International Journal of Advances in Applied Sciences (IJAAS)
Vol. 15, No. 2, June 2026, pp. 1166~1192
ISSN: 2252-8814, DOI: 10.11591/ijaas.v15.i2.pp1166-1192

Comparative review on control strategies for doubly fed induction generator-based wind energy harnessing system

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Article Info

Article history:

Received Jan 5, 2026
Revised Jul 16, 2026
Accepted Jul 25, 2026

Keywords:

Control strategies
Doubly fed induction generator
Hybrid control strategies
Intelligent control
Renewable energy systems
Variable-speed wind turbines
Wind energy

ABSTRACT

Doubly fed induction generator (DFIG)-based variable-speed wind energy harvesting systems (WEHS) are widely employed owing to high efficiency and reliable grid integration under variable wind conditions. This paper presents a comprehensive review of conventional, intelligent, and hybrid control strategies for DFIG-based WEHS. Unlike previous studies that primarily focus on specific control techniques, this study systematically compares different approaches based on key performance indicators-dynamic response, total harmonic distortion (THD), robustness, and fault ride-through (FRT) capability. Conventional controllers such as proportional–integral (PI) control, field-oriented control (FOC), and direct torque control (DTC) are evaluated alongside intelligent techniques, including fuzzy logic control (FLC), artificial neural networks (ANNs), adaptive control, and optimization techniques. The comparison shows that intelligent and hybrid control strategies achieve superior dynamic response, lower THD, enhanced robustness, and improved FRT capability, although they require higher computational resources. Furthermore, this review highlights critical research challenges, including the lack of experimental validation, the absence of standardized benchmarking frameworks, and the complexity of real-time implementation in high-power WEHS. Finally, future research should focus on developing hybrid intelligent controllers, establishing evaluation methodologies, and integrating advanced control strategies with smart grid technologies to improve power quality, voltage regulation, and reliability of modern wind energy systems.

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1. INTRODUCTION

The global transition toward renewable energy has accelerated significantly due to rising energy demand and the urgent need to mitigate environmental degradation. Conventional fossil fuel-based generation is increasingly unsustainable from both economic and environmental perspectives, prompting a shift toward cleaner and more sustainable energy solutions. Among renewable resources, wind energy has emerged as a leading option owing to its technological maturity, scalability, and relatively low cost of generation. It produces zero emissions during operation, requires no fuel, and supports flexible deployment through both onshore and offshore installations. Recent statistics highlight this rapid growth. According to the International Energy Agency (IEA), global wind power capacity reached approximately 823.9 GW in 2024, with projections indicating that wind and solar will account for over 80% of new global power capacity additions by 2030 [1]. In India, installed wind capacity reached 50.04 GW by mid-2025, making it the fourth-largest wind power market globally [2]. Furthermore, global installations exceeded 1,136 GW, with 117 GW of new capacity added in 2024. These figures emphasize the crucial role of wind energy in achieving carbon neutrality and long-term energy security.

The doubly fed induction generator (DFIG) has become a cornerstone technology in variable-speed wind energy harnessing systems (WEHS) due to its superior controllability, cost-effectiveness, and adaptability under fluctuating wind conditions [3]. In DFIG-based systems, the stator is directly connected to the grid, while the rotor is interfaced through partially rated power electronic converters, typically sized at 25–30% of the generator capacity [4]. This configuration enables independent control of active and reactive power, facilitating efficient grid integration and ancillary services such as voltage and frequency support [5].

DFIG systems offer high efficiency over a wide operating range and enable maximum energy extraction compared to fixed-speed generators [6]. The use of partially rated converters reduces system cost and losses while maintaining full four-quadrant power control capability [7]. Additionally, variable-speed operation reduces mechanical stress on turbine components, enhancing system reliability and lifespan [8]. Owing to these advantages, DFIG-based configurations are widely deployed in medium- and large-scale wind energy systems [9], [10].

Despite these benefits, DFIG systems are highly sensitive to grid disturbances such as voltage sags, harmonic distortions, and unbalanced faults, which can result in rotor overcurrent and system instability. These challenges are particularly critical during grid faults due to the direct stator-grid coupling. Moreover, maintaining stable operation under varying wind conditions requires effective coordination between rotor-side and grid-side converter control (GSCR) control strategies. With increasing wind penetration, ensuring grid stability, power quality, and compliance with stringent grid codes has become a major challenge [11].

Conventional control strategies, such as proportional–integral (PI) controllers, are widely used due to their simplicity and ease of implementation; however, their performance degrades under nonlinear and disturbed operating conditions [12]. To address these limitations, intelligent control techniques—including artificial neural networks (ANN), fuzzy logic control (FLC), and adaptive neuro-fuzzy inference systems (ANFIS)—have been introduced, offering improved robustness against uncertainties and nonlinear dynamics. Furthermore, metaheuristic optimization methods such as genetic algorithms (GA) and particle swarm optimization (PSO) have been employed to enhance control performance and parameter tuning [13].

Nevertheless, several research gaps remain. Existing studies often focus either on conventional or intelligent control approaches in isolation, with limited attention given to integrated or hybrid frameworks. Comprehensive comparative analyses across different control strategies are scarce, particularly in terms of dynamic performance, fault ride-through (FRT) capability, harmonic suppression, and grid code compliance [14]–[17]. Additionally, large-scale validation and real-time implementation of advanced control techniques remain limited [18].

In this context, the main contribution of this paper is to present a comprehensive and systematic comparative review of conventional, intelligent, and hybrid control strategies for DFIG-based variable-speed WEHS [19]. The study evaluates key control objectives, including maximum power point tracking (MPPT), reactive power regulation, grid synchronization, and fault tolerance. It further provides a unified benchmarking framework to compare performance metrics across different control approaches. The potential of hybrid and predictive control architectures is also analysed to highlight their effectiveness in enhancing system robustness under dynamic grid conditions [20]. By consolidating and critically analysing existing literature, this paper provides valuable insights for researchers and practitioners. It identifies key challenges and proposes future research directions, emphasizing hybrid intelligent control frameworks, real-time validation, and smart grid integration to enhance the reliability, efficiency, and grid compliance of modern wind energy systems [21]–[23].

The following is an outline of this article's structure: the DFIG's mathematical modeling and architecture are explained in section 2. Section 3 presents the converter control schemes associated with DFIG-based WEHS. Section 4 outlines the control objectives of DFIG systems. Section 5 briefs traditional control strategies, while section 6 highlights intelligent control techniques and offers a comparative evaluation of the control methods; section 7 discusses recent developments and case studies, followed by section 8, which identifies research gaps and existing challenges. Future study directions are suggested in section 9. The practical scalability of the system is illustrated in section 10, and the paper's main conclusions and contributions are summed up in section 11.

2. SYSTEM FRAMEWORK

2.1. Architecture of doubly fed induction generator-based wind energy harnessing system

A variable-speed WES employing a DFIG as the wind generator is presumed for the study, and the same is depicted in Figure 1. The gear arrangement links the DFIG to the wind turbine. The DFIG is rated to about 1 kW and delivers a stator voltage of 575 V, and a 1.75 kVA transformer (T_1) steps up the voltage from 575 V to 25 kV. The transmitted power travels along a 30 km transmission line to reach the 25 kV bus. At transformer T_2, the voltage is again stepped up to 120 kV to join the utility grid. The rotor end is interfaced with the rotor-side converter (RSCR), and the direct current (DC) end is linked to a DC-link capacitor. This DC terminal is then tied to the stator side series converter (SSSCR), whose alternating current (AC) end is connected in series with the generator stator. The SSSCR is connected to the 575 V bus, which serves as the point of common coupling (PCC). The DC-link capacitor maintains a constant V_{dc} to accommodate power fluctuations arising from variations in generator output and grid disturbances.

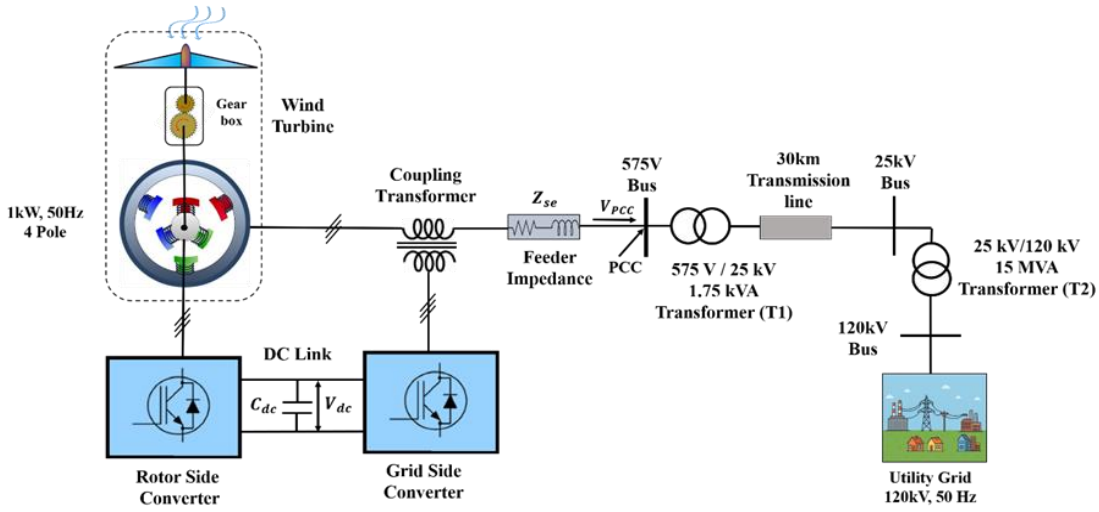

Figure 1. Single-line schematic of the presumed wind energy system

2.2. Mathematical modeling of wind energy harnessing system

2.2.1. Modeling of wind turbine

The wind turbine model is formulated based on aerodynamic power extraction, where the mechanical power depends on wind velocity, air density, and turbine characteristics. The coefficient of performance is expressed as a nonlinear function of tip-speed ratio and pitch angle, enabling realistic emulation of wind variations. The wind energy captured by the turbine is computed in (1) with ρ (1.225 kg/m^3), indicating the specific density of air, V_w indicating the wind velocity, A is indicating the circulation path of the wind turbine blades, and C_{eff} indicating the coefficient of turbine power, which is computed in (2) and (3).

$$P_m = 0.5C_{eff}(\lambda_0,\beta)\rho A V_w^3 = 0.5C_{eff}(\lambda_0,\beta)\rho\pi r2V_w^3 \tag{1}$$

$$\frac{WtR}{V_w} \tag{2}$$

$$C_{eff}(\lambda_0,\beta) = C_1(\frac{C_2}{\lambda_0} - C_3\beta - C_4)e^{-C_5/\lambda_0} + C_6\lambda_0 \tag{3}$$

Where β denotes the blade pitch angle and λ_0 denotes tip speed ratio. The coefficient constants are C_1-C_6 are 0.52, 120, 0.6, 4.77, 23, and 0.0056, respectively [24], [25].

2.2.2. Modeling of wind generator

The equations governing the stator and rotor are articulated in the d–q reference frame fixed to the stator. The d-axis is aligned with the stator flux, while the q-axis is 90 degrees ahead of it, maintaining orthogonality between the axes. The following are the voltage equations of the DFIG using flux linkage (4) to (7).

$$u_{ds} = R_{str}i_{ds} + \dot{f}_{ds} - \omega f_{qs};\ u_{qs} = R_{str}i_{qs} + \dot{f}_{qs} + \omega f_{ds} \tag{4}$$

$$u_{dr} = R_{rtr}i_{dr} + \dot{f}_{dr} - (\omega - \omega_r)f_{qr};\ u_{qr} = R_{rtr}i_{qr} + \dot{f}_{qr} - (\omega - \omega_r)f_{dr} \tag{5}$$

$$f_{ds} = L_{str}i_{ds} + Mi_{dr};\ f_{qs} = L_{str}i_{qs} + Mi_{dqr} \tag{6}$$

$$f_{dr} = L_{rtr}i_{dr} + Mi_{ds};\ f_{qr} = L_{rtr}i_{qr} + Mi_{qs} \tag{7}$$

In this formulation, the variables u_{dr} and u_{qr} denote the terminal voltages in the rotor d–q-axis, while u_{ds} and u_{qs} represent the terminal voltages in the stator d–q-axis. The stator currents are denoted by i_{ds} and i_{qs} and the corresponding rotor currents by i_{dr} and i_{qr} in the d–q reference frame. The flux coupling f_{ds}, f_{qs}, f_{dr}, and f_{qr} represent the magnetic interaction between the windings and $\dot{f}_{ds}$, $\dot{f}_{qs}$, $\dot{f}_{dr}$ and $\dot{f}_{qr}$ indicate the flux coupling time derivative. Here, ω refers to the electrical speed of the rotating reference frame, and ω_r denotes the rotor electrical speed. The parameters L_{str} and L_{rtr} correspond to the stator-side and rotor-side inductances, respectively, while M signifies the mutual inductance between stator and rotor windings. The stator and rotor resistances are given by R_{str} and R_{rtr}. The electromagnetic torque and the rotational dynamics of the rotor are presented in (8).

$$T_e = \left(\frac{3P}{4}\right)\left(f_{dr}I_{qs} - f_{qs}I_{ds}\right) \tag{8}$$

To prevent rotor iron and friction losses during wind gusts, a speed of range between ±10% around synchronous speed is examined. The overall power output, P_{to} delivered by the DFIG can be expressed as shown in (9).

$$P_{to} = P_{sp} + P_{rp} = P_{sp} + (1 + |s|)\,P_{sp} \tag{9}$$

Where P_{sp} represents the stator-side power, P_{rp} refers to the rotor-side power, and the machine slip is indicated by s [26].

2.2.3. Modeling of rotor-side converter and grid-side converter

The RSCR together with the GSCR facilitates slip power recovery and ensures efficient power transfer to the utility grid. Their operation and design principles are mathematically represented in (10).

$$\begin{bmatrix} \frac{dI_{xd}}{dt} \\ \frac{dI_{xq}}{dt} \\ \frac{dV_{dc}}{dt} \end{bmatrix} = \begin{bmatrix} 0 & \omega_x & \frac{-u_{xd}}{L_f} \\ -\omega_x & 0 & \frac{-u_{xq}}{L_f} \\ \frac{u_{xd}}{C_{dc}} & \frac{u_{xq}}{C_{dc}} & 0 \end{bmatrix} \begin{bmatrix} I_{xd} \\ I_{xq} \\ V_{dc} \end{bmatrix} + \begin{bmatrix} \frac{1}{L_f} & 0 & 0 \\ 0 & \frac{1}{L_f} & 0 \\ 0 & 0 & -\frac{1}{C_{dc}} \end{bmatrix} \begin{bmatrix} V_{xd} \\ V_{xq} \\ I_{dc} \end{bmatrix} \tag{10}$$

Where L_f is the impedance in the feeder, V_{dc} is the voltage in the DC connection, I_{dc} is the current in the DC connection, ω_x is the angular speed u_{xd}, u_{xq} are the switching pulses, and V_{xd} and V_{xq} represent the d–q components of the AC-side voltage of the converter, and I_{xd}, I_{xq} are input currents of the converters on the AC end, where the subscript x serves as a common notation denoting either r for the RSCR or s for the SSSCR.

Where V_{xcr_k} represents the phase voltage of the converter, expressed in magnitude and phase form as in (11), and subscript 'k' denotes the individual phase – a/b/c. Here, m_{index} is the modulation index controlled by the pulse width modulation (PWM) strategy, V_{dc} is the DC-link voltage, and θ_x denotes the phase angle of the converter voltage. The subscript 'x' is a generalized notation, where x = r corresponds to the RSCR and x = s corresponds to the GSCR [27].

$$V_{xcr\_k} = \frac{m_{index}.V_{dc}}{\sqrt{2}}\angle\theta_x \tag{11}$$

2.2.4. Modeling of alternating current grid

The AC grid interfaced with the DFIG stator terminal is represented by an equivalent series impedance, which accounts for the resistive line losses and the capacitive effects associated with the transmission path. The GSCR, coupled in series with the stator through the coupling transformer, plays a key role in dynamic voltage compensation under grid disturbances. At the interconnected node, the stator terminal voltage is influenced by the interaction of the LV bus voltage, the voltage drops across the transmission line impedance, and the compensating voltage injected by the GSCR, as expressed in (12).

$$V_{gscr} = Z_{se} \cdot I_{PCC} + V_{PCC} + V_i \tag{12}$$

Where V_{gscr} denotes the stator-side terminal voltage, V_{PCC} represents the PCC bus voltage of the grid, Z_{se} is the equivalent series impedance of the transmission line, I_{PCC} indicates the line current at PCC, and V_i corresponds to the compensating voltage injected by the GSCR through the coupling transformer [28].

3. CONTROL METHODOLOGY FOR RSCR AND GSCR

The system utilizes two converters, namely the RSCR and GSCR, to accomplish multiple control objectives such as bidirectional slip power exchange, maintaining voltage and frequency regulation on the stator-side LV bus, restoration of voltage during unbalanced conditions, and maintenance of unity power factor at the grid interface.

3.1. Control scheme of rotor side converter

The RSCR control architecture, depicted in Figure 2, implements a cascaded control scheme. It consists of an inner feedback loop for maintaining current and an outer feedback loop for voltage regulation to enhance the system's dynamic response. In this configuration, the 3φ stator voltages are transformed from abc frame into 2φ d–q orthogonal parameters, which are compared with their references. A conventional PI controller processes the error that follows and subsequently determines the reference rotor currents. The observed rotor currents I_{rabc} are turned into I_{rdq} by implementing the Park transformation. These modified currents, I_{rdq} are compared to their reference values to calculate current errors. These errors are fed into PI controllers to convert the control voltages V_{rd} and V_{rq}. A speed feedback loop is incorporated into this scheme by evaluating the deviation between the measured rotor speed and the desired nominal synchronous speed. The resulting error provides the necessary angular frequency signal for synchronization. The inverse of the Park transformation is applied to the control voltages and angle, converting them into the 3φ abc frame and producing the voltage V_{rabc}, which is fed to the RSCR. This closed-loop vector control approach ensures that the rotor current references are tracked accurately and improves the system's performance in both normal and disturbed conditions.

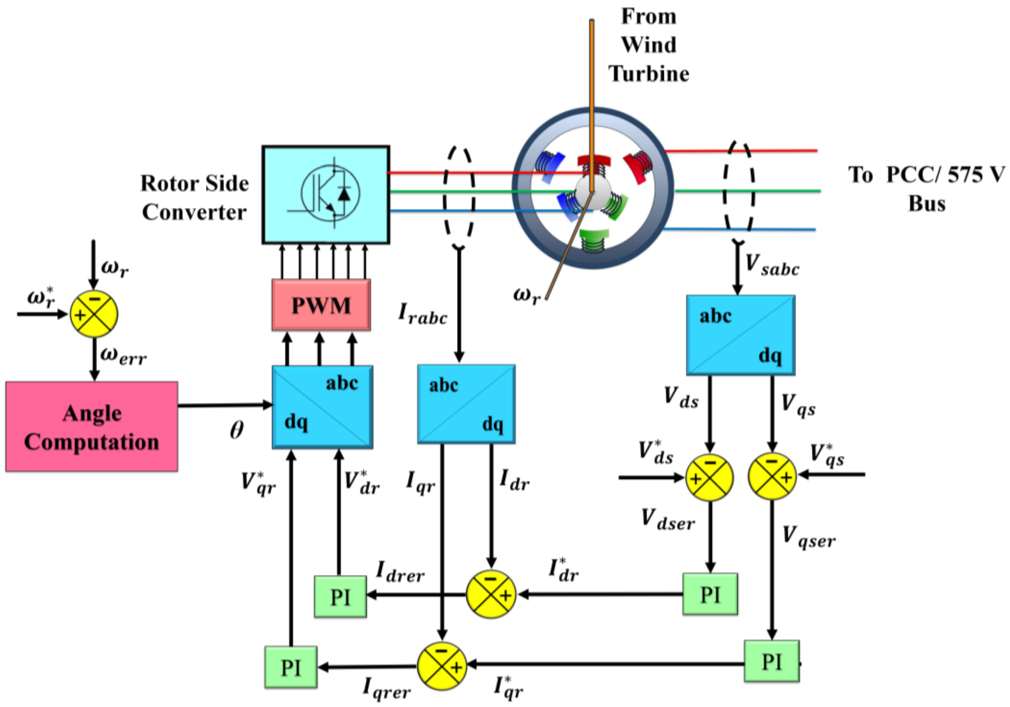

Figure 2. Schematic of RSCR control scheme of the presumed system

3.2. Control scheme of grid-side converter

The complete control architecture of the GSCR is depicted in Figure 3. The GSCR functions primarily as a series voltage regulator at the low voltage (LV) bus, especially under non-linear and unbalanced loads. The GSCR compensates during disturbances by injecting a series voltage with the LV bus, ensuring that the voltage remains at its nominal value. This compensation voltage is derived from the GSCR's converter through DC-link support and is applied via coupling transformer connected to the LV bus. The instantaneous symmetrical component theory (ISCT), a widely adopted method for mitigating load voltage disturbances, based on which GSCR works. This enhances the controller's ability to mitigate various voltage irregularities such as phase unbalances, non-linearities, sags, and swells.

When a disturbance is detected, the ISCT is triggered by sensing the LV bus voltage. A signal is obtained by the product of the stator voltage and current, which is then combined with the real and oscillatory power components. To extract the real power from the combined signal, a low-pass filter (LPF) is executed. This real power is subsequently used by the stator voltage to get the reference current I_{ref} as resultant. A PI controller processes the deviation between the regulated real-power reference and the measured active power to generate the control signal δ_p. The stator voltage is aligned utilizing a phase-locked loop (PLL) to estimate the system phase detection and frequency. The phase angle, denoted as ωt, which is the resultant from the PLL, is then combined with δ_p and I_{ref} to get the desired signal of the stator current I_{sabc}^{*}. This is then evaluated against the actual current signal of the stator I_{sabc} and processed by the hysteresis controller. The resultant error signal from the controller, which produces the switching signals for the GSCR converter.

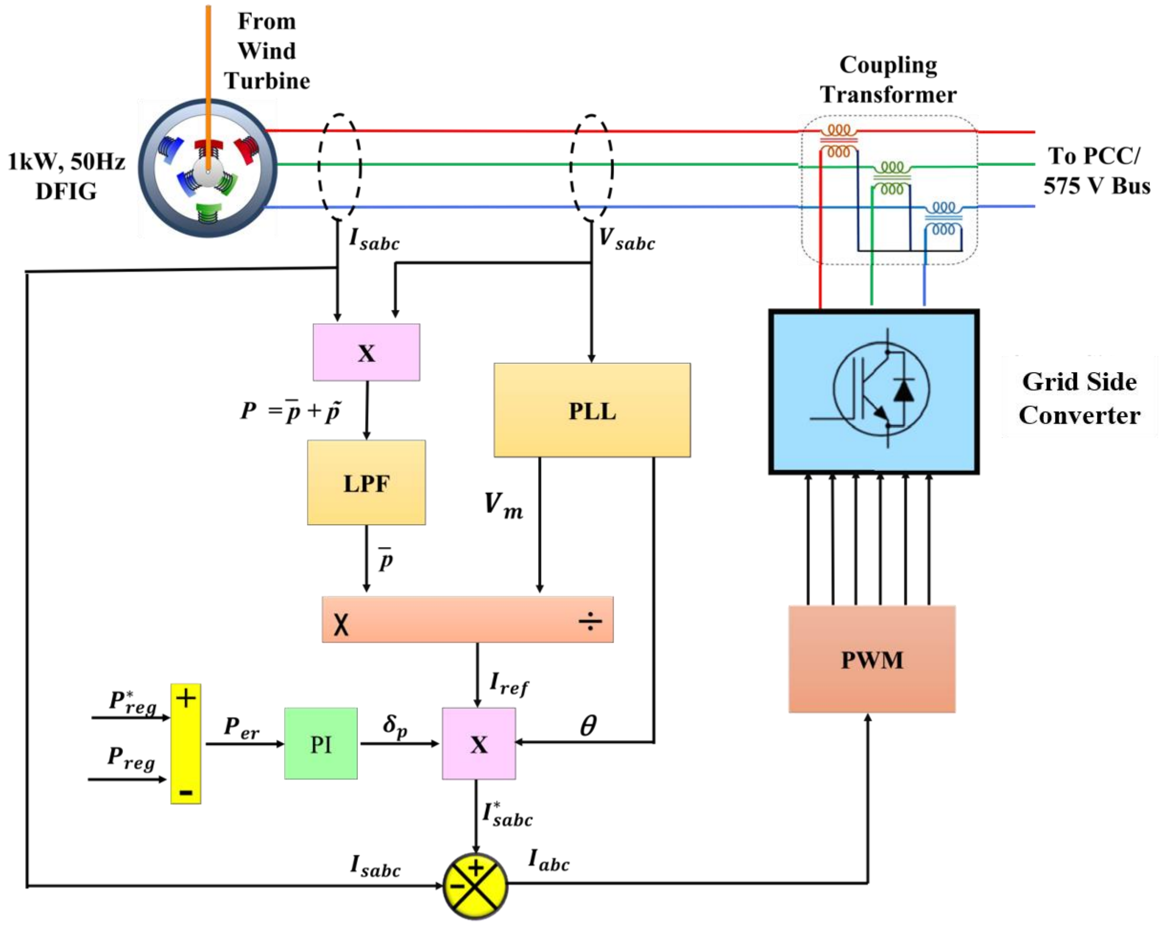

Figure 3. Schematic of the GSCR control scheme in the proposed system

4. CONTROL OBJECTIVES FOR VARIABLE SPEED WEHS

In any wind energy harnessing system, control objectives are essential to ensure efficient, reliable grid-compliant operation. The key objectives addressed by different researchers in a much contributing way are described as follows. The architecture of the operational objectives of the WEHS is depicted in Figure 4.

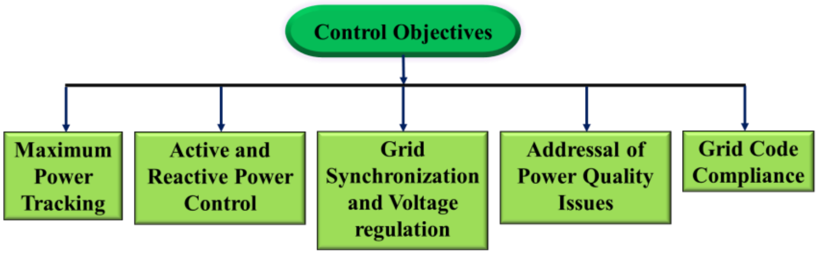

Figure 4. Architecture of control objectives in DFIG-based variable speed WEHS

4.1. Maximum power tracking

Maximum power tracking (MPT) in DFIG-based wind energy systems is critical for maximizing energy extraction, as wind turbine mechanical power varies cubically with wind speed, making the maintenance of an optimal tip-speed ratio essential for aerodynamic efficiency [29]–[31]. Conventional MPT methods are simple but less effective under dynamic wind conditions, whereas intelligent control techniques provide superior adaptability and robustness against nonlinearities and uncertainties. Hybrid intelligent strategies, such as radial basis function neural networks (RBFNN) combined with multi-swarm particle swarm optimization (MPSO), enable accurate wind speed estimation and rotor speed optimization, enhancing system reliability and reducing converter losses [32]. ANN-based MPT approaches dynamically estimate electromagnetic torque for optimal turbine speed, improving power extraction with faster response [33]. Advanced hybrid methods like chaotic salp swarm optimization-tuned-adaptive neuro-fuzzy inference systems (CSSO-ANFIS) coordinate RSCR and GSCR control to maximize power while ensuring grid stability through harmonic mitigation and reactive power balancing [34]. Sliding mode control (SMC) integrated with fuzzy logic supervisors further enhances robustness and dynamic response, while fuzzy SMC combined with intelligent optimization reduces chattering and improves tracking under small wind speed variations. Dual-mode intelligent strategies expand the MPT operating range, improving power output across varying wind conditions [35]. These approaches outperform traditional methods by effectively handling nonlinearities, uncertainties, and disturbances, resulting in higher energy yield, reduced mechanical stress, and enhanced fault tolerance. Abdeddaim and Betka [36] proposed a wind speed estimation-based MPPT technique for DFIG wind turbines, demonstrating improved tracking accuracy and enhanced energy capture under varying wind conditions. A hybrid fuzzy logic-based MPPT algorithm for permanent magnet synchronous generator (PMSG)-based wind energy conversion system (WECS), improving maximum power extraction efficiency and dynamic response in smart grid environments, is introduced in [37].

4.2. Real and reactive power control

By employing vector control in the rotor reference frame, DFIG systems achieve decoupled regulation of real and reactive power, allowing independent control of torque and flux [38]. Real power management ensures grid synchronization and frequency stability, while reactive power control maintains voltage support and power factor correction. This decoupled approach offers a clear advantage over traditional fixed-speed wind turbines by enabling dynamic responses to grid conditions [39]. Coordinated control between the RSCR and GSCR enhances system flexibility, supports grid code compliance, and improves power quality under variable load and fault conditions [40]. Dynamic reactive power allocation methods across DFIG units prioritize stator contribution and switch between stator and GSCR to optimize voltage support in weak grids while respecting unit limits and grid requirements [41]. Advanced nonlinear strategies, including static feedback linearization and passivity-based control [42], further enhance transient response, tracking precision, and robustness. Techniques for mitigating flicker and improving voltage stability have been proposed through direct RSCR reactive power control [43] and nonlinear SMC-based direct power control schemes [44]. Real-time platforms incorporating vector control for consolidated power and DC-link voltage management [45], as well as enhanced direct reactive power control (DRPC) with three-level inverters, demonstrate improved robustness, dynamic response, and power quality under varying wind conditions [46].

4.3. Grid synchronization and voltage regulation

Grid synchronization ensures matching of voltage, frequency, and phase between the DFIG and utility grid to avoid power surges and ensuring smooth operation. The GSCR regulates voltage at the PCC and maintains constant DC voltage [47]. Advanced synchronization techniques using PLLs and high-order sliding mode control (HOSMC) provide accurate phase tracking and dynamic performance under grid disturbances [48]. Robust PLLs embedded in generator-side converters enhance phase synchronization during grid fluctuations [49], while real-time imbalance detection enables autonomous frequency regulation in converter-fed microgrids [50]. In the presence of grid unbalance, dedicated control loops for sequence-specific components ensure soft connection and stable performance [51]. The GSC also operates analogously to a static synchronous compensator (STATCOM), generating or absorbing reactive power for voltage support [52]. Coordinated voltage and frequency regulation strategies ensure reliable off-grid and on-grid DFIG operation [53].

4.4. Addressal of power quality issues

Power electronic converters in DFIG systems introduce harmonics into the grid, which can affect the performance of sensitive equipment and violate power quality standards. Harmonic distortion must be minimized to comply with IEEE 519 and other international regulations [54]. Techniques such as LCL filters, PWM optimization, and active harmonic compensation are commonly employed to minimize distortion and ensure high-quality voltage and current at the PCC [55]. Enhanced controllers like proportional–integral–resonant (PIR) regulators and load-side compensators (LSC) can suppress both harmonic and unbalanced distortions in stand-alone systems [56]. Active filtering techniques [57] and coordinated STATCOM–DFIG voltage support schemes further improve grid power quality and voltage stability during transient events [58].

4.5. Grid code compliance

Compliance with modern grid codes ensures reliable and safe DFIG operation during faults. Standards such as IEEE Std 1547-2018, IEC 61400-21, and the Indian grid code specify voltage ride-through capabilities, reactive power support, and post-fault recovery performance [11]. Under asymmetrical or LV conditions, DFIG controllers must mitigate negative sequence effects, supply reactive current to support grid voltage, and sustain connection during voltage sags reaching 15% of desired value for up to 0.625 s [59]. The Indian grid code mandates recovery to 80% of nominal voltage within 300 ms and reactive current injection within 50 ms of disturbance detection [60]. Additionally, DFIGs must meet FRT requirements to maintain synchronization throughout the voltage dips and surges [61]. These standards collectively ensure that DFIG-based systems enhance grid resilience, maintain quality of the power, and aid system stability during disturbances. The FRT characteristics of grid code requirements are illustrated in Figure 5.

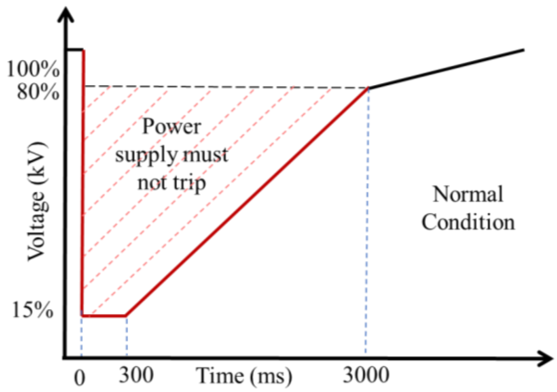

Figure 5. FRT characteristics of Indian grid code source: IEGC

5. TRADITIONAL CONTROL STRATEGIES

The functional representation of the PI controller, widely utilized in modern converter control architectures, is illustrated in Figure 6. The controller minimizes the deviation between desired and measured system responses by using proportional action for immediate correction and integral action to remove steady-state error [62]. This controller provides accurate and stable regulation of key electrical parameters by continuously processing the error in a closed-loop system. Despite its simplicity, it remains fundamental to advanced methods like field-oriented control (FOC) and direct torque control (DTC), ensuring reliable performance in both steady-state and dynamic conditions [63].

The PI controller is preferred owing to its simple structure, ease of implementation, minimal computational demand, and excellent steady-state performance when applied to linear dynamic systems [64]. Although Ziegler-Nichols makes gain tuning easy, its performance drops under parameter changes, non-linearity, or grid perturbation, often causing overshoot, oscillations, and integrator windup issues [65]. These restrictions require advanced modifications like anti-windup methods, adaptive gain adjustment, or hybrid intelligent controller integration [66].

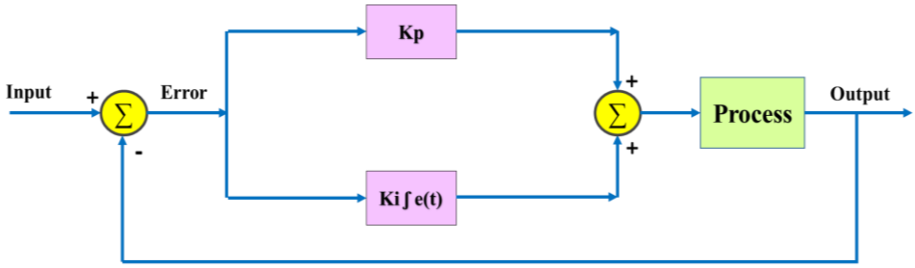

Figure 6. Functional depiction of PI controller

5.1. Vector control (field-oriented control)

The FOC applied to a DFIG-WEHS is shown in Figure 7. In this control strategy, acquired 3φ parameters such as currents and voltages from the generator are mathematically transformed (using Clarke and Park transformations) into an orthogonal 2φ d–q rotating frame, allowing the independent regulation of electromagnetic torque and reactive power. To generate reference currents, which are then converted back into 3φ signals via inverse transformations and applied as switching signals to the power converter, the 2φ d–q-axis components are processed by current controllers. This precise, decoupled control enables the DFIG system to efficiently track the desired speed, maintain grid code compliance (grid synchronization, voltage, and reactive support), and maximize energy extraction, making vector control a cornerstone in modern wind turbine grid integration [67]–[69].

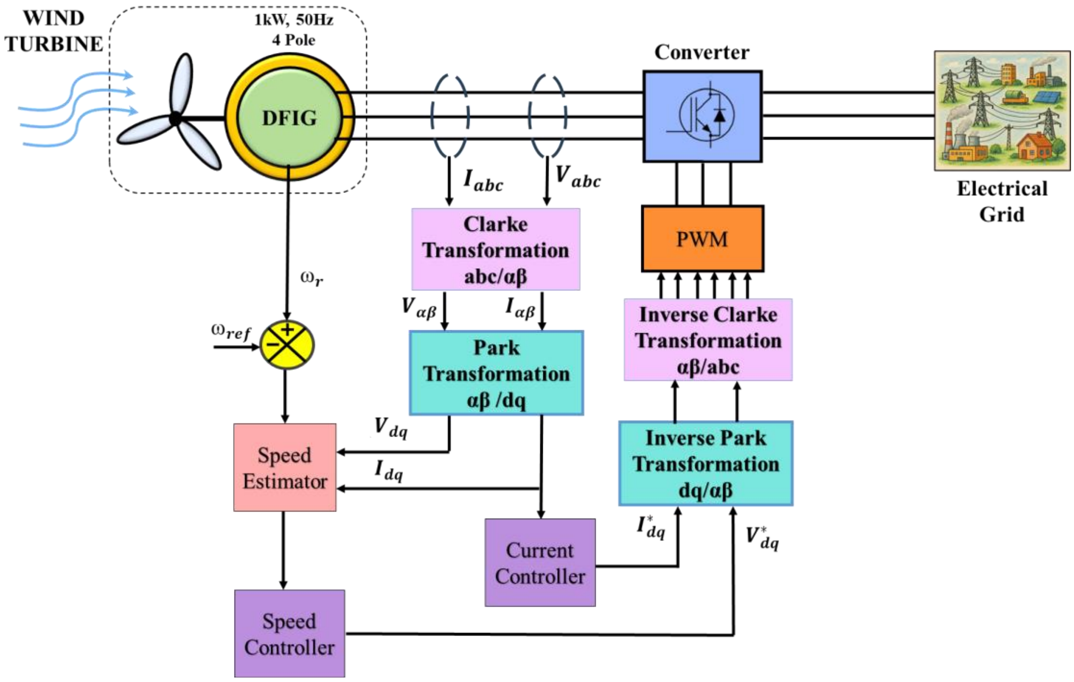

Figure 7. Schematic diagram of FOC

It is extensively employed in the control strategy for regulating DFIG-WEHS because it enables precise and independent management of active and reactive power [70]. The FOC implements Clarke and Park transformations to convert the 3φ parameters into synchronous reference frame with two axes (d–q frame), where the d-axis is positioned along the rotor flux vector so that torque and flux can be regulated independently [71]. This decoupling makes the control structure simpler and improves transient response and performance under wind and grid variations. In implementation, vector control begins by measuring the parameters and converting them into the rotating d–q reference frame [72]. The control architecture defines desired values for power parameters, computes the deviation between these desired and observed values, and processes it using PI controllers to derive the control output signals, which are subsequently modulated to control the switching of the RSCR and GSCR using PWM) A closed-loop feedback mechanism continuously adjusts the control actions to uphold operational stability, refined power regulation, and adherence to grid code requirements [73].

The key advantages of FOC include decoupled regulation of power parameters, rapid transient response, and robust operation under fluctuating wind conditions. It facilitates smooth MPT, enhances grid stability, and ensures compliance with FRT standards. Despite this, its operational effectiveness is contingent upon the precise estimation of parameters, making it sensitive to modeling inaccuracies and measurement errors [74].

5.2. Direct torque control

DTC in DFIG-based WEHS, shown in Figure 8, directly regulates electromagnetic torque and stator flux without using coordinate transformations or complex current controllers. It continuously estimates the stator flux and torque from electrical signals and rotor speed, compares them with their reference values, and then selects the appropriate converter switching state from a predefined lookup table. By instantly applying the corresponding voltage vector, DTC corrects flux and torque deviations in real time, resulting in dynamic response, high efficiency, and robust performance under varying wind and grid conditions. Despite its simplicity and reduced dependency on machine parameters, DTC can suffer from torque ripple and flux estimation errors, driving further research into optimized and hybrid DTC strategies.

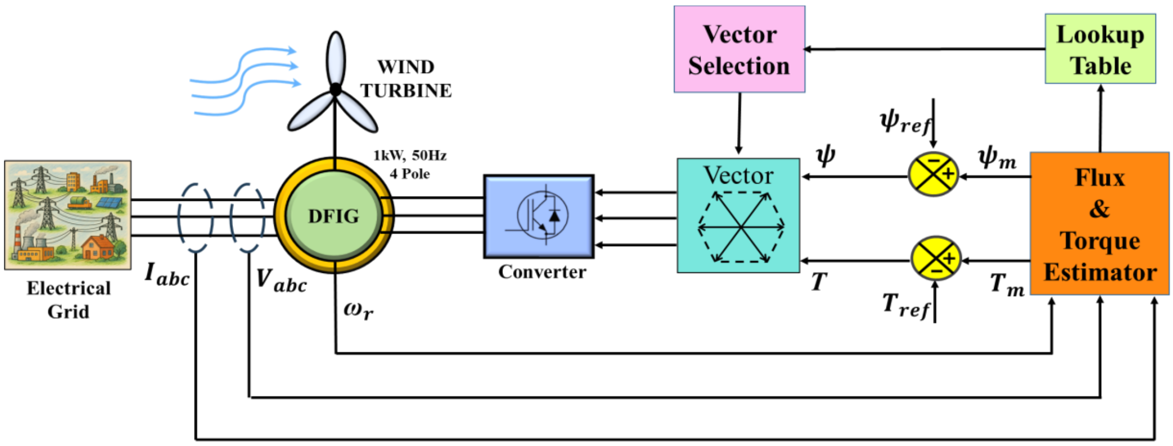

Figure 8. Schematic diagram of DTC

DTC operates by tracking the stator flux and torque in real time from measured electrical signals. The deviations between the derived quantities and reference values are processed through hysteresis comparators [75]. In accordance with the controller signals, a predefined switching table determines the optimal voltage vector that ensures the machine flux and torque are closer to their reference operating levels. DTC directly controls the inverter switching states, which means that changes to flux and torque may be made quickly without using modulation methods like PWM. This cuts down on control delays and makes the system more responsive [76].

DTC has a number of benefits, such as a quick dynamic reaction, a high level of resistance to changes in machine parameters, and an easier implementation than vector control because it doesn't need current regulators or coordinate transformations [77]. Its rapid response capability is particularly beneficial for improving low-voltage ride-through (LVRT) performance, allowing the turbine to react swiftly to grid voltage dips. But the approach is restricted by elevated torque and flux oscillations that are caused by the hysteresis control scheme and are also sensitive to measurement errors when estimating flux. To make things work better, these problems frequently require the adoption of advanced methods like space vector modulation (SVM) or adaptive switching schemes [78].

In DFIG-based wind turbines, DTC is primarily applied to the RSCR to achieve precise torque and power control, facilitating MPT and dynamic grid support [79]. DTC can also be used with smart controllers like fuzzy logic or neural networks to reduce torque ripple and improve switching performance. This makes it a good choice for next-generation wind energy control techniques.

5.3. Sliding mode control

SMC is a nonlinear and highly robust control method used in DFIG-WEHS, particularly under uncertain or fault-prone operating conditions. SMC is different from traditional controllers because it can handle system nonlinearities, outside disturbances, and changes in parameters without needing to model the system very well. In this method, the system state evolution is forced onto a prescribed sliding manifold and maintained by a discontinuous control signal, ensuring desired stability and dynamic performance. The control law switches between different structures depending on the system position relative to the sliding manifold, ensuring rapid convergence to the surface (reaching phase) and subsequent controlled evolution along it (sliding phase) [80]. Although SMC offers strong reliability and stability, a common challenge is chattering, an oscillation near the sliding manifold that requires mitigation techniques in practical implementations. Overall, SMC's resilience and adaptability make it a powerful choice for controlling nonlinear systems like DFIG-WEHS. The implementation of SMC follows two key stages. Initially, a switching control component manipulates the system trajectory toward the sliding surface (reaching phase). Once the states reach the surface, a reduced-order model defines the system's dynamics along it (sliding phase), maintaining performance despite parameter variations or external disturbances. In DFIG systems, SMC is typically applied in the d–q coordinate frame to regulate rotor currents, electromagnetic torque, and reactive power [81]. The schematic representation of SMC is illustrated in Figure 9.

SMC provides strong robustness to system uncertainties, fast dynamic response, and effective disturbance rejection, making it well-suited for nonlinear behaviour and enhancing LVRT/high-voltage ride-through (HVRT) performance in DFIG systems [82]. Its main drawback is chattering near the sliding surface, which can cause mechanical stress, noise, and power losses; this is typically mitigated through boundary-layer methods, higher-order SMC, and hybrid intelligent techniques such as fuzzy or neural network integration [83]. In DFIG-based wind turbines, SMC is widely applied in the RSCR for power regulation and MPT, and in the GSCR for DC-link voltage control and reactive support, offering high resilience under voltage dips, grid disturbances, and unbalanced conditions [84]. Emerging hybrid SMC–optimization approaches further reduce chattering while maintaining robustness, making SMC a strong candidate for next-generation wind turbine control solutions [85].

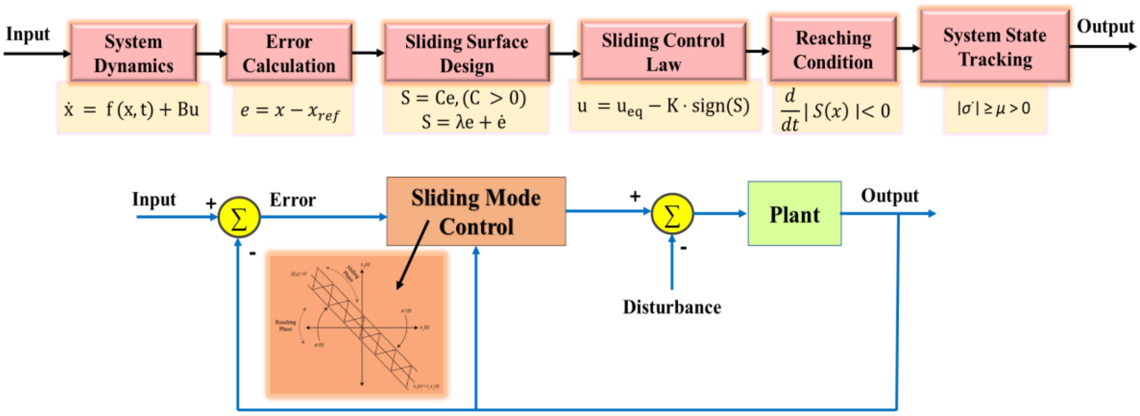

Figure 9. Schematic diagram of SMC

5.4. Model predictive control

Model predictive control (MPC) has emerged as an innovative control framework for DFIG-WEHS, owing to its capability to handle multi-variable interactions, input-output constraints, and predictive optimization [86]. MPC is different from regular controllers since it adopts a computational model to forecast how the system will behave in the future during a certain time period and then optimizes the control actions based on it. MPC can manage the trade-off between performance and control effort because it can foresee the future. This makes it perfect for modern wind turbines that work in dynamic and unpredictable grid conditions [87].

The schematic of MPC implementation is illustrated in Figure 10. In this approach, at every sampling instant, the controller uses the dynamic model to predict the evolution of key variables. An optimization problem is then solved to minimize a cost function, which typically combines reference tracking, control effort, and constraint enforcement. Only the first input of the computed control sequence is executed, after which the optimization is repeated at the following sampling instant. This allows the controller to continuously adjust to system changes and disturbances through a receding horizon strategy.

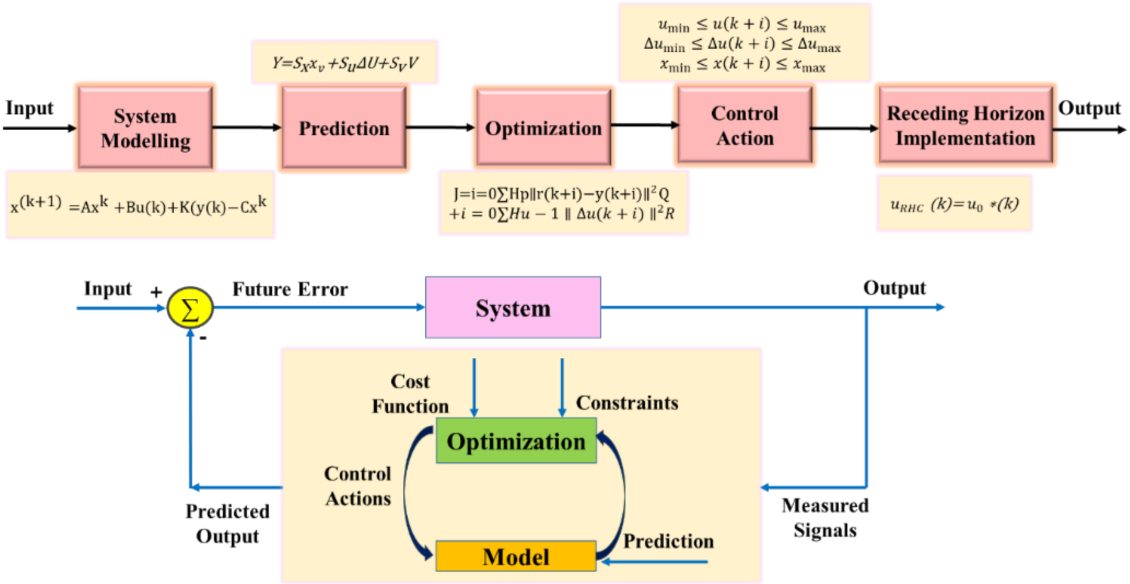

Figure 10. Schematic diagram of MPC

MPC operates through three stages: prediction, optimization, and implementation, where a system model forecasts future states, an optimizer selects the control action that minimizes a cost function within constraints, and only the first optimal input is applied before repeating the cycle [88]. This enables rapid adaptation to varying wind velocity, grid, and nonlinear variations, offering excellent dynamic performance, smooth torque and current profiles, and strong disturbance rejection. However, MPC is computationally intensive and highly sensitive to model accuracy, requiring powerful processors and precise system modeling [89]. In DFIG-based WEHS, MPC is applied in the RSCR for power control and MPT, and in the GSCR for the maintenance of DC circuit and reactive support, with notable advantages during FRT. Emerging hybrid-intelligent optimization approaches further reduce computational burden while maintaining robustness, making MPC a strong candidate for advanced DFIG control in smart grid and hybrid AC/DC microgrid environments [90].

6. INTELLIGENT CONTROL STRATEGIES

Intelligent control systems extend conventional control by incorporating learning, adaptability, and self-organization to manage complex, nonlinear, and uncertain processes that traditional methods cannot handle effectively. By continuously analysing system data and adapting to evolving conditions, intelligent controllers enhance robustness, enable real-time decision-making, and improve overall performance. This makes intelligent control especially valuable in dynamic and complex applications where precision and flexibility are critical.

6.1. Fuzzy logic control

FLC is a computational intelligence-based approach widely applied in DFIG-based WEHS owing to its capability to handle nonlinearities, uncertainties, and imprecise inputs more effectively than conventional controllers such as PI regulators [91]. Unlike model-based control methods, FLC relies on a rule-based framework that emulates human reasoning, providing resilience against parameter variations and external perturbations [92]. The overall schematic of the same is shown in Figure 11.

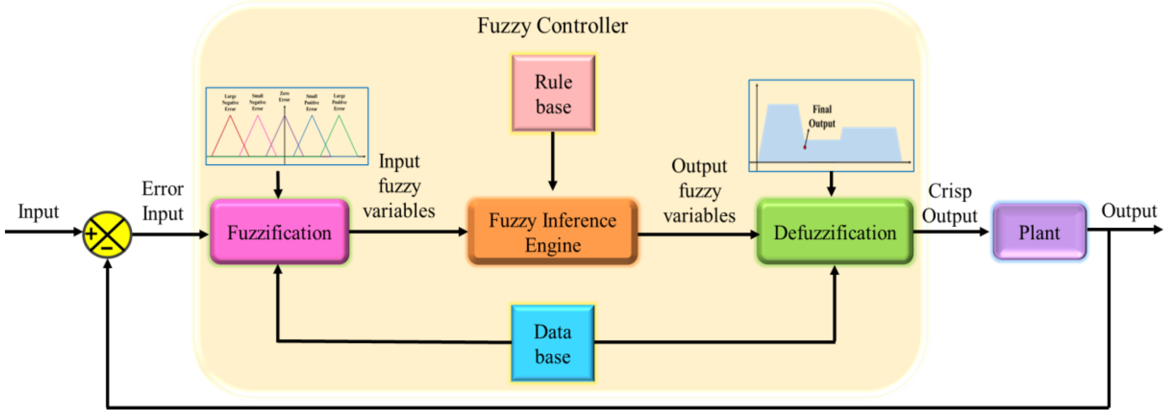

Figure 11. Schematic diagram of FLC

The adaptability and learning capability of an FLC depend on its implementation. In conventional FLCs, experts define the rule base and membership functions based on known system parameters [93]. In contrast, advanced FLCs integrate adaptive or intelligent techniques, such as neuro-fuzzy systems or optimization algorithms, to automatically tune membership functions and update rules. This learning capability enhances the controller's flexibility, enabling robust performance under varying operating conditions, grid disturbances, and parameter uncertainties [94]. A typical FLC architecture consists of four main components: the fuzzification interface, which converts crisp input variables, such as speed error or reactive power deviation, into fuzzy sets; the knowledge base, which contains a collection of expert-defined inference rules; the inference engine, which evaluates the fuzzy inputs according to the knowledge base; and the fuzzy to crisp converter, which transforms the fuzzy output into a precise control signal to operate the DFIG converters effectively.

FLC has proven highly effective for MPT, active and reactive power management, and providing grid support during LVRT and HVRT events [95]. Simulation studies indicate that FLC achieves smoother dynamic responses, superior disturbance rejection, and improved FRT capability related to conventional PI controllers. For instance, when the wind velocity fluctuates abruptly or the voltage drops, FLC keeps the system stable and reduces the amount of torque and current that oscillate, thereby making both the turbine and the grid work better [96]. To further improve fault tolerance, [97] proposed an FLC for the RSCR, enhancing voltage regulation and power management under grid fault conditions. A comprehensive survey demonstrating that fuzzy controllers in DFIG wind turbines deliver superior performance compared to conventional methods is furnished in [98]. A fuzzy logic-based control strategy for DFIG systems that offers robust converter regulation under faulty operating conditions is developed in [99]. An FLC to replace conventional PI controllers in DFIG systems, improving dynamic response, is designed and simulated in [100].

FLC has many benefits, such as being able to handle system nonlinearities, not needing an accurate mathematical model to work, quickly adapting to changing conditions, and performing better in fault and transient situations. But it also has certain problems. It takes a lot of specialist knowledge to make a good rule base and membership functions, and the more input variables there are, the harder it gets. Also, FLC works well in simulations, but it can be hard to use in real time because it takes a lot of processing power, especially when combined with optimization-based learning methods. Despite these limitations, FLC remains a strong candidate for advanced DFIG control, particularly when integrated with hybrid strategies that incorporate optimization algorithms or neural network-based learning to enhance adaptability and efficiency.

6.2. Artificial neural networks

ANN is a processing architecture that is cognitively inspired, designed to model complex nonlinear relationships, as illustrated in Figure 12. Their adoption in DFIG systems has increased for functions such as control, forecasting, and refinement. An ANN consists of interconnected layers of neurons, i.e. an input interface, multiple intermediate interfaces, and a final output interface. Each neuron computes a weighted input sum and processes it through a nonlinear transformation function, and propagates the result forward to represent sophisticated nonlinear dynamics [32]. In DFIG control, ANNs are often used as adaptive mapping tools to complement or replace conventional controllers, generating control signals that respond to variations in wind and grid conditions [101].

Training an ANN involves adjusting synaptic weights to minimize errors between predicted and actual outputs, typically via supervised learning using methods like backpropagation and gradient descent [102]. Advanced approaches such as deep learning, reinforcement learning (RL), and neuro-fuzzy systems enhance adaptability and robustness [103]. ANNs can be trained offline with historical datasets or online to respond in real time to nonlinearities and unexpected changes [103]. Structurally, inputs are processed through hidden layers using weighted sums and activation functions, producing outputs that are iteratively refined. In DFIG-based wind energy systems, ANNs effectively support MPT, predictive control, fault detection, and grid assistance [104]. They handle nonlinearities and disturbances without precise models, but require large datasets, significant computation, and careful regularization to avoid overfitting, while remaining less interpretable than traditional controls [105].

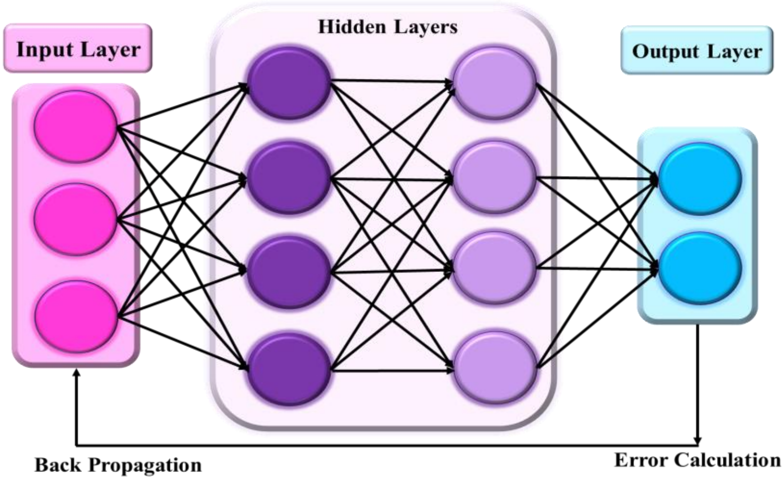

Figure 12. Schematic diagram of ANNs

6.3. Genetic algorithms

GA is a category of evolutionary computation techniques that draw inspiration from the mechanisms of biological evolution and inheritance, as depicted in Figure 13. GAs have been extensively implemented in DFIG-based WEHS to optimize controller parameters, boost dynamic performance, and reinforce FRT capabilities [106]. The GA process emulates biological evolution through iterative steps of selection, crossover, and mutation. Initially, a set of potential solutions, referred to as chromosomes, is randomly generated. Each candidate solution is assessed using a fitness function that evaluates how effectively it meets the control objectives, such as minimizing active power error, stabilizing DC-link voltage, or ensuring LVRT compliance [107]. Fittest individuals are chosen via roulette wheel or tournament selection, then undergo crossover and mutation to maintain diversity. The process repeats until a performance target or generation limit is reached [108]. This cycle repeats over multiple generations until a predefined stopping criterion, such as a target fitness value or maximum number of generations, is achieved. Over successive iterations, the population evolves toward optimal or near-optimal solutions, providing adaptive tuning for complex nonlinear systems such as DFIGs [109].

The GA begins by generating a population of candidate solutions, or chromosomes, initialized randomly. Each solution is evaluated using a fitness function, and the best-performing individuals are selected as parents for the next generation. Offspring are created via crossover and mutation to maintain diversity, replacing fewer fit individuals. This cycle continues until a stopping criterion, such as target fitness or a set number of generations, is reached, progressively evolving toward optimal or near-optimal solutions. In wind energy systems, GA effectively tunes controllers like PI, FLC, and MPC, improving transient response, reducing overshoot, and enhancing stability under variable wind and grid conditions [110]. GA-based optimization also boosts MPT, mitigates torque and current fluctuations during disturbances, and strengthens LVRT and HVRT performance. Integration with intelligent or robust strategies, such as ANN or SMC, further enhances adaptability [111]. GA's advantages include global optimization, robustness to nonlinear multi-objective problems, and independence from gradient information [112]. Limitations include high computational demand and sensitivity to parameters like population size, crossover, and mutation rates [113]. While not always guaranteeing a global optimum, GA reliably produces near-optimal solutions, enabling real-time controller optimization and advanced energy management.

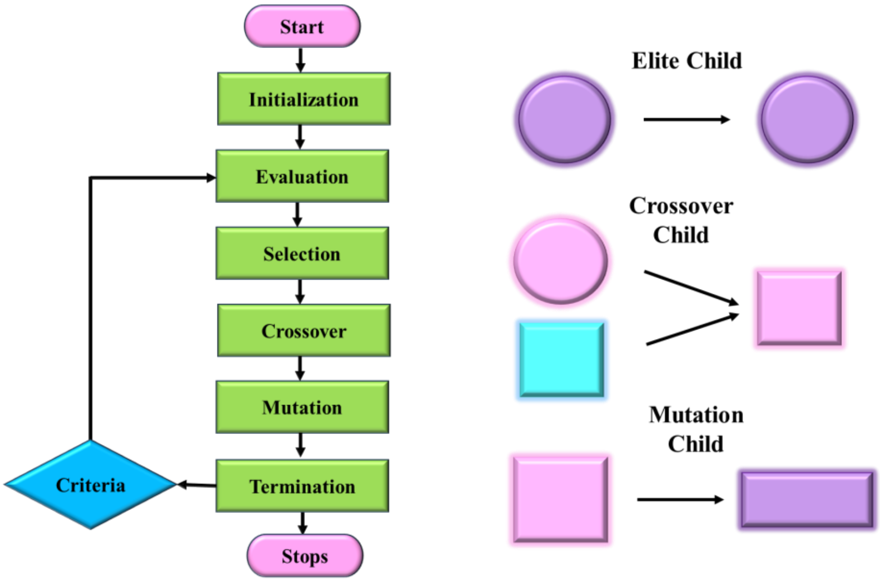

Figure 13. Schematic diagram of GA

6.4. Particle swarm optimization

PSO is a population-based probabilistic algorithm inspired by the swarming behaviour of birds and fishes, commonly used in DFIG-based wind energy systems for controller tuning, improving MPT, and enhancing stability under variable grid conditions [114]. Each candidate solution is modelled as a particle moving through a high-dimensional search space, updating its position and velocity based on its personal best and the global best experiences [115]. Starting with random positions and velocities, particles evaluate fitness using an objective function, such as minimizing power error, controlling DC-link voltage, reducing torque oscillations, or improving FRT performance [116]. Velocity updates account for inertia and distances from personal and global bests, while positions are adjusted accordingly [117]. This iterative process balances exploration and exploitation, guiding the swarm toward optimal or near-optimal solutions while avoiding local minima. The overall schematic of the PSO is shown in Figure 14.

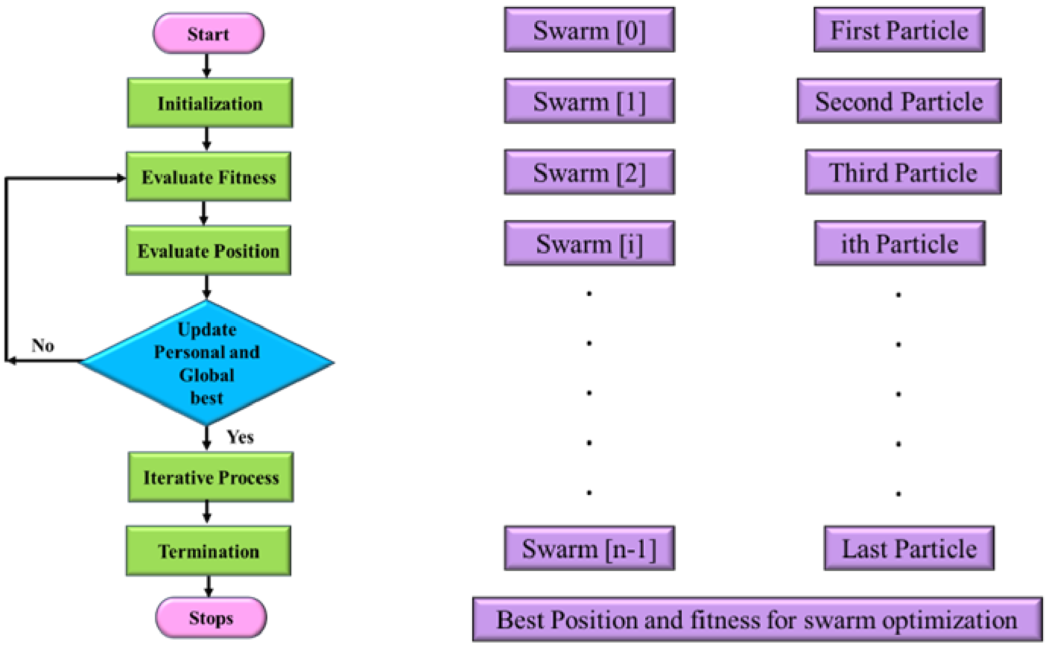

Figure 14. Schematic diagram of PSO

PSO has been widely applied in DFIG-based wind energy systems to optimize conventional and hybrid intelligent controllers [118]. It enhances MPT under rapid wind variations and improves DC-link voltage regulation during FRT events. PSO combined with ANN or SMC further increases adaptability and robustness under nonlinear and uncertain grid conditions [111]. The algorithm converges quickly, explores the search space without gradient information, and can handle multi-objective optimization in real time [119]. However, performance depends on parameter selection, and like other metaheuristics, PSO can require significant computational resources for large-scale or real-time implementations. In PSO, particles representing candidate solutions explore the search space by updating positions and velocities based on their own best positions and the global best found by the swarm. Through iterative adjustments and information sharing, the swarm balances exploration and exploitation, converging toward optimal or near-optimal solutions. PSO is particularly effective for complex, nonlinear, and multidimensional optimization problems, such as control of DFIG-based wind energy systems.

6.5. Adaptive neuro-fuzzy inference system

The ANFIS is an intelligent control approach that integrates the learning capabilities of ANN with the reasoning strengths of fuzzy logic, making it highly effective for controller design, fault diagnosis, and dynamic optimization in DFIG-based wind energy systems [120]. ANFIS typically combines a Sugeno-type fuzzy inference system with a multi-layer feedforward neural network, automatically learning and adjusting fuzzy membership functions and rules from training data without manual rule formulation [121]. Training uses a hybrid method of least-squares estimation and backpropagation in a supervised manner, where input parameters (e.g., wind speed, rotor speed, and active/reactive power) are mapped to control objectives [122]. During this process, membership functions and rule weights are iteratively refined to minimize discrepancies between predicted and actual outputs, allowing ANFIS to adapt to nonlinear, uncertain, and time-varying conditions such as sudden grid disturbances or system faults [123]. Structurally, ANFIS fuzzifies inputs, applies interface rules, normalizes rule strengths, computes output functions, and defuzzifies the results. The hybrid learning algorithm continuously updates parameters, enhancing the system’s ability to capture complex nonlinear relationships between inputs and outputs. The schematic chart of an ANFIS is shown in Figure 15.

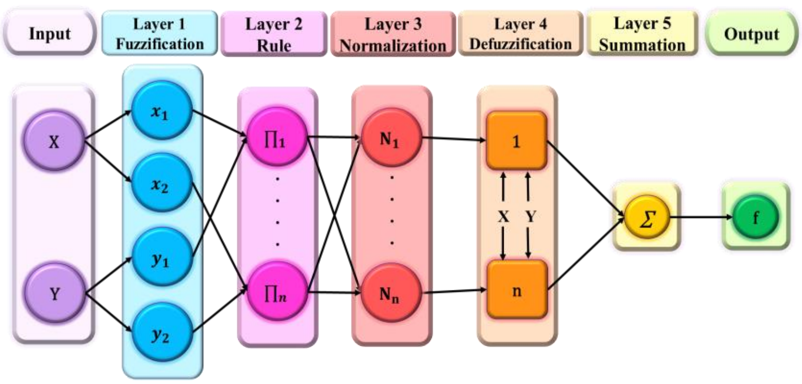

Figure 15. Schematic chart of ANFIS

In DFIG-based wind energy systems, ANFIS enhances the performance of MPT, power parameter regulation, rotor current control, and DC-link voltage stability. Simulation studies indicate that controllers based on ANFIS outperform conventional PI and static fuzzy controllers, showing improvements in settling time, overshoot, and resilience to disturbances [124]. ANFIS-based RSCR and GSCR control systems can keep the electricity stable and keep working even when the grid goes down or the wind blows hard, making sure they follow the grid code. ANFIS also finds early signs of problems and changes how controls respond in real-time condition monitoring [125]. Because of its nonlinear mapping capabilities, self-learning nature, and adaptive behavior, ANFIS is highly effective for real-time control of complex systems such as DFIGs. Its hybrid structure, combining fuzzy logic with neural networks, allows it to handle input data that is incomplete, uncertain, or ambiguous [126]. But ANFIS has some limits. The system works better when it has more and better training data, and it gets harder to compute when there are more inputs and fuzzy rules. To minimize overfitting and generalization, real-time implementation needs a lot of processing power and careful tuning. Even with these problems, ANFIS is a potential tool for smart wind energy regulation, especially when used with optimization algorithms or hybrid control frameworks.

6.6. Reinforcement learning

RL enables control systems to learn optimal strategies through environmental interaction using a reward-and-penalty framework rather than direct supervision. It has emerged as an effective approach for adaptive and autonomous control of DFIG-based wind energy systems, especially under grid variability and instability [127]. An RL system comprises an agent that makes decisions, an environment representing the DFIG and grid dynamics, and a reward signal evaluating the agent's actions [128], [129]. The agent iteratively refines its policy to maximize cumulative rewards. Techniques such as Q-learning, deep Q-networks (DQN), and policy gradient methods are widely used for power system control and optimization, with deep RL enabling neural networks to handle high-dimensional state spaces and continuously adapt without requiring a system model [130]. The schematic depiction of RL is shown in Figure 16.

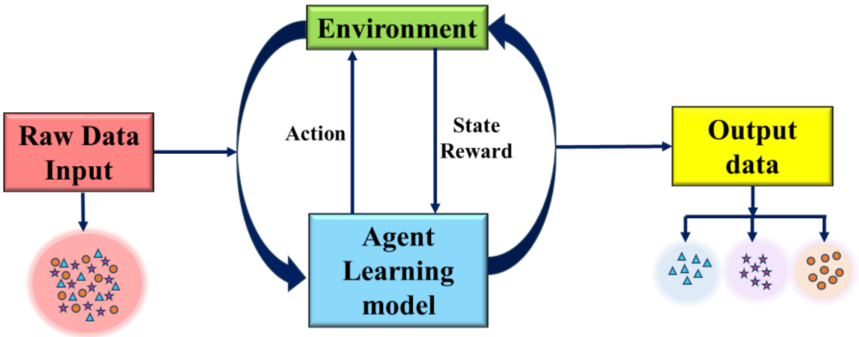

Figure 16. Schematic diagram of RL

RL is a goal-directed approach where an agent learns optimal decisions through continuous interaction with its environment. The agent observes the current state, selects actions based on a policy, and receives rewards reflecting the desirability of outcomes, which are used to refine the policy and maximize cumulative rewards over time. In DFIG-based wind turbines, RL is applied for MPPT, converter control, FRT enhancement, and dynamic reactive power compensation [131]. Hybrid approaches combining RL with optimization methods or neural networks improve adaptability across varying operating conditions. RL enables model-free, real-time learning and can identify strategies that maximize power while minimizing losses. However, training requires extensive environment interaction, which can be costly and potentially unsafe [132]. Safe RL and offline training using high-fidelity simulations mitigate these challenges, making RL a promising tool for intelligent control in DFIG-based wind energy systems. The comparative performance of the different control strategies, along with their key characteristics, is summarized in Tables 1 to 3, respectively.

Table 1. Performance metrics

References	Method	Stability	Speed of response	Robustness to parameter variation	Grid-disturbance handling	Computational complexity	Real-time implementability
[133]	Vector/FOC	H	M–H	M	M–H	L–M	H
[134]	DTC	M–H	H	M	M	L–M	H
[135]	PI-based controller	M	M	L–M	M	L	H
[136]	SMC	H	H`	H	H	M	M
[137]	MPC	H	H	M–H	H	H	M

*L-Low, M-Medium, H-High

Table 2. Quantitative performance comparison of control strategies

References	Method	Total harmonic distortion (THD) (%)	Transient response (ms)	Overshoot (%)	Steady-state error (%)	Settling time (ms)
[138]	Vector/FOC	3–5	40–0	5–10	< 1	80–120
[139]	DTC	4–8	20–40	8–15	1–2	60–100
[140]	PI-based controller	5–10	60–120	10–20	2–5	120–200
[141]	SMC	2–4	15–30	2–5	< 1	40–80
[142]	MPC	1–3	10–25	< 5	< 1	30–60

Table 3. Comparative table of traditional and intelligent control strategies based on the features

Feature	Traditional control strategies	Intelligent control strategies
Control objective	Active/reactive power regulation, stability	Adaptive regulation, optimization under uncertainty
Complexity	Low–moderate (linear models)	High (nonlinear models, learning, adaptive tuning)
Parameter dependency	High (requires accurate machine/grid parameters)	Low–moderate (can adapt to variations)
Robustness	Limited under parameter variations and grid disturbances	High robustness to nonlinearity, faults, and uncertainty
Computational burden	Low (easy to implement in real-time controllers like DSPs)	Medium–High (requires faster processors or embedded systems)
FRT	Basic support and limited voltage sag handling	Enhanced FRT with adaptive/optimized control
MPPT integration	Conventional torque-based MPPT	Hybrid artificial intelligence (AI)-based MPPT for optimal tracking
Scalability	Widely adopted and industry standard	Emerging, requires validation for large-scale deployment

7. RECENT TRENDS AND CASE STUDIES

Intelligent control and optimization techniques are increasingly employed in DFIG-based wind energy systems to enhance adaptability, efficiency, and resilience under nonlinear, uncertain, and time-varying conditions. ANNs leverage learning from historical or real-time data to predict system responses, perform MPT, fault detection, and grid support, though they require large datasets and careful regularization [102]. ANFIS integrates ANN learning with fuzzy reasoning to automatically adjust membership functions and rules, offering robust performance in nonlinear and uncertain environments. Metaheuristic algorithms, such as GA and PSO, optimize controller parameters—including PI, FLC, and MPC—enhancing transient response, MPT, DC-link voltage regulation, and FRT, with GA providing global search capabilities [143] and PSO offering rapid convergence and multi-objective optimization without gradient information. RL enables model-free, goal-directed adaptation by iteratively refining policies through reward feedback, supporting MPPT, converter control, and dynamic reactive power compensation, with deep RL handling high-dimensional state spaces and hybrid RL further improving generalization. Current trends emphasize hybrid intelligent controllers that combine conventional control strategies with soft computing, such as PI + ANN or type-2 fuzzy + SMC, as well as hybrid optimization algorithms like differential evolution (DE)-PSO and ant colony optimization (ACO)-PSO, enhancing convergence, exploration-exploitation balance, and robustness. Furthermore, the integration of AI, machine learning, and internet of things (IoT) enables predictive maintenance, adaptive control, and digital twin frameworks, improving grid integration, system reliability, and energy output, consistent with Industry 4.0 smart grid trends [144]. A comparison of RL and ANN-based inverter control strategies for grid-connected photovoltaic systems, highlighting their effectiveness in improving dynamic performance and power quality under varying operating conditions, is explained in [145]. The use of AI techniques to enhance the speed and position control performance of a DC servo motor, showing improved dynamic response and tracking accuracy under varying operating conditions [146].

8. CHALLENGES AND RESEARCH GAPS

The deployment of controllers for WEHS encounters the following challenges and research gaps:

i) High computational requirements for intelligent systems: intelligent controllers for DFIG systems—including neural networks, fuzzy logic, and hybrid optimization-based methods—often involve complex algorithms that demand substantial computational resources. Real-time implementation on wind turbines requires high-performance processors or digital signal controllers (DSPs), as limited computational capacity can introduce delays in control signal generation, potentially degrading dynamic performance and overall system stability [147].

ii) Real-time adaptation and convergence issues: many intelligent controllers depend on learning-based or iterative optimization methods, such as PSO or online ANN tuning, which must converge rapidly to respond to fluctuating wind speeds and grid disturbances. Slow convergence or delayed adaptation can lead to suboptimal performance, instability, or the inability to maintain desired rotor currents and active/reactive power outputs during transients [148].

iii) Unavailability of accurate models: certain intelligent control methods require detailed knowledge about the DFIG system, such as the rotor and stator characteristics, the grid impedance, and the converter dynamics. Discrepancies between the real-time system and its model—arising from parameter uncertainties or environmental variations—can reduce the controller's effectiveness, robustness, and its ability to manage faults or provide adequate grid support [149].

iv) Implementation complexity and cost: advanced intelligent controllers require additional hardware like high-speed processors, ADCs, and communication modules, as well as complex software platforms for real-time implementation. This increases both the cost and design complexity compared to conventional controllers, which may limit their adoption in commercial DFIG wind turbine systems [150].
v) Limited by the lack of standardized testing and validation: intelligent controllers lack widely established benchmarks or defined testing processes for DFIG systems like conventional controllers. This makes it difficult to compare performance, certify controllers, or predict behaviour under extreme operating conditions, slowing down large-scale deployment [151].

9. FUTURE RESEARCH DIRECTIONS

The existing methodologies reported in this review necessitate that future research may be directed as follows:

i) Hybrid control strategies: future research on DFIG-based systems should focus on developing hybrid control strategies that merge the robustness of conventional controllers with the adaptive capabilities of intelligent techniques. For example, combining PI or vector control with fuzzy logic, neural networks, or optimization algorithms can substantially enhance FRT performance, system stability, and dynamic response. These hybrid approaches offer a balance between computational efficiency and adaptability, making them suitable for implementation in large-scale wind energy applications. The optimal control and performance enhancement of grid-connected PV and wind hybrid systems using an electric eel foraging optimization algorithm (EEFO), demonstrating improved system efficiency and operational optimization under varying conditions [152].
ii) Edge-AI-based controllers for real-time wind farm optimization: the application of Edge-AI in wind turbine controllers offers promising opportunities for real-time optimization of wind farms. By processing data locally at the turbine level, edge intelligence reduces latency and dependence on cloud-based systems, ensuring rapid adaptation to wind speed fluctuations and grid conditions. Edge-AI also enables predictive maintenance, decentralized fault detection, and improved efficiency of large wind farms through distributed intelligence [153].
iii) Integration with smart grid and IoT platforms: DFIG-based wind energy systems need to evolve towards seamless integration with smart grids and IoT infrastructures. Intelligent controllers connected to IoT platforms can enable advanced functionalities such as cooperative control, predictive analytics, and coordinated energy trading. This integration supports demand-side management, enhances system reliability, and facilitates large-scale renewable energy penetration into smart grids [154].
iv) Development of benchmark datasets for AI training: a critical research gap lies in the lack of standardized benchmark datasets for AI model training and validation in wind energy systems. Currently, most studies rely on limited or proprietary datasets, which reduces reproducibility and comparability. Developing large-scale, open-access datasets with wind speed profiles, fault events, and grid disturbances will accelerate the training of intelligent controllers, ensuring higher reliability and transferability across different wind farm settings [155].
v) Adaptive control under extreme weather and fault conditions: with the rising incidence of extreme weather and grid disturbances, adaptive intelligent controllers for DFIG systems are becoming essential. These controllers are capable of dynamically tuning their control parameters in real time to handle abrupt voltage sags, frequency fluctuations, and mechanical stresses. Adaptive schemes equipped with self-learning or online tuning mechanisms will enhance resilience, FRT, and system stability, ensuring reliable operation under harsh and uncertain conditions [156].

10. PRACTICAL SCALABILITY

The proposed control architecture is inherently extendable to high-power WECS ($\geq$ 4–6 MW) employing DFIG technology. However, its practical deployment introduces several scalability and robustness considerations. In high-power ratings, increased converter current stress, thermal loading, and switching losses necessitate the use of multi-level converter topologies and advanced thermal management, which may influence the dynamic response of both the RSCR and GSCR. Additionally, parameter sensitivity—particularly in filter inductance, DC-link capacitance, and machine parameters—becomes more pronounced, potentially affecting controller tuning and stability margins under grid disturbances. The DC-link voltage regulation loop must handle larger energy fluctuations, especially during FRT events, requiring enhanced control bandwidth and robust protection mechanisms such as crowbar circuits or DC choppers. Furthermore, grid code compliance in high-power systems imposes stricter requirements on LVRT capability, reactive power support, and harmonic mitigation, which may challenge the decoupled control strategy under weak grid conditions. Communication delays and measurement inaccuracies also become non-negligible in large-scale systems, impacting real-time control performance. Despite these challenges, the proposed coordinated control of RSCR and GSCR remains structurally scalable, provided that appropriate controller re-tuning, higher-rated power electronic interfaces, and robust adaptive or nonlinear control enhancements are incorporated. Thus, while the fundamental control philosophy remains valid, its implementation in high-power WECS demands careful consideration of hardware constraints, dynamic interactions, and grid compliance requirements to ensure reliable and stable operation.

11. CONCLUSION

This review presents a critical comparative assessment of conventional and intelligent control strategies for DFIG-based variable speed WEHS. Conventional control methods such as PI, FOC, DTC, and SMC offer simplicity and reliable baseline performance. However, their limitations become evident under nonlinear dynamics, parameter uncertainties, and grid disturbances. In contrast, intelligent control techniques including fuzzy logic, ANNs, adaptive control, and metaheuristic optimization demonstrate enhanced robustness, adaptability, and fault-tolerant capability. The comparative analysis indicates that hybrid control frameworks, which combine the stability of conventional control methods with the adaptability of intelligent methods, represent the most effective solution for improving dynamic performance, power quality, and grid compliance. These strategies enable better maximum power extraction, reactive power support, and disturbance mitigation. However, existing studies often rely on limited validation conditions and lack standardized benchmarking and coordinated control for large-scale grid integration. Future work should focus on developing robust hybrid architectures, conducting real-time experimental validation, and smart grid-oriented control frameworks to ensure scalable, reliable, and efficient operation. Addressing these gaps will further strengthen the role of DFIG-based WEHS in enabling resilient and sustainable renewable energy integration.

ACKNOWLEDGMENTS

The authors acknowledge the support for this work by Department of Science and Technology - ASEAN India S&T Development Fund (DST-AISTDF), New Delhi for the project CRD/2022/000669. The authors also acknowledge the support of Control, Energy & Testing Laboratory, SRM Institute of Science and Technology, Kattankulathur for in-kind support.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors confirm that they have no conflicts of interest to disclose.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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