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APPLICATION OF MACHINE LEARNING IN GRID CONNECTED DFIG BASED WIND ENERGY SYSTEMS FOR FAULT DIAGNOSIS AND CONTROL: A REVIEW

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Abstract: *Environmental climate change has increased the demand for pollution-free electrical energy generation systems. Among renewable energy technologies, wind turbines (WTs) have emerged as one of the most efficient and environmental friendly power generation sources due to their low operational emissions, scalability and relatively low installation costs. However, the reliability and maintenance of wind turbine systems remain critical challenges because mechanical and electrical faults can significantly reduce energy production and increase operational costs. Recent advances in Artificial Intelligence (AI), particularly Machine Learning (ML) have demonstrated strong potential for improving fault diagnosis and condition monitoring in wind turbines. Techniques such as Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and deep learning models including Convolutional Neural Networks (CNN) have been widely applied to detect early-stage faults and predict failures in turbine components such as generators, gearboxes and induction motors. Hybrid frameworks including spatiotemporal pattern networks (STPN) integrated with deep CNN architectures have further improved diagnostic accuracy by capturing complex temporal and spatial fault patterns. Despite these advancements, challenges remain in handling incomplete, noisy or missing sensor data, which can affect model training and real-time monitoring performance. This review critically analyzes existing state-of-the-art of ML and hybrid approaches for wind turbine fault diagnosis and highlights emerging research directions for automated, data-driven fault detection and intelligent control strategies aimed at improving reliability, predictive maintenance, and operational efficiency in modern wind energy systems.*

Keywords: *DFIG, Artificial Intelligence, Faults and Diagnosis, Wind Turbines, CNN*

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1. Introduction:

In Renewable Energy resources like wind system, the different learning techniques of machine are increasingly used for condition monitoring of wind system, which helps in forecasting and diagnosing faults before they lead to substantial failures. To analyse data, different machine learning models are positioned and designed to detect electrical faults in DFIGs. During severe grid faults wind turbines (WTs) are easily prone to lose the synchronization. SCADA and Machine learning [1] have played a great role in overcoming this issue and enhance the transient synchronization stability and active power balance. To compensate the power loss on the network and to avoid frequency error all these techniques can control the active power of WT. DFIG performance has been enhanced under fault conditions by using reinforcement learning (RL) technique to control the parameters according to optimal operating position [2]. These advancements are crucial for sustainable energy to maintain the reliability and efficiency of DFIG based wind system in future.

Both control system of wind plant i.e grid side converter and rotor side converter may be designed with the implementation of Machine Learning techniques. At the current scenario a high performing and significant innovations are emerged in control theory with modern artificial intelligence (AI). There are different faults that occur at any level of wind turbine systems due to temperature change, corrosion of material, distortions of mechanical parts and voltage variations etc. So far the stable operation of grid is concerned, a reliable online fault detection and diagnosis is required to prevent further failures, stable operation and early detection of fault. Machine learning and AI has revealed the significant role in fault diagnosis and controlling of DFIG based wind system [3]. A key innovation of current scenario is the deployment of a high performance computing and data flow management of ML/AL, which is effective in prediction of vast fluctuations in wind speeds. Various techniques have been anticipated to enhance the capabilities of DFIGs to improve grid synchronization in a fault condition [4]. The method of separating the stator from the grid using static thyristor switches was the most common employed technique earlier. Determination of fault location and detection becomes a challenge among the researchers in case of DFIG connected to grid. When power is transmitted from the generating station to end user, the grid frequently meets a number of shunt faults which harms system reliability, damages the load and raises the cost of fault line repair. A noise-immune and accurate fault diagnostic model is desirable for the unhealthy phases to be repaired quickly [5]. PI controllers have been used to control the diverged parameters in case of faults. Basic PI controllers create problems in parameter settling, auto tuning and in achieving minimum overshoot under different load-changing conditions. After a long technical development in artificial intelligence, AI-based approaches have been introduced in fault detection that includes training requirements and new evaluated models. AI-driven fault detection in electric grids offers different methods, which incorporate deep learning and machine learning methods [6]. The two main categories of these training-based learning techniques are model-based and skill-based techniques, such as support vector machines (SVM), artificial neural networks and deep learning architecture in which convolution (CNNs) and recurrent neural network (RNNs) being commonly employed.

1.1 Control Structure Model of Wind Turbine Connected to The Grid:

There are two interdependent control movements such as rotor side control and grid side control in basic control model of wind turbine consisting of DFIG (shown in figure 1). A systematic balancing between RSC and GSC is the most important criteria for the stable operation of control system. These control techniques utilize both direct power control (DPC) and direct torque control (DTC). Active power and reactive powers are controlled under DPC and torque is balanced by DTC.

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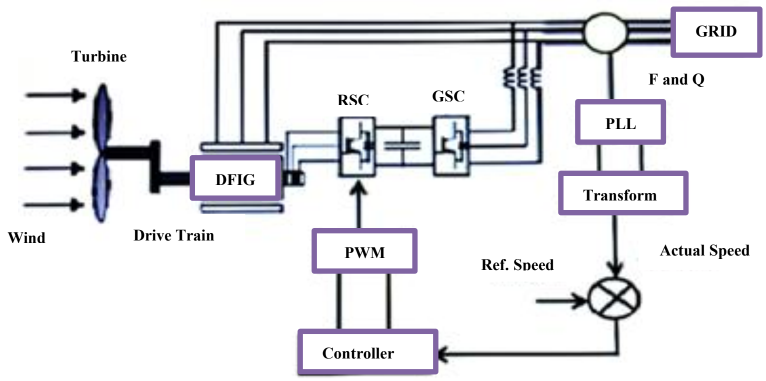

Figure 1: A wind turbine control model with a grid controller and rotor controller

1.2 Fault Created Power Quality Issues:

Power quality problems occur at the time of incorporation of the fault in wind system with the existing grid. Most of the power quality issues that exist in standard system given by IEEE are voltage problems, interruption of voltage and harmonics [7] (given below in Table 1).

Table 1: Different Faults and their Causes in Wind System with the Existing Grid

Issues	Causes
Voltage Unbalance	In the case of a single line or double line failure, all single phase loads are incorrectly distributed among the three phases of the system.
Voltage Interruptions	Unexpected load changes, such arc furnaces, electric motors that start and stop repeatedly, like lifts, oscillating loads, etc.
Voltage Sag	Faults in electrical networks, heavy load connections, customer installation matters and large motor start up issues.
Voltage Swell	Heavy load switch on/off, mismatched power sources and inadequately controlled transformers during off-peak hours.
Harmonic Distortion	Power electronic devices, switched mode types power supply and data processing equipment (i.e non-linear loads).
Short Interruption	Opening and automatic closing of safety equipment like circuit breakers etc. to decommission a faulty network component.
Long Interruption	In the incidence of drastic weather change, human mistake, safety failure and material breakdown in the electrical network.

1.3 Internal Faults in DFIG Based Wind Turbine:

In wind plant system DFIGs usually operate in a harsh operating condition like extreme mechanical and electrical stresses. These stresses are concerns with voltage dips and fluctuations. Because of the fast switching effect of the converter and higher-order harmonics, thermal stresses become higher in the rotor winding that usually begin as insulation degradation and some windings can be shorted with a very high current passing through [8,9]. As converters are connected both sides of DFIG i.e. stator and rotor, these switching and loading conditions affects both windings, insulations, bearing etc.

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The main faults of Doubly Fed Induction Generator (DFIG) can broadly be classified as: Stator winding faults, broken rotor bar or cracked rotor end-rings, air-gap eccentricities, bend shaft, rotor winding short-circuits, bearing and gearbox failures [10-12]. Internal faults that mostly occur can be given in the rational form of wind system shown below in the Figure 2.

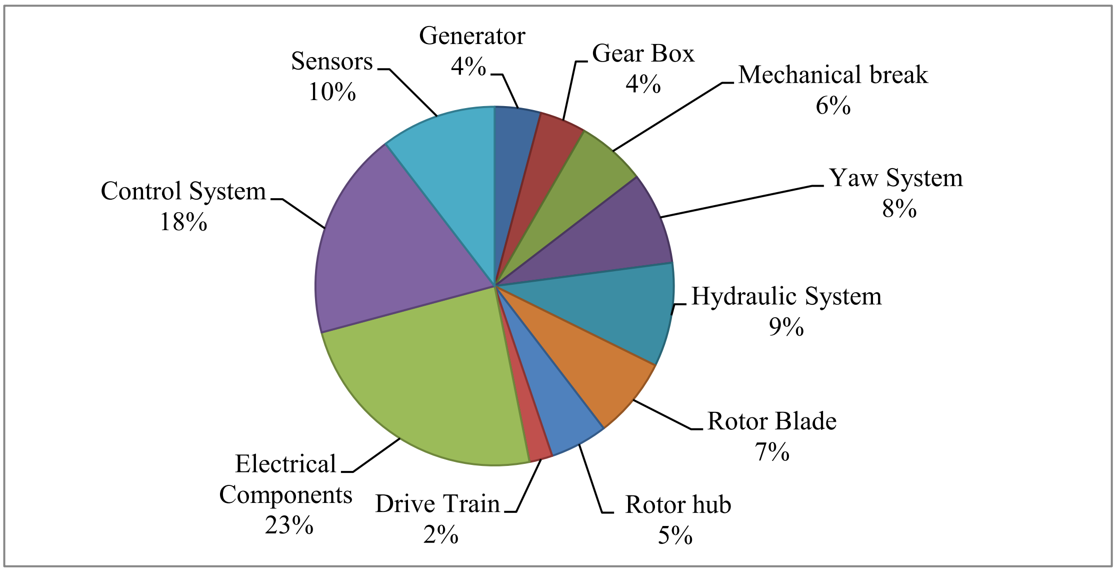

Figure 2: Internal Fault Portions Associated with DFIG Based Wind System

Reasons of Faults and Fault Levels: Due to the complex design of DFIG and operated in harsh environments, it is prone to various faults. These faults could be internal faults, mechanical failures and grid-related issues like insulation degradation, converter issues, over-heating, gear box issues, blade damage, shaft misalignment, bearing failure, voltage dips and fluctuations, grid fault and unbalancing. In a power system, the fault level defines the value for the symmetrical condition of voltage and current. In the above mentioned figure 2 various fault proportion are shown but they are of different priorities. These priorities can be defined as 1st, 2nd and 3rd priority and accordingly needed accurate and time bounded attentions (shown in Table 2).

Table 2: Causes of Fault and Fault levels

No.	Reasons	Main System	Fault Level
1.	Excess temperature, excess current or voltage, radiation, mechanical shock, stress or impact, Excess Demand, insulation failure, manual connection faults, calibration errors. Computer software default errors.	Electrical components	3rd priority fault
2.	Improper maintenance, Faulty modules, PLC memory corruption, Irregularities in voltage, electronic chip or component failure, software failure.	Control system	3rd priority fault
3.	Contaminated lubricant, Water pollution, Temperature problems, Fluid leaks, Hydraulic fluid contamination, Over pressurization, Pressure drops, Seal failure, Abrasion, Aeration, Corrosion, Cylinder bore scoring,	Hydraulic system	3rd priority fault

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	Fluid Levels, Hydraulic cylinder side loads, Incorrect oil change frequency		
4.	Misalignment, fatigue, yaw bearing friction, yaw brake mechanical failure, yaw counter mechanical failures.	Yaw system	2nd priority fault
5.	Brake fluid leaks, brake overheating, worn brake pads, bad brake hoses brake imbalance, excessive brake pedal gap, brake rotor damage, brake caliper problems, brake disc.	Mechanical brake system	1st priority fault
6.	Axial cracking in bearing, lubricant contamination, high loads, wear and tear, lack of lubrication, wind turbine gear oil, contamination control, low lubricating practices, bad condition monitoring, gears, filtration, system problems.	Gearbox	1st priority fault
7.	These include wear and tear, corrosion, surface material, bird strikes, deterioration, lightning strikes, rainfall, delamination, leading-edge corrosion or cracks, misaligned blades, and lightning strikes.	Rotor blade	2nd priority fault
8.	Bearing failure, gear failures, fuel system issues, ignition coil failure catalytic converter malfunction, driveshaft, spark plugs, axle fuel injectors, low transmission fluid, Transmission axial cracking in bearings, lubricant contamination, overloading	Drive train	2nd priority fault
9.	Wind loading, weather extremes cracks, fatigue, wear, corrosion, deflection	Rotor hub	2nd priority fault
10.	Bearing fault, rotor failure, coolant issues etc.	Generator	1st priority fault

2. Fault Detection Techniques of DFIG Based Wind Turbine:

As elaborated in the above section of internal faults of DFIG based wind turbines, almost all types of faults are explained, in which commonly experience faults are in stator windings, rotor currents, sensors and mechanical components. Based on those faults, detection techniques also vary in wind turbines, requiring robust detection methods for reliable operation that include model-based observers, signal processing and machine learning approaches tailored to variable wind conditions. These rely on DFIG mathematical models to estimate states and detect inconsistent faults. Proportional-Integral Observers (PIO) and Unknown Input Observers (UIO) using Takagi-Sugeno (TS) fuzzy models estimate inter-turn short-circuit (ITSC) faults in stator windings, robust to wind speed variations. Sliding mode observers and Extended Kalman Filters (EKF) diagnose current sensor faults by comparing measured and predicted signals. In signal processing method techniques analyse vibration, current or flux signals for fault signatures and Fast Fourier Transform (FFT) combined with Lissajous curves identifies DFIG electrical defects by comparing faulty spectra to healthy references. Motor Current Signature Analysis (MCSA) with Blackman windowing detects rotor imbalances via enhanced spectral accuracy. Zero-sequence components and Concordia transformation localize current sensor faults in real-time. While in ML approach methods, data driven methods process multi-sensor inputs for fault classification and detection. Convolutional Neural Networks (CNN) with SVM classifies emerging mechanical faults like gearbox issues from raw multichannel data, improving robustness under noise and fuzzy logic monitors phase currents for stator ITSC and open-phase faults, while advanced classifiers like bi-directional LSTM categorize anomalies.

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2.1 Internal Fault Detection Techniques in Grid Connected Wind Plants:

The internal fault detection techniques analyse signals from the generator, in that power spectrum analysis, vibration analysis and stator/rotor current analysis are often utilized methods. Signal pattern and system model recognition are the foundations of external defect detection systems. Stator windings, cracked rotor bars or fractured rotor end rings, eccentricity of air-gap, curved shafts, rotor windings, bearing and gearbox failures etc. are typically the main causes of problems with doubly fed induction generators [13-14]. Under any DFIG model, there are certain helpful methods (shown in Figure 3) that take into account various aspects including fault location, fault timing and current spectrum.

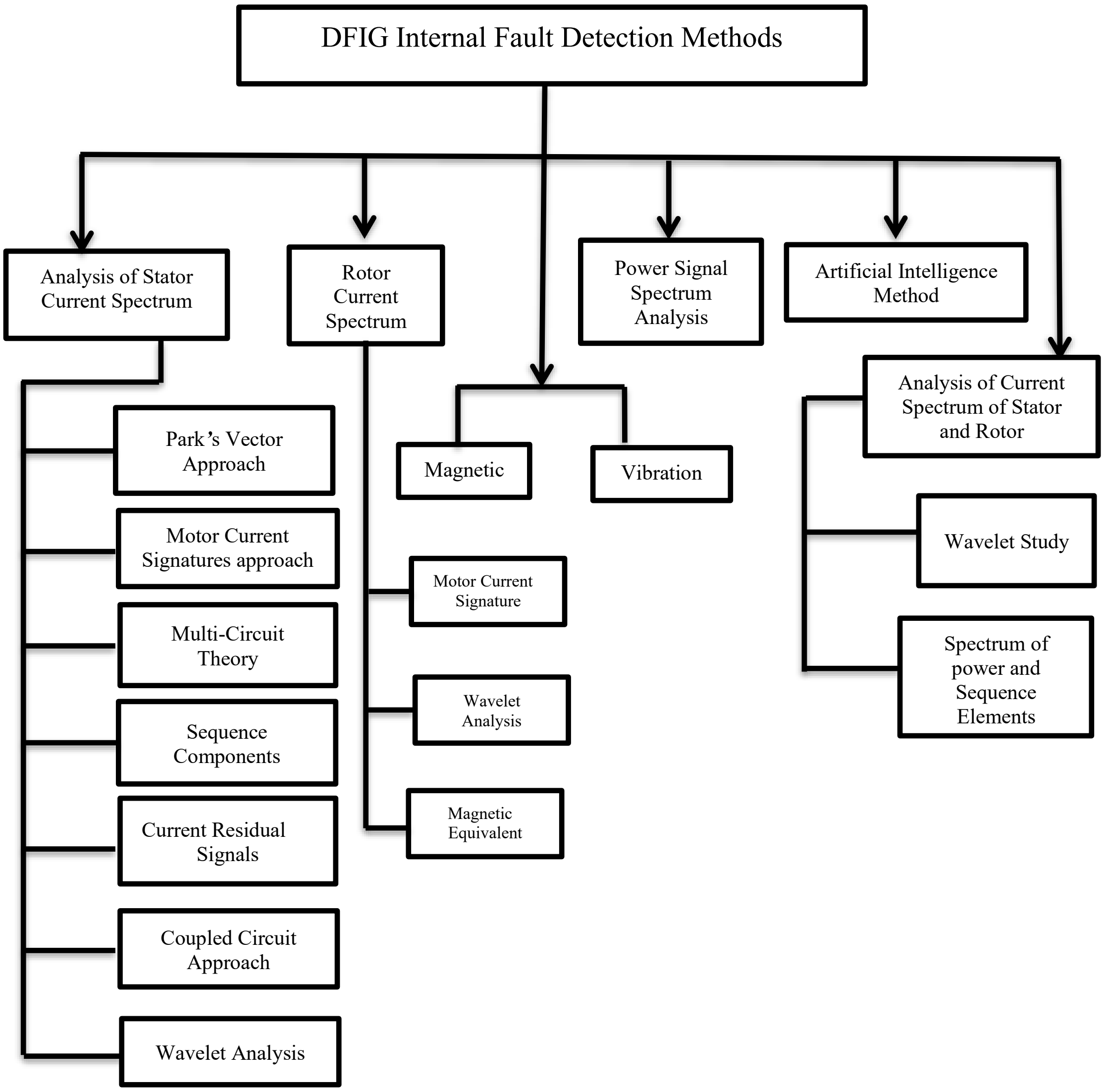

Figure 3: Chart of Internal Fault Detection Methods in DFIG

2.2 Grid Connected Fault Detection Techniques:

Fault detection and diagnosis systems play a very crucial role in wind plants, as fault in wind system results in hazardous loss. Some fault diagnosis methods include: model-based diagnosis, rule-based diagnosis and pattern recognition diagnosis. Most Commonly used techniques for fault diagnosis and control are:

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A. **Automated fault detection (AFD) algorithms:** A systematic step by step process is used to monitor and analyse the performance of system structure [15]. AFD algorithms use a various techniques to identify problems before they cause performance concerns or system failures.
B. **Model-based analytical methods**: The "model based method" is used to diagnose and detect faults by first creating models based on the intended system. The main distinctions in defect identification and diagnosis techniques are whether or not suitable models are employed and what kinds of models are employed. In some application fundamental models are used. Basic or standard models are influenced by different information like in physical systems, delay, and control of different parameters.
C. **Classifiers, Identification of patterns, and Signs of faults:** One general method utilised by CNN (Artificial Intelligence System) is pattern recognition (identification of pattern). It seeks the greatest outcomes by directly utilising previously identified symptoms of a fault and comparing them to a list of recognised indications for every potential obstruction. [16-17].This method uses the "pattern", or "fault signature", as a vector of signs for each defined fault.
D. **Signal-Based Techniques:** In real time "Signal-based techniques" for fault detection use sensor data to diagnose faults [18]. They are efficient for detecting and diagnosing mechanical and electrical faults in complex systems.

3. Review Methodology:

This methodology section outlines a systematic review framework, data handling, model architectures and evaluation protocols drawn from recent research work. This review paper methodology integrates simulation-based data, model architectures and rigorous evaluation, drawing from prominent journals like IEEE Transactions, Elsevier and Wiley for comprehensive coverage. The reviewed/searched paper databases are from Scopus, IEEE sensors, Web of Science, MDPI Energies, KeAi-Chinese Roots Global Impact, Nature Scientific Reports, Science Direct and Wiley. This literature review paper has analytically summarised in between the timeline of 2020 to 2026. The recent research work can be categorised under these major current trends:

Ogaili et al presents an experimental validation of Discrete Wavelet Transform (DWT) for detecting erosion faults in lab-scale wind turbine blades via vibration analysis [48].The research paper validates the advantages of utilising discrete wavelet transform for future structural health monitoring of wind turbines. An experimental research using DWT and FFT are presented in this publication to identify faults in a wind turbine blade in which experimental setup consists of a computer controlled wind energy unit. To capture vibration signals a PCB 352C65 uniaxial accelerometer is used as a transducer, which is suitable at higher frequencies for fault detects. In this research paper all vibration analysis has done on non- stationary vibration data instead of using conventional fixed speed vibration data. DWT is de-compositioned into 5-levels and 250-point FFT is applied to the Discrete Wavelet Transform coefficients at each decomposition level at 1000Hz data rate sampling. Raw vibration signals are decomposed via 5-level DWT using Daubechies-4 (db4) wavelet, followed by FFT on level-5 and presented a unique capability for sensitive monitoring of wind turbine blade by combining an approach of DWT filtering and FFT analysis for fault signature. **Modal signatures:** The healthy blade exhibits a dominant 16 Hz first bending mode, while the eroded blade introduces a distinct 24 Hz fault peak (absent in the healthy case), with 8 Hz separation enabling 98% automated classification accuracy. **DWT efficacy:** Decomposition of 5-level isolates low-frequency fault sub-bands and energy ratios in detail D3–D5 quantifies damage progression. Erosion reduces modal damping, shifting peaks rightward.

This research paper study shows that vibration/DWT analysis is used only for detection purpose in which 98% classifier accuracy reflects clean separation of modal signatures i.e 16 Hz for healthy and 24 Hz for eroded blades. Each blade assigned "H0" (healthy) or "E1/E2/E3" (mild/moderate/severe erosion) labels. Healthy and Faulty blades labels were distinguished using multi-modal physical measurement in two steps: primary diagnosis and secondary confirmation. The primary criteria were that if any blade exceeding depth > 0.1 mm will be faulty and the secondary confirmation was at mass loss >0.5% and thrust drop will be at 8–15%. FFT Spectral Analysis and DWT correlation show that each spectral waveform class produces distinct modal signatures for healthy and faulty blades i.e. healthy blades has 16 Hz peak: eroded blades (E1- E5) have 18 to 24 Hz, shown in Table 3.

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Table 3: Frequency and FFT Response of Healthy and Eroded blade

DWT Level	Frequency Band	Healthy Blade FFT Response	Eroded Blade FFT Response	Comprehension of Major Diagnostic
A5 (Fundamental)	0–1 Hz	Single 16 Hz peak (1st bending mode)	24 Hz dominant and 16 Hz secondary low amplitude peak occurs at 8 Hz.	Primary fault discriminated as modal stiffening from erosion mass loss.
D5	1–2 Hz	Broadband noise occurs	Minor elevation at 20–24 Hz	Early damping reduction indicated
D4	2–4 Hz	Flat response	Subtle harmonic at 18 Hz	Transitional less separation starts
D3	4–8 Hz	Minor 2nd harmonic occurs of 32 Hz	Elevated energy at (24-32Hz)	Fault energy accumulation shows
D2	8–16 Hz	Rotor harmonics starts at 8, 16 Hz	Distorted sidebands generates at16 Hz	Operational interference dominates
D1	16–32 Hz	High-frequency noise initiated	High-frequency noise	Non Diagnostic and too noisy.

The major short coming of this research paper is the fault type which has been taken like un-tested on cracks, delamination, lightning strikes or composite matrix failures. Test has been performed on fixed conditions and constant wind speed. No validation across operational envelopes or turbulence intensity and also no real-time simulation have been done.

Boaz Wadawa et al the study introduces a novel method to detect and classify faults across multiple components of DFIG wind turbines, addressing limitations in prior techniques that focus on isolated elements without holistic system analysis [49]. It emphasizes global wind system evaluation for improved reliability and maintenance. The Methodology used here is likely integrates signal processing or machine learning on DFIG currents/voltages to identify anomalies, differing from traditional single-component diagnostics. Simulations validate the strategy under various fault scenarios, building on common practices like spectral analysis in DFIG fault studies. The authors bifurcated wind-system faults into three classes: set point disturbance-related faults (FLDS), model uncertainty-related faults (FLMU) and parameter uncertainty-related faults (FLPU). The motivation is that simultaneous faults/noise can cause fault concealment and ambiguous detection when only residuals are used. The entire testing process went through under the 3 steps- modelling, residual generation of signal and classification of faulty signal. **Modelling Part:** This research paper used an LFT structured representation of the DFIG to incorporate mixed uncertainties of model plus parameters in an augmented framework. **Residual generation:** This methodology applies parity-space/static redundancy to eliminate states and derive a parity matrix and residual generator in their derivation one residual is sensitive to direct and quadrature axis faults and another residuals.**Classification:** In this authors have trained a supervised ANN (Artificial neural network) with 4 inputs and 1 output in which hidden neurons are 10 and output neuron is 1 with back-propagation to classify hidden/indistinguishable fault situations.

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The ANN training/validation/testing shows very low MSE reported best validation performance around 3.0532×10−93.0532×10^{-9} at epoch 1000) and regression R≈1, indicating strong fit between outputs and targets in their experiments. Simulation scenarios (multiple disturbance/noise combinations) are used to validate the residual sensitivity table and then demonstrate how the ANN-derived residual helps separate low-amplitude or masked fault signatures. This paper presents a novel polytopic ANFIS ensemble strategy for comprehensive fault detection and classification in DFIG-based wind turbines, addressing stator, rotor, and grid-side faults through multi-domain signal analysis. The approach decomposes DFIG three-phase currents via polychromatic transformation into αβ-frame, followed by modelling of fault subspaces. ANFIS classifiers fuse spectral features of FFT-derived harmonics with temporal residuals from Luenberger observers, optimized via particle swarm for Lyapunov-stable decision boundaries. This research paper deployed simulations with a 2 MW DFIG model under PSCAD/EMTDC, injecting faults like 20% stator inter-turn shorts, rotor bar breakages, and 15% grid voltage dips at variable wind speeds (8-15 m/s). The paper reports the following key accuracy and error metrics from simulations on DFIG wind turbine faults:

Fault detection accuracy: 98-99% across stator, rotor, and grid faults
Classification precision: >97% for fault types using ensemble classifiers.
False alarm rate: <2% under noisy conditions.
Mean error reduction: 15-20% vs. traditional methods in power/voltage deviations.

New strategy outperforms traditional methods in DFIG fault detection with superior accuracy metrics. The limitations of this research work are that it relies solely on simulated data, lacking experimental validation on physical wind turbines or field data under variable weather conditions. Another thought provoking factor is that performance degrades slightly in extreme noise levels (>20% SNR) or simultaneous multi-faults, with accuracy dropping to 92-95% and also high computational demands of the ANFIS-polytopic ensemble that limits real-time deployment on resource-constrained turbine controllers.

Ramesh Kumar Behara et al research work introduces an optimized neural network model for detecting faults in wind turbine converters in which focusing on grid-side converter (GSC) in DFIG systems using variational mode decomposition (VMD) method [50].The approach employed VMD to decompose converter current signals into intrinsic mode functions, extracting fault-sensitive frequency components degraded by noise. Enhanced CNN or LSTM architectures are employed for optimized neural network are trained on these features for healthy/faulty elements and multi-class fault localization. This research used CNN and LSTM architectures surpasses the traditional FFT or wavelet methods in non-stationary wind conditions (8-20 m/s). In this methodology hyper parameters are tuned via genetic algorithms or Bayesian optimization for minimal validation loss. The model that utilised here, have the following dataset details like **Source:** source data has generated via MATLAB/Simulink modeling of a 690V GSC with PWM modulation having carrier frequency of 2 kHz. **Samples:** 25,000 time-series samples have created from current/voltage waveforms at 10 kHz sampling, sampled are splited in 70 for training purpose, 15 for validation and testing. **Fault Scenarios:** for analysis purpose one healthy baseline case and 6 fault classes are considered at wind speeds 8-20 m/s and at a 5-15% voltage dips grid disturbances. This research study evaluates specific open-circuit faults in the IGBTs connected grid-side converter of DFIG wind turbines, focusing on realistic failure modes in power electronics.

Fault Types Assessed:

a) Single IGBT open-circuit faults in upper and lower legs of the three-phase GSC bridge.
b) Dual IGBT failures adjacent and non-adjacent combinations across phases.

Severity Levels Tested

Level 1 (Mild): 1 IGBT failure per leg (20-30% current distortion).

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Level 2 (Moderate): 2 IGBT failures (40-60% distortion, torque ripple onset).

Level 3 (Severe): Full leg open (phase loss > 80% distortion).

Evaluation Conditions: The analysis part tested under variable wind speeds i.e 8-12 m/s for mild faults and 14-20 m/s for severe faults. Another analysis has been done under grid voltage sags of 5-15% and PWM carrier frequencies of 1.5-2.5 kHz that ensures robustness across operational transients. The research analysis achieves 99.2% fault detection accuracy and 98.5% classification precision on benchmark datasets, with (Performance metric) F1-scores > 0.98 for IGBT faults under varying modulation indices.

Aspect	**Behara's Established CNN –VMD Model**	**ANFIS Polytopic DFIG**
Target Faults	Converter IGBT and GSC focused	Stator/Rotor/Grid
Accuracy	99.2%	98.7%
Latency	8.7ms	12.4ms
Noise Robustness	Superior ~ 10db SNR	Good ~ 15db SNR
Limitations	Converter specific needs SCADA integration	Simulation only for multi fault degradation

The research works offers converter-centric model with faster, higher-precision detection for power electronics failures but lacks the holistic DFIG coverage of the Global Energy Interconnection strategy as study has utilized simulated datasets from a 2 MW DFIG wind turbine model, incorporating grid-side converter (GSC) with IGBT open-circuit faults only under variable operating conditions. The Classical VMD's static filtering waveform which is utilized in this work fails on chirp-like converter signals during wind transients (8-20 m/s), that further loses 15% fault energy in broadband components. Also decomposition demands 3-5 times runtime of EMD (iterative ADMM solver) that is impractical for real-time turbine SCADA. MATLAB Simulation taken in this research is 25000 samples but ignored real-world factors like sensor drift, partial discharges and thermal aging that reduced the field accuracy up to 8-12%.

Damala and Patnaik et al the system uses simple decision trees to classify disturbances in real-time, leveraging local measurements like voltage[51], current and ROCOV (Rate of Change of Voltage) to detect faults or oscillations without needing communication between ends. Damala et al's research paper proposes a lightweight decision tree (DT)-based system for real-time disturbance monitoring and classification in VSC-HVDC links integrated with DFIG wind farms, addressing fault detection challenges in hybrid AC/DC grids. This paper incorporated an algorithm called "Teager–Kaiser Energy Operator (TKEO) "to detect and classify various DC faults. The DT classifier processes synchro phasor data of voltage, current magnitudes and phase angles from phasor measurement units at HVDC terminals and DFIG points further extracting features like rate-of-change of voltage, active/reactive power deviations and sequence components. In the simulation process DT system trained on PSCAD/EMTDC simulation software in which simulated scenarios contains of 31-level MMC-VSC with 500 MW DFIG farm connected to ±320 kV DC link. This model categorizes disturbances into AC faults (LL, LG), DC faults of pole-ground and pole to pole, power swings and wind variability.

The paper considered model for simulation contains bipolar 150km HVDC transmission system having a voltage source converter (VSC) and is feeded by a combination of offshore wind farms of four units and each unit has a capacity of 9MW. Further that model combines a 200 MVA, ± 100 kV capacity transmission line of length 150 km connects the two converter stations with smoothing reactors (8mH). They evaluated a comprehensive set of AC and DC oscillatory disturbances in their DT-based monitoring system for VSC-HVDC/DFIG setups using resistance-based severity modeling. The fault types which have been considered are: **AC-Side Faults**: Line-to-ground (LG), line-to-line (LL), three-phase (LLL, LLG). **DC-Side Faults**: Pole-to-ground (PTG), pole-to-pole (PTP), **Fault due to Disturbances:** Power swings, DFIG torque oscillations from wind variability.

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In this work fault analysis has been done with the help of teager energy. The TKEO algorithm generates a unique "Teager Energies" from each fault which yielded 8 derived indices that are energy, amplified energy, mean, standard deviation, kurtosis, entropy, variance and maximum amplitude (P1 to P8) that are generated at the same location. After the initialization, stability condition of the proposed designed model system has been tested by converting the AC voltage from the wind generator into a DC voltage. Simulations run faults at every km, storing graphs and data. The proposed methodology runs in these steps: (1) At first level, to detect the change in current wave form method is applied to the HVDC Transmission line, whenever fault occurs. (2) For a nonlinear fault signal analysis, "Teager Energies" have been extracted either from differential or average currents at different distances on HVDC Line.(3) Further TKEO tracks these teaser energies for three current samples that was used.(4) In the last step, a Simple Decision Tree-based fault classifier is used for fault detection and classification.

In this work, total of 1192 data set is taken into account and 477 random data sets is utilised for testing which results in 98.75% efficiency. If we take a comparative analysis of efficiency with other existing methods like Hilbert–Huang transform (HHT) method, it has only 90.41% efficiency and artificial neural network (ANN) method 95.90%. Also the other major and important factor like required average operating time is less, robustness is good and computational burden is low than other methods.

3.1 Conventional/Traditional Fault Detection Methods in Wind Plant:

The main goal of conventional fault detection techniques in wind farms is to track and diagnose the state of essential parts like gearboxes, bearings, and blades. To detect possible failures and stop deterioration, these approaches frequently rely on machine learning algorithms, vibration measurement tools and conventional signal processing techniques. However, the need for sophisticated and trustworthy fault detection techniques grows as wind plants become more complicated and are placed in difficult environments. Some conventional Techniques are elaborated in Table 4.

Table 4: Different Conventional Approaches for Fault Detection and Classification in DFIG Wind Plant

No.	Method/Approach	Fault Features /Characteristic	Types of Fault Detected	Ref
1.	Fast Fourier Transform (FFT) and Discrete Wavelet Transformation (DWT), Wavelet Packet Transform (WPT)	Fixed and varying Blade speed vibration-based fault detection, Eroded blade faults at different vibrations.	Blade fault, Over voltage and Overcurrent fault, Overload faults, Corrosion or Cracks, misaligned blades.	[22]
2.	Time-Domain Analysis (Statistical Analysis, Hilbert Transform, and Envelope Analysis, Empirical Mode Decomposition, Spectral Correlation, Bicoherence And Blind Deconvolution)	Fault caused by transient impulses, Faults suppressed with noisy vibration signals, Faults and vibration with shocks.	Wind turbine gearbox fault, Bearing Fault, Axial cracking faults in bearing, high loads.	[23] [24]
3.	Sensor Based and Data Driven Condition Monitoring Fault Diagnosis(CMFD)	Faults due to short circuit and voltage dips.	Current and voltage sensor connected to stator and rotor	[25]
4.	Sweep Frequency Response Analysis (SFRA)	Faults with single and multiple ground faults	Single ground faults multiple ground faults of stator and rotor winding of DFIG generator.	[26]

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5.	Winding Function Approach (WFA)	Faults consisted of variable noise and variable loading condition.	Rotor faults, Broken rotor-bar fault, Stator faults.	**[27] [28]**
6.	Finite Element Modelling(FEM) and Magnetic Equivalent Circuit(MEC)	Single and multiple type potentially hazardous and unwanted noise containing faults.	Inter-turn short-circuit faults of the stator windings of DFIG or in any machine.	**[29]**
7.	Ensemble Empirical Mode Decomposition (EEMD) and Empirical Wavelet Transformation (EWT)	Multiple faults with power quality issues	Hybrid failures of gearbox of generator.	**[30]**
8.	Extended Kalman Filter (EKF)Bank Approach	Single or multiple faults with lower amplitude current and voltage.	Real phase current sensors fault in both rotor and grid side converters, sensor fault connected to rotor /stator.	**[31]**

3.2 Artificial Intelligent/Machine Learning (AI/ML) Based Fault Detection Methods in Wind Plants/Farms:

For better reliability, early fault detection and good accuracy, AI/ML utilized fault detection techniques in wind plant/Farms becomes a crucial tool. These methods employ advanced algorithms to identify and diagnose faults in wind turbines including machine learning and deep learning. That not only uses data driven methodology but also validate the experimental results. By bridging theoretical AI advancement with practical deployment challenges these methods aim to update next generation fault diagnosis method. Some AI/ML based techniques, limitations and it's benefits are given in Table 5.

Table 5: Different AI/ML based Approaches for Fault Detection and Classification in DFIG Wind Plant

S No.	Methods	Detectable Faults	Benefits	Limitations
1.	Feed forward Neural Network (FNN)	All types of trans-mission line faults, Motor overloading, [32] cooling system mal-function, tool breakage.	Detect faults of the non-linear and complex data model.	Noisy signal can't be easily detectable with good accuracy.
2.	Convolution Neural Network (CNN)	External Line faults and internal faults like relay rotor, bearing, wind farms. [33 ,34]	Better accuracy under noisy, variable and raw data than SVM, RNN and ANN, Reducing dependence on manual expert analysis.	Require large datasets under harsh environments like variable wind speeds. Non-linear, unstable vibration signals degrade performance unless converted to images that further increases computational

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				demands and require high training times.
3.	Gated Recurrent Unit GRU (simplified RNN)	Main bearing faults, Blade pitch system faults, gearbox faults [35].	Early detection of main bearing faults using SCADA data like temperature and wind speed, reducing downtime and maintenance costs.	Require careful hyper-parameter tuning for real-time wind farm-scale use.
4.	Long short term memory network (LSTM)	Pitch system faults, generator, gearbox and power system faults and general operational faults.	LSTM is excellent at modeling sequential degraded patterns with non-stationary signals like vibration and power output. Outperforming CNN (91% vs. 96.5% in accuracy) and Random Forest (83.5%) in multi-feature fusion scenarios.	Long-term time based dependencies on SCADA data [36, 37].
5.	Support Vector Machine (SVM)	Imbalance faults, Misalignment faults, Gearbox bearing Anomalies, [38, 39] Sensor/Actuator Faults.	They enable real-time irregularities detection in turbines and yaw/pitch systems via optimized hyper-parameters (e.g., Bayesian tuning), reducing false positive based maintenance.	SVMs require wide manual feature engineering like vibration re-sampling, statistical moments, limiting scalability to raw time-series data as compared to CNN/GRU/LSTM.
6.	Logistic Regression	Generator and Cooling systems faults feeding issues fault, excitation errors and mains power supply failures [40, 41].	Easy model develop-ment and low computational cost as compare to neural networks, Strong performance in multi-class tasks for electrical and environmental faults.	Struggles with non-linear patterns and wind data of different seasons, leading to higher false alarms and reduced early detection. Less accurate as compared to neural models (NN) in case of non linear data.
7.	Catboost, XGboost	Blade mass imbalance, [42] Icing faults, Generator and pitch system faults, Gearbox bearing issues.	Ideal for rare faults like icing under variable winds. Superior handling of categorical and im-balanced data via ordered boosting (CatBoost) and regularization (XGBoost).	Less effective on purely sequential data without hybrids (e.g., CNN-XGBoost), unlike LSTM. Require high memory usage and longer training times for massive SCADA datasets as compare to logistic regression.

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8.	Random Forest (RF)	Gearbox faults Pitch system faults pinpoint short-circuit locations and durations in grid-connected farms, icing, mass imbalance, [43] and sensor drifts under seasonal discrepancies of power.	Can withstand with high-dimensional, [44] imbalanced data well, reducing over fitting compared to single trees; ideal for rare faults like icing or blade imbalance.	Computationally intensive for very large datasets, Faces computational problem with purely sequential patterns.
9.	Natural Learning Process (NLP)	Pitch and yaw system issues /faults, unusual noise and vibration contained faults.[45]	Reducing manual log reviews for predictive maintenance, Extracts human-descriptive fault.	Relies on abundant and high quality text data.
10.	Generative Adversarial Networks (GAN)	Gearbox, Bearing, Generator Faults, Pitch/Yaw, System Faults	Faster convergence on SCADA datasets, early anomaly detection in new turbines using data from existing ones	[46] High computational demands suit offline use but challenge real-time deployment on edge devices.
11.	Unified Transformer	Excitation generated errors/faults, heating related faults, Blade issues i.e cracks, pitch system faults, imbalance, Gearbox and bearing anomalies Trans-former specific faults like overheating, winding deformations, insulation breakdown, inter-turn shorts.	Superior captures of long-range dependencies, [47] enabling early anomaly detection (e.g., 92-98% accuracy) and outperforms CNN /RNN in noisy or scarce data scenarios. Robustness to variable wind conditions.	Needs large, representative normal-operation datasets, Poor performance with new turbines or unrepresentative data, High computational demands require significant resources for training and inference.

3.3 Analytical and Data Based Comparative Analysis of Artificial Intelligent Techniques and Methods in Fault Diagnosis:

The above described explanations incorporate many AI based techniques to solve the fault detection problem. Previously proportional integral controllers are used for controlling the parameters of converters. But a more accurate fault diagnosis could be possible after a revolutionary progress in artificial techniques. After reviewing the different and recent research papers the comparative chart are prepared (Table 6) for further more precise analysis in this area.

Table 6: Analytical Comparison of different Artificial Intelligent techniques and methods in fault diagnosis:

S. No.	Controller or Methodology	Performance Features	Simulation Results	Ref.

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1.	ANFIS PI controller	Tracking Time **Moderate** Error Rate **Higher** Efficiency **Good** Response time **Higher**	R^2 Error **00.776** Accuracy **85.091%** Sensitivity **91.279%**	[52]
2.	ANN PI controller	Tracking Time **Higher** Error Rate **Less** Efficiency **Average** Response time **Faster**	R^2 Error **00.863** Accuracy **91.279%** Sensitivity **86.418%**	[52]
3.	NTM PI controller	Tracking Time **Higher** Error Rate **Minimum** Efficiency **Best** Response time **Less**	R^2 Error **00.911** Accuracy **93.268%** Sensitivity **89.546%**	[52]
4.	Support Vector Machine (SVM)	If we select the kernel parameter as radial basis function, the SVM can detect the WT blade pitch position and generator failure instantly. It also solves the optimal phenomenon brought on by the incorrect sample parameter selection with strong generalization performance.	The SVM approach can markedly improve the fault detection capability for a specific fault type and accurately characterize the fault type. Accuracy **High** Real time Processing **Yes** Handling Nonlinear Relationship **Yes** Ease of interpretation **Yes**	[53]
5.	Kernel Neural Network (KNN) Method	For sorting and regression jobs, KNN is not only a non-structural learning approach in its parameter but also have flexible methods that learn the training dataset. KNN outperforms all supervised learning algorithms when the data size is constrained.	KNN's drawbacks include its large memory capacity, lengthy forecast period and excessive sensitivity to inconsequntial characteristics. Accuracy **Highest (99.9%)** Training time **Fast** Prediction Speed **Fast** Ease of interpretation **Yes**	[54]
6.	Decision tree Method	A decision tree classification model is utilized for both classification and regression tasks and makes use of multi-feature fusion to increase precision.	Decision tree improves learning ability and boosts gradient capabilities (generalization of the derivative of multivariate functions). Accuracy Rate **72.7%** Prediction Speed(obs/sec) **350** Training time (Sec) **1.567**	[55]
7.	Deep Learning Method (CNN)	Authors proposed an innovative convolutional neural network structure for fault detection named : 1. AOC–ResNet50 2. Oct–ResNet50 3. ResNet50 AOC–ResNet50 is identified as the best model for fault detection in terms of judging parameters.	All fault prediction results are shown for AOC–ResNet50 CNN structure: **3 Days before failure occurrence** Accuracy **98.04%** Precision **98.41%** Specificity **98.43%** Negative Precision **97.68%** **7 Days before failure occurrence** Accuracy **96.11%** Precision **93.57%** Specificity **93.19%** Negative Precision **98.97%**	[56]

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<table>
<tr>
<td>8.</td>
<td>Fuzzy System And Neural Network</td>
<td>In this paper Fuzzy System (FS) and Neural Network (NN) approaches are used for fault diagnosis incorporating different fault condition and cases.
They show actual wind speed sequence readings, with ranges ranging from 5 to 20 meters per second. Single fault occurrences and a number of samples N = 440,000 for a sampling frequency of 100 Hz are included in the 4400 s simulations. Step functions with duration of 100s are used to model nearly all fault signals.</td>
<td>Results using Fuzzy System
<table>
<tr><td>METHOD</td><td>Case 1</td><td>Case 2</td><td>Case 3</td></tr>
<tr><td>RMSE</td><td>1.61%</td><td>2.22%</td><td>1.95%</td></tr>
<tr><td>Std. Dev.</td><td>±0.02%</td><td>±0.03%</td><td>±0.01%</td></tr>
</table>
Results using Neural Network
<table>
<tr><td>METHOD</td><td>Case 1</td><td>Case 2</td><td>Case 3</td></tr>
<tr><td>RMSE</td><td>0.91%</td><td>0.92%</td><td>0.94%</td></tr>
<tr><td>Std. Dev.</td><td>±0.01%</td><td>±0.01%</td><td>±0.01%</td></tr>
</table>
</td>
<td>[57]</td>
</tr>
<tr>
<td>9.</td>
<td>K means Clustering</td>
<td>This research study introduced an innovative model for early warning and diagnostics of wind turbine faults with the help of clustering.
(1) The k-means cluster analysis was used to examine the fault parameter pair of a WT.

(2) The concepts of “window length”, “detection threshold”, “effective value of early warning”, and “possible value of early warning” are used to determine for alarm of early warning model.

(3) The real issue is identified seven hours and nineteen minutes before the SCADA system's threshold warning time. The early warning and fault diagnostic goals are met, and the results outperform those of the conventional threshold approach.</td>
<td>1. At Warning threshold value 0.6
Warning accuracy(ACC) 97.5%
Window length 40 min
Error rate(ER) 2.5%
Recall(RC) 95%
Precision(P) 100%

2. At Warning threshold value 0.7
Warning Accuracy(ACC) 95%
Window length 40 min
Error Rate(ER) 5%
Recall(RC) 90%
Precision(P) 100%

3. At Warning threshold value 0.8
Warning Accuracy(ACC) 91.25%
Window length 40 min
Error Rate(ER) 8.75%
Recall(RC) 85%
Precision(P) 97.14%</td>
<td>[58]</td>
</tr>
<tr>
<td>10.</td>
<td>Digital Twin Technology</td>
<td>This study establishes how to acquire dynamic data of the wind turbine drive system instantaneously which is necessary for the digital twin's input. Achieving an intelligent transmission system and creating a 3D virtual model of the wind turbine drive system depend on the real-time transfer of dynamic data. The EMD-ASO-SVM (Empirical mode decomposition Atom search optimization–Support vector machine) paradigm is developed to establish data communication between the virtual model and physical entity.</td>
<td>Model Accuracy 94%
(EMD-ASO-SVM Model)
Accuracy 87.33%
of SVM based Model
<hr>Delay Low
Efficiency High
Applicability Universally
Specialty of the methodology is the internal operation process of the wind turbine can monitored in digital frame and in real time frame.</td>
<td>[59]</td>
</tr>
</table>

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<table>
<tr><td rowspan="7">11.</td><td rowspan="7">Long Short-Term Memory networks (LSTM)</td><td rowspan="7">The pitch and yaw system, electrical network and gearbox are the four parts of a wind turbine that are simultaneously monitored in this research study, which overcomes the restriction of only monitoring one part. The model has greater sensitivity to the diagnostic identification of fault that is crucial aspect of early fault diagnosis and detection. It is demonstrated by the increased true positive rate for the three different kinds of faults.</td><td colspan="4">CNN-LSTM Model Result</td><td rowspan="7">[60]</td></tr>
<tr><td></td><td>Prec-ision</td><td>Recall</td><td>F1 Score</td></tr>
<tr><td>Normal State</td><td>95.48 ± 0.34</td><td>80.32 ± 0.61</td><td>87.25 ± 0.21</td></tr>
<tr><td>Yaw System fault</td><td>87.13 ± 0.46</td><td>94.09 ± 0.35</td><td>90.48 ± 0.63</td></tr>
<tr><td>Electric system fault</td><td>89.33 ± 0.08</td><td>88.48 ± 0.44</td><td>88.90 ± 0.32</td></tr>
<tr><td>Pitch System Fault</td><td>86.37 ± 0.06</td><td>96.46 ± 0.39</td><td>90.83 ± 0.52</td></tr>
<tr><td>Gear Box Fault</td><td>93.42 ± 0.16</td><td>97.39 ± 0.29</td><td>95.36 ± 0.33</td></tr>
</table>

4. Conclusion and Future Recommendations:

Wind turbine fault detection in DFIG-based wind energy systems now relies on a rich toolbox spanning vibration and signal analysis, data-driven condition monitoring and advanced AI/ML techniques, enabling earlier and more reliable identification of electrical, mechanical and grid-side faults for proactive maintenance. In table-2 fault severity has been classified according to the different faults and its causes for further implantation of exact method of controlling. Numerous approaches and procedures (given in figure 3) for the defect diagnosis and WT component detection have been offered by various studies. If we examine table 4, in contrast to PI controllers, which have issues under varying load-changing patterns in respect of parameter settling, the NTM-PI controller was initially developed with minimal maximum overshoot of 8.23% and settling time of 0.93sec having a remarkable accuracy of 93.268%. Recent work shows that intelligently tuned controllers and learning models (e.g. NTM-PI, ANFIS, ANN, CNN–LSTM, digital twin, transformer based techniques and optimized neural networks) can achieve fault detection and classification accuracies above 93–99% under simulated conditions, outperforming conventional PI controllers and classical signal-processing-only schemes in terms of overshoot, settling time and robustness to noise. However, the predominance of simulated datasets, limited coverage of complex damage modes and incomplete or noisy SCADA measurements still constrain real-world reliability, especially under multi-fault conditions and harsh, non-stationary operating environments.

Despite the rapid advancement of AI/ML-based fault diagnosis in wind energy systems, there is a substantial lack of research addressing the detection of external faults in wind plants connected to the grid. The majority of existing studies concentrate on internal turbine faults, leaving external fault detection through AI/ML methods significantly under-investigated. Therefore, one of the key future directions in AI/ML-based fault diagnosis should focus on the identification and analysis of external faults in grid-connected wind plants, as such disturbances can critically influence system synchronization, grid stability, and the overall reliability of wind power integration. Further studies move beyond simulation and should therefore prioritise experimental validation on operating wind farms, fusion of heterogeneous data (SCADA, vibration, electrical and textual logs) and transfer-learning, transformer/unified models or digital-twin strategies that generalise across turbine types. In addition, integrating IoT-based monitoring and cloud-edge computing frameworks can enable continuous data acquisition and faster model deployment across large wind farms. Finally, future studies should emphasize experimental validation, scalability, and cyber-secure implementation to ensure that ML-based diagnostic and control frameworks are robust, practical, and suitable for next-generation renewable energy systems.

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Abbreviations

GSC: Grid side converter
RSC: Rotor side converter
ANFIS: Adaptive network-based fuzzy inference system
NTM: Neural Turing Machine
CNN: Convolutional neural network
EMD**:** Electrical Machine Design
ADMM**:** Alternating Direct Methods of Multipliers
WT: Wind turbine, **RMSE**: Root Mean Squared Error
ResNet50: Residual Network with 50 layers
Oct–ResNet50: Octave convolution
AOC–ResNet50: Attention Octave convolution

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