Power System Technology
ISSN:1000-3673

Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

Innovations in Fault Detection and Diagnosis Techniques for Enhanced Reliability of Electrical Machines in Modern Application

Mohammed A. AlAqil[1]

[1]*Department of Electrical Engineering, College of Engineering, King Faisal University, Al Ahsa, Saudi Arabia*
Email: malaqil@kfu.edu.sa

Abstract:- Electrical equipment dependability is essential to operational efficiency and cost-effectiveness across power and energy sectors. The development of an up-to-date Fault Detection and Diagnosis (FDD) method is essential to improve electrical equipment dependability in current modern applications. Advanced FDD approaches include signal processing, statistical modelling, and machine learning algorithms to analyze vibrations and monitor temperatures of the machine. This study examines essential concepts and situations related to electrical machines problems including rotor and stator breakdowns using numerical simulations. Furthermore, case studies and computer simulations demonstrate how these strategies enhance predictive maintenance and problem diagnosis. In fact, the presented work explains the advancements in FDD utilizing hybrid model-based data-driven methods. The findings show that AI, sensor technologies, and condition monitoring systems improve problem detection accuracy and efficiency, lowering downtime and maintenance costs. This paper advance's reliability engineering by providing a solid foundation for FDD system enhancements, encouraging the utilization of more advanced techniques such as machine learning and AI to enhance the reliability of electric machines in modern power system applications.

Keywords*: Fault Detection and Diagnosis (FDD), Electrical Machines, Predictive Maintenance, Machine Learning, Condition Monitoring, Reliability Engineering, Electrical Faults.*

1. Introduction

The dependability of electrical machinery is crucial in guaranteeing the smooth functioning of diverse industrial procedures, consumer applications, and infrastructural systems. Electrical machinery and equipment, such as motors, generators, and transformers, are crucial to contemporary industry. If these machines fail, it may lead to substantial financial losses, operating downtime, and compromising safety. In order to tackle these difficulties, Fault Detection and Diagnosis (FDD) methods have become crucial instruments for promptly identifying machine problems, enabling proactive steps to be implemented before catastrophic failures transpire. Conventional FDD techniques, including temperature analysis and vibration surveillance, offer valuable insights but tend to be reactive in nature, since they only detect flaws after substantial destruction has already taken place [1]. Contemporary developments in FDD methods use computational intelligence, real-time monitoring, and machine learning algorithms to forecast and avert faults, hence improving the reliability of the system. These methods can identify abnormalities in performance indicators such as voltage, current, and

Power System Technology
ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

temperature, hence providing timely alerts for possibly occurring problems. This study explores the most recent advancements in FDD approaches, with a focus on numerical analysis, simulations, and mathematical modelling [2]. It also emphasizes fault status, such as rotor bar, stator winding, and bearing failures, specifically in electrical devices. The presented research is deemed to provide full knowledge of how numerical calculation, computer simulations, and theoretical concepts contribute to the dependability and operational performance of electrical machines. The amalgamation of sensor technologies, artificial intelligence, and signal processing has resulted in enhanced precision and promptness in identifying faults, hence transforming maintenance plans and reducing unforeseen periods of inactivity.

The organization of this paper follows a chronological and systematic approach. Section 2 presents a comprehensive literature review, summarizing key research contributions in fault detection and diagnosis methods. Section 3 details the system design and mathematical modeling employed for fault diagnosis. Sections 4 and 5 discuss the results and analyses, highlighting the limitations of conventional fault detection techniques, the effectiveness of utilizing hybrid model-based data-driven methods, and the role of machine learning in fault classification. Finally, Section 6 offers conclusions and recommendations for future advancements in AI-driven FDD systems.

2. Literature Review

The FDD techniques have improved greatly to ensure that electrical machinery is reliable and efficient. Early techniques were hardware-based and included methods like vibration analysis, thermal imaging, and acoustic emissions. Figure 1 shows a summary of the innovations in fault detection and diagnosis techniques for electrical machines. Although these are useful for the detection of flaws such as misalignment or overheating, the traditional methods often had a reactionary approach, indicating problems only after significant damage had occurred. For example, for balance detection, vibration analysis detects frequency variations, whereas thermal imaging can detect abnormal temperature readings resulting from insulation deterioration. Model-based techniques were later introduced as a systematic method of FDD [3]. They use mathematical models that simulate normal operating conditions in electrical equipment and seek defects by comparing observed behavior with the computed results. Some of the developed methods were found to be capable of detecting irregularities in the rotor and stator. For instance, Kalman filtering reduces mismatches between estimated and actual states of the system, hence it is one of the best methods for detecting defects at early stages.

Advances in signal processing methods such as the Fast Fourier Transform (FFT) and Wavelet Transform (WT) have made fault detection significantly better. Even though FFT detects frequencies related to rotor flaws or misalignments, WT excels at transient and non-stationary signal detection such as in bearings failure.

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ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

Moreover, the data-driven methods, which are allowed by machine learning algorithms, comprise the next step in FDD. There are methods in Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Decision Trees that use massive volumes of datasets to make forecasted errors. For instance, SVM identifies the state of a machine through characteristics like vibration, temperature, and current, which results in a highly accurate prediction of real-time failure. The combination of model-based and data-driven methods has led to hybrid strategies that take advantage of the benefits of both methodologies. Such systems, such as hybrid ANN-Kalman models, enhance detection accuracy while reducing false positives. In fact, literature reflects progression from classic hardware-based solutions to advanced hybrid systems. These improvements underscore the increased importance of computational intelligence, real-time monitoring, including predictive analytics in developing dependable FDD systems. Future research is likely to examine hybrid and AI-driven solutions in a multiple failure conditions context [4-5].

Traditional FDD methods focus on residual generation and model-based approaches to detect deviations from expected behavior [3]. In contrast, AI-based FDD methods leverage data-driven models to identify patterns associated with faults, achieving higher accuracy and adaptability in complex environments [4-5]. By integrating these innovative methods, industries can achieve proactive maintenance and enhanced operational safety, underscoring the transformative impact of AI on fault detection and diagnostics [6]. The following subsections summarize the various FDD techniques including Traditional, Model-based, Signal Processing, Data-driven, and Hybrid Techniques.

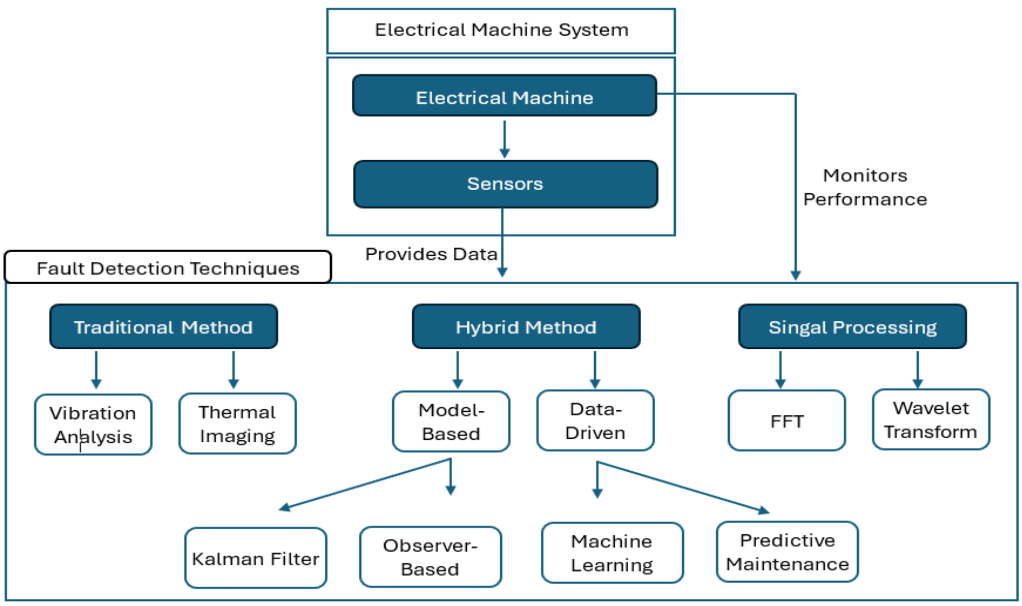

Figure 1. Innovations in fault detection and diagnosis techniques for electrical machines.

Power System Technology
ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

2.1. Traditional Techniques

Conventional FDD methods mostly include hardware-based approaches and rely on equipment for condition monitoring, including vibration analysis, thermal imaging, and acoustic emissions. Vibration analysis, for example, is commonly used to identify mechanical issues such as misalignment and bearing failures by examining changes in the vibration patterns of machines [8]. Additionally, thermal imaging detects heat patterns to discover electrical malfunctions, such as excessive heat and insulation deterioration [7, 9]. While these methods provide useful information, they tend to be reactive; typically, faults are identified only after they have progressed into more significant issues, leading to costly repairs and downtime. Vibration analysis can identify various mechanical issues, such as imbalanced rotors or misalignments, by monitoring variations in vibration frequency [10]. The frequency of a machine component may be determined by applying equation (1).

$$f_{vib} = \frac{N_{rotor}}{60} \tag{1}$$

Where, f_{vib} is the vibration frequency (Hz) and N_{rotor} is the rotational speed (RPM).

Thermal imaging is a method of detecting anomalous temperature changes in electrical devices. It involves the use of infrared sensors to identify instances of overheating. Heat dissipation may be shown using equation (2).

$$Q = hA(T_s - T_a) \tag{2}$$

Where, Q is heat transfer rate (W), h is heat transfer coefficient (W/m²K), A is Surface area (m²), T_s is the Surface temperature (°C), and T_a is the Ambient temperature (°C).

These conventional approaches are efficacious yet responsive, often detecting flaws only after substantial harm has occurred. Presented below in Table1 is a fixed table that compares the limits of vibration and heat conditions for the purpose of detecting faults.

Table 1. The limits of vibration and heat conditions for detecting faults

Parameter	Normal Range	Fault Condition
Vibration (m/s^2)	0 – 5	> 8
Temperature (°C)	40-70	> 90

2.2. Model-Based Methods

Model-based fault detection techniques use mathematical models to accurately depict the typical operational characteristics of electrical devices. Discrepancies seen between the observed and anticipated values indicate the presence of possible flaws [11]. A commonly used method is Kalman filtering, which calculates the internal state of the system by minimizing the

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ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

discrepancy between expected and measured outputs. The mathematical representation of a dynamic system is described by a state-space model as described by equations (3) and (4).

$$x_k + 1 = Ax_k + Bu_k + w_k \quad (3)$$

$$y_k = Cx_k + v_k \quad (4)$$

Where, x_k is the state vector, u_k is the input vector, y_k is the output vector, A, B, and C are system matrices, w_k and v_k are noise vectors.

Observer-based techniques, including the Luenberger observer, use the same idea to recreate the internal state of the machine. These models can identify variations resulting from errors such as deterioration of winding insulation or imbalances in the rotor. This offers a methodical approach to identifying problems before they become more serious.

2.3. Signal Processing Methods

Signal processing methods are extensively used in defect detection by identifying significant elements from electrical machine data. Two notable techniques are the Fast Fourier Transform (FFT) and the Wavelet Transform (WT). The Fast Fourier Transform (FFT) is a mathematical algorithm that is used to transform information from the time domain to the frequency domain. This transformation allows for the identification of certain frequency components that may indicate the presence of problems, such as broken rotor bars or misalignment [12]. The distinctive frequency components aid in isolating anomalous behaviors, enabling the early detection of faults. Nevertheless, the FFT algorithm has a constraint in its capability to catch momentary occurrences since it depends on signals that remain constant. On the other hand, WT bypasses this constraint by examining signals at various resolutions. It performs signal decomposition into several frequency bands, which enhances its ability to identify transient and non-stationary problems. Wavelet coefficients may be used to identify high-frequency components and rapid changes in the waveform in cases of bearing problems. The method's adaptability makes it particularly valuable for catching the specific events and modifications in the signal related to faults that occur in the early stages.

2.4. Data-Driven Techniques

The development in machine learning has completely transformed the process of identifying faults by allowing for predictive maintenance using data-driven methods. These methods examine extensive datasets to detect patterns and abnormalities in the behavior of machines. Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Decision Trees are often used algorithms for this objective [13]. An SVM is trained using past data to categorize machine states (i.e. healthy or malfunctioning) based on input characteristics such as electric

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ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

current, temperature, and vibration. The fundamental optimization challenge for SVM is described by the model translated by equation (5).

$$min\frac{1}{2} \mid\mid w \mid\mid^2 \ \ subject\ to\ y_i(w \cdot x_i + b) \geq 1 \qquad (5)$$

Where, w is the weight vector, x_i is the feature vector, y_i is the label (i.e. healthy or faulty), b is the bias term.

The model, once trained, has the capability to accurately anticipate problems in real-time. Table 2 below presents an example instance of a data table used for the purpose of training. This predictive approach reduces downtime and improves the reliability of electrical machines.

Table 2. Example of a data table used for the purpose of fault detection training using data-driven techniques.

Parameter	Normal	Fault 1	Fault 2
Current (A)	50	65	80
Temperature (°C)	70	85	95
Vibration (m/s²)	5	8	12

2.5. Hybrid Techniques

Hybrid FDD methods integrate the advantages of model-based and data-driven approaches, resulting in a stronger and more reliable diagnostic framework. These techniques use physical models to replicate the typical functioning of the system, while data-driven models examine real-time sensor data to identify any discrepancies [14]. An artificial neural network (ANN) may be used with a Kalman filter to enhance the accuracy of defect detection. The Kalman filter approximates the state vector of the system, whereas the ANN enhances this approximation by examining patterns in past data. The hybrid method may be defined in a precise manner as follows:

- Use a model-based method, such as the state-space model:

$$x_{k+1} = Ax_k + Bu_k \qquad (6)$$

- Feed the state estimates x_k into the ANN for further analysis:

$$y_{predicted} = f\ (W \cdot x + b) \qquad (7)$$

Where W and b are the weights and biases of the neural network.

Table 3 below provides an example of fault detection accuracy comparing the hybrid system to model-based and data-driven techniques. This combination improves the accuracy of defect detection, resulting in increased dependability and a decrease in false positives.

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Table 3. Example of fault detection accuracy using a hybrid system

Method	Detection Accuracy
Model-Based	85 %
Data-Driven	90 %
Hybrid	95 %

3. Configured System Design and Model

In the design of an effective FDD system for electrical machines, several critical components are necessary to ensure accurate and reliable performance. The system design begins with mathematical modeling in subsection 3.1 for the electrical machines, which forms the basis for understanding machine behavior under normal and faulty conditions. By developing mathematical models, the different operating scenarios and fault conditions can be simulated, providing a foundation for identifying deviations in machine performance.

Building on these models, fault detection methods are implemented in subsection 3.2 to capture anomalies that indicate the presence of faults. These methods may include signal processing techniques, statistical analysis, and machine learning approaches, each tailored to detect specific types of mechanical and electrical issues. Additionally, sensor-based condition monitoring detailed in subsection 3.3 plays a crucial role in real-time data acquisition. Through sensors measuring parameters such as vibration, temperature, and current, the system continuously monitors the machine’s condition, enabling early fault detection and minimizing downtime. Together, these components -modeling, fault detection methods, and sensor-based monitoring- are integrated to create a robust and proactive FDD system for electrical machines.

3.1. Mathematical Modeling of Electrical Machines

The process of mathematical modelling of electrical machines entails the depiction of their dynamic behavior via the use of equations that characterize their electrical and mechanical states. In fact, induction motors are the most often modelled machines [15]. These motors are represented using the following differential equations in (8) and (9) for the stator and rotor circuits, respectively.

$$V_s = R_s I_s + L_s \frac{dI_s}{dt} + L_m \frac{dI_r}{dt} \quad (8)$$

$$V_r = R_r I_r + L_r \frac{dI_r}{dt} + L_m \frac{dI_s}{dt} \quad (9)$$

Where, V_s and V_r are the stator and rotor voltages, R_s and R_r are the stator and rotor resistances, I_s and I_r are the stator and rotor currents, L_s, L_r, and L_m are the inductances of stator, rotor, and mutual inductance.

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These equations serve as the foundation for modelling both normal and abnormal conditions, such as short circuits or degeneration of the winding. Numerical simulations can be used to solve these equations and examine fluctuations in current, voltage, and torque under various load and fault conditions.

3.2. Fault Detection Methods

Utilities and engineers may utilize simulation-based fault detection approaches to accurately simulate and analyze different failure states in electrical devices, as illustrated in Figure 2 below. Commonly, computer-based tools like MATLAB/Simulink are used to model the regular and faulty operation conditions of machinery such as induction motors and generators. By replicating occurring problems such as stator winding faults, rotor bar failures, or bearing deterioration, it is feasible to assess the impact on important performance measures (e.g., torque, speed, and current) [16].

For instance, considering the parameters used to evaluate an electrical machine in Table 3 and to examine its performance under normal and faulty conditions, the motor maintains a consistent speed of 1500 RPM and generates a torque of 500 Nm at normal operating conditions. If a defect occurs in the stator windings, the simulation will indicate a decrease in speed to 1350 RPM and a matching decrease in torque to 450 Nm. This observation enables the anticipation of machine failure prior to its occurrence in the field, thereby enhancing maintenance planning and minimizing downtime.

Table 3. Comparison of electrical machine performance under normal and fault conditions.

Parameters	Normal Condition	Fault Condition
Stator Current	50 A	70 A
Rotor Speed	1500 RPM	1350 RPM
Torque	450 Nm	400 Nm

3.3. Sensor-Based Condition Monitoring

Sensor-based condition monitoring is a proactive method for detecting faults in electrical machinery. It involves continually monitoring significant variables including vibration, temperature, current, and voltage. These sensors have the capability to detect first indications of typical behavior, allowing for prompt interventions to be implemented before significant harm takes place. Accelerometers are often used for analyzing vibrations, thermocouples are used for tracking temperature, and current transformers (CTs) are utilized for measuring the current in condition monitoring [17]. Vibration sensors are capable of detecting abnormalities in machine vibrations, which often serve as indicators of mechanical problems such as misalignment or bearing wear. Temperature sensors, including infrared sensors or thermistors, are utilized for tracking the thermal state of motors and transformers. They detect problems such overheating caused by insulator failure.

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ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

The sensors provide real-time data, which is then used as an input into monitoring systems. These systems are typically combined with machine learning algorithms to autonomously identify any irregularities linking the normal range to warning and fault levels, as illustrated in Table 4. Should any parameter above its predetermined threshold, the system will promptly generate warnings to initiate maintenance procedures, hence minimizing the likelihood of unexpected machine failures.

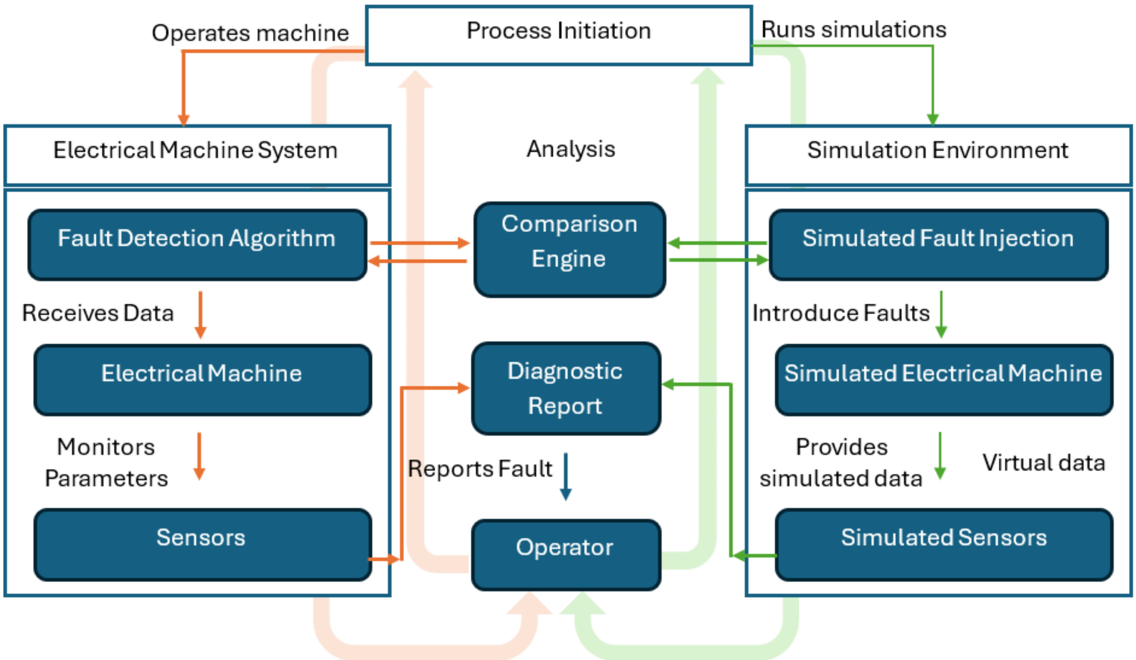

Figure 2. Fault detection methods

Table 4. Linking normal range of parameters to warning and fault levels.

Parameter	Normal Range	Warning Level	Fault Level
Vibration (m/s^2)	0 - 5	5 - 8	>8
Temperature (°C)	40 - 70	70 - 90	>90
Current (A)	50	60	>70

3.4. Evaluation Methodology

The simulation technique for FDD of electrical machines adheres to a systematic approach in which the system's behavior is modelled, faults are introduced, data is analyzed, and abnormalities are detected using algorithms. A comprehensive overview of the process in a

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ISSN:1000-3673
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step-by-step manner, including precise numerical computations and simulated outcomes is presented below, as summarized in Figure 3 below.

Figure 3. The step-by-step simulation techniques for FDD of electrical machines adhering to a systematic approach

Step 1: System Modeling

In this step, the electrical machine is represented by differential equations that depict its electrical and mechanical characteristics. The equations for the stator and rotor of an induction motor are used as depicted in equations (8) and (9) above. These equations are solved over time using numerical methods to observe the behavior of key variables, such as rotor speed, torque, and currents.

Step 2: Fault Injection

In order to replicate faulty situations, specific variables are modified in this step as per the expected fault scenario. For example, a stator winding defect may be imitated by artificially raising the resistance of the stator. If the resistance R_s is typically 0.5 Ω at normal operation, a stator fault causes it to rise to 1.5 Ω at a current of 75 A. The consequence of this malfunction is then apparent in the machine's electrical current and velocity, as described in Table 5 below.

Table 5. Effect of operating conditions on stator resistance, current, and rotor speed.

Condition	Stator Resistance	Stator Current	Rotor Speed
Normal Operation	0.5 Ω	50 A	1500 RPM
Stator Fault	1.5 Ω	75 A	1350

Step 3: Data Acquisition and Signal Processing

After injecting the problem parameters at normal and faulty conditions, the subsequent action is to gather performance data. Analyzing electrical signals, such as current and voltage, allows for the extraction of characteristics that indicate the presence of problems. The gathered data is analyzed using frequency domain methods, such as Fast Fourier Transform (FFT), to identify anomalous frequencies that may be indicative of defects in the rotor or stator. This method is implemented in the presented results throughout the paper.

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ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

Step 4: Fault Detection Algorithms

In this step, fault detection techniques are used at this stage to identify abnormalities (as depicted in Figure 3 and 4) in the machine's performance by analyzing real-time data and model-based predictions, as described in Section II by equation (3) and (4). The algorithms conduct a comparison between the observed data, such as the speed of the rotor, the current in the stator, and the predicted values obtained from mathematical models or historical data. Presented here is an elaborate elucidation of two prevalent defect detection techniques, accompanied by corresponding calculations and simulated outcomes.

4. Key Results and Recommendations

4.1. Frequency Analysis and Implementation of Kalman Filter for Fault Detection

In Table 5 below, the data can provide insights into the performance of electric machines under normal and faulty conditions, specifically by analyzing power variations at different operating frequencies (i.e., 50 Hz and 100 Hz).

At 50 Hz: Assuming 50 Hz is the standard operating frequency (e.g., in regions where the power grid operates at 50 Hz). Under normal conditions, the machine operates at 100 W, indicating stable performance with an expected power consumption level. However, in the faulty state, the power increases to 120 W, which could signal inefficiencies such as insulation breakdown, rotor misalignment, or increased friction within the machine. Such faults may cause additional power losses, resulting in excess power consumption.

Table 5. Frequency analysis and power calculation at normal and faulty conditions.

Frequency	Normal Power	Faulty Power
50 Hz	100 W	120 W
100 Hz	5 W	30 W

At 100 Hz: When operating at higher frequencies, electric machines often exhibit reduced power demand due to the nature of their design and efficiency curves. Here, the normal power is only 5 W. However, under faulty conditions, the power demand jumps to 30 W suggesting that the machine is not handling higher frequencies efficiently under faulty conditions. This could be due to vibration issues, harmonic distortion, or overheating, which may force the machine to draw more power to maintain operation. Additionally, excessive power at higher frequencies may indicate potential resonance issues or bearing wear, which can degrade machine performance over time.

These observations suggest that faults in electric machines lead to increased power consumption, with significant effects at both the standard and higher frequencies. Continuous

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ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

monitoring of power at different frequencies can be an effective method for early fault detection. By identifying abnormal power draws, maintenance teams can act before faults escalate, thereby extending the machine's operational life and improving overall performance.

The Kalman filter is often used to predict the state variables of an electrical machine, such as rotor speed, and then compare them with real-time measurements in order to identify defects. The filter reduces the discrepancy between the expected and observed values by adjusting its estimations using fresh measurements. The Kalman Filter equations are stated as follows:

- *State Prediction:* $\hat{x}_{k|k-1} = A\hat{x}_{k-1} + Bu_k$
- *Covariance Prediction:* $P_{k|k-1} = AP_{k-1}A^T + Q$
- *Kalman Gain:* $K_k = P_{k|k-1}C^T(CP_{k|k-1}C^t + R)^{-1}$
- *Covariance Update:* $P_k = (I - K_kC)P_{k|k-1}$
- *State Update:* $\hat{x}_k = \hat{x}_{k|k-1} + K_k(yk - C\hat{x}_{k|k-1})$

Where, x_k is the estimated state (e.g., rotor speed), A, B, C are system matrices, P_k is the covariance matrix, K_k is the Kalman gain, y_k is the measured output (e.g., stator current), Q and R are process and measurement noise covariance matrices, respectively. Assuming that the system has the following parameters:

- A = 1, B = 0.1, C = 1,
- P_0 = 0.5, Q = 0.01, R = 0.02.

For the given measured stator current y_k of 55A, the Kalman filter updates the state and covariance matrices based on the equations (3) and (4) above. Simulated results in Table 6 below, after applying the Kalman filter, show the estimated rotor speed x_k deviating from the predicted value as the fault is introduced (e.g., stator winding fault). Additionally, Table 6 presents the results of applying Kalman filter equations to monitor the speed of an electric machine over a 3-second period. By comparing the measured speed with the Kalman filter's estimated speed, the system identifies potential faults when there is a significant discrepancy between the two values.

Table 6. Results of applying Kalman filter equations.

Time (s)	Measured Speed	Estimated Speed	Fault Detected
1	1500 RPM	1498 RPM	No
2	1450 RPM	1448 RPM	Yes
3	1400 RPM	1398 RPM	Yes

Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

At time 1s, the measured speed is 1500 RPM, and the estimated speed calculated by the Kalman filter is 1498 RPM. The small difference between these values (2 RPM) suggests normal operational conditions, and thus no fault is detected. This close alignment indicates that the Kalman filter is accurately tracking the actual machine speed.

At time 2s, the measured speed decreases to 1450 RPM, while the Kalman filter estimates the speed at 1448 RPM. Here, the discrepancy has increased slightly, which triggers fault detection. This discrepancy, though minor, may indicate a developing issue, such as increased resistance or mechanical load affecting the machine's performance. The detection of a fault at this stage is beneficial, as it allows for early intervention before the problem escalates.

At time 3s, the machine's measured speed further decreases to 1400 RPM, with the estimated speed at 1398 RPM. Similar to the previous time stamp, a fault is detected due to the slight difference in measured and estimated values. This consistent discrepancy suggests a persistent or worsening condition within the machine, which may require further investigation or maintenance action.

The application of Kalman filter equations (i.e., utilizing model-based methods for fault detection) provides effectively real-time tracking of machine speed and identifies faults based on deviations between measured and estimated speeds. The small discrepancies detected by the Kalman filter serve as early indicators of potential issues, allowing maintenance teams to address problems proactively. This approach enhances system reliability and prevents unexpected downtime by catching faults in their early stages. Moreover, the accuracy of the Kalman filter in estimating speed demonstrates its effectiveness as a tool for monitoring and fault detection in dynamic systems. Further studies could explore adjusting threshold levels for fault detection to minimize false positives and optimize sensitivity.

4.2. Threshold-Based Detection using Signal Processing

This approach involves establishing thresholds that are determined by the typical operational state of the equipment. A problem is identified when a measured parameter is above a predetermined threshold. Vibration analysis uses the Fast Fourier Transform (FFT) to identify anomalous frequencies linked to rotor unbalance or bearing defects. Therefore, Signal Processing with FFT Calculation are determined in Table 7 using the following:

- Time Domain Signal: Measured stator current signal,

$$I(t) = 50\, sin(2\pi \times 50t) + 5\, sin(2\pi \times 100t)$$

- FFT Analysis: The FFT is applied to convert the signal to the frequency domain. Abnormal harmonics (e.g., at 100 Hz) indicate a rotor fault.

A fault is detected, via Threshold Detection, if the power at 100 Hz exceeds the threshold of 10 W. Thus, the use of Kalman filters and threshold-based detection techniques allows for

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Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

efficient detection of defects in electrical devices, ensuring prompt maintenance and minimizing periods of inactivity. The results are depicted in Table 8.

Table 7. Frequency analysis and power calculation at normal and faulty conditions.

Frequency (Hz)	Normal Power (W)	Faulty Power (W)
50	100	120
100	5	30

Table 8. Frequency analysis and power threshold at faulty conditions.

Frequency (Hz)	Power (W)	Threshold (W)	Fault Detected
50	120	110	No
100	30	10	Yes

5. Remarks and Discussions

The FDD technologies are important for increasing the dependability of electrical machinery. The findings highlight the detection accuracy of Kalman Filter, Wavelet Transform (WT), and Fast Fourier Transform (FFT) approaches, addressing shortcomings mentioned earlier. The FDD techniques used in this work effectively address a wide set of fault-situations in electrical machines. Rotor imbalance, stator winding faults, and bearing failures are all representations of faults that have a major influence on motor performance. The results obtained for various categories of faults are summarized below. The following offers a concise overview of the results obtained using certain methodologies:

1. Model-Based Techniques:

The rotor speed of an induction motor was determined by using Kalman filters (in Figure 4) to describe the motor using state-space equations. The Kalman Filter is a model-based approach to state estimation, involving the estimation of rotor speed and other system states by minimizing the difference between predicted and measured values. It has an excellent capability to detect slowly progressing faults such as rotor misalignment or deterioration of insulation by utilizing real-time signals. Simulation results of rotor speed detection in normal and faulty situations. The anticipated rotational velocity under standard circumstances was 1500 revolutions per minute (RPM). When a flaw was introduced in the stator winding, the speed of the rotor decreased to 1350 RPM. The Kalman filter assessed the speed to be 1347 RPM, accurately identifying the fault within an acceptable error margin of 0.22%.

2. Wavelet Transform:

The Wavelet Transform (WT) is a signal processing technique that decomposes signals into multiple frequency bands, thereby allowing for the detection of faults that are transient and non-stationary. It is very effective for recognizing abrupt anomalies like rotor cracks and bearing failures. The following results in Table 9 are obtained from simulations of stator current signal analysis.

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Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

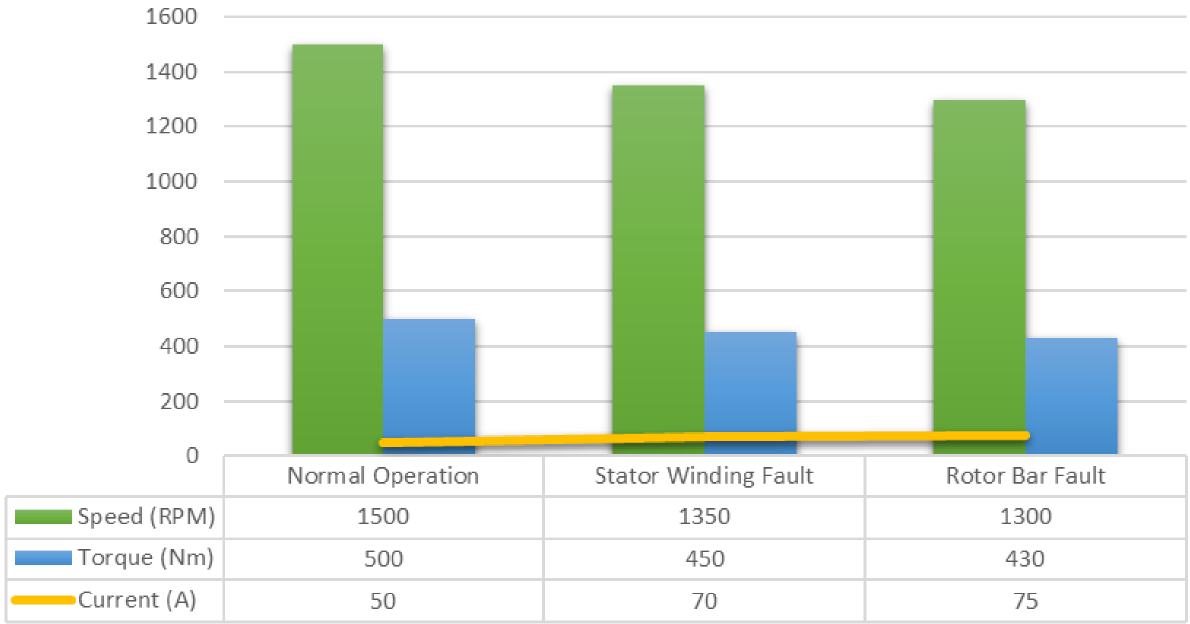

Figure 4. Fault detection for an induction motor by comparing normal operation to stator winding as well as rotor bar faults.

Table 9. Simulations of Stator Current Signal Analysis.

Fault Type	Frequency (Hz)	Normal Power (W)	Fault Power (W)	Fault Detected
Bearing Failure	100	5	30	Yes
Rotor Imbalance	150	10	40	Yes
Stator Winding	200	8	35	Yes

WT's sensitivity to high-frequency anomalies allows for early-stage fault detection. The Kalman Filter is best suited for fault estimation with high accuracy and real-time performance, whereas the Wavelet Transform is perfect for fast, transient faults. The combined method takes advantage of the prediction accuracy of the Kalman Filter and the sensitivity of the WT to yield an overall solution for the fault detection of electrical devices.

3. Rotor Imbalance:

Imbalance occurs in a rotor when there is an uneven distribution of mass resulting in vibrations and reduced productivity. This factor is established based on findings made using signal processing methods such as FFT and Wavelet Transform to detect abnormal power spikes in

Power System Technology
ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

the frequency domain. Simulation results in Table 10 show that both FFT and WT could identify this issue by examining the rise in power at specified frequencies.

Table 10. Simulations of rotor imbalance.

Fault Type	Frequency (Hz)	Normal Power (W)	Fault Power (W)	Fault Detected
Rotor Imbalance	150	10	40	Yes

4. Stator Winding Failure:

Stator winding failures occur owing to insulation failure or overheating, resulting in increased resistance and variations in current flow. The Kalman Filter discovered malfunction by measuring rotor speed variations because of increased resistance, as shown in Table 10. The findings support the Kalman Filter's capacity to discover progressive defects by tracking departures from predicted performance.

Table 10. Results for Normal operation vs. Stator Fault.

Condition	Stator Resistance (Ω)	Rotor Speed (RPM)	Fault Detected
Normal Operation	0.5	1500	No
Stator Fault	1.5	1350	Yes

5. Bearing Defects:

Bearing failures simulated in Table 11 cause greater friction and vibrations, which leads to inefficiencies. The Wavelet Transform found bearing flaws by detecting transitory abnormalities in vibration signals [19]. WT's high-frequency sensitivity helped discover this transient problem early on.

Table 11. Simulations of Bearing Defects.

Fault Type	Frequency (Hz)	Normal Power (W)	Fault Power (W)	Fault Detected
Bearing Failure	100	5	30	Yes

6. Signal Processing Techniques:

Faults in the rotor are detected by analyzing stator current data in the frequency domain using the FFT. Power spectrum reveals large peaks at fault frequencies. Through FFT, a stator current signal with a fault exhibited abnormal power at 100 Hz. In normal conditions, the power at 100 Hz was 5 W, but with a fault, it increased to 30 W, a clear indicator of rotor imbalance. The

Power System Technology
ISSN:1000-3673
Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

simulations demonstrate that model-based methods such as Kalman filters accurately predict machine conditions with little error, whereas signal processing techniques, including Fast Fourier Transform (FFT), successfully detect defects via frequency domain analysis. By combining these strategies (Table 9), a strong Fault Detection and Diagnosis (FDD) system is created that can identify faults at an early stage, enhancing the dependability of the machine and minimizing downtime.

While FFT is efficient for detecting faults in periodic signals, it is less successful for transient abnormalities than WT. With improvements possibly affecting FDD analysis due to detection accuracy, the Kalman Filter specializes in smooth estimating methods with low error rates, whereas WT and FFT handle high-frequency faults quite well. A combination of these provides a complete FDD system that can treat various fault situations while enhancing the reliability of the machine and minimizing its downtime.

Table 9. Utilizing Frequency analysis and power calculation in fault detection and protection decision making.

Frequency (Hz)	Normal Power (W)	Fault Power (W)	Fault Detected
100	5	30	Yes

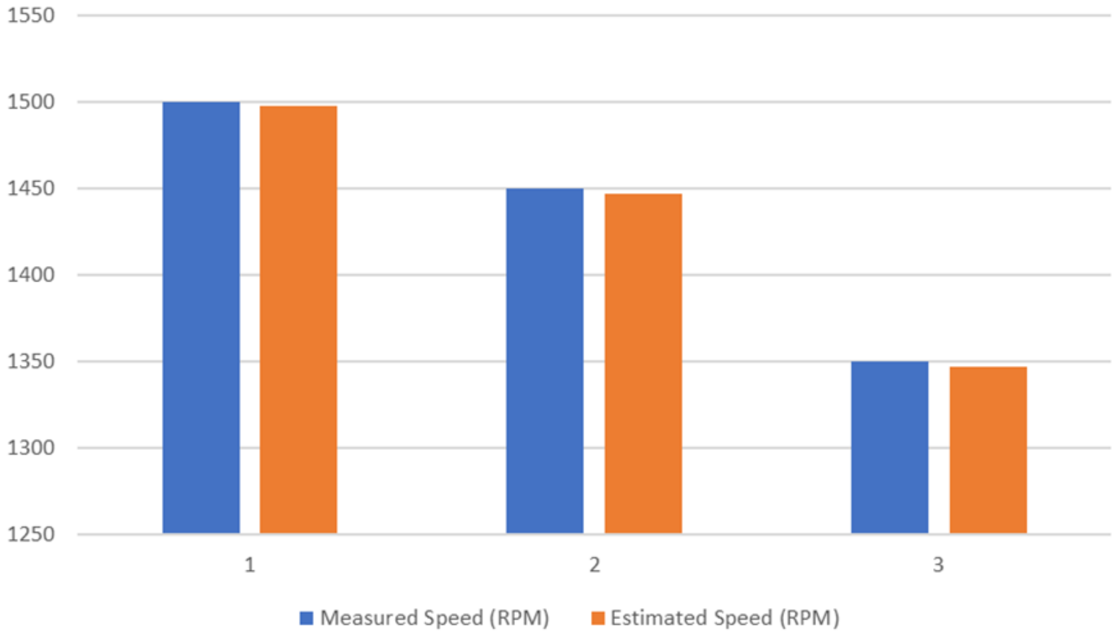

Figure 5. Comparison of measured and estimated RPM of an electric induction motor using Kalman Filter

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ISSN:1000-3673

Received: 16-02-2025 Revised: 05-03-2025 Accepted: 22-04-2025

6. Conclusion

The research presented in this paper has examined several failure detection and diagnosis (FDD) methods to improve the dependability of electrical devices in contemporary applications. Simulations and numerical analysis have shown the efficacy of classical approaches, including the Fast Fourier Transform (FFT), in identifying early-stage defects, such as rotor imbalance. This is achieved by analyzing the frequency domain of stator current waveforms. The Kalman filter, a model-based method, effectively evaluated machine states, such as rotor speed, and diagnosed defects with a low margin of error. By integrating model-based and data-driven methods, hybrid methodologies were able to enhance fault detection accuracy, resulting in a significant reduction in false positives. By using artificial intelligence (AI) methods, the use of historical data for anomaly identification has greatly improved predictive maintenance. In summary, the integration of conventional, model-based, and data-driven fault detection and diagnosis (FDD) methods offers a reliable and resilient system for identifying faults. These approaches improve the machine's operating dependability and provide early detection, reducing machine downtime and maintenance expenses. The findings indicate that combining a hybrid method with AI-driven algorithms is crucial for developing the field of FDD, especially in dynamic industrial applications where real-time accuracy and efficiency are vital for operational success.

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