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The Influence of Measurement Errors on the Fault Diagnosis of Power Electric Drive Systems

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ABSTRACT: This paper addresses the use of machine learning classification methods for predictive maintenance and fault diagnosis in power drive systems, with emphasis on reducing misclassification risks caused by measurement errors. An artificial neural network (ANN) model trained on vibration signals is applied for electrical fault detection in asynchronous motors. The approach supports early fault identification, reduces downtime, and lowers maintenance costs. Additionally, the incorporation of measurement uncertainty improves diagnostic reliability and enables more informed preventive decisions.

KEY WORDS: Fault Diagnosis; Predictive Maintenance; Machine Learning; Vibration Analysis; Asynchronous Motors.

I.INTRODUCTION

With the rise of Industry 4.0, industrial systems have experienced significant growth in complexity, interconnectivity, and performance. Electric motors play a crucial role as primary actuators in industrial processes, and their reliable operation directly affects productivity, product quality, and operating costs. Electrical and mechanical failures in motors can lead to unexpected downtime, safety risks, and substantial economic losses, encouraging the adoption of effective maintenance strategies.

Traditional maintenance approaches range from **reactive maintenance**, which intervenes only after a fault occurs, to **preventive (scheduled) maintenance**, where components are periodically inspected or replaced regardless of their condition. However, advancements in sensing technologies, signal processing, and smart monitoring systems have supported the evolution of **predictive maintenance**, which aims to detect early signs of degradation and prevent failures before they occur. Lower sensor costs and the availability of real-time industrial data have further enhanced predictive maintenance adoption, reducing downtime and maintenance expenditures while improving operational safety.

Several condition parameters can indicate the health of electric motors, such as temperature, absorbed current, acoustic emissions, frequency response, and mechanical vibrations. Among these, vibration analysis is particularly effective for detecting mechanical and electrical anomalies, including bearing wear, rotor faults, misalignment, and imbalance.

Recent research has explored machine learning (ML) and deep learning models for vibration-based fault diagnosis, including SVM, CNN, GANs, gradient boosting models, and hybrid approaches. While these studies demonstrate promising performance, many rely primarily on simulated data, which may not fully reflect real operating conditions. In addition, the influence of measurement noise and uncertainty on diagnostic performance is often overlooked, even though real sensor data inevitably contains variability that can lead to misclassification and reduced reliability in practical environments.

In this work, we investigate vibration-based fault detection in induction motors with artificially introduced defects. Accelerometer data are analyzed in the frequency domain and processed by an Artificial Neural Network (ANN) for fault identification. Furthermore, measurement uncertainty is incorporated into the diagnostic process to assess confidence levels and enhance system robustness. This approach contributes to more reliable predictive maintenance strategies and supports the transition toward smarter industrial monitoring systems under the Industry 4.0 paradigm.

II. SIGNIFICANCE OF THE SYSTEM

Reliable motor operation is critical for industrial productivity, safety, and cost-efficiency. Mechanical and electrical faults can cause downtime and economic losses. Traditional reactive and preventive maintenance can be costly or inefficient, while predictive maintenance allows interventions based on actual equipment condition.

A vibration-based fault diagnosis system, using accelerometer data and machine learning models such as ANNs, can detect and localize faults early, even those not visible to human inspection. Incorporating measurement uncertainty improves confidence in diagnostics, reduces false alarms, and supports more effective, condition-based maintenance, lowering costs and extending equipment life.

III. LITERATURE SURVEY

The fault diagnosis of induction motors has been widely studied using various techniques, including signal processing, machine learning, and deep learning methods. Vibration analysis, current monitoring, and acoustic measurements are commonly used to assess motor health. Traditional approaches often rely on Fourier Transform, Park's vector method, Hilbert transform, and wavelet analysis to extract features from measured signals.

Recent studies have applied machine learning models such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), Generative Adversarial Networks (GAN), and gradient boosting models for motor fault detection.[1-3] These models have shown high accuracy in identifying rotor, stator, and bearing faults, even under varying load conditions. However, many works are based on simulated data, which may not fully capture real-world operating conditions. Measurement uncertainty, sensor noise, and environmental variability are rarely considered, potentially limiting the reliability of these diagnostic systems in practice.

Furthermore, functional data analysis techniques, such as Functional Principal Component Analysis (FPCA) and Functional Data Modeling (FDM), have been proposed to reduce dimensionality and improve fault detection efficiency.[4] Despite these advancements, there remains a need for robust systems that combine vibration measurements, machine learning models, and uncertainty assessment to provide accurate and reliable fault diagnosis in real industrial settings.

IV. METHODOLOGY

The methodology for diagnosing faults in induction motors involves systematic procedures for data acquisition, processing, and fault identification. Diagnostic procedures convert measurements of machine parameters and collected data into actionable information about potential faults. The process includes analysis and synthesis of specific physical quantities, enabling short- and long-term evaluations of motor reliability. The main objectives are fault detection, localization, and identification, preferably without intrusive inspections.

The methodology incorporates the following steps:

1. **Data Acquisition:** Vibration signals, electrical parameters, and environmental factors are measured using accelerometers and other sensors installed on the motor. These measurements capture both normal operating conditions and variations caused by potential faults.
2. **Data Processing:** Raw signals are processed to extract meaningful features using frequency-domain analysis, signal filtering, and statistical techniques. Thresholds are established to differentiate between "healthy" and "faulty" conditions, accounting for measurement uncertainty to reduce the probability of diagnostic errors.

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3. **Fault Diagnosis and Classification:** Machine learning models, particularly Artificial Neural Networks (ANNs), are employed to identify patterns corresponding to specific mechanical and electrical faults, including rotor and stator defects, bearing failures, and insulation degradation. Measurement uncertainty is incorporated into the models to provide confidence levels for the predictions.
4. **Maintenance Strategy Integration:** The results of diagnostics are used to inform maintenance actions. The methodology supports reactive, preventive, predictive, and proactive maintenance strategies, with an emphasis on predictive maintenance to minimize downtime and optimize maintenance resources. By monitoring vibration patterns, electrical parameters, and environmental conditions, the system can anticipate failures and prioritize interventions effectively.

Mechanical faults, such as bearing wear, misalignment, and lubrication issues, and electrical faults, such as short circuits, insulation degradation, and overload, are linked to characteristic changes in vibration and current signals. For instance, rotor-related electrical anomalies increase vibrations in the rotor area, whereas stator issues produce vibrations in the stator region, as shown in Fig 1. Environmental factors, such as dust, debris, or poor ventilation, can also exacerbate overheating and accelerate insulation deterioration.

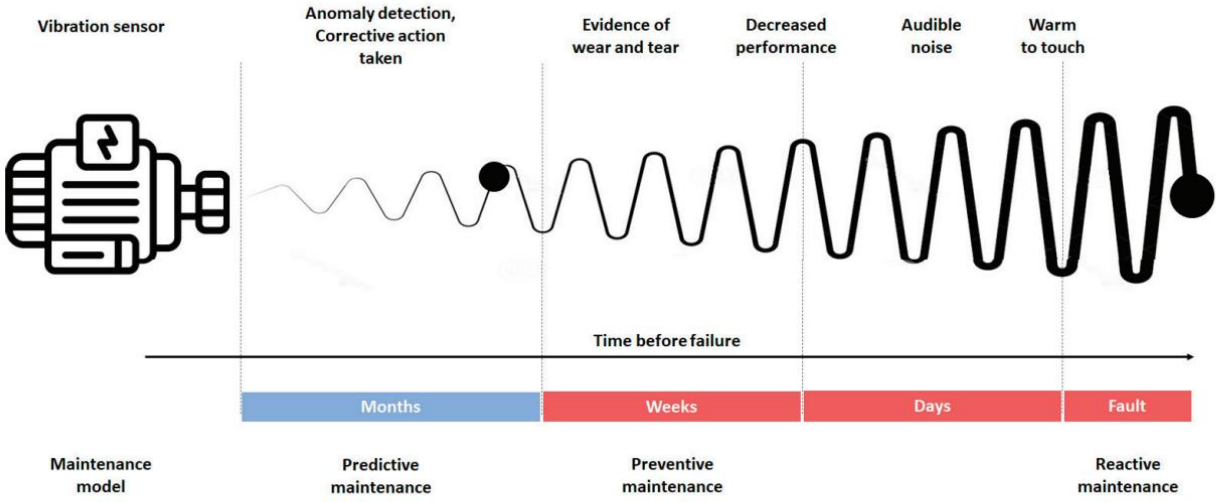

Fig 1. Maintenance models and intervention times.

If the temperature of the windings exceeds the allowable limits, the insulation's service life can be reduced by half. Electrical anomalies create asymmetries in the magnetic flux distribution across the air gap, which in turn alter the electromagnetic force patterns within the motor, affecting its vibration behavior.[5-8] These anomalies also cause variations in the dispersed magnetic flux both inside and outside the machine, making it possible to detect vibrations on the motor casing or at the stator winding heads.

Mechanical faults, such as bearing failures, can result from insufficient lubrication, design flaws, overheating, or misalignment. Ensuring proper power supply quality and the correct operation of protective devices is also critical. In general, effective management of electrical and mechanical faults in induction motors requires regular inspections, preventive maintenance, and the use of specialized sensors to quickly identify and mitigate potential problems. Fig 2 illustrates the frequency of common failures in induction motors.

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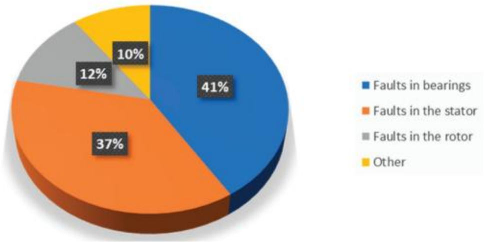

Fig2. Common faults in induction motors.

V. EXPERIMENTAL RESULTS

Experimental tests were performed on four new three-phase asynchronous motors, model BE 90 LA4, manufactured by Bonfiglioli. The motors operate at a frequency of 50 Hz and are characterized by the following specifications: a rated voltage of 230/400 V (Δ/Y), a rated current of 6.1/3.5 A (Δ/Y), and a power output of 1.5 kW. They have a nominal speed of 1430 rpm, a power factor of 0.74, and an efficiency of 82.5% at full load, meeting the IE2 efficiency class according to IEC EN 60034 standards. The motors are equipped with class F insulation and IP55 protection.

The experimental test bench was designed to replicate the real operating conditions of the induction motors. The motors were powered using a Guasch MTL-B2B0060F12IXHF inverter (Guasch, Barcelona, Spain), a compact, ready-to-use unit suitable for motor control and various inverter applications. The power stage includes IGBTs (2× CBI modules) with heat sinks, opto-coupled drivers, output phase current sensors, DC-Link voltage sensors, and internal NTC temperature sensors. Various inverters were tested at the motors' nominal operating point, showing no significant differences in the harmonic content of vibration measurements. The Guasch MTL-B2B0060F12IXHF inverter was selected for its flexible control capabilities, enabling precise regulation and versatile management of motor operating conditions.

Load was applied using a Magtrol HD 815 hysteresis dynamometer (Magtrol, Buffalo, NY, USA) equipped with a Magtrol TM 108 torque and speed transducer. The brake system was controlled through a Magtrol DSP 6001 unit, which simultaneously acquired torque and rotational speed data.

Vibrations from the motors under different operating conditions were measured with a triaxial ICP® accelerometer with a sensitivity of 10 mV/g, a measurement range of ±500 g, and a frequency range of 2–7 kHz. Signals from the accelerometer were conditioned using a 4-channel, line-powered ICP® sensor signal conditioner with selectable gain settings of ×1, ×10, and ×100. Ambient temperature and humidity were monitored using a Fluke 971 Temperature Humidity Meter , while motor temperature was measured with a Fluke 62 Mini Thermometer. Supply voltage and current were recorded using a Yokogawa WT 3000 Wattmeter . Each test condition was repeated five times to minimize random measurement errors.

Although ISO 13373-9:2017 recommends placing accelerometers at strategic locations such as bearings and motor shafts for precise vibration measurement, in this study, the accelerometer was attached to the motor casing using beeswax. This method reduces the sensor bandwidth to approximately 30 kHz, which is sufficient since the harmonic content of the vibrations was found to be mostly below 5 kHz, as illustrated in Figure 4.

For fault diagnosis, the STEVAL-STWINKT1B board was used. This platform features a power-efficient ARM Cortex-M4 processor with a 120 MHz FPU and 2048 kB of flash memory (STM32L4R9), capable of handling the computational requirements of vibration-based fault detection. The board is also equipped with an IIS3DWB MEMS sensor designed for vibration measurement, providing appropriate sensitivity in the critical frequency range for mechanical fault diagnosis (DC to 6 kHz), with user-selectable full-scale options of ±2 g, ±4 g, ±8 g, and ±16 g.

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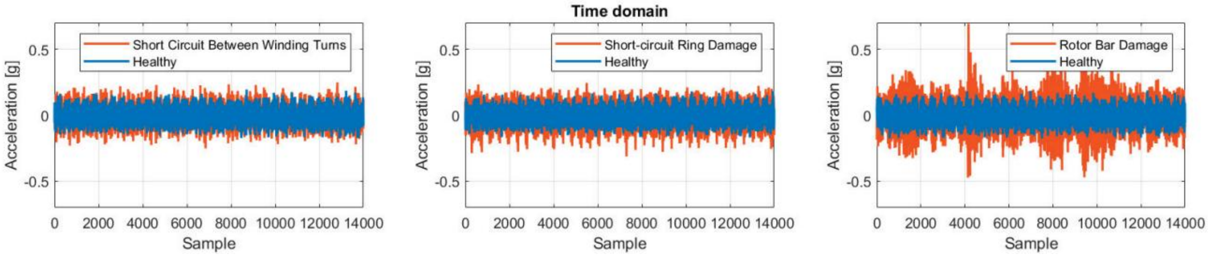

Fig 3: Vibration measurements acquired along with their respective harmonic content.

The dataset, as described in Section 4.1, consists of 66,640 samples and was divided into 37,318 training samples, 9,330 validation samples, and 19,992 test samples. The classification results obtained using the ANN for measurements along the x, y, and z axes are presented, with performance metrics and confusion matrices provided for each axis.

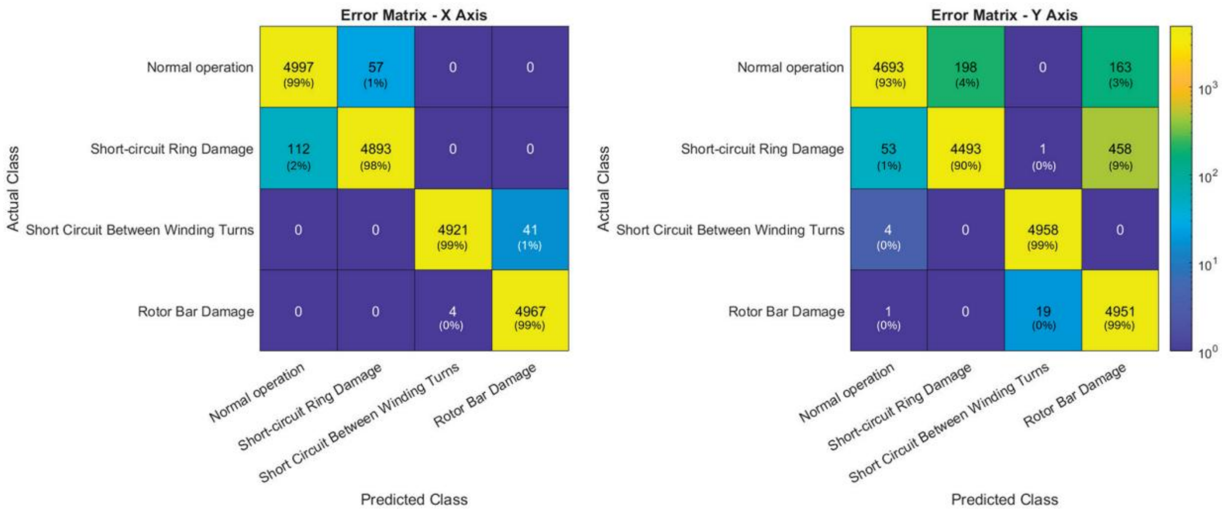

Figure 6. ANN error matrices for measurements recorded along the x-axis (left) and y-axis (right).

Figure 6 illustrates the confusion matrices resulting from ANN training with data collected along the x-axis (left) and y-axis (right).

Table 1 Performance obtained by training and testing the ANN with measurements acquired

Classes	Precision	Recall	F1-Score	Accuracy
Normal Operation	0.99	0.93	0.96	0.93
Short-circuit Ring Damage	0.96	0.90	0.93	0.90
Short Circuit Between Winding Turns	1.00	1.00	1.00	1.00
Rotor Bar Damage	0.89	1.00	0.94	1.00
Overall	**0.96**	**0.96**	**0.96**	**0.96**

Table 1 presents the performance metrics obtained from training and testing the ANN using measurements collected along the x-axis and y-axis, respectively. The metrics include precision, recall, F1-score, and overall accuracy for each axis. To account for the class balance within the dataset, overall metrics were calculated using the macro-average method, which treats all classes equally regardless of their frequency. This approach provides a fair evaluation of the model's performance across all classes, ensuring that less frequent classes are not overshadowed by the more common ones.

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VI. CONCLUSION AND FUTURE WORK

This study presented an ANN-based electrical fault diagnosis system for induction motors using vibration measurements. The system effectively detects and localizes motor faults, reduces downtime, and supports predictive maintenance. Incorporating measurement uncertainty improved the reliability of fault classification, reducing misclassification rates by up to 67%. Results showed high accuracy along the x- and y-axes, while the z-axis was less effective, highlighting the importance of sensor placement.

Unlike previous studies relying on simulated data, this work considered real-world measurement uncertainties, demonstrating a practical approach to improving predictive maintenance. The methodology can be extended to other industrial machinery and ML-based classification systems, enhancing operational reliability and minimizing false alarms. Future studies should address additional uncertainties, such as variations in defect size and geometry, to further improve diagnostic generalization.

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