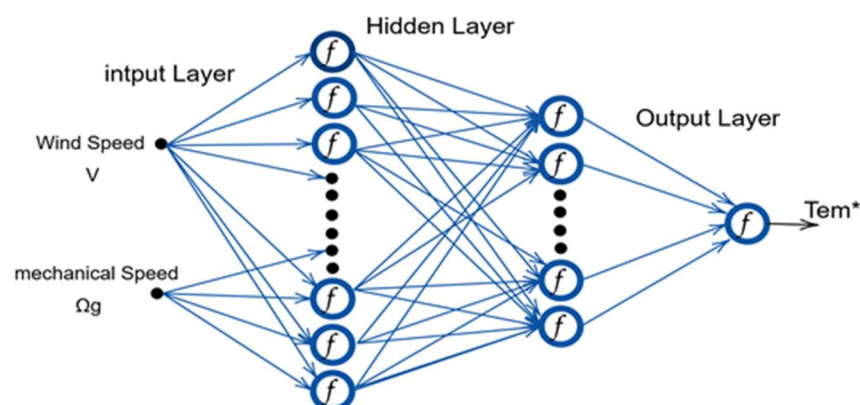


Figure 4. ANNC internal structure.

The architecture of the neural network includes two neurons constituting the input layer, modeling wind and mechanical speeds. The architecture includes as well two hidden layers and a terminal layer with a single neuron assigned to the reference electromagnetic torque. After multiple training iterations, the extracted results are represented in Figures 5 and 6.

The ANNC training was performed using the Levenberg–Marquardt algorithm, valued for its effectiveness and resilience [16,23]. The dataset was partitioned into three subsets: 75% for training, 15% for testing, and 10% for validation. As depicted in Figure 6, the suggested structure (2-5-5-5-1) exhibits rapid convergence to an optimal solution until the 30th iteration, followed by slight error fluctuations, attaining 3.6155×10^{-4} at the 100th epoch.

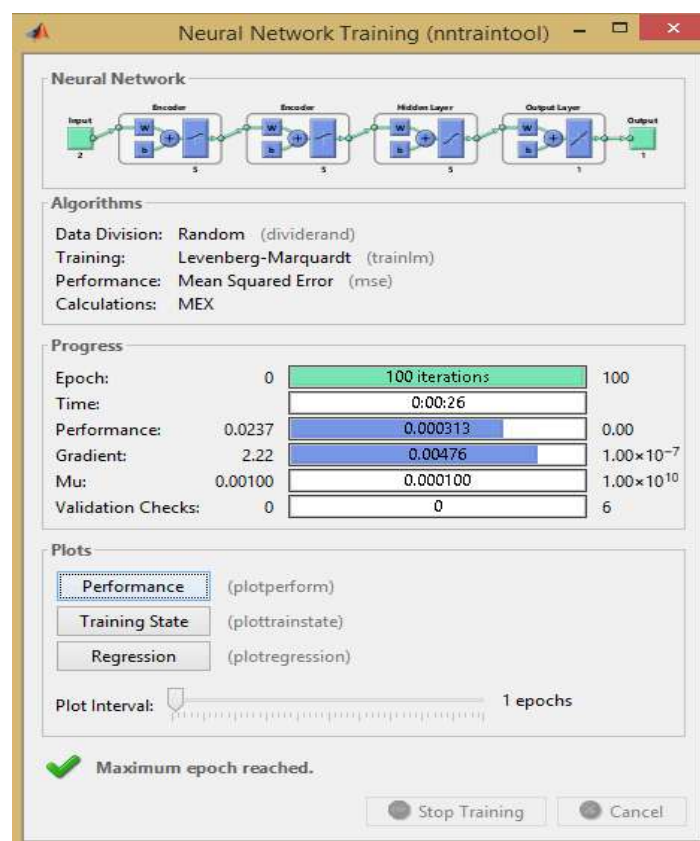


Figure 5. Training progression of the ANN.

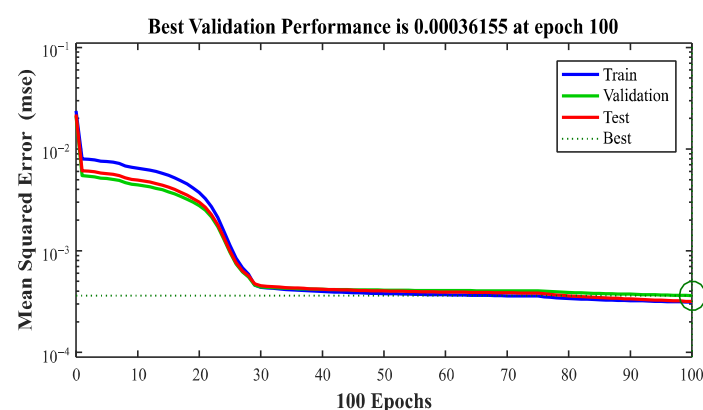


Figure 6. Training error evolution and convergence characteristics of the proposed ANN architecture.

2.2. Mathematical Model of DFIG

A three-phase DFIG can be described using the dynamic equation in the synchronously rotating d-q reference frame, as shown in Equations (5)–(7) below [17,33]:

Voltage's analytical representation is as follows:

$$\begin{cases} V_{sq} = -\omega_s \phi_{sd} + \frac{d}{dt} \phi_{sq} + R_s i_{sq} \\ V_{sd} = -\omega_s \phi_{sq} + \frac{d}{dt} \phi_{sd} + R_s i_{sd} \\ V_{rq} = -(\omega_r - \omega_s) \phi_{rd} + \frac{d}{dt} \phi_{sq} + R_r i_{rq} \\ V_{rd} = (\omega_r - \omega_s) \phi_{rq} + \frac{d}{dt} \phi_{sd} + R_r i_{rd} \end{cases} \quad (5)$$

Flux's analytical representation is as follows:

$$\begin{cases} \phi_{sq} = i_{sq} \times L_s + i_{rq} \times L_m \\ \phi_{sd} = i_{sd} \times L_s + i_{rd} \times L_m \\ \phi_{rq} = i_{rq} \times L_r + i_{sq} \times L_m \\ \phi_{rd} = L_r \times i_{sd} + L_m \times i_{rd} \end{cases} \quad (6)$$

Power's analytical representation is as follows:

$$\begin{cases} P_s = \frac{3}{2} \times \text{Re}\{\vec{I}_s^* \times \vec{V}_s\} = \frac{3 \times (i_{sq} V_{sq} + i_{sd} V_{sd})}{2} \\ Q_s = \frac{3}{2} \times \text{Im}\{\vec{I}_s^* \times \vec{V}_s\} = -\frac{3 \times (i_{sq} V_{sd} - i_{sd} V_{sq})}{2} \end{cases} \quad (7)$$

In these equations, ω_s and ω_r indicate the stator and rotor pulsations, whereas R_s and R_r are set-aside for the stator and rotor resistances, respectively.

The torque generated electromagnetically is defined in Equation (8) below [22,34]:

$$C_{em} = \frac{3}{2} \frac{L_m}{L_s} p \times \text{Im}\{\vec{I}_r^* \times \vec{\Psi}_s\} = -\frac{3}{2} \frac{L_m}{L_s} p \times (i_{rq} \phi_{sd} - i_{rd} \phi_{sq}) \quad (8)$$

2.3. Control of DFIG

- Field-oriented control

Among the various control methods for DFIG-based wind turbines, field-oriented control is a commonly adopted strategy in the literature. Its objective is to replicate the dynamics of an independently excited DC machine, with the inductive current governing the magnetic flux and the armature current governing the electromagnetic torque [17,21,22]. The current paper presents a field-oriented control technique that employs a PI controller, ensuring decoupled control of reactive power, active power, and electromagnetic torque.

The active and reactive power expressions for the stator and rotor voltages are formulated as given in Equation (9) [22]:

$$\begin{cases} Q_s = -\frac{3 \left(\frac{M}{L_s} i_{rd} - \frac{\Psi_s}{L_s} \right) V_s}{2} \\ P_s = \frac{-3 V_s M}{2 L_s} i_{rq} \end{cases} \quad (9)$$

The expression governing the electromagnetic torque is introduced in Equation (10), as follows:

$$C_{em} = \frac{-3}{2} \Psi_s \frac{L_m}{L_s} p i_{rq} = \frac{-3}{2} \frac{V_s}{\omega_s} \frac{L_m}{L_s} p i_{rq} \quad (10)$$

The resultant rotor voltages are mathematically described as shown in Equation (11):

$$\begin{cases} V_{rq} = L_r \sigma \frac{di_{rq}}{dt} + R_r i_{rq} + L_r \omega_s \sigma i_{rd} + g \frac{L_m}{L_s} V_s \\ V_{rd} = L_r \sigma \frac{di_{rd}}{dt} + R_r i_{rd} - L_r \omega_s \sigma g i_{rq} \end{cases} \quad (11)$$

where σ stands for the DFIG's dispersion coefficient, expressed as: $\sigma = \left(\frac{L_r L_s - M^2}{L_r L_s} \right)$.

The Park (d-q) reference frame-based schematic of the DFIG model is depicted in Figure 7.

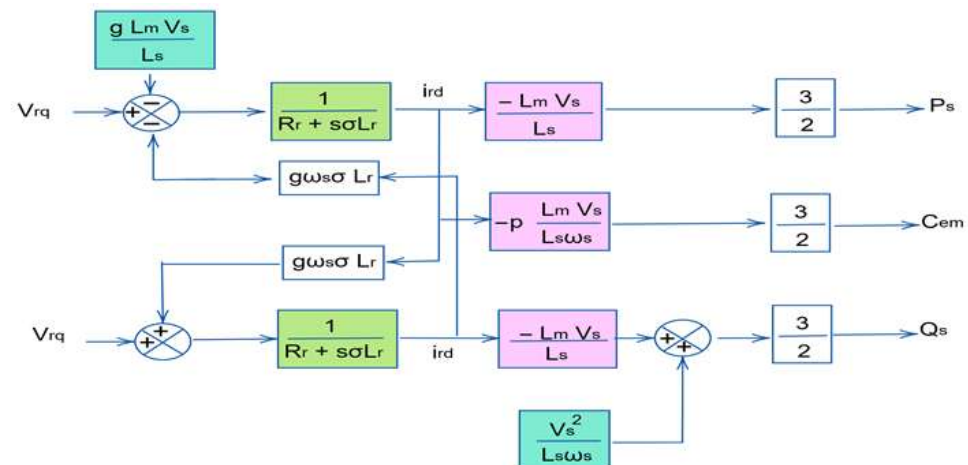


Figure 7. DFIG's structural diagram in the Park (d-q) reference frame.

- Artificial Neural Network Controller

This section introduces a novel intelligent control technique to address the drawbacks associated with traditional methods such as vector control with PI controllers, backstepping control (BAC), and nonlinear sliding mode control (SMC). To refine vector control, neural network-based controllers are implemented, ensuring better regulation of active and reactive power, currents, and torque while enhancing system performance. ANNs are widely adopted due to their straightforward implementation and higher accuracy compared to alternative techniques [23,32]. Moreover, the implementation of ANNs accelerates system response and significantly improves robustness [32]. The suggested intelligent control technique in this section is designed for the Rotor Side Converter (RSC). Three main points below underline the original contribution of this research:

1. The suggested intelligent approach compensates for system non-linearity caused by parametric variations, typically induced by technical issues like mechanical wear and generator overheating.
2. The new strategy proposed for power control of the DFIG is presented and benchmarked against other techniques of recent studies reported in the literature.
3. This intelligent control is noted for its durable performance, minimal design complexity, and adaptability to technological platforms.
4. The improvement of power control through ANN controllers can be considered an innovative combination according to existing literature. A multilayer perceptron (MLP) network is adopted in this work, comprising three layers: an input, an intermediate, and an output. The input layer receives sensor measurements, while neurons in the hidden layers process the data in a feedforward manner, ensuring no feedback connections. The final layer delivers the anticipated outputs.

The architectural diagrams of the two MLP-based neural controllers designed for DFIG reactive and active power control are shown in Figure 8. The architecture of the two MLP-type neural controllers included an input layer with two neurons corresponding to

the active power error (ξ_{Ps}) and its derivative (ξ_{Ps}'), and the reactive power error (ξ_{Qs}) and its derivative (ξ_{Qs}'). Additionally, the structure had two hidden layers and an output layer containing one neuron, which defined the reference rotor voltage components V_{rq_ref} and V_{rd_ref} [23,32]. As shown in Table 2, the tuning variables of the ANN controllers are outlined. Hyperbolic sigmoid neurons were selected as activation functions for the hidden layers, as defined in Equation (12), whereas the output layer employed a linear activation function [1,16,23].

$$sgm = -\frac{\exp(-2x) - 1}{1 + \exp(-2x)} \quad (12)$$

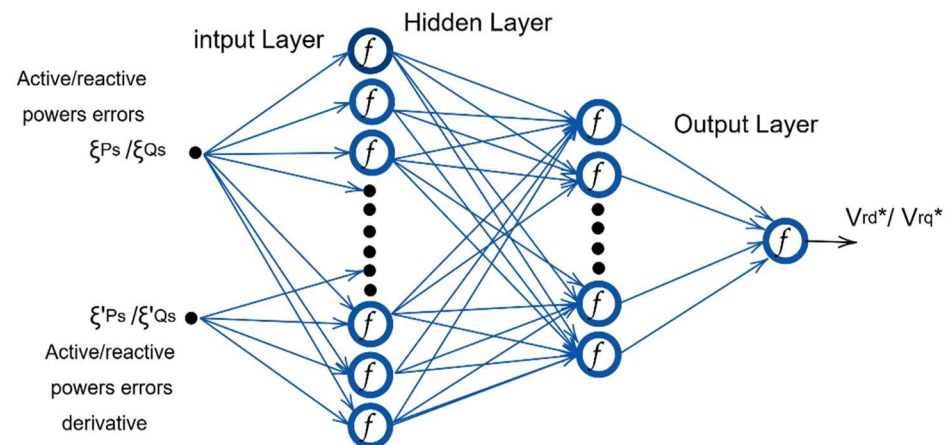
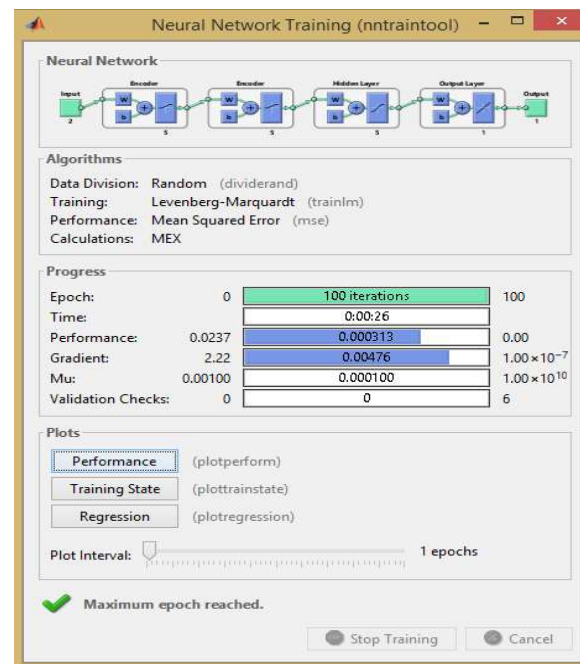


Figure 8. Structural schematics of the implemented MLP networks.

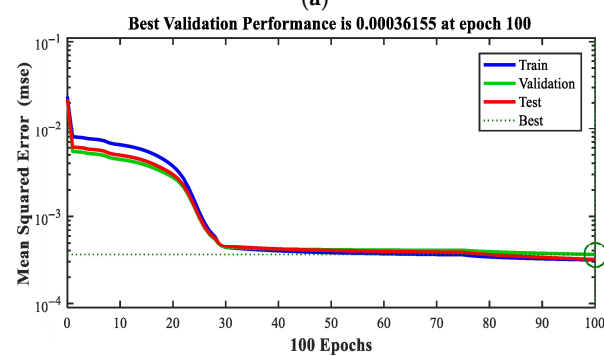
Table 2. Parameters of the two used MLP-type neural controllers.

ANN Parameters	Methods/Value	
	ANN- P_s	ANN- Q_s
MLP Learning Process	Levenberg–Marquardt Algorithm	
Neural Network	Multilayer Perceptron (MLP)	
Proposed Structure	2-5-5-5-1	2-5-5-5-1
Number of Iterations	100	100
Input Layer (two neurons)	ξ_{Ps} and ξ_{Ps}'	ξ_{Qs} and ξ_{Qs}'
Learning Function	Trainlm	Trainlm
Activation Functions	Tansig	Tansig
Output Layer (one neuron)	V_{rq_ref}	V_{rd_ref}

Figures 9a and 10a display the progressive learning behavior of the neural controllers for active and reactive power adjustment. As depicted in Figures 9a and 10a, the neural controllers for active and reactive power exhibit fast learning progress. The proposed (2-5-5-5-1) architectures achieve convergence, with the active power P_s controller reaching an optimal solution by the 30th iteration and the reactive power Q_s controller by the 50th iteration. The progression of the mean squared error (MSE) concerning the iteration count for active and reactive power controllers is depicted in Figures 9b and 10b. Notably, both controllers achieve low MSE values, stabilizing at 3.62×10^{-4} and 3.69×10^{-4} by the 100th iteration.

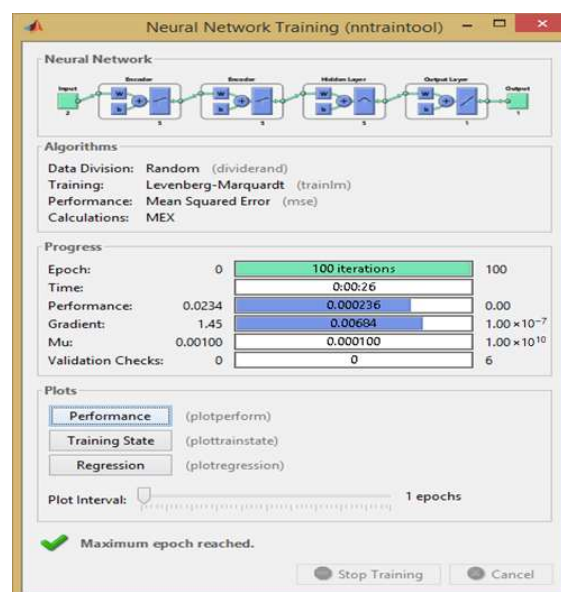


(a)



(b)

Figure 9. Learning process progress for the active power ANN controller and its progress during learning: (a) graphical user interface of learning and (b) learning performance using the mean squared error (MSE).



(a)

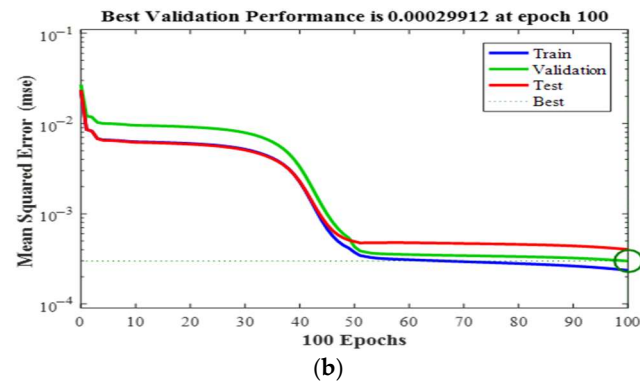


Figure 10. Learning process progress for the reactive power ANN controller and its progress during learning: (a) graphical user interface of learning and (b) learning performance using the mean squared error.

A block diagram of the complete system is depicted in Figure 11, illustrating the power control capabilities of a DFIG regulated by artificial neural networks on the generator-side converter.

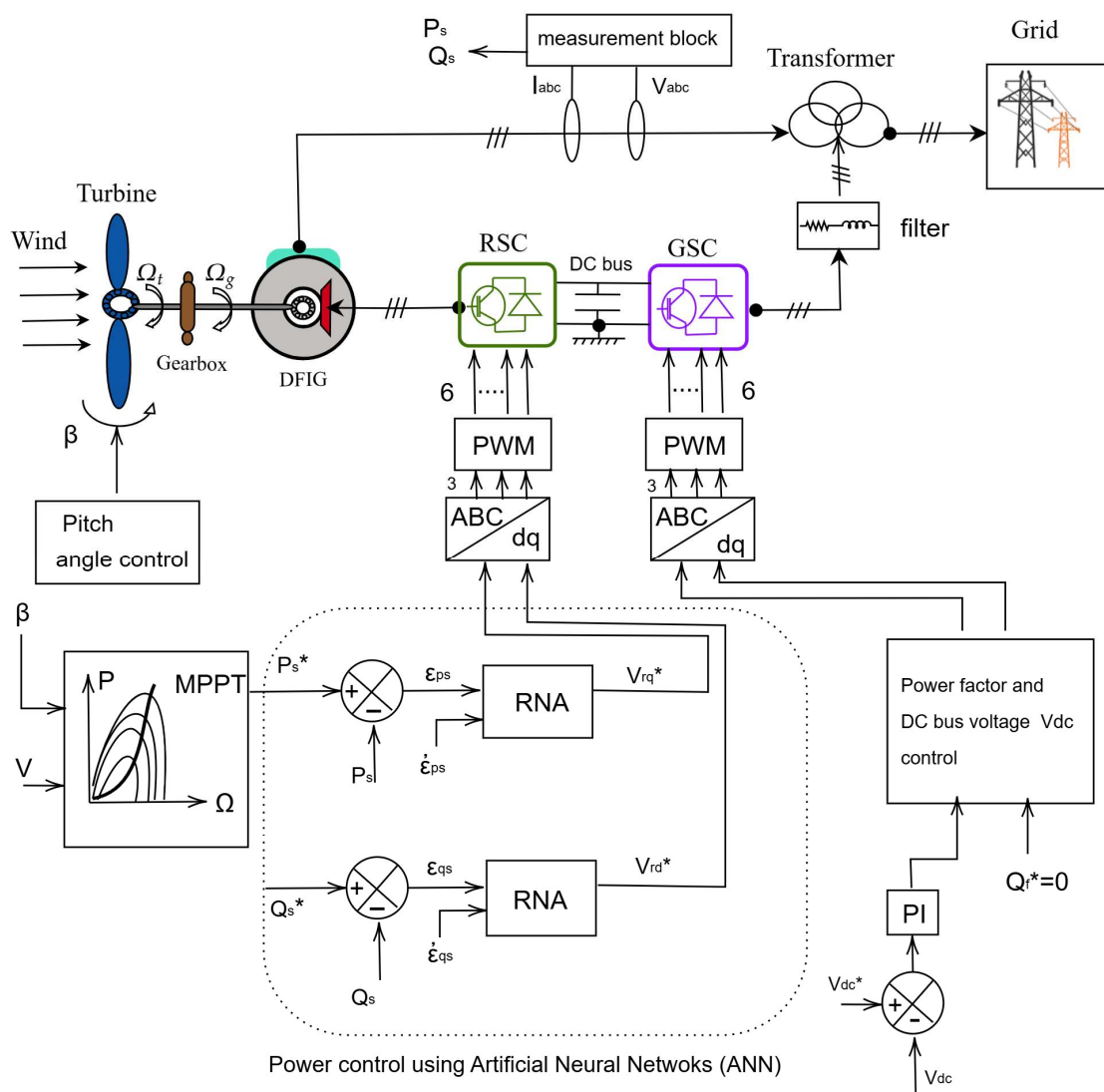


Figure 11. Illustrative configuration of the wind turbine with DFIG.

3. Results and Discussions

A simulation test is conducted under MATLAB/SIMULINK software to assess the effectiveness of the newly introduced control methods, using a 1.5 MW DFIG-based wind turbine model. The parameters of the global system under study are provided in Table 3. The WECS control system simulation was performed using the wind profile illustrated in Figure 12.

Table 3. Specifications of the Simulink Model.

Turbine, RL Filter, and DC Bus Specifications			
DFIG's Parameters	Value	DFIG's Parameters	Value
Poles' pair number, p	2	Mutual inductance, M (H)	0.0135
Number of blades	3	Rated power, P_n (MW)	1.5
Gearbox gain G	90	Stator resistance, R_s (Ω)	0.012
Stator rated voltage, V_s (V)	698	Stator inductance, L_s (H)	0.0137
Filter resistance R_f (Ω)	0.012	Rotor resistance, R_r (Ω)	0.021
Stator rated frequency, f_s (Hz)	50	Rotor Inductance, L_r (H)	0.0136
DC-bus voltage V_{dc} (V)	0.012	Friction coefficient f (N.m.s/rad)	0.0024
Moment of inertia J (kg.m ²)	1000	Filter inductance L_f (H)	0.005
DC-bus capacitor C (F)	8×10^{-3}	Rotor radius R (m)	35.25

Figures 13 and 14 indicate that the $C_p(\beta, \lambda)$ value is nearly identical to its maximum value of $C_{p_max}(\beta, \lambda) = 0.479$ for $\beta = 0^\circ$, which is achieved when the tip speed ratio λ_{opt} reaches its optimal value of $\lambda_{opt} = 8.2$. Figure 15 depicts the DFIG's mechanical speed, achieved by applying MPPT with speed control using the ANN-based control method. From the figure, it is observed that the recorded mechanical speed matches the reference precisely.

The generator current components i_{rd} and i_{rq} are shown in Figure 16. Figure 17 depicts the stator power, including active power P_s and reactive power Q_s . Figure 18 compares the stator current i_{sab} for both controllers, (a) FOC-PI and (b) ANN, whereas Figure 19 displays the rotor current i_{rab} for both controllers using the same configurations.

According to Figures 16 and 17, the active power mirrors the behavior of i_{rq} , while the reactive power follows the pattern of i_{rd} . This relationship confirms that P_s is controlled by i_{rq} and Q_s by i_{rd} , demonstrating the successful decoupling of the system. From Figures 16 and 17, it is also observed that the active and reactive powers of the stator, as well as the currents i_{rq} and i_{rd} , accurately follow their reference values under both control approaches. Nevertheless, the ANNC demonstrates superior performance compared to the FOC-PI, characterized by a quicker response, lower power curve overshoot, and fewer disturbances and oscillations. As shown in Figure 17, the stator active power retains a negative value, indicating that the DFIG is operating in generator mode. Similarly, the reactive power remains zero ($Q_{s-ref} = 0$ VAR), affirming a unitary power factor, as shown in Figure 18b.

According to Figures 18 and 19, representing the stator and rotor current characteristics under the FOC-PI and ANNC methods, the stator current frequency remains stable, and the rotor current frequency adapts to variations in generator speed. The spectral analysis of the stator current for phase (a) I_{sa} is illustrated in Figure 20, which shows that the THD is 0.91% for FOC-PI, complying with the IEEE-519 standard [7]. By implementing ANNC, the THD is significantly reduced to 0.38%. Accordingly, ANNC proves to be the most efficient approach for reducing current harmonics.

As can be seen in Figure 21a, with wind speed fluctuations, the DC bus voltage remains steady, achieving its reference value precisely with the ANNC technique compared to the FOC-PI control. As shown in Figure 21b, the power factor of the DFIG is

approximately equal to 1, with more noticeable ripples observed under the FOC_PI control compared to the ANNC technique. Operating with zero reactive power results in a unit power factor regime. Additionally, Figure 22a illustrates a clear phase opposition in the voltage waveforms, while Figure 22b presents a zoomed view. As shown, a near-perfect phase opposition is observed between the voltage and current profiles, indicating the effective achievement of a unity power factor. This result confirms the negligible exchange of reactive power with the grid, which is a key requirement for efficient power delivery and grid compliance.

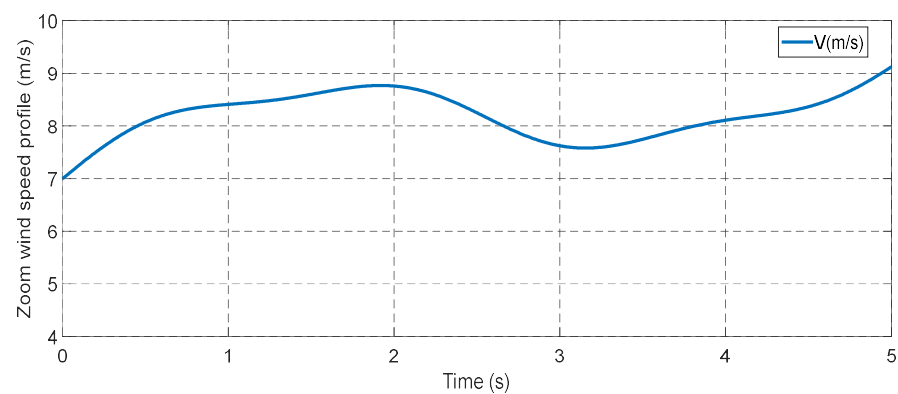


Figure 12. Wind speed profile.

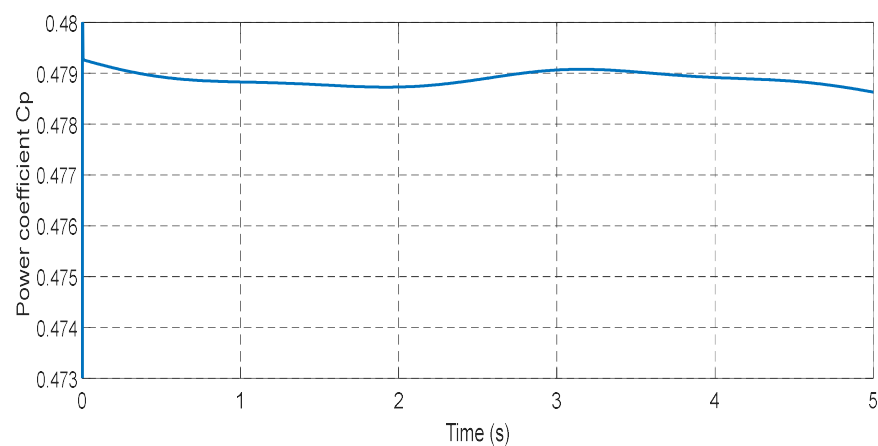


Figure 13. Power coefficient.

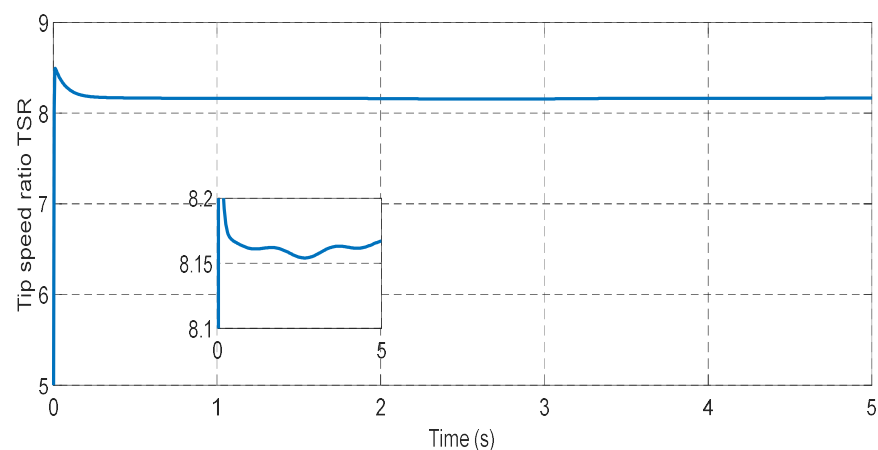


Figure 14. Variation in the tip speed ratio over time.

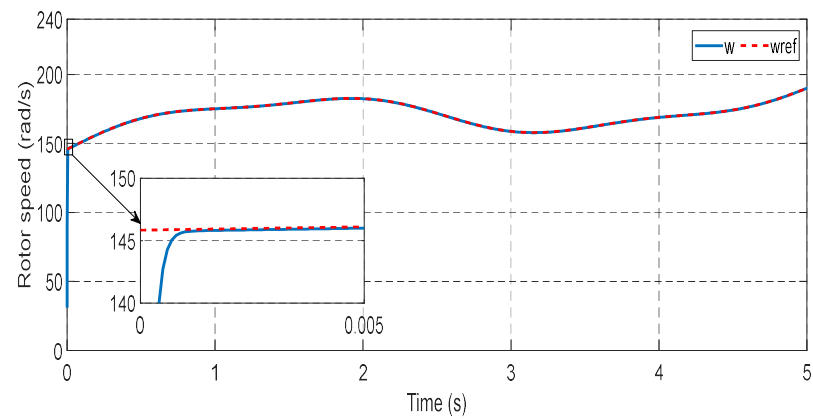
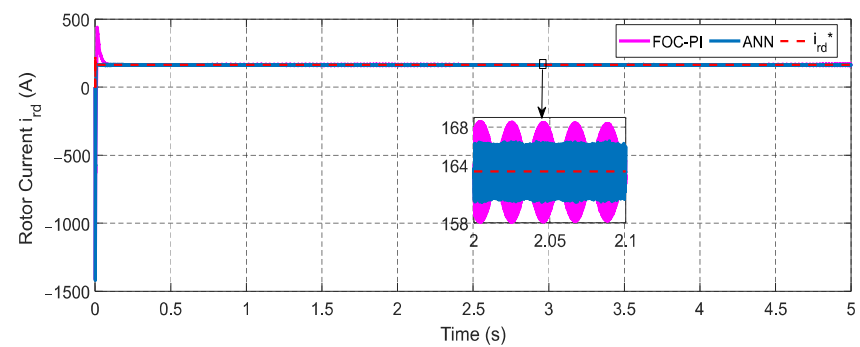
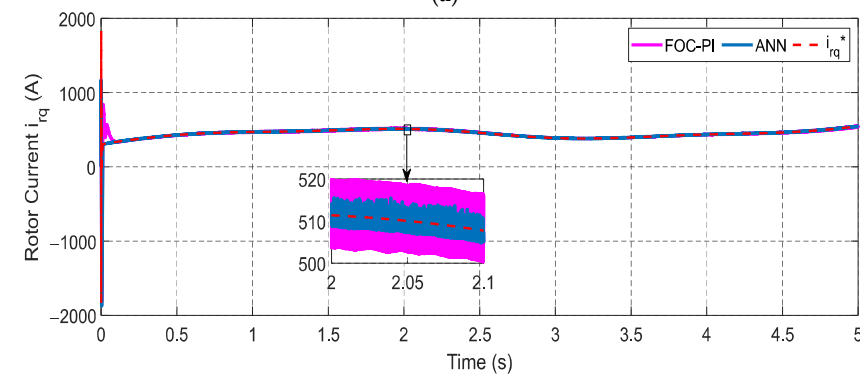


Figure 15. Real-time variations in the mechanical rotor speed.

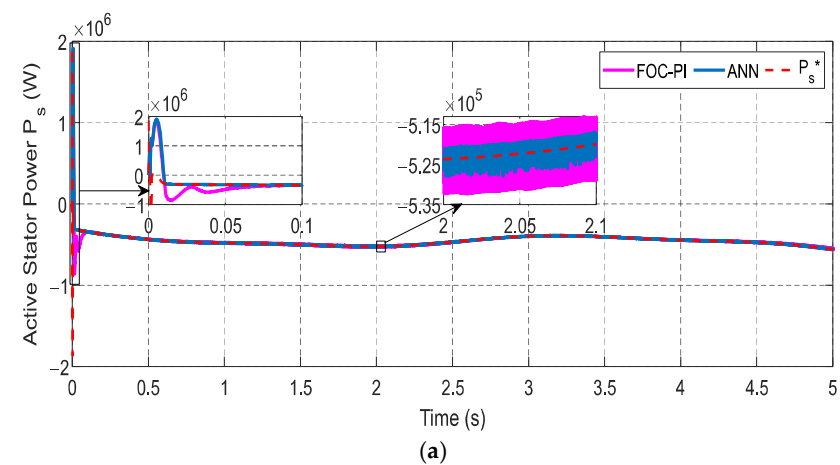


(a)



(b)

Figure 16. Generator current: (a) i_{rd} and (b) i_{rq} .



(a)

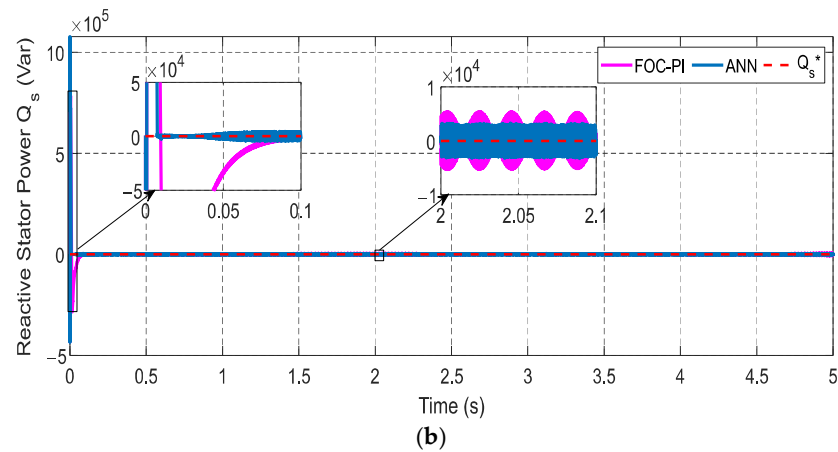


Figure 17. Real-time variations of (a) active power P_s and (b) reactive power Q_s .

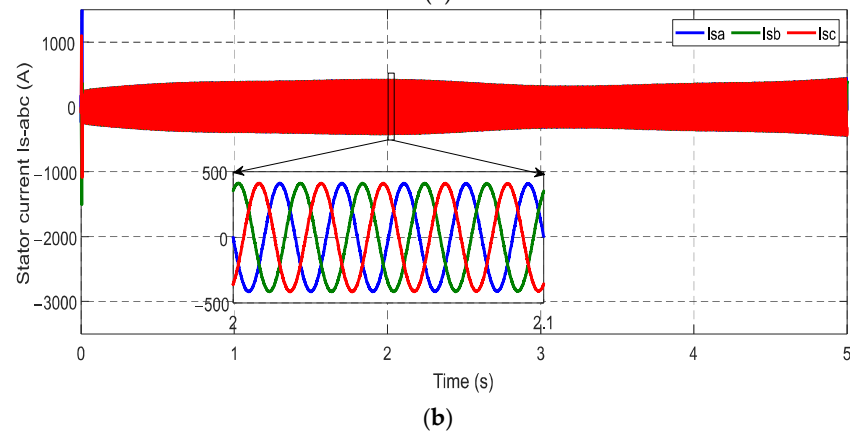
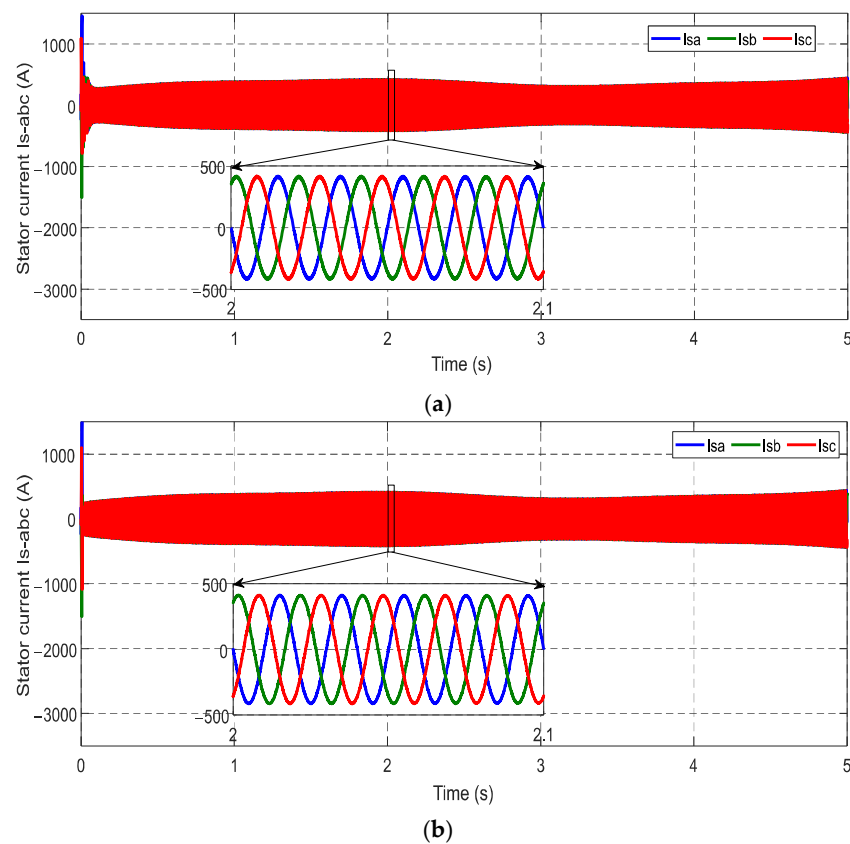
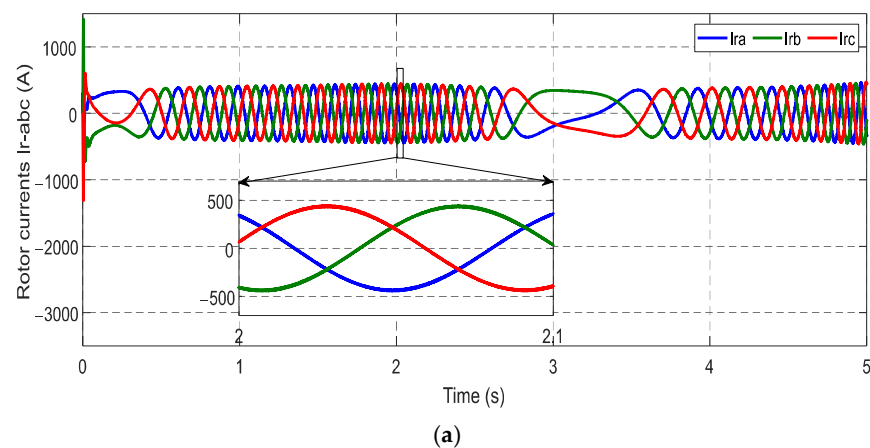


Figure 18. Stator current i_{sabc} of (a) FOC_PI controller and (b) ANN controller.



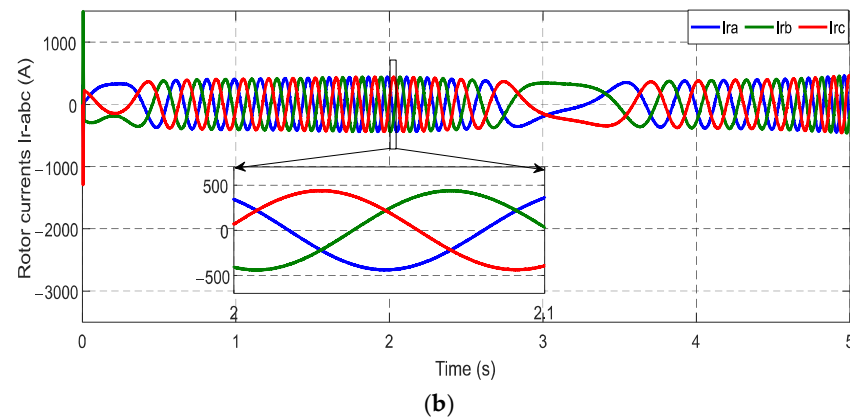


Figure 19. Rotor current i_{rabc} of both controllers: (a) FOC_PI and (b) ANN.

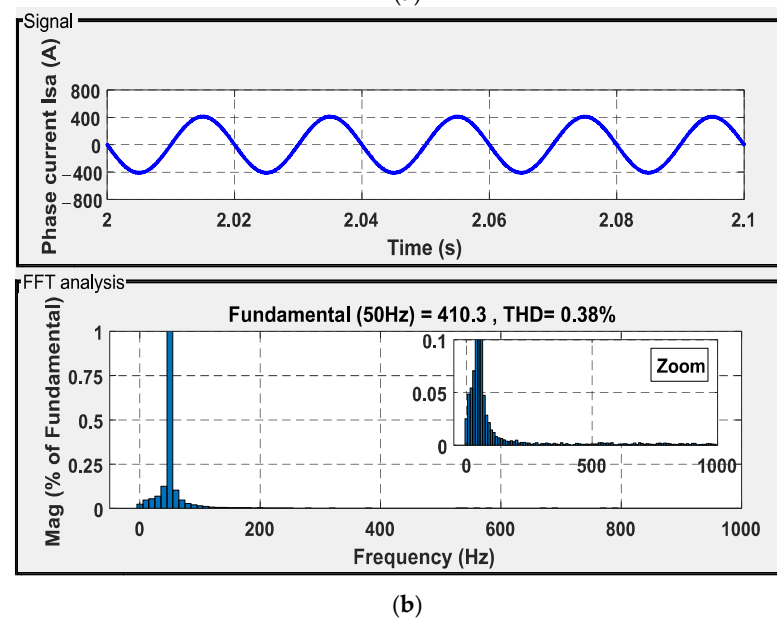
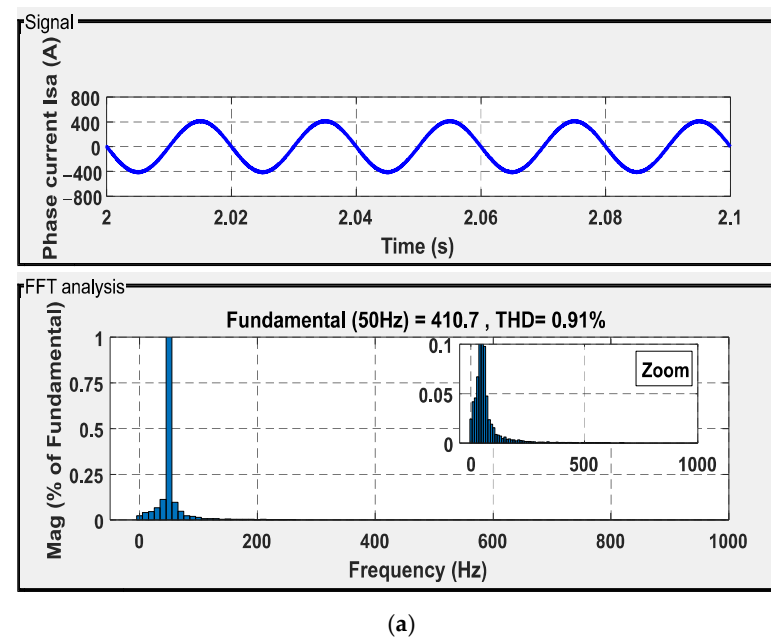


Figure 20. Stator current i_{sa} THD comparison under different control strategies: (a) FOC_PI and (b) ANN.

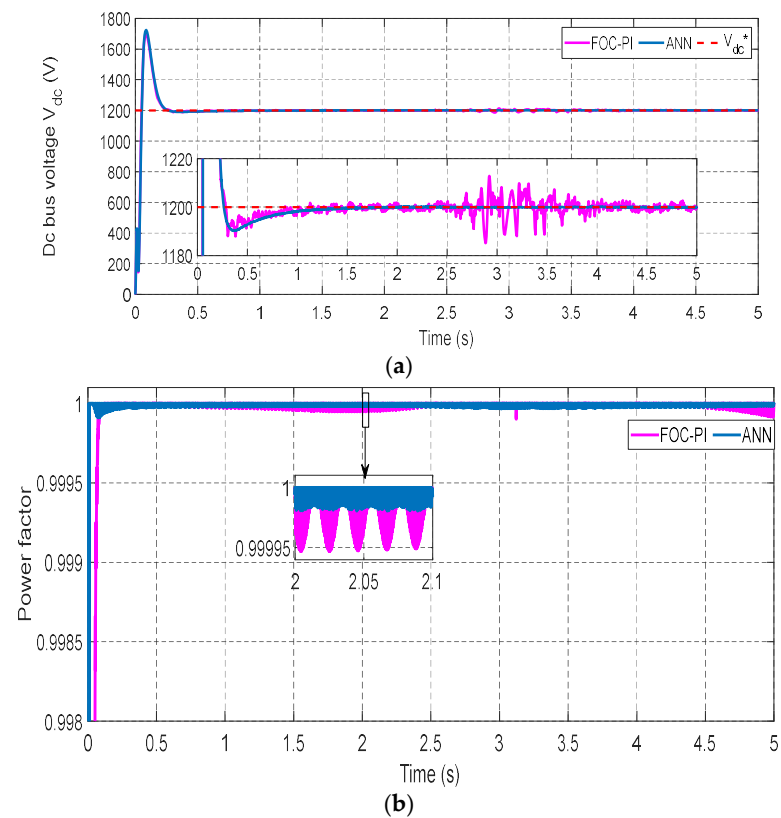


Figure 21. (a) Dc bus voltage V_{dc} and (b) power factor.

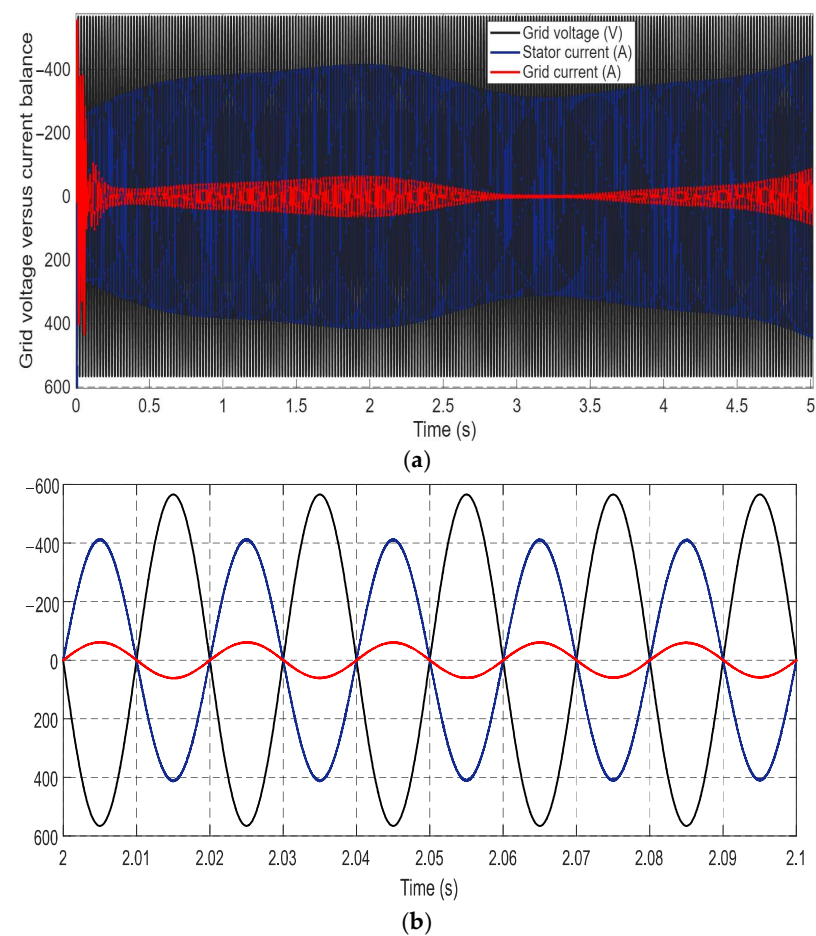


Figure 22. (a) Grid voltage versus current balance, (b) zoomed-in view.

A detailed assessment was carried out to gain insights into the most efficient control strategy for the system, aiming for peak performance. The findings are summarized in Table 4, showcasing the notable improvements obtained using ANNC.

Table 4. Performance evaluation of FOC_PI and adaptive ANN control strategies.

Parameter	FOC Used PI	ANN	Improvement (%)
THD of the current I_{sa} (%)	0.91	0.38	58.26
Response time (s)	0.403	0.287	30.23
Overshoot (%)	Important ($\approx 17\%$)	Neglected ($\approx 4.9\%$)	69.52
Rise time (s)	0.229	0.154	27.97
Static errors (%)	0.267	0.165	28.46
Set-point tracking	Medium	High	/
Precision	Good	Very good	/

To test the effectiveness of the proposed controllers, various performance measures, such as the MRE (Mean Relative Error), the ITAE (Integral Time Absolute Error), the IAE (Absolute Error), the ITSE (Integral Time Square Error), and the ISE (Integral Square Error), can be considered. In this work, the ITAE is chosen as the primary evaluation metric due to its frequent use in controller performance assessment. This indicator is defined as reported in Equation (13) [21]:

$$\text{ITAE} = \int t|\varepsilon| dt \quad (13)$$

A lower ITAE value indicates improved controller performance. Table 5 summarizes the quantitative analysis of active power, DC-bus voltage, reactive power, and rotor currents along the d- and q-axes. The results indicate that ANNC achieves the lowest ITAE values compared to FOC-PI, confirming its enhanced control capability.

Table 5. ITAE of ANN and FOC-PI errors.

	FOC Used PI	ANN
Q-axis rotor current i_{rq}	70.09	23.06
D-axis rotor current i_{rd}	31.95	11.95
Reactive power Q_s	51930.2	421.7
Active power P_s	30981.7	479.1
DC-bus voltage V_{dc}	4017.2	2491.3

Establishing the novelty of this study involves evaluating it alongside other control approaches reported in the recent literature. This comparative study is illustrated in Table 6. It should be noted that these studies were not conducted under entirely identical conditions, as it is quite rare to find multiple works in this field carried out in exactly the same circumstances. The results from this comparison indicate that the suggested method outperforms the alternatives in terms of ripple minimization, steady-state error, overshoot, and stator current THD compared to some methods presented in recent studies from the literature, such as the backstepping, sliding mode, HLRNN, and Fuzzy SMC strategies.

Table 6. Review of the proposed control versus recent works from the literature.

References	Techniques	Static Error (%)	THD i_{sa} (%)	Ripples	Overshoot (%)
[35]	Backstepping	0.29	4.52	Low	Moderate ($\approx 9\%$)
[36]	Fuzzy SMC	0.19	3.1	High	Negligible ($\approx 6\%$)
[37]	SMC	1.84	4.99	High	Significant ($\approx 18\%$)
[38]	HLRNN	0.16	----	Moderate	Significant ($\approx 24\%$)
Proposed technique	ANNC	0.158	0.38	Low	Negligible ($\approx 5\%$)

Real-Time Implementation of the Proposed Controller

This subsection presents the experimental implementation and evaluation of the suggested control strategy. The designed experimental setup, shown in Figure 23, includes an eZdsp TMS320F28335 board and a computer running MATLAB software [39]. A PWM-based strategy is employed to drive the inverter, generating a five-volt logical signal used to control the IGBTs [40,41]. The suggested control technique is implemented under Matlab 2020. Through this system, the devised control methodology is transmitted to the eZdsp TMS320F28335 controller board. In order to test the validity of the proposed strategy, a series of tests was conducted using the eZdsp TMS320F28335 board and the real-time workshop tool.

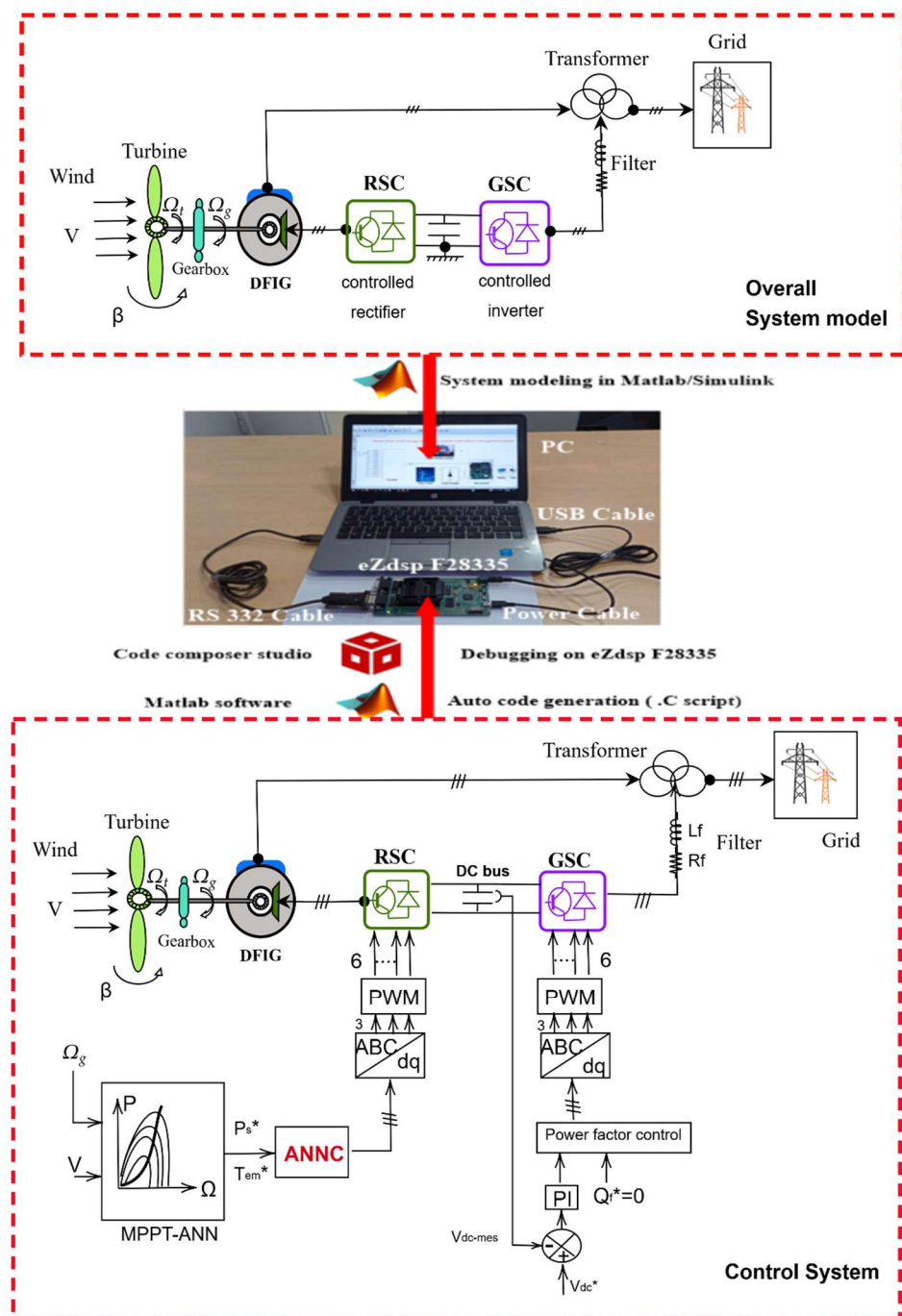


Figure 23. Real-time implementation system.

Additionally, the tests previously conducted in the preceding section were upheld to validate the simulated outcomes and gain insights into how the designed control mechanism responds to fluctuations in wind speed profiles.

The illustrations of Figures 24 to 35 show the outcomes of the real-time implementation using the eZdsp TMS320F28335 board, which aims to demonstrate the effectiveness of tracking and control over a varying wind profile. From the results, nearly identical behavior is shown in both numerical and experimental study scenarios. Figure 24 shows the considered realistic wind speed profile. Figure 25 presents the tip speed ratio profile, which remains close to 8.16, corresponding to the optimal TSR for maximizing wind power extraction. Figure 26 illustrates the power coefficient variations, which directly reflect the amount of power captured. Figure 27 shows the generator's mechanical speed, which tracks smoothly the wind speed variation, which confirms the validity of the adopted ANNC.

Figure 28a,b show, respectively, the quadrature i_{rq} and direct i_{rd} rotor current components obtained in real time. The variation in i_{rq} tracks the variation in active power; meanwhile, the variation in i_{rd} follows the variation in reactive power. This fact is confirmed through Figure 29a,b, which illustrate the profiles of the generator's active and reactive powers, respectively. Figure 30 illustrates the generator's encounter torque, which follows the fluctuation in the applied wind speed and also tracks the variation in the active power. It is also observed that the reactive power is preserved correctly at zero VAR, ensuring a unity power factor operation. This is confirmed by Figure 31, which shows that the pf value is correctly maintained at unity.

The generated stator and rotor currents, as well as the grid-injected current, are displayed in Figures 32 and 33, respectively. The currents' illustrations confirm the reliability of the adopted control in reaching good tracking for the applied wind speed profile. In addition, both the stator current and injected grid current have a similar frequency of 50 Hz, which reveals good synchronization with the grid. Figure 34 displays the DC bus voltage profile, which preserves a fixed value at 1200 V. This requirement is vital to enable regulating the injected power to the grid via regulating the injected current. Finally, Figure 35 shows the real-time signals of grid voltage and current. This illustration confirms that a unity of operation is maintained at the grid terminals, which reconfirms the validity of the proposed ANNC.

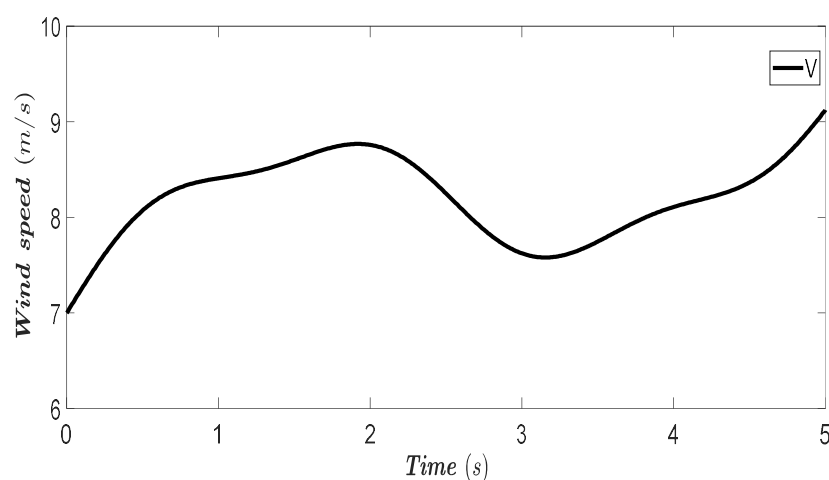


Figure 24. Real-time wind speed variation.

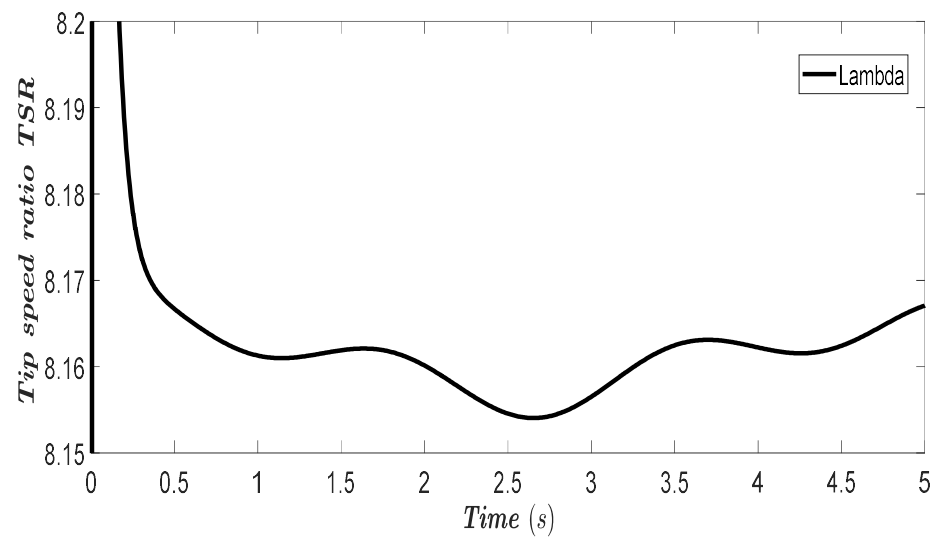


Figure 25. Tip speed ratio.

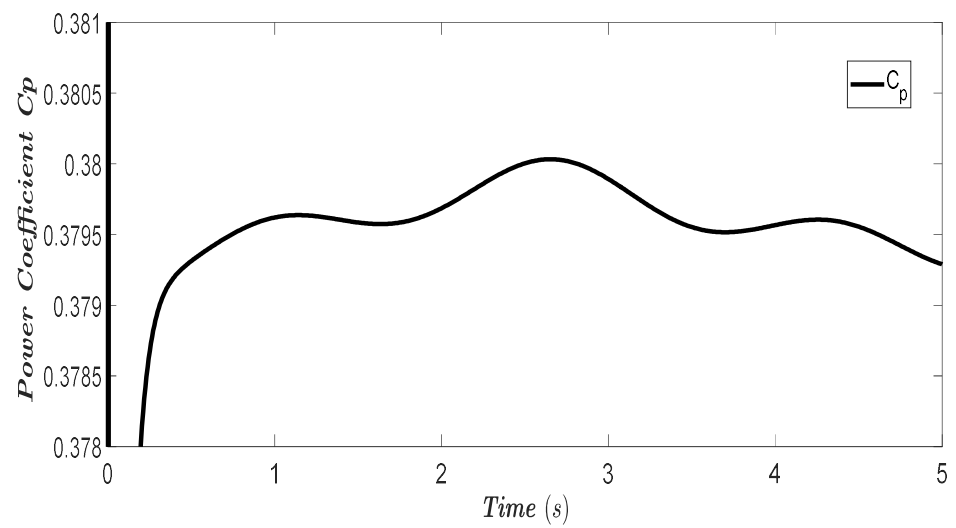


Figure 26. Power coefficient.

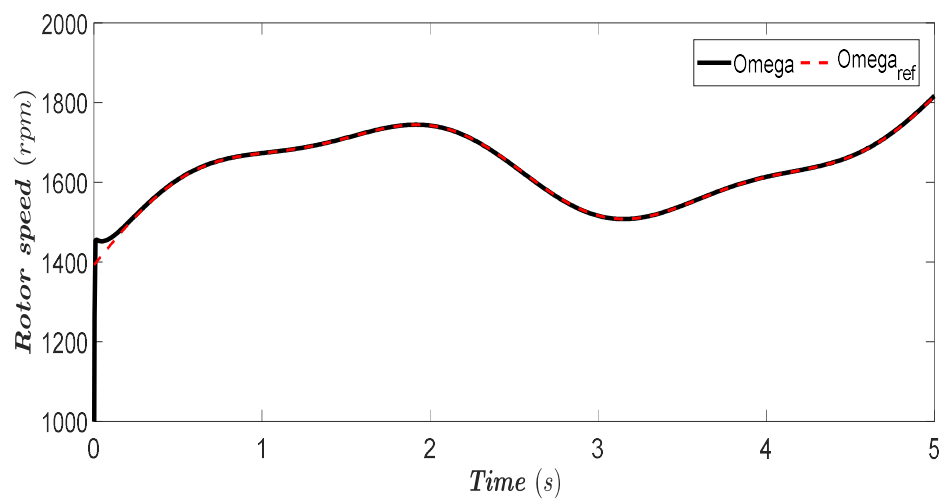
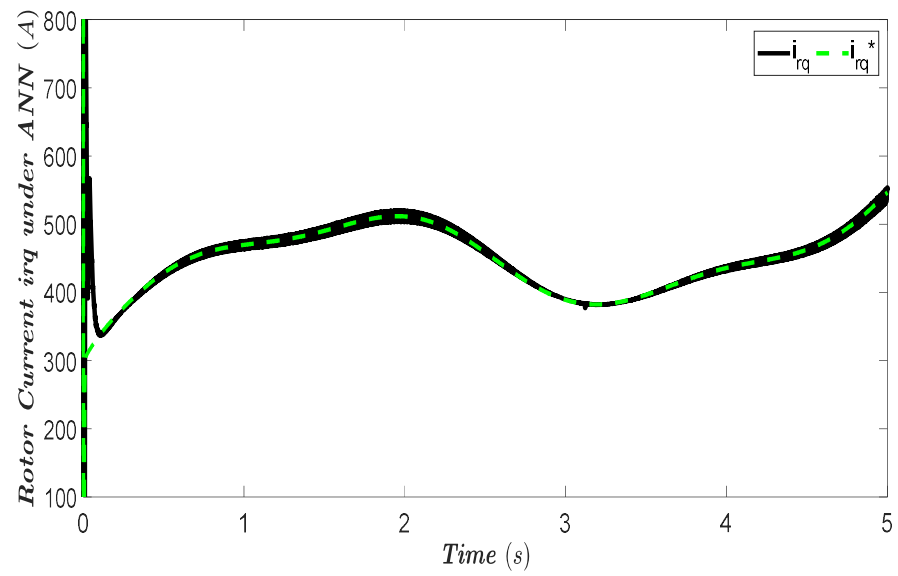
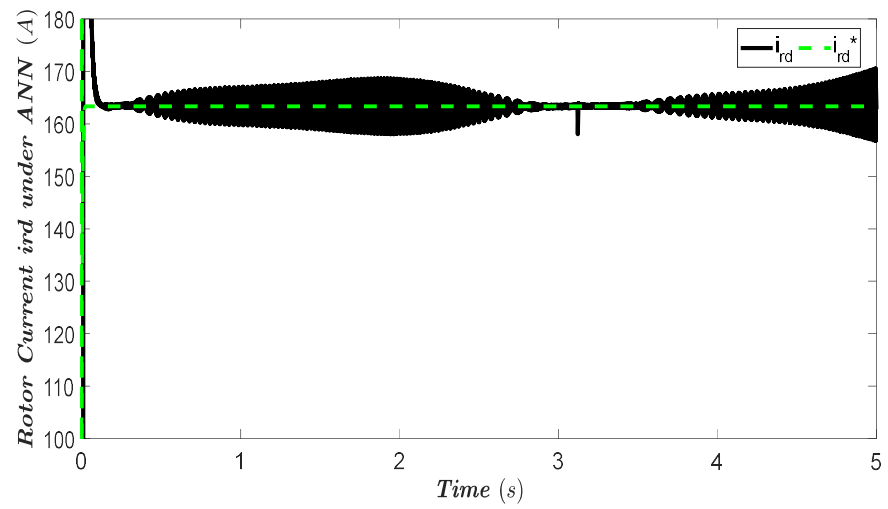


Figure 27. Generator speed.

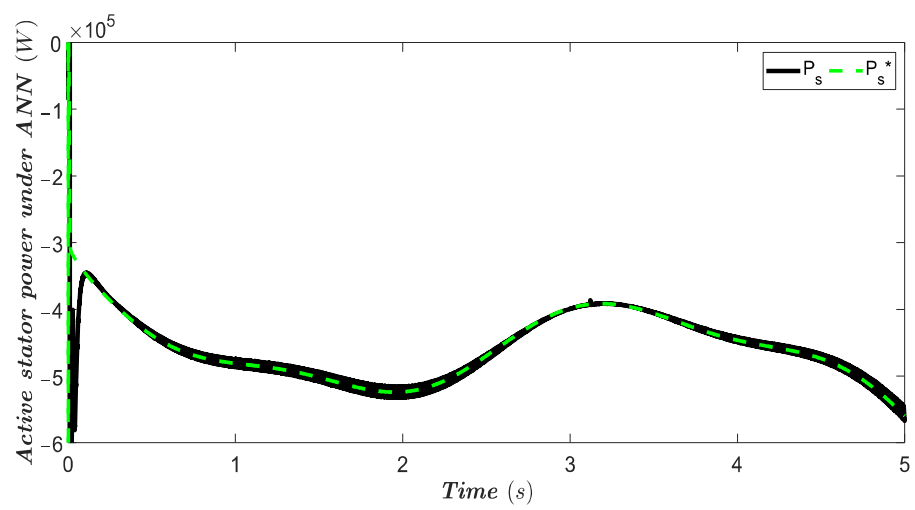


(a)



(b)

Figure 28. Generator's (a) i_{rq} current and (b) i_{rd} current.



(a)

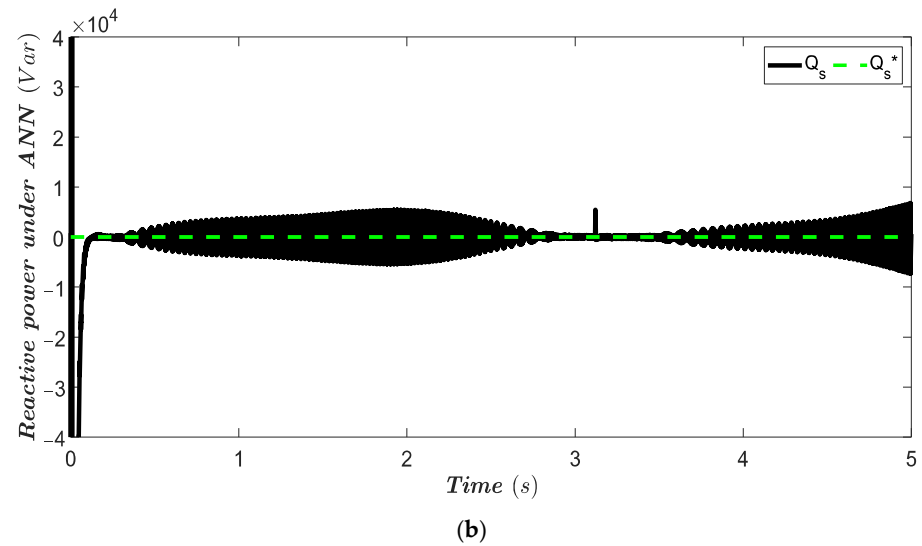


Figure 29. (a) Active power P_s of the stator. (b) Reactive power Q_s of the stator.

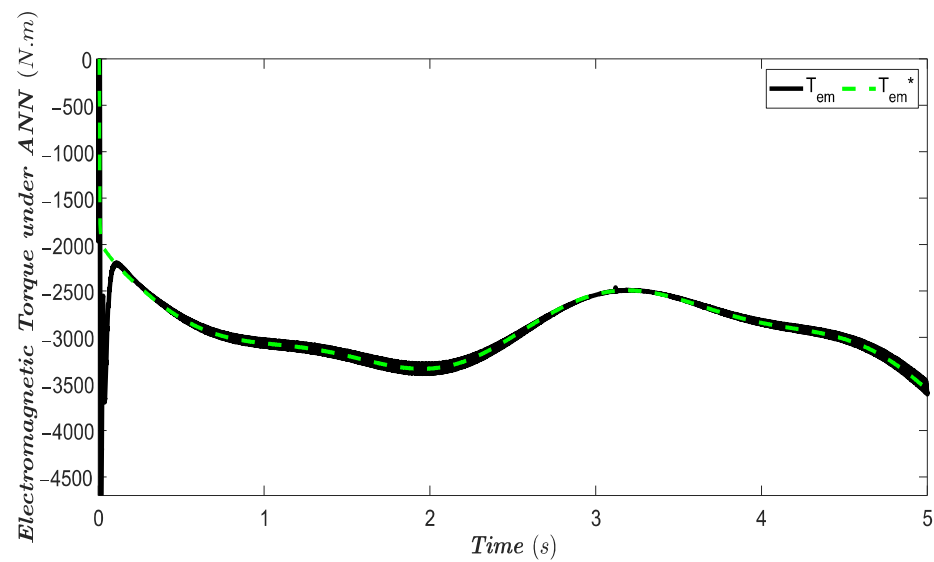


Figure 30. Real-time variations in the electromagnetic torque under the proposed ANN.

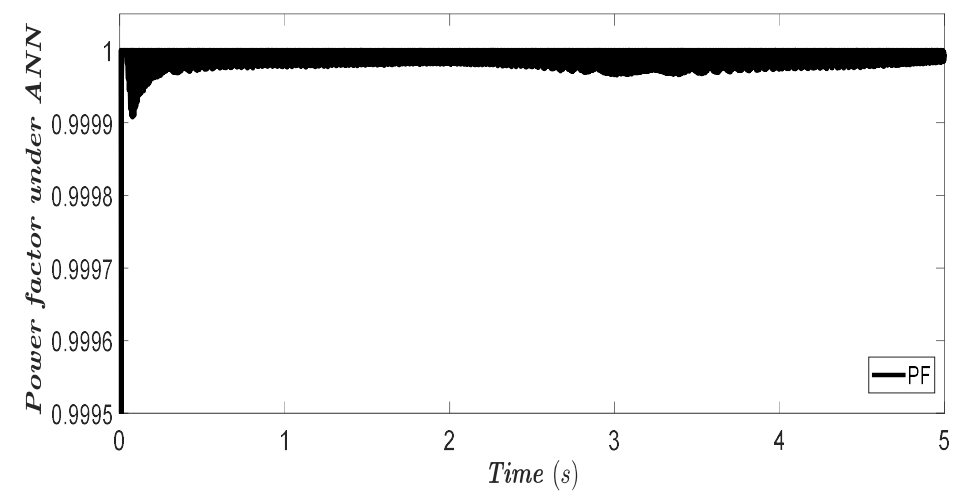


Figure 31. System power factor under the proposed ANN.

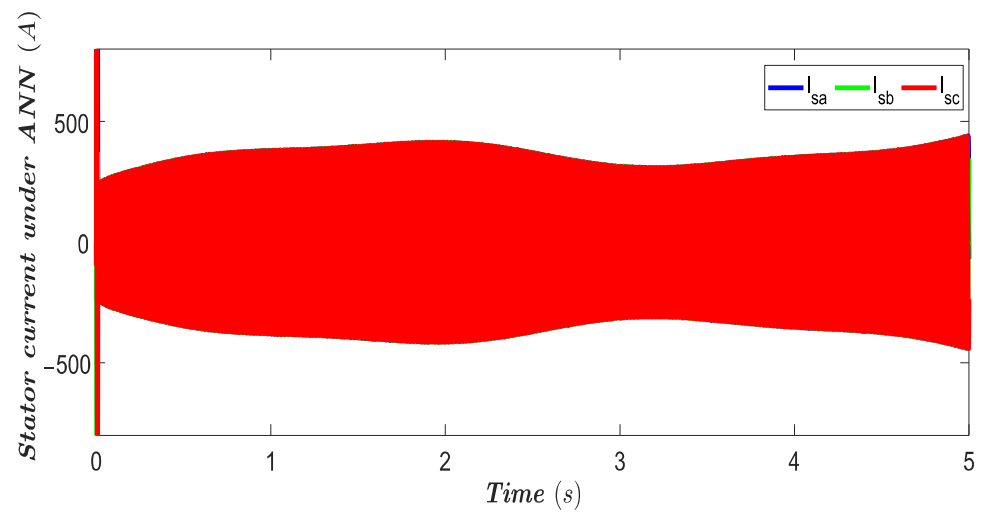


Figure 32. Real-time stator currents i_{sabc} under the proposed ANN.

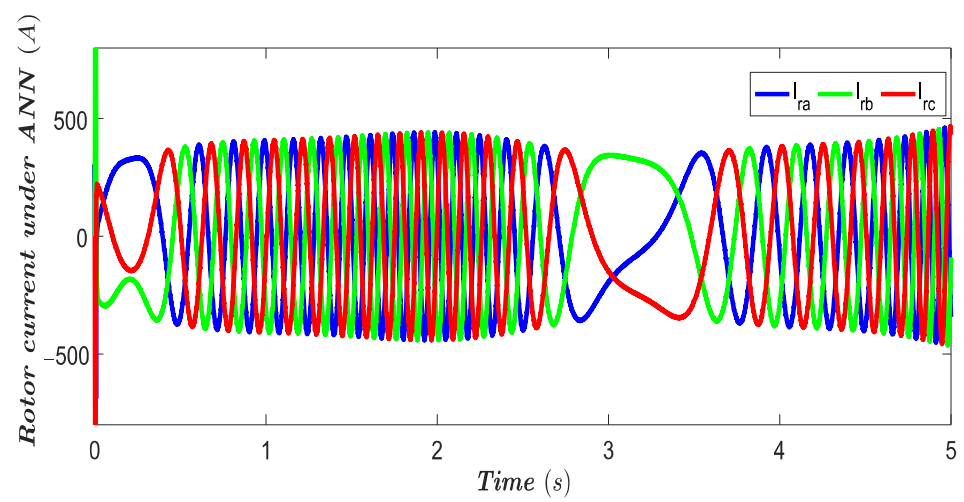


Figure 33. Real-time rotor currents i_{rabc} under the proposed ANN.

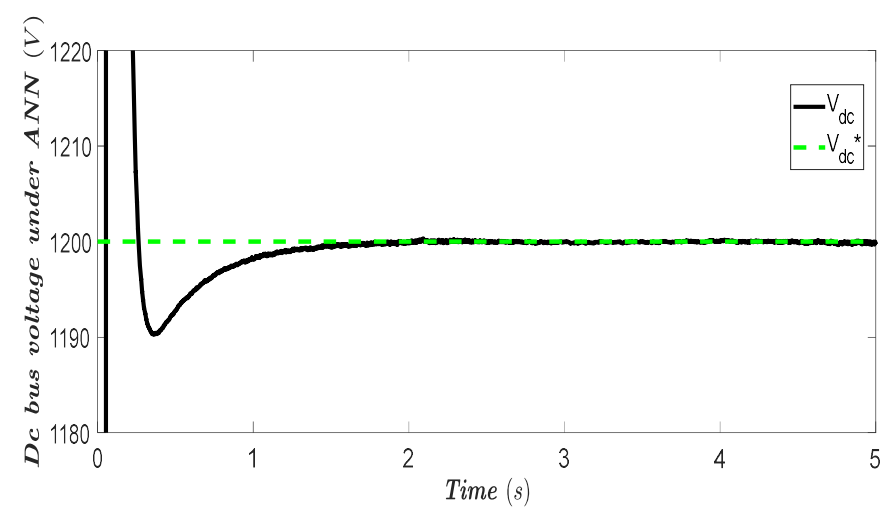


Figure 34. Real-time DC bus voltage using the proposed ANN.

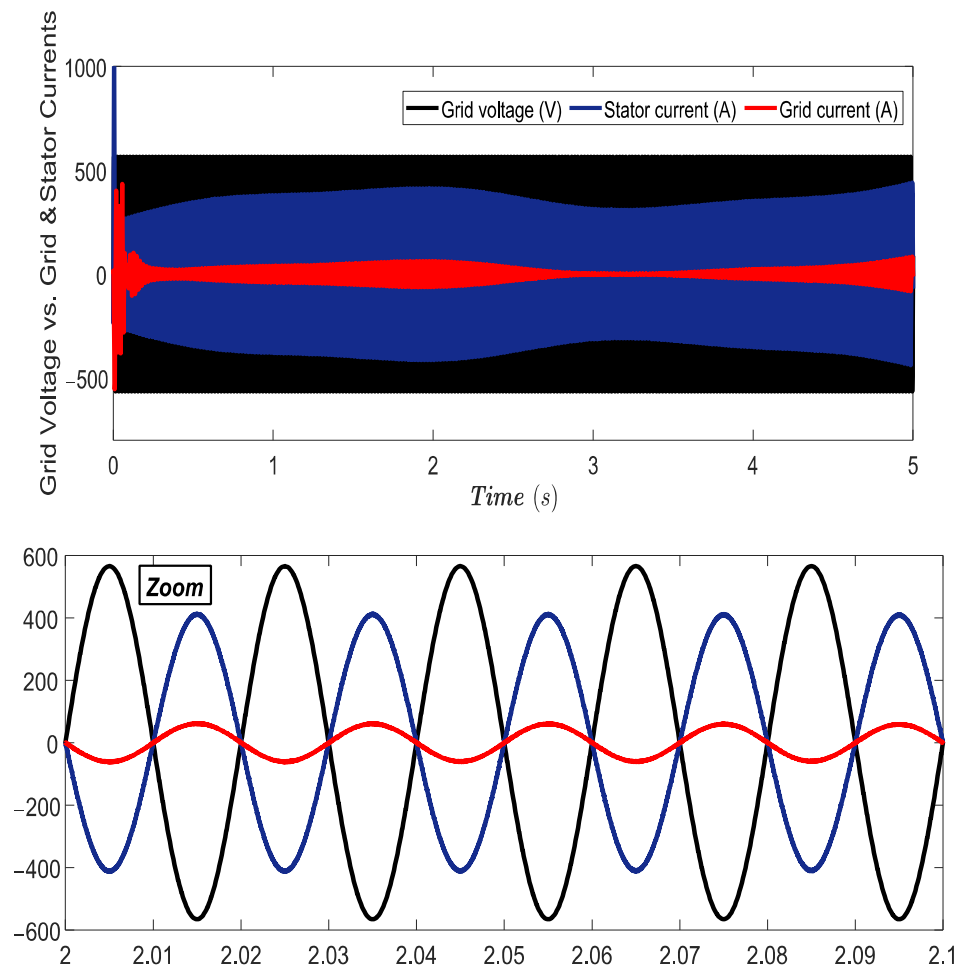


Figure 35. Real-time signals of grid voltage versus grid current.

4. Conclusions

This paper presented a complete modeling, control, and experimental validation of an ANN-based control framework for a DFIG-based wind energy conversion system. The proposed strategy combines an ANN-based MPPT speed regulator directly generating the electromagnetic torque reference from wind and mechanical speed, with two dedicated MLP-based ANN controllers for stator active and reactive power control, replacing classical PI regulators in the RSC under FOC. Simulation and experimental results demonstrate that the proposed ANN control approach significantly improves dynamic performance and power quality compared with the conventional FOC–PI strategy under identical operating conditions. In particular, the ANN-based controllers ensure fast convergence with a low mean square error of approximately 3.6×10^{-4} , precise tracking of active and reactive power with a static error below 0.16%, limited overshoot lower than 5%, and a very low total harmonic distortion of the stator current ($\text{THD} \approx 0.38\%$). These quantitative results confirm the effectiveness of the proposed approach in enhancing robustness, reducing harmonic distortion, and improving tracking accuracy under variable wind speed conditions. Furthermore, the real-time implementation on an eZdsp TMS320F28335 DSP board validates the practical feasibility of the proposed control scheme and confirms its robustness against sensor noise, quantization effects, and inherent implementation delays. Unlike many existing studies limited to simulations or partial experimental validation, this work provides a complete simulation-to-experiment transition and a fair quantitative comparison with a conventional FOC–PI controller. Overall, the obtained numerical and experimental results demonstrate that the proposed ANN-based control strategy

is a reliable and efficient solution for improving power quality, dynamic response, and robustness of DFIG-based wind energy systems.

Following this study, several perspectives and future directions can be suggested to further refine system efficiency:

- The development of novel control strategies based on artificial intelligence (such as Fuzzy Logic, Bald Eagle Search Algorithm, etc.) for wind turbine control.
- Integrating a storage system and improving the conversion chain from both technical and economic perspectives.

Author Contributions: Conceptualization, H.C.; methodology, M.A.M. and M.M.A.; software, H.C.; validation, H.C. and K.T.; formal analysis, M.A.M.; investigation, M.M.A. and A.D.; resources, M.A.M. and K.T.; data curation, K.T. and H.C.; writing—original draft preparation, H.C. and M.A.M.; writing—review and editing, A.D. and M.M.A.; visualization, M.M.A. and A.D. All authors have read and agreed to the published version of the manuscript.

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Abbreviation

Nomenclature

β (Degree °)	Blade pitch angle
λ	Tip speed ratio
ϕ_r and ϕ_s (Wb)	Stator and rotor fluxes
Ω_g (rad/s)	Generator's mechanical speed
ω_r and ω_s (rad/s)	Rotor and stator pulsations
ρ (Kg/m ³)	Air density
C_{mec}	Mechanical torque coefficient
C_p	Power coefficient
C_g	Generator torque coefficient
C_f	Friction coefficient
C_{em}	Electromagnetic torque coefficient
f (N.m.s/rad)	Friction coefficient
f_s (Hz)	Stator rated frequency
G	Gearbox gain
i_r and i_s (A)	Rotor and Stator currents
J (kg.m ²)	Moment of inertia
L_m (H)	Magnetizing inductance
L_f (H)	Filter inductance
L_r (H)	Rotor inductance
L_s (H)	Stator inductance
M (H)	Mutual inductance
N_b	Blades' number
p	Number of pole pairs
P_n (MW)	Rated power
P_s (W)	Stator active power
P_t (W)	Wind turbine power
Q_s (Var)	Stator reactive powers
R (m)	Blade radius
R_f (Ω)	Filter resistance
R_s and R_r (Ω)	Stator and rotor resistances
t (s)	Time
T_{em}	Electromagnetic torque

Abbreviation

ANNC	Artificial Neural Network Controller
ANN	Artificial Neural Network
DTC	Direct Torque Control
DFIG	Doubly Fed Induction Generator
FFT	Fast Fourier Transformation
FOC	Field-Oriented Control
MPPT	Maximum Power Point Tracking
FOSMC	Fractional-Order STC
GSC	Grid-Side Converter
GOA	Grasshopper Optimization Algorithm
MLP	Multi-Layer Perceptron
MSE	Mean Squared Error
FLC	Fuzzy Logic Control
RSC	Rotor-Side Converter
WECS	Wind Energy Conversion System
PWM	Pulse Width Modulation
NNC	Neural Network Control
SMC	Sliding Mode Controller
TSR	Tip Speed Ratio

THD (%)	Total harmonic distortion
V_{dc} (V)	DC bus voltage
V (m/s)	Wind speed
V_{dc} (V)	DC-bus voltage
V_r and V_s (V)	Rotor and stator voltages
$\vec{\psi}_s$	Stator flux

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