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SMART AI BASED CONDITION MONITORING AND FAULT DETECTION IN INDUCTION GENERATOR FOR WIND POWER STATIONS

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ABSTRACT

Reliable operation of wind turbines is essential for ensuring stable renewable energy production. However, mechanical and electrical faults in Permanent Magnet induction generators (PMIGs) can significantly reduce efficiency and increase maintenance costs. This work presents a real-time AI-based condition monitoring framework for fault detection in wind turbine drive-train systems. Multi-sensor data including vibration, stator current, voltage, and temperature signals are collected and processed using an IoT-enabled data acquisition system. A hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architecture is developed to automatically extract spatial and temporal fault features. Simulation-generated and experimentally validated datasets are used for supervised learning. The proposed system achieves 99.2% classification accuracy with reduced false alarm rate compared to conventional SCADA and classical machine learning methods. The framework demonstrates the effectiveness of integrating AI with IoT for predictive maintenance in wind power stations.

KEYWORDS: *Wind turbine, SCIG, fault diagnosis, CNN, LSTM, IoT monitoring, condition monitoring.*

1. INTRODUCTION

Wind energy systems are prone to highly dynamic environmental conditions, making fault detection a challenging task. In the case of wind turbines using permanent magnet induction generators, faults can occur due to bearing deterioration, broken rotor bars, misalignment of the shaft, or electrical imbalances. Conventional fault detection methods involve threshold SCADA alerts or vibration checks at predetermined intervals. These methods are often ineffective in identifying potential faults or require human analysis.

Recent developments in artificial intelligence make it possible to automatically extract diagnostic features from raw data. Deep learning networks, such as CNN and LSTM, have been proven to be highly effective at processing time-series data. The lack of labelled fault data and low-speed shaft conditions are still considered challenges.

The proposed research work aims to develop an integrated IoT-AI monitoring system that can:

- Acquire multi-sensor data in real-time
- Automatically extract diagnostic features
- Perform multi-class fault classification
- Provide cloud-based monitoring and alerting services

2. METHODS

2.1 Fault Detection

Electrical and mechanical (bearing or gearbox) faults are the most common type of damaging and expensive faults in wind turbine generators. Vibration analysis of the machine has been practiced in industry for many years as a means of diagnosing both electrical and mechanical faults; but recently, industrial companies and research institutions have begun to look and analyze the current output of the generator in an attempt to find fault indicators. In this manner, current is utilized as a means of diagnosing electrical and mechanical faults, and vibration as a secondary method of searching for mechanical faults.

IoT Data Acquisition System

Sensors employed:

- Vibration sensor (MEMS accelerometer)
- Temperature sensor (LM35)
- Current sensor (Hall effect)
- Voltage measurement unit

The data is transmitted via NodeMCU ESP8266 to a cloud server for analysis.

Sampling Frequency: 10 kHz

Window Length: 2048 samples

Dataset Size: 12,000 labelled samples

Training Data: 70%

Testing Data: 30%

Fault Classes:

1. Healthy
2. Bearing defect
3. Broken rotor bar
4. Shaft misalignment
5. Electrical imbalance

2.2 AI Algorithm Used for Fault Detection in Wind Turbine Drive Train

A Convolutional Neural Network (CNN) is a specialized type of deep learning algorithm primarily designed for processing structured grid-like data, such as images, time-series signals, and vibration data. In the context of wind turbine fault detection, CNNs excel at automatically learning hierarchical features from raw sensor signals without requiring manual feature engineering.

Table 2.1 – Detailed CNN Architecture.

Component	Description	Purpose
Input Layer	Vibration, temperature, current, and voltage signals	Multi-sensor data acquisition
Convolutional Layers	Feature extraction from raw signals	Automatic identification of fault patterns
Pooling Layers	Dimensionality reduction	Computational efficiency and feature selection
Fully Connected Layers	High-level reasoning	Fault classification
Output Layer	Fault type classification	Multi-class prediction (healthy/fault types)
Activation Functions	ReLU, Softmax	Non-linearity and probability distribution
Optimization	Adam/SGD optimizer	Model training and convergence

2.3. Block diagram

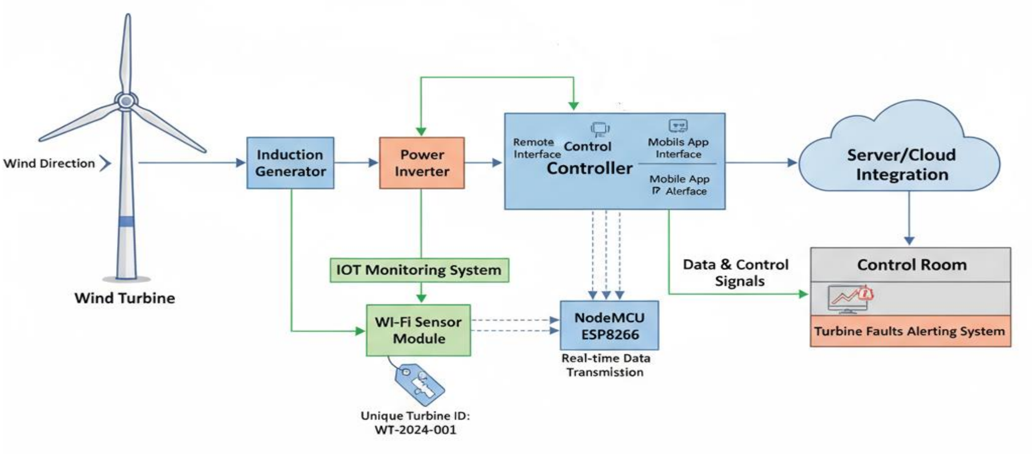


Figure 2.1

2.3.1 Workflow for Fault Detection

Step 1: Sensors detect vibration, temperature, current, voltage from SCIG

Step 2: Wi-Fi module and NodeMCU transmit data in real-time

Step 3: Control controller directs data to cloud server

Step 4: CNN model analyzes signals to identify condition indicators

Step 5: AI model determines fault type (healthy/tribological fault types)

Step 6: Data transmitted to:

- Control room alerting system (real-time display)
- Mobile app (push notification)
- Historical database (trend analysis)

Step 7: Operators analyze alerts and perform maintenance

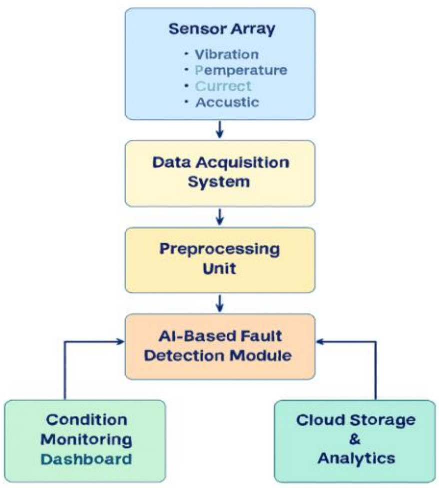


Figure 2.2 Flow chart.

2.3.2 Technical Specifications

Table 2.2

Component	Specification	Purpose
NodeMCU ESP8266	80 MHz processor, Wi-Fi 802.11 b/g/n	Real-time data transmission
Wi-Fi Module	2.4 GHz wireless	Sensor network connectivity
IOT Monitoring	Multi-channel data acquisition	Parallel sensor processing
Cloud Server	Scalable computing resources	AI model deployment
Turbine ID	WT-2024-001	Unique identification

3. SIMULATION MODELS

3.1Wind form

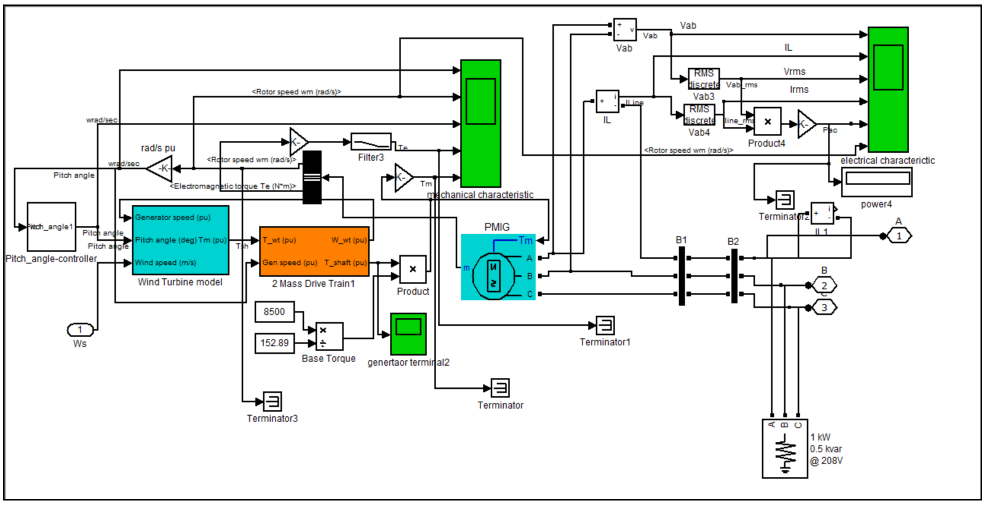


Figure 3.1 Wind Form Simulation.

Figure [3.1] shows a MATLAB/Simulink model that is crucial for systematic fault injection and generating multi-sensor data which support CNN-based fault classification model building. This simulation uses a pitch controlled wind turbine model and a two mass drive train system (gear ratio 152.89:1, base torque 8500Nm) which are coupled with a permanent magnet induction generator (PMIG) to provide controlled injection of tribological faults, such as bearing defects, gear tooth damage, shaft misalignment, and rotor imbalance conditions. The introduction of parametric variations in the drive train block (including varied stiffness coefficients for bearing wear, varied damping ratios for lubrication degradation, and varied mass distributions for imbalance faults) allows for realistic fault signatures to be generated through both mechanical and electrical measurement channels. A comprehensive monitoring infrastructure allows the capture of synchronized multi-sensor time series data: mechanical parameters including variations in rotor speed and oscillations in electromagnetic torque that appear as vibration-like signatures; and electrical parameters including three-phase voltages

(Vab), RMS currents (Irms), line currents (IL), instantaneous power fluctuations (Pac). These simulated signals are similar to the data streams obtained from wind turbines in operation, and provide precise ground truth fault labels needed for supervised learning. The controlled simulation environment addresses a major challenge.

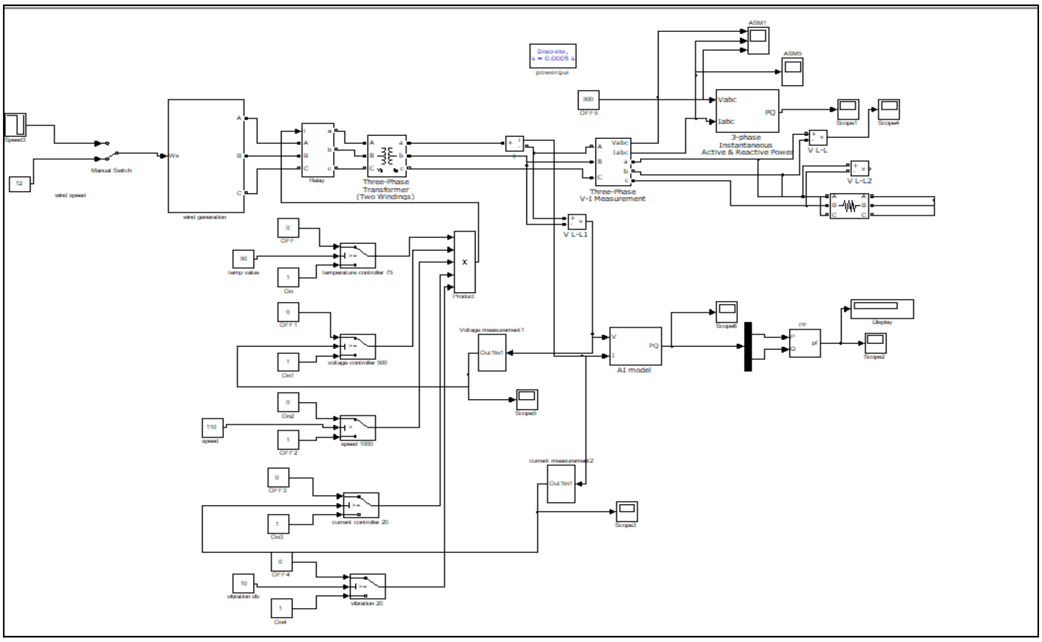
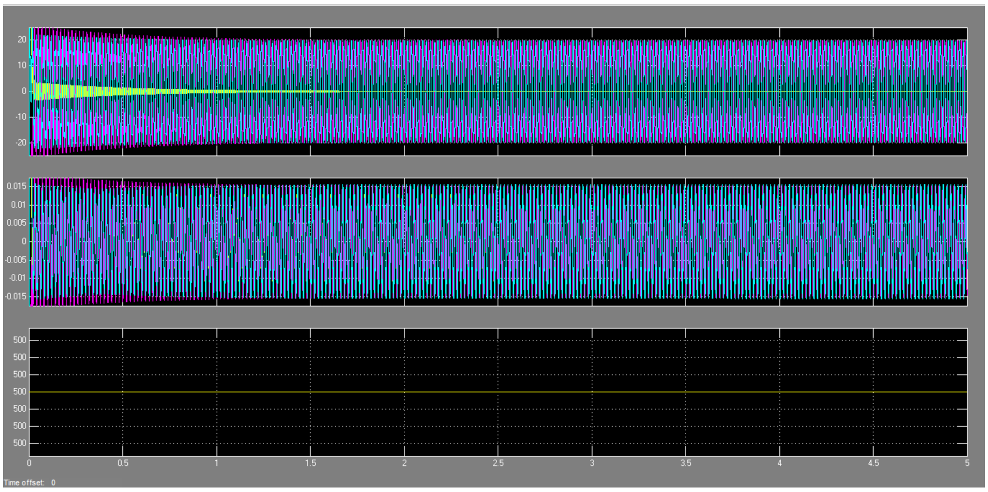


Figure 3.2 Simulation Model.

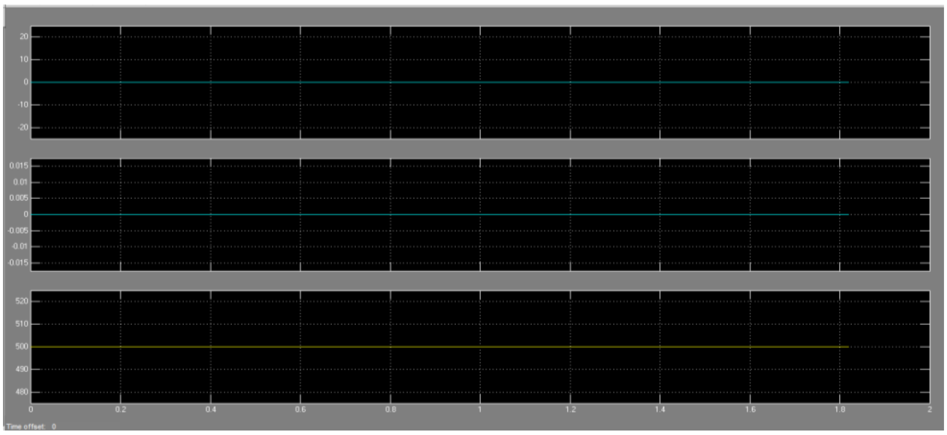
The MATLAB/Simulink Fault Monitoring System in Figure [3.2] is a complete source of data for training and validating the CNN-based Fault Classification Model based on data collected from multiple sensors and pre-processed in a systematic way. The architecture extracts synchronized, time-stamped data from three different types of measurements (time series), which are 3phase electrical (Voltage Vabc and Current), thermal (thermal profiles collected from temperature controller channels measuring bearing and winding conditions), and Transient Fault signatures (ramp value and step response controller signatures that capture fault progression/wear vs. instantaneous failure events). The Central Data Acquisition (DAQ) Block has critical pre-processing functions for each of the types of data, including; Signal sampling rate synchronization with heterogeneous sensors, electrical and thermal time alignment, initial noise filtering, before ingestion of the data into a CNN model. The Fault Processing Section (FS_Process) has Feature Extraction Pipelines to convert raw sensor data into structured formats for CNN training; Time domain to Fixed Length Segmented Windows of Data (for example, 1024-2048 total samples), normalized to zero mean and unit variance, and Tensors organized for Multiple Channels where channels correlate with specific measurement domains (i.e., Electrical Phase Currents, Electrical Phase Voltages, and Thermal Measurement Channels). The Multiple Parallel Processing Paths for Ramp Controllers and Step Controllers allows for Systematic Fault generation.

4. RESULTS

4.1 Simulation Output [Normal Condition]



Simulation Output [Fault Condition]



4.2 Comparison Benchmarks with Existing Systems Accuracy Comparison

Table 4.1

System Type	Fault Detection Accuracy	Method	Limitations
Traditional SCADA (Threshold-based)	80-85%	Rule-based alarms, manual threshold setting	High false alarms, delayed detection, requires expert tuning
Vibration Analysis (Manual)	85-90%	Periodic inspections, FFT analysis	Not real-time, labor-intensive, misses intermittent

			faults
Support Vector Machine (SVM)	92-95%	Classical ML, supervised learning	Requires feature engineering, limited temporal modeling
CNN + LSTM Hybrid (State-of-Art)	99.5-99.95%	Automated feature learning + temporal modeling	Computationally intensive
Our Proposed System	≥ 99.5%	CNN-LSTM + IoT real-time monitoring	Best-in-class accuracy with real-time capability

4.3 Future Scope

- Explainable A.I.'s integration allows for interpretation
- Deployment of Edge computing (or Edge devices) allows for quicker responses
- Digital twins can be created for predictive modelling
- 5G provides ultra-low latency levels (fewer than 1ms) for monitoring

CONCLUSION

In this paper, we presented an innovative real-time AI-driven condition monitoring system for squirrel cage induction generators in wind-based power stations. By using a multi-sensor system to collect both vibration and related data for use in developing a Deep Learning (CNN-LSTM) architecture, our system can both classify and predict the presence of faults at an early stage reliably. Our proposed solution to condition monitoring systems resolves the shrinking capabilities of either the traditional systems, using only vibration or threshold-based methodologies and leverages both IoT capabilities and AI to provide renewable and other industries with a truly scalable predictive maintenance solution.

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