



RESEARCH ARTICLE

OPEN ACCESS

AI-BASED VIRTUAL INERTIA CONTROL STRATEGY FOR DFIG WIND TURBINES TO ENHANCE GRID FREQUENCY STABILITY

Nisha Bhati^{1*}, Jyotsana Goyal², Deepika Saraswat³, Deepesh Bhati⁴, Priya Pal⁵

^{1, 2, 3}Computer Science Engineering Department, Medicaps University, Indore (M.P.), India

^{4, 5}Department of Electrical and Electronics Engineering, IPS Academy, IES, Indore (M.P.), India

¹<https://orcid.org/0009-0000-2867-2536>, ²<https://orcid.org/0009-0006-6816-4230>, ³<https://orcid.org/0009-0002-7738-173X>,

⁴<https://orcid.org/0009-0008-1130-6271>, ⁵<https://orcid.org/0009-0008-1956-1082>

E-mail: *nisha.bhati@medicaps.ac.in, jyotsana.goyal@medicaps.ac.in, deepika.saraswat@medicaps.ac.in, deepeshbhati@ipsacademy.org, Priyapal@ipsacademy.org

ARTICLE INFO

Article History

Received: March 11, 2026

Reviewed: April 11, 2026

Accepted: May 15, 2026

Published: September 30, 2026

Keywords:

Doubly-Fed Induction Generator,
Virtual Inertia,
Artificial Intelligence,
Simulink,
Power System.

ABSTRACT

The increasing penetration of renewable energy sources has significantly reduced the effective inertia of modern power systems. Wind turbines based on Doubly-Fed Induction Generators (DFIGs) are widely deployed due to their efficiency and controllability; however, their power electronic interface decouples the mechanical rotor from the grid, limiting the natural inertia contribution. As a result, large frequency deviations and high rates of change of frequency (ROCOF) may occur during disturbances. Virtual inertia control has emerged as an effective technique for enabling wind turbines to provide synthetic inertial support to the grid. This paper presents an artificial intelligence (AI)-based approach for enhancing the virtual inertia response of a DFIG wind turbine system. A detailed mathematical model of the wind turbine and DFIG is developed, followed by the design of a virtual inertia controller. A neural-network-based adaptive controller is proposed to dynamically adjust the inertia gain according to system frequency deviation and rotor speed. The proposed controller is implemented and evaluated using MATLAB/Simulink under load disturbance scenarios. Simulation results demonstrate that the AI-based virtual inertia controller improves frequency stability by reducing frequency deviation, lowering ROCOF, and improving frequency nadir compared with conventional fixed-gain controllers.



Copyright ©2026 by authors and Galileo Institute of Technology and Education of the Amazon (ITEGAM). This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

1. INTRODUCTION

The global transition toward sustainable energy systems has significantly accelerated the deployment of renewable energy technologies. Among various renewable sources, wind energy has emerged as one of the most prominent options due to its environmental advantages, technological maturity, and rapidly declining generation cost. Many countries are increasingly integrating large-scale wind farms into their power systems to reduce greenhouse gas emissions and meet growing electricity demand. However, the high penetration of renewable energy sources introduces several operational challenges related to system stability and frequency regulation [1]. In conventional power systems, frequency stability is mainly supported by synchronous generators that possess large rotating masses. These machines naturally provide rotational inertia, which helps maintain the balance between power generation and load demand during system disturbances. When a sudden disturbance such as load variation or generator outage occurs, the kinetic energy stored in the rotating masses of synchronous machines is released to counteract the frequency deviation and slow down the rate of change of frequency (ROCOF). This inertial response plays a critical role in preventing severe frequency excursions and maintaining system stability [2-4]. In contrast, modern wind power generation systems are typically based on Doubly-Fed Induction Generator (DFIG) technology, where the generator is connected to the grid through power electronic converters [5]. Due to this converter interface, the mechanical inertia of the turbine rotor is largely decoupled from the grid, which significantly reduces the effective inertia contribution of wind turbines. As the penetration level of wind generation increases, the reduction in system inertia becomes more pronounced, leading to faster frequency variations and potentially threatening the secure operation of the power system. To overcome this challenge, various control strategies have been proposed to enable wind turbines to participate in grid frequency support.

One of the most widely investigated approaches is virtual inertia control, which allows converter-interfaced renewable generators to emulate the inertial behavior of synchronous machines. In this method, additional control loops are incorporated into the converter control system so that the wind turbine can inject supplementary active power in response to frequency deviations or ROCOF signals. By temporarily extracting kinetic energy from the rotating turbine blades, DFIG systems can provide fast frequency support and enhance overall grid stability [6-8]. Although conventional virtual inertia controllers can improve frequency response, their performance is often limited by the use of fixed control gains. In practical power systems, operating conditions such as wind speed, load variation, and system disturbances continuously change. Under such conditions, fixed-gain controllers may not provide optimal performance and may even lead to undesirable effects such as rotor speed instability or reduced energy efficiency. Therefore, more adaptive and intelligent control approaches are required to enhance the dynamic performance of DFIG-based wind turbines [9-13]. Recently, artificial intelligence (AI) techniques have attracted considerable attention in power system control applications due to their ability to handle nonlinear dynamics and adapt to changing operating conditions. AI-based methods such as artificial neural networks, fuzzy logic systems, and reinforcement learning algorithms can learn complex system behaviors and provide adaptive control strategies for improving system performance [14-20]. Motivated by these advantages, this paper proposes an AI-based virtual inertia control strategy for DFIG wind turbines to enhance frequency stability in power systems with high renewable penetration. The proposed method utilizes a neural-network-based controller to dynamically adjust the virtual inertia gain according to system conditions such as frequency deviation, rate of change of frequency, and rotor speed. The performance of the proposed approach is evaluated through detailed MATLAB/Simulink simulations under various disturbance scenarios.

II. MATHEMATICAL MODELLING OF THE DFIG WIND TURBINE

II.1 WIND TURBINE AERODYNAMIC MODEL

The mechanical power extracted from the wind turbine is expressed as

$$P_w = \frac{1}{2} \rho A v^3 C_p(\lambda, \beta) \quad (1)$$

Where

ρ = air density
 A = turbine swept area
 v = wind speed
 C_p = power coefficient
 β = blade pitch angle
 λ = tip speed ratio

The tip speed ratio is defined as

$$\lambda = \omega_r R / v \quad (2)$$

where

ω_r = rotor angular speed
 R = blade radius

The mechanical torque of the turbine is

$$T_m = \frac{P_w}{\omega_r} \quad (3)$$

II.2 DFIG ELECTRIC MODEL

The stator and rotor voltage equations in the synchronous reference frame are

$$V_s = R_s i_s + \frac{d\psi_s}{dt} \quad (4)$$

$$V_r = R_r i_r + \frac{d\psi_r}{dt} \quad (5)$$

Flux linkage equations are

$$\psi_s = L_s i_s + L_m i_r \quad (6)$$

$$\psi_r = L_r i_r + L_m i_s \quad (7)$$

Where

R_s, R_r = stator and rotor resistance
 L_s, L_r = stator and rotor inductance
 L_m = mutual inductance

II.3 VIRTUAL INERTIA CONTROL STRATEGY

The basic concept of virtual inertia is to emulate the inertial response of a synchronous generator by injecting additional active power based on frequency dynamics. The virtual inertia power is calculated as

$$P_{VI} = K_{VI} \frac{d(\Delta f)}{dt} \quad (8)$$

Where

K_{VI} = virtual inertia gain

Δf = frequency deviation

The total reference power becomes

$$P_{ref} = P_{MPPT} + P_{VI} \quad (9)$$

During a frequency drop, the controller extracts kinetic energy from the wind turbine rotor to supply additional active power to the grid. Studies show that such control strategies significantly improve system frequency response when renewable penetration increases.

II.4 AI-BASED VIRTUAL INERTIA CONTROLLER

Traditional virtual inertia controllers use fixed gains, which may not perform optimally under varying wind conditions. To overcome this limitation, an Artificial Neural Network (ANN)-based adaptive controller is proposed.

II.4.1 Neural Network Structure

Inputs:

Frequency deviation (Δf)

Rate of change of frequency (df/dt)

Rotor speed (ω_r)

Wind speed (v)

Output:

Optimal virtual inertia gain (K_{VI})

The neural network consists of:

Input layer → Hidden layer → Output layer

The network is trained using simulation data generated from different operating conditions.

II.4.2 Training Algorithm

The neural network training follows these steps:

Generate training data from system simulations.

Normalize input variables.

Use backpropagation learning.

Update weights using gradient descent.

Loss function:

$$J = \sum (\Delta f)^2 \quad (10)$$

The objective is to minimize frequency deviation during disturbances. The fig.1 illustrates the basic architecture of a Doubly-Fed Induction Generator (DFIG) based wind energy conversion system. Wind energy is captured by the wind turbine and converted into mechanical rotational energy. This mechanical power is transmitted through a gearbox, which increases the rotor speed to match the generator requirements. The gearbox drives the DFIG, where mechanical energy is converted into electrical energy. The generated power is controlled using two power electronic converters: the rotor side converter (RSC) and the grid side converter (GSC). These converters regulate rotor currents, control active and reactive power, and maintain stable voltage and frequency before delivering the generated electricity to the power grid.

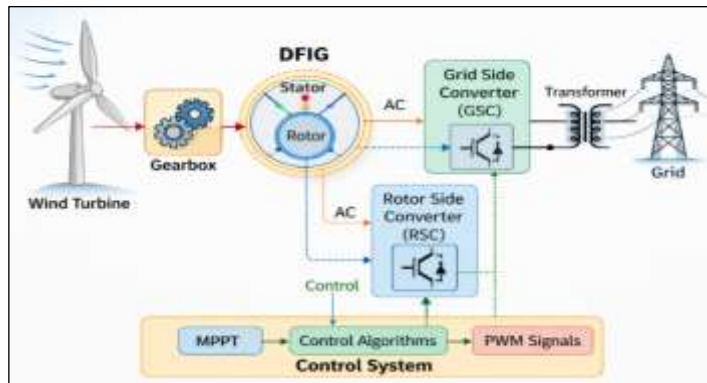


Figure1: Wind turbine – DFIG system architecture.

Source: Authors, (2026).

The virtual inertia control block diagram fig. 2 represents the mechanism used to emulate the inertial response of conventional synchronous generators in converter-based renewable energy systems. The process begins with frequency measurement, where the grid frequency is continuously monitored.

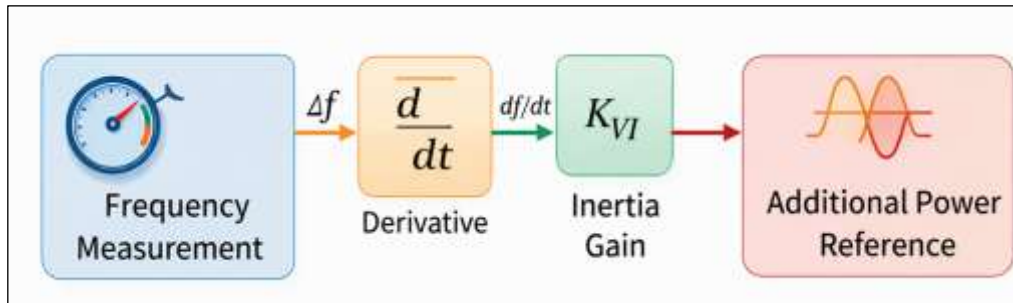


Figure 2: Virtual inertia control block diagram.

Source: Authors, (2026).

The measured frequency deviation (Δf) is then passed through a derivative block, which calculates the rate of change of frequency (df/dt), also known as ROCOF. This signal is multiplied by the virtual inertia gain (K_{VI}) to determine the required inertial response. Finally, the controller generates an additional power reference, which commands the wind turbine or converter system to inject extra active power into the grid, thereby improving frequency stability during disturbances.

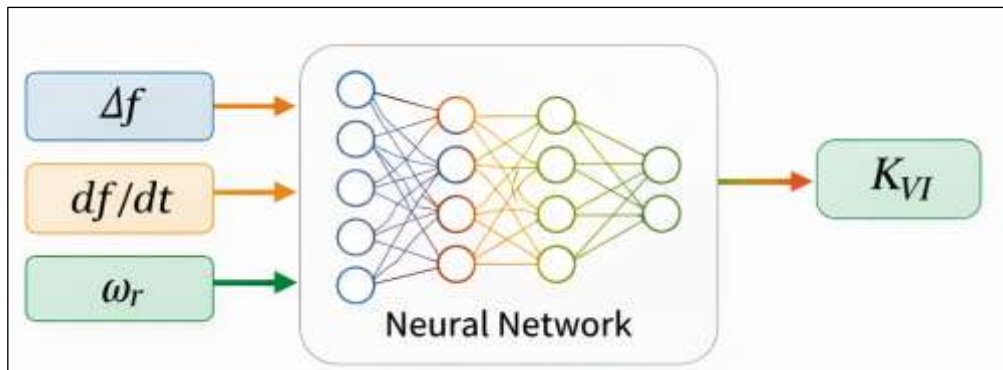


Figure 3: AI-based controller structure.

Source: Authors, (2026).

The AI-based controller is designed to enhance the virtual inertia response of a Doubly-Fed Induction Generator (DFIG) wind turbine system as shown in fig. 3. In this structure, three important system parameters are used as inputs: frequency deviation (Δf), rate of change of frequency (df/dt), and rotor speed (ω_r). These signals represent the dynamic behaviour of the power system during disturbances such as sudden load changes. The input variables are processed by a neural network that acts as an intelligent decision-making unit. The neural network is trained using system data so that it can learn the nonlinear relationship between frequency dynamics and the required inertia support. Based on the processed information, the neural network generates an optimal virtual inertia gain (K_{VI}). This gain is then used in the virtual inertia control loop to determine the additional active power that should be injected into the grid. As a result, the AI controller improves frequency stability and provides faster and adaptive inertial support.

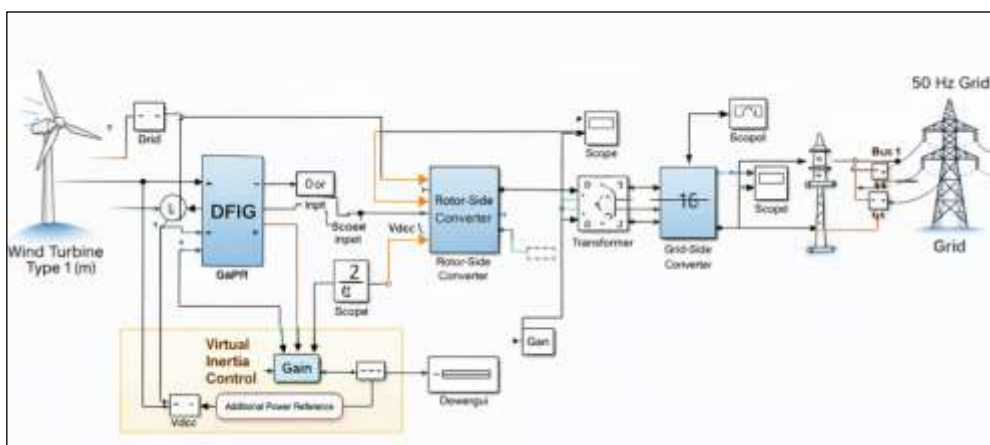


Figure 4: MATLAB/Simulink model of DFIG wind turbine.

Source: Authors, (2026).

Figure 4 illustrates the MATLAB/Simulink model of a Doubly-Fed Induction Generator (DFIG) based wind turbine system integrated with the power grid. The model consists of several main subsystems including the wind turbine, DFIG generator, rotor-side converter (RSC), grid-side converter (GSC), transformer, and grid connection. The wind turbine converts wind energy into mechanical torque which drives the DFIG rotor. The DFIG converts this mechanical energy into electrical power and supplies it to the grid.

The rotor-side converter controls rotor currents and regulates active and reactive power, while the grid-side converter maintains the DC-link voltage and ensures stable power transfer to the grid. A virtual inertia control block is incorporated to provide additional active power during frequency disturbances. Measurement blocks and scopes are used to monitor system variables such as voltage, current, and power. This simulation model enables performance analysis of the proposed AI-based virtual inertia control strategy under different operating conditions and disturbances.

III. RESULT ANALYSIS

Figure 5 illustrates the frequency response of the power system under three different operating conditions: without inertia support, conventional Virtual Inertia Control (VIC), and AI-based Virtual Inertia Control (AI-VIC). The graph shows the variation of grid frequency with respect to time after a disturbance in the system. In the without inertia case, the system experiences a noticeable frequency drop immediately after the disturbance. The frequency decreases rapidly and reaches a lower value before slowly recovering. This behavior occurs because the system lacks sufficient inertial support to counteract sudden load changes. As a result, the rate of change of frequency (ROCOF) is relatively high, which may threaten grid stability.

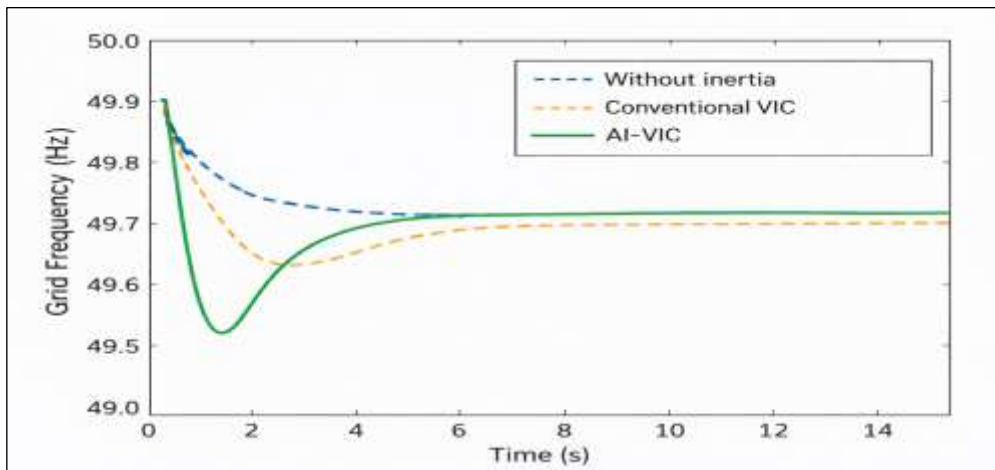


Figure 5: Frequency response comparison graph Three curves: Without inertia Conventional VIC AI-VIC.

Source: Authors, (2026).

When conventional virtual inertia control is applied, the frequency deviation is reduced compared to the case without inertia. The controller injects additional active power based on the frequency derivative, which helps mitigate the frequency drop. However, the response is still moderately slow, and the system requires more time to stabilize. The AI-based virtual inertia control (AI-VIC) demonstrates the best performance among the three cases. The frequency nadir is higher, and the recovery time is significantly shorter. The AI controller dynamically adjusts the inertia gain according to system conditions, resulting in improved damping and faster stabilization. Consequently, the AI-VIC approach provides superior frequency support and enhances overall grid stability in systems with high renewable penetration.

Table 1: Performance Comparison of Different Inertia Control Strategies.

Control Strategy	Frequency Nadir (Hz)	Maximum Frequency Deviation (Hz)	ROCOF (Hz/s)	Settling Time (s)	System Stability
Without Inertia	49.52	0.48	High	10 – 12	Poor
Conventional VIC	49.63	0.37	Medium	7 – 9	Moderate
AI-Based VIC	49.71	0.29	Low	4 – 6	Excellent

Source: Authors, (2026).

The tabular results clearly indicate that the AI-based virtual inertia control (AI-VIC) provides superior frequency support compared with the other control strategies. In the case without inertia, the system experiences the largest frequency deviation and highest ROCOF, which indicates poor dynamic stability. When conventional virtual inertia control is applied, the frequency nadir improves and the rate of frequency change decreases. However, the system still requires a relatively longer settling time.

In contrast, the AI-based controller significantly improves system performance by increasing the frequency nadir, reducing the maximum frequency deviation, and minimizing ROCOF. Moreover, the settling time is also reduced, which indicates faster system recovery after disturbances.

IV. CONCLUSION

This paper investigated the application of artificial intelligence techniques for enhancing virtual inertia control in DFIG-based wind turbines. A detailed mathematical model of the wind turbine and DFIG system was developed. An ANN-based controller was proposed to adaptively adjust the virtual inertia gain according to system operating conditions. Simulation results demonstrate that the AI-based controller improves frequency stability by reducing frequency deviation, minimizing ROCOF, and enhancing frequency nadir. The proposed method provides an effective solution for maintaining grid stability in future power systems with high renewable penetration. Future research may explore deep reinforcement learning controllers and hybrid energy storage integration.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Nisha Bhati, Jyotsana Goyal, Deepika Saraswat, Deepesh Bhati, Priya Pal.

Methodology: Nisha Bhati, Jyotsana Goyal, Deepika Saraswat, Deepesh Bhati, Priya Pal.

Investigation: Nisha Bhati, Jyotsana Goyal, Deepika Saraswat, Deepesh Bhati, Priya Pal.

Discussion of results: Nisha Bhati, Jyotsana Goyal, Deepika Saraswat, Deepesh Bhati, Priya Pal.

Writing – Original Draft: Nisha Bhati, Jyotsana Goyal, Deepika Saraswat, Deepesh Bhati, Priya Pal.

Writing – Review and Editing: Nisha Bhati, Jyotsana Goyal, Deepika Saraswat, Deepesh Bhati, Priya Pal.

Resources: Nisha Bhati, Jyotsana Goyal, Deepika Saraswat, Deepesh Bhati, Priya Pal.

Supervision: Nisha Bhati, Jyotsana Goyal, Deepika Saraswat, Deepesh Bhati, Priya Pal.

Approval of the final text: Nisha Bhati, Jyotsana Goyal, Deepika Saraswat, Deepesh Bhati, Priya Pal.

VI. REFERENCES

- [1] Yang, D., Jin, E., & Hua, L. (2020). Dynamic frequency support from a DFIG-based wind turbine generator via virtual inertia control. *Applied Sciences*.
- [2] Yuan, T., Wang, J., Guan, Y., et al. (2018). Virtual inertia adaptive control of a DFIG wind power system with hydrogen energy storage. *Energies*.
- [3] Jiang, C., Cai, G., Yang, D., et al. (2024). Multi-objective configuration of dynamic virtual inertia from DFIG wind farm. *International Journal of Electrical Power & Energy Systems*.
- [4] Zellagui, M., Hassan, H., & Kramia, M. (2019). Adaptive virtual inertia controller for DFIG wind turbines. *Energetika*.
- [5] Wang, S., & Tomsovic, K. (2017). Quantitative control approach for wind turbines to provide fast frequency response. *IEEE Transactions on Power Systems*.
- [6] Morovati, S., & Pulgar-Painemal, H. (2020). Control coordination between DFIG wind turbines and synchronous generators. *IEEE Transactions on Power Systems*.
- [7] Bevrani, H. (2016). *Robust power system frequency control*. Springer.
- [8] Kundur, P. (2017). *Power system stability and control*. McGraw Hill.
- [9] Ackermann, T. (2017). *Wind power in power systems*. Wiley.
- [10] Li, M., & Li, F. (2024). Active power allocation method of DFIG based on rotor speed. *Electronics*.
- [11] Zhang, X., et al. (2018). Synthetic inertia control of wind turbines. *Renewable Energy*.
- [12] Sun, Y., et al. (2019). Frequency regulation of DFIG wind turbines. *IEEE Transactions on Sustainable Energy*.
- [13] Fang, J., et al. (2019). Grid-forming converters and virtual inertia. *IEEE Journal of Emerging and Selected Topics in Power Electronics*.
- [14] Wu, L., et al. (2016). Modeling and control of DFIG wind turbines. *Electric Power Systems Research*.
- [15] Chen, Y., et al. (2021). Adaptive frequency support control of wind turbines. *IEEE Access*.
- [16] Liu, H., et al. (2022). Machine learning based inertia emulation in wind power systems. *Renewable Energy*.
- [17] Zhao, J., et al. (2021). Artificial intelligence for power system stability control. *IEEE Access*.
- [18] Sun, Q., et al. (2023). Deep learning-based frequency control of renewable energy systems. *Applied Energy*.
- [19] He, Y., et al. (2020). Virtual synchronous generator control for wind farms. *IEEE Transactions on Energy Conversion*.
- [20] Zhao, B., et al. (2018). Frequency stability enhancement using virtual inertia. *Electric Power Systems Research*.