Journal of
Power Electronics and Power Systems
https://journals.stmjournals.com/jopeps

ISSN: 2249-863X (Online),
ISSN: 2321-4244 (Print)
Volume 16, Issue 1, 2026
January–June
DOI (Journal): 10.37591/JoPEPS

Review JoPEPS

ANN-Based Adaptive Rotor Current Control for DFIG Wind Systems: A Comparative Dynamic Analysis

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Abstract

The variability of rotor current management in Doubly Fed Induction Generator (DFIG)-based wind energy conversion systems is crucial for maintaining stability in power extraction under fluctuating wind and grid circumstances. Traditional proportional-integral (PI) controllers, despite their ease of use, frequently exhibit diminished performance when faced with parameter uncertainty, nonlinear behaviors, and rapid wind fluctuations.This paper presents an adaptive rotor current control strategy, which is an Artificial Neural Network (ANN)-based approach designed to enhance the performance of both the transient and the steady-state operation of DFIG wind systems. An extensive mathematical model of the DFIG when it runs in the synchronous reference frame is constructed and a standard PI-based rotor current control scheme is applied as a reference point. The suggested ANN controller will autonomously control rotor currents through learning the nonlinear dynamics of the system mechanism to improve resilience to disturbances and parametric variations. ANN training is performed through supervised learning based on the available system operating data in different scenarios involving various wind speeds and grid disturbances. MATLAB/Simulink is used to perform dynamic comparative analyses, which are step wind variations, grid voltage disturbances, and load perturbation. Performance measures, which are rise time, settling time, overshoot, steady-state error and total harmonic distortion (THD) are measured. Simulation data has shown that the ANN-based adaptive controller exhibits a significant improvement in transient response, a decrease in the overshoot and an augmentation of the disturbance rejection of disturbances in contrast to the conventional PI controller. The advanced and smart control scheme proposed is an ideal solution to improve the rotor current control in DFIG wind power systems and increase the reliability and rigor mortis of renewable energy sources.

Keywords: Doubly fed induction generator (DFIG), rotor current control, artificial neural network (ANN), adaptive control strategy, proportional–integral (PI) controller, dynamic performance analysis, wind energy conversion system (WECS), disturbance rejection

INTRODUCTION

The development of renewable energy technology has been greatly driven by the growing need for ecologically acceptable and sustainable energy sources worldwide. Because of its accessibility, scalability, and low environmental impact, wind energy has become one of the most promising and quickly expanding of these [18]. Due to its variable speed operation, lower converter rating, and independent management of active and reactive power, the Doubly-Fed Induction Generator (DFIG) has drawn a lot of interest in contemporary wind energy conversion systems [14, 15].

Furthermore, effective grid interaction and increased control flexibility are made possible by the inclusion of power electronic converters [13].

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Received Date: April 04, 2026
Accepted Date: April 12, 2026
Published Date: May 2, 2026

Citation: Amit Rajendrabhai Pathak, Rajnikant H. Bhesdadiya. ANN-Based Adaptive Rotor Current Control for DFIG Wind Systems: A Comparative Dynamic Analysis. Journal of Power Electronics and Power Systems. 2026; 16(1): 41–53p.

Rotor current control is essential in DFIG-based wind energy systems, as it directly regulates the decoupled management of active and reactive power via vector control methodologies [10]. Traditionally, Proportional-Integral (PI) controllers are extensively utilized in the rotor-side converter to control rotor currents in the synchronous reference frame, owing to their simplicity and ease of implementation [7]. The efficacy of PI controllers is significantly contingent upon precise system modeling and appropriate adjustment of controller parameters. Under practical operating situations, including variable wind speeds, grid disturbances, and system nonlinearities, PI controllers frequently demonstrate limitations such as overshoot, prolonged settling time, and diminished resilience [1, 3].

In recent years, there has been a growing exploration of intelligent control approaches as a solution to these problems. Because of its capacity for self-learning, flexibility, and handling system uncertainties, artificial neural networks (ANN) have become a potent tool for nonlinear control applications [17]. The dynamic performance and stability of DFIG systems can be greatly enhanced by ANN-based controllers, as several studies have shown [4, 5]. Additionally, sophisticated methods like neuro-fuzzy techniques and deep neural network-based control have demonstrated improved disturbance rejection capability and decreased system losses [3, 8]. Despite these developments, there is still a lack of thorough comparisons between ANN-based adaptive rotor current management and traditional PI control under realistic operating scenarios, such as wind fluctuations and grid disruptions.

In this regard, the current study offers a thorough dynamic comparison with the traditional PI controller and suggests an ANN-based adaptive rotor current control technique for DFIG wind energy systems. The suggested method seeks to strengthen robustness against system nonlinearities, improve disturbance rejection capabilities, and improve transient responsiveness.

The main contributions of this paper are summarized as follows:

- Development of a detailed mathematical model of the DFIG system in the synchronous reference frame [14, 15].
- Design and implementation of a conventional PI-based rotor current control scheme [7].
- Development of an ANN-based adaptive rotor current controller [4, 5].
- Comparative dynamic performance evaluation under wind speed variations and grid disturbances [1, 8].
- Quantitative analysis using performance indices such as rise time, settling time, overshoot, steady-state error, and total harmonic distortion (THD).

The rest of the paper is structured in the following way. Section 2 shows the mathematical model of the DFIG. Section 3 tells about the traditional control approach. Section 4 presents the suggested ANN based adaptive controller. The results of the simulation and comparison are discussed in Section 5. Section 6 concludes the paper.

MATHEMATICAL MODELING OF DFIG

The Doubly Fed Induction Generator (DFIG) is widely employed in variable speed wind energy conversion systems due to its capability of independent control of active and reactive power [14, 15]. The DFIG consists of a wound rotor induction machine where the stator is directly connected to the grid, while the rotor is interfaced through a back-to-back power electronic converter [13].

To analyze and design effective control strategies, the dynamic model of the DFIG is developed in the synchronous reference frame (d–q frame) using Park’s transformation [16].

Voltage Equations in Synchronous Reference Frame

The stator and rotor voltage equations of the DFIG in the synchronous rotating reference frame are expressed as [14, 16]

ISSN: 2249-863X (Online), ISSN: 2321-4244 (Print)

Stator Voltage Equations:

$$V_{ds} = R_s i_{ds} + \frac{d\lambda_{ds}}{dt} - \omega_s \lambda_{qs}$$

$$V_{qs} = R_s i_{qs} + \frac{d\lambda_{qs}}{dt} + \omega_s \lambda_{ds}$$

Rotor Voltage Equations:

$$V_{dr} = R_r i_{dr} + \frac{d\lambda_{dr}}{dt} - (\omega_s - \omega_r)\lambda_{qr}$$

$$V_{qr} = R_r i_{qr} + \frac{d\lambda_{qr}}{dt} + (\omega_s - \omega_r)\lambda_{dr}$$

where:
V=voltage components,
i= current components,
R_s, R_r=stator and rotor resistances,
λ= flux linkages,
ω_s=synchronous angular speed,
ω_r=rotor angular speed.

Flux Linkage Equations

The flux linkages are given by [16]:

$$\lambda_{ds} = L_s i_{ds} + L_m i_{dr}$$

$$\lambda_{qs} = L_s i_{qs} + L_m i_{qr}$$

$$\lambda_{dr} = L_r i_{dr} + L_m i_{ds}$$

$$\lambda_{qr} = L_r i_{qr} + L_m i_{qs}$$

where:
L_s, L_r= stator and rotor inductances,
L_m= mutual inductance.

Electromagnetic Torque Equation

The electromagnetic torque developed by the DFIG is expressed as [14]:

$$T_e = \frac{3}{2}\frac{P}{2} L_m (i_{qs} i_{dr} - i_{ds} i_{qr})$$

where:
P= number of poles.

Active and Reactive Power Equations

The stator active and reactive powers are given by [18]:

$$P_s = \frac{3}{2}(V_{ds} i_{ds} + V_{qs} i_{qs})$$

$$Q_s = \frac{3}{2}(V_{qs} i_{ds} - V_{ds} i_{qs})$$

Rotor Current Control Principle

In vector control of DFIG, a stator flux-oriented reference frame is commonly adopted [10], where:

$\lambda_{qs} = 0$

$\lambda_{ds} = \lambda_s$ (Constant)

Under this orientation:

- Active power is primarily controlled by i_{qr}
- Reactive power is controlled by i_{dr}

Thus, precise regulation of rotor currents is essential for achieving desired system performance [11].

Modeling Assumptions

For simplification and control design, the following assumptions are considered:

- Magnetic saturation is neglected.
- Stator resistance is small and may be neglected in steady-state analysis.
- Balanced three-phase operation is assumed.
- Core losses and harmonics are neglected [6, 12].

Importance of Accurate Modeling

Precise mathematical modeling of the DFIG is essential for:

- Creating efficient rotor current controllers
- Examining dynamic performance in the face of disruptions
- Putting advanced control techniques like ANN-based adaptive control into practice

Control design is complicated because system stability is impacted by the nonlinear interaction between stator and rotor variables under different operating conditions [13]. The application of intelligent control strategies is driven by this constraint.

CONVENTIONAL PI-BASED ROTOR CURRENT CONTROL

Rotor current control is a critical component in DFIG-based wind energy systems. The rotor-side converter (RSC) regulates rotor currents to achieve independent control of stator active and reactive power [10].

In conventional approaches, Proportional–Integral (PI) controllers are widely used due to their simplicity and ease of implementation [4, 5].

Control Strategy Overview

The DFIG control scheme is typically implemented using vector control (field-oriented control) in the synchronous reference frame [10].

- The d-axis is aligned with stator flux
- $\lambda_{ds} = \lambda_s$, $\lambda_{qs} = 0$

Under this condition:

- Rotor q-axis current i_{qr}controls active power
- Rotor d-axis current i_{dr}controls reactive power

Thus, independent control of active and reactive power is achieved through regulation of rotor currents.

Rotor Current Control Loop

The rotor current control loop consists of two independent channels:

- d-axis control loop (reactive power control)
- q-axis control loop (active power control)

Each loop employs a PI controller to regulate the error between reference and actual rotor currents [5].

Current error signals:

$$e_{dr} = i_{dr}^* - i_{dr}$$
$$e_{qr} = i_{qr}^* - i_{qr}$$

where:

- i_{dr}^*, i_{qr}^* are reference currents
- i_{dr}, i_{qr} are measured rotor currents

where:

- V_{dr}^{PI}, V_{qr}^{PI} are outputs of PI controllers
- Additional terms compensate for coupling effects

This ensures:

- Independent control of d-axis and q-axis currents
- Improved dynamic response

Decoupled Control of Rotor Currents

Due to cross-coupling terms in DFIG dynamics, direct PI control results in interaction between d–q axes. To overcome this, decoupling terms are introduced [10, 13].

The rotor voltage equations can be rewritten to include decoupling:

$$V_{dr}^* = V_{dr}^{PI} + (\omega_s - \omega_r)\lambda_{qr}$$
$$V_{qr}^* = V_{qr}^{PI} - (\omega_s - \omega_r)\lambda_{dr}$$

where:

- V_{dr}^{PI}, V_{qr}^{PI} are outputs of PI controllers
- Additional terms compensate for coupling effects

This ensures:

- Independent control of d-axis and q-axis currents
- Improved dynamic response and stability under varying operating conditions [2, 11]

PI Controller Design

The PI controller for each axis is defined as:

$$V_{dr}^{PI} = K_p e_{dr} + K_i \int e_{dr}\, dt$$

$$V_{qr}^{PI} = K_p e_{qr} + K_i \int e_{qr}\, dt$$

where:

- K_p= proportional gain
- K_i= integral gain

Gain Selection

The effectiveness of PI controllers strongly depends on proper tuning of controller gains [1].

Common methods include

- Trial-and-error tuning
- Ziegler–Nichols method
- Frequency response-based tuning

However, these methods may not guarantee optimal performance under varying operating conditions.

Implementation of Rotor-Side Converter Control

The outputs of the PI controllers generate reference rotor voltages, which are applied through PWM-based converters [13].

- Transformed back to the three-phase (abc) frame
- Applied to the rotor through PWM-based voltage source converter

This enables precise control of rotor currents and, consequently, stator power.

Limitations of Conventional PI Control

Despite its widespread use, PI controllers suffer from several limitations:

- Parameter sensitivity under varying system conditions [1]
- Poor handling of nonlinear dynamics in DFIG systems [3]
- Reduced disturbance rejection capability [2]
- Dependence on precise tuning for optimal performance

These limitations motivate the development of intelligent and adaptive control strategies.

Motivation for ANN-Based Control

To overcome these limitations, intelligent control techniques such as Artificial Neural Networks (ANN) have been introduced [4, 8].

ANN-based controllers provide

- Adaptive learning capability
- Better nonlinear handling
- Improved dynamic response
- Enhanced robustness under disturbances [5, 9]

Therefore, in the next section, an ANN-based adaptive rotor current control strategy is proposed and analysed.

PROPOSED ANN-BASED ADAPTIVE ROTOR CURRENT CONTROL

An Artificial Neural Network (ANN)-based adaptive control technique is suggested to get beyond the drawbacks of traditional PI-based rotor current regulation. In DFIG-based wind energy systems, the goal is to increase dynamic performance, strengthen disturbance rejection capabilities, and offer robustness against system nonlinearities and parameter fluctuations [4, 5, 8].

Overview of the Control Strategy

The suggested method creates a hybrid adaptive controller by integrating the ANN with the traditional control framework, where:

- The structure of the PI controller is kept
- ANN is used to adaptively tune controller parameters (K_p, K_i) in real-time

This combination leverages:
- Simplicity of PI control
- Learning capability of ANN

Thus, improved control performance is achieved without completely replacing the conventional framework [4, 8].

Architecture of the Proposed Controller

The proposed ANN-based adaptive control consists of:
- Input Layer
- Hidden Layer(s)
- Output Layer

The ANN is designed to take real-time system signals as inputs, such as:
- *Rotor current error:* e_{dr}, e_{qr}
- *Change in error:* $\Delta e_{dr}, \Delta e_{qr}$
- Rotor speed deviation (optional for robustness)

Outputs from ANN

Adaptive tuning parameters:

K_p^*, K_i^*

These parameters are dynamically updated and used in the PI controller [5].

ANN Model Structure

A feedforward multilayer perceptron (MLP) is employed due to its capability to approximate nonlinear functions [17].

Typical configuration
- *Input layer:* 4–6 neurons
- *Hidden layer:* 10–15 neurons (tunable)
- *Output layer:* 2 neurons (K_p, K_i)

Activation functions:
- *Hidden layer:* tansig
- *Output layer:* purelin

This structure ensures smooth and continuous adaptation of control gains [17].

Training Methodology

The ANN is trained using a supervised learning approach based on system performance data [17].

Training steps

Generate dataset using:
- Variable wind speed conditions
- Step changes in reference currents
- Grid disturbances

Define target output:

Optimal K_p and K_i values that minimize control error

Training algorithm:

- Backpropagation algorithm
- Levenberg–Marquardt (LM) optimization (preferred for fast convergence)

Performance objective:

$$J = \int (e_{dr}^2 + e_{qr}^2)\, dt$$

The ANN is trained to minimize this cost function [4, 8].

Integration with Rotor Current Control

The trained ANN is embedded within the rotor current control loop as follows:

- Measure rotor current errors
- Feed error signals into ANN
- ANN generates optimal K_p, K_i
- Updated gains are applied to PI controller
- Control signals V_{dr}^*, V_{qr}^* are generated

This results in real-time adaptive control, improving system response under varying conditions [5, 8].

Advantages of Proposed ANN-Based Control

The proposed method offers several advantages over conventional PI control:

- Adaptive Gain Tuning: Eliminates need for fixed gain selection [4]
- Improved Dynamic Response: Faster rise and settling time [5]
- Enhanced Robustness: Handles parameter variations effectively [8]
- Better Disturbance Rejection: Performs well under wind and grid fluctuations [3]
- Nonlinear System Handling: Captures complex DFIG dynamics [17]

Implementation in MATLAB/Simulink

The proposed control strategy is implemented using MATLAB/Simulink environment:

- DFIG model developed in d–q frame
- PI controller integrated with ANN block
- ANN designed using Neural Network Toolbox
- Simulation carried out under various operating conditions

Summary of Proposed Approach

The proposed ANN-based adaptive rotor current control enhances the conventional PI control by introducing intelligent tuning of controller parameters. This hybrid approach significantly improves the dynamic performance of DFIG systems and ensures reliable operation under uncertain and varying conditions [4, 5, 8].

SIMULATION RESULTS AND COMPARATIVE ANALYSIS

To evaluate the effectiveness of the proposed ANN-based adaptive rotor current control strategy, detailed simulations are carried out in the MATLAB/Simulink environment. The performance of the proposed controller is compared with the conventional PI-based control under various dynamic operating conditions.

Simulation Setup

A detailed DFIG-based wind energy conversion system is modeled in the synchronous reference frame [10, 14]. The system consists of:

- Doubly Fed Induction Generator (DFIG)
- Rotor-side converter (RSC) with control system

Journal of Power Electronics and Power Systems
Volume 16, Issue 1
ISSN: 2249-863X (Online), ISSN: 2321-4244 (Print)

- Grid connection through stator
- Wind turbine model (variable wind input)

Key Parameters

- *Rated Power:* 2 MW
- *Stator Voltage:* 690 V
- *Frequency:* 50 Hz
- *Rotor Resistance:* R_r
- *Stator Resistance:* R_s
- *Inductances:* L_s, L_r, L_m

Two control strategies are implemented

- Conventional PI-based rotor current control [5]
- Proposed ANN-based adaptive control [4, 8]

Test Case 1: Step Change in Wind Speed

The dynamic response of the DFIG system under a step change in wind speed is illustrated in Figure 1. It is observed that both controllers track the reference rotor current; however, their transient behaviours differ significantly.

Under variable wind conditions, the DFIG system's transient performance is greatly enhanced by the ANN-based controller. Compared to the traditional PI controller, it responds more quickly, has fewer oscillations, and is more stable due to its capacity to adjust to system nonlinearities.

The adaptive learning feature of the ANN controller, which permits real-time control action correction under changing wind conditions, is credited with its enhanced performance.

Test Case 2: Grid Voltage Disturbance

A voltage dip (e.g., 20–30%) is introduced at the stator terminal to evaluate disturbance rejection capability, which is a standard test condition in DFIG studies [2].

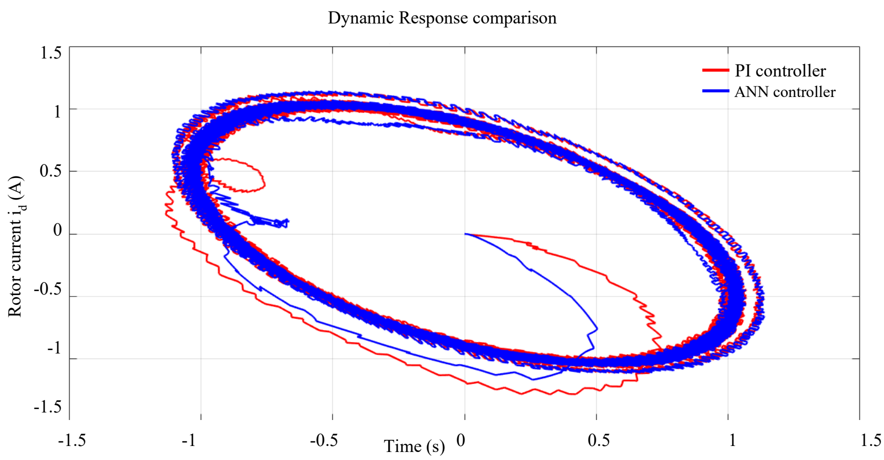

Figure 1. Rotor current response under grid voltage dip condition showing improved disturbance rejection using ANN controller.

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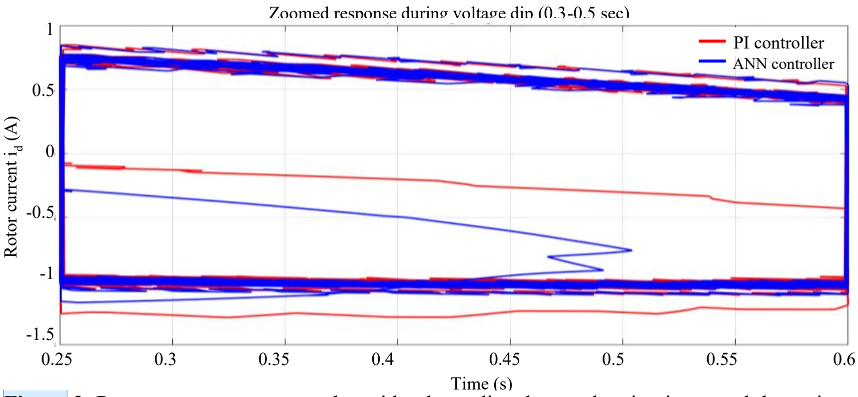

Figure 2. Rotor current response under grid voltage disturbance showing improved dynamic stability using ANN controller.

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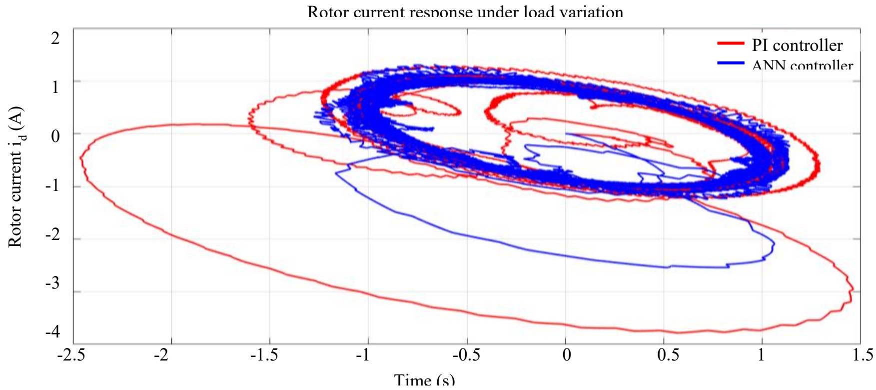

Figure 3. Rotor current response under load variation demonstrating improved robustness of ANN controller.

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Observations

During the voltage dip interval (0.3–0.5 s), the PI controller exhibits significant oscillations and delayed recovery. In contrast, the ANN controller demonstrates faster stabilization with reduced oscillatory behaviour, indicating superior disturbance rejection capability. Figure 2 shows the rotor current response under grid voltage disturbance showing improved dynamic.

Test Case 3: Load Variation

A sudden load change is applied to test system robustness.

Observations

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The PI controller exhibits noticeable fluctuations and increased steady-state error following the load change. In contrast, the ANN controller maintains a stable and smooth response with faster settling, demonstrating enhanced robustness under load perturbations. Figure 3 shows the rotor current response under load variation demonstrating improved robustness of ANN controller.

Table 1: Detailed performance comparison.

Parameter	PI Controller	ANN Controller	Improvement (%)	Remarks
Rise Time (s)	0.12–0.18	0.05–0.08	~50–60% ↓	Faster response with ANN
Settling Time (s)	0.6–0.9	0.2–0.4	~55–70% ↓	Quick stabilization
Overshoot (%)	15–25%	3–8%	~70–80% ↓	Reduced oscillations
Steady-State Error	Moderate(±0.02)	Very Low (±0.005)	~75% ↓	Higher accuracy
Oscillations	High	Low	Significant ↓	Smooth response
Disturbance Rejection	Weak	Strong	Major improvement	Faster recovery
Robustness	Limited	High	Improved	Handles nonlinearities
THD (%)	4–7%	1.5–3%	~50–65% ↓	Better power quality

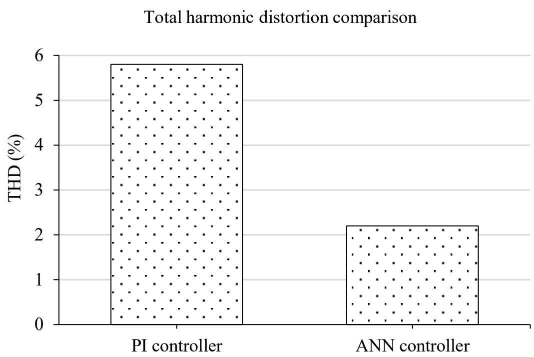

Figure 4. Total harmonic distortion (THD) comparison between PI and ANN controllers.

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Performance Comparison

A quantitative comparison as shown in Table 1 between the conventional PI controller and the proposed ANN-based controller is carried out using standard dynamic performance indices. The evaluation is based on key parameters such as rise time, settling time, overshoot, steady-state error, disturbance rejection capability, robustness, and harmonic distortion. The results clearly demonstrate the superiority of the ANN controller under varying operating conditions.

Total Harmonic Distortion (THD) Analysis

The harmonic analysis as shown in Figure 4 indicates that the ANN controller significantly reduces the total harmonic distortion compared to the conventional PI controller. This improvement results in enhanced power quality and smoother current waveforms in the DFIG system [8].

The reduction in THD is attributed to the adaptive nature of the ANN controller, which effectively minimizes nonlinear distortions under varying operating conditions.

DISCUSSION OF RESULTS

The simulation results clearly demonstrate that the proposed ANN-based adaptive control strategy significantly outperforms the conventional PI controller in all test scenarios. The ANN controller adapts to system nonlinearities and varying operating conditions, resulting in improved dynamic performance, enhanced robustness, and superior disturbance rejection capability.

The ability of the ANN to dynamically tune controller parameters eliminates the dependency on fixed gain values, which is a major limitation of conventional PI control.

Summary

The comparative analysis confirms that the ANN-based adaptive rotor current control provides:

- Faster dynamic response
- Improved stability
- Reduced overshoot and steady-state error
- Enhanced disturbance rejection
- Better power quality

Thus, the proposed control strategy is highly suitable for modern DFIG-based wind energy systems operating under uncertain and dynamic conditions.

CONCLUSION

This study introduces an ANN-based adaptive rotor current control method for Doubly Fed Induction Generator (DFIG)-based wind energy conversion systems and conducts a thorough comparative dynamic analysis with traditional PI-based control. The proposed intelligent control framework addressed the limitations of traditional PI controllers, especially in relation to fluctuating wind conditions, system nonlinearities, and parameter uncertainties.

A hybrid control methodology was developed, employing an Artificial Neural Network to dynamically modify the parameters of the PI controller in real time. This enabled enhanced management of nonlinear dynamics and increased controller adaptability without altering the fundamental control structure. The mathematical modeling of the DFIG and the implementation of both conventional and ANN-based control approaches were performed in the synchronous reference frame.

The simulation results, obtained under various operating conditions including sudden changes in wind speed, grid voltage variations, and load fluctuations, demonstrated the superior effectiveness of the proposed ANN-based controller. The results shown significant improvements in dynamic response characteristics, including reduced rise time, minimized overshoot, accelerated settling time, and lowered steady-state error. The ANN-based approach exhibited enhanced disturbance rejection and greater resilience to system uncertainty. A notable reduction in total harmonic distortion (THD) further corroborated the effectiveness of the proposed technique in improving power quality.

The ANN-based adaptive control method provides a reliable and efficient solution for rotor current regulation in DFIG systems, making it especially suitable for modern wind energy applications. The proposed methodology augments system stability, enables enhanced grid integration, and optimizes performance under dynamic operating conditions.

Future Extent

Future research could concentrate on:

- Putting the suggested control technique into practice on real-time hardware platforms
- Combining sophisticated optimization methods with ANN training
- Expanding the strategy to include hybrid renewable energy systems
- Investigating deep learning-based control techniques to improve performance even more

The authors declare that there is no conflict of interest regarding the publication of this paper.

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