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Fault Diagnosis of Induction Motors

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Abstract: Bearing failures in electric machinery pose significant challenges and have attracted considerable attention in diagnostic research. The growing use of variable-speed drives across various motor applications has amplified the effects of bearing currents, spurring detailed investigations in both academic and industrial contexts. This paper provides key insights into identifying and addressing bearing-related issues in electrical equipment. It offers an in-depth analysis of damage mechanisms and diagnostic techniques specific to bearing currents in induction motors.

Furthermore, the study presents experimental results from controlled laboratory settings designed to replicate bearing current faults. As advanced technologies are increasingly integrated into manufacturing processes, the importance of preventive maintenance continues to rise. In response, the paper expands its focus to include signal pre-processing techniques to improve fault prediction accuracy by enhancing machine signal clarity.

Recognizing the dynamic nature of industrial standards and the growing demand for predictive maintenance, this study proposes a forward-looking approach to early fault detection. By aiming to boost operational efficiency, reduce downtime, and increase system reliability, the strategies outlined in this paper make a meaningful contribution to the evolving field of predictive maintenance.

Keywords: Induction Motor, Faults of Bearing, Technology

I. LITERATURE SURVEY

In many industries, approximately 90% of machinery relies on induction motors (IM). Research shows that bearing failures account for roughly 40% of the faults identified in AC machines across these sectors. Bearings are intricate components made up of two ring tracks with rolling elements positioned between them. These elements—which may include balls, cylindrical rollers, tapered rollers, needle rollers, or barrel rollers—are housed within a cage that maintains even spacing and minimizes internal impact.

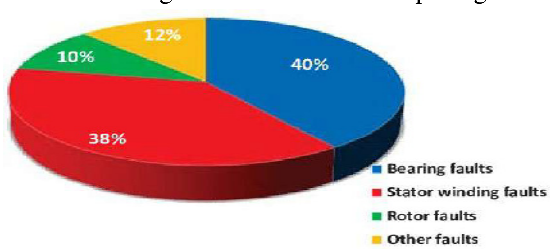


Fig. Percentage-wise Fault of Induction Motor

Bearing signals are inherently non-stationary due to slippage between interacting components, such as rolling elements and raceways. Each rotating part of a bearing generates vibration signals, and all components are vulnerable to damage. Bearing defects are generally categorized into two types: distributed and localized.

Distributed defects include issues such as surface roughness, waviness, misaligned races, and incorrectly sized rolling elements. These are typically caused by design flaws, manufacturing errors, improper assembly, wear, or corrosion.

Localized defects, on the other hand, manifest as cracks, pits, or spalling on the rolling surfaces. These arise mainly from material fatigue, plastic deformation, or brinelling.

Both types of defects lead to increased noise and vibration levels, which can ultimately cause machinery to fail. From a condition monitoring standpoint, localized faults are of greater concern because spalling in races or rolling elements is the most common failure mode in real-world applications. Furthermore, many distributed issues can originate from localized damage.

Bearing health monitoring usually involves two key stages:

1) Feature Extraction – This step involves isolating condition-relevant features from signals using appropriate signal processing methods.
2) Fault Diagnosis – Based on the extracted features, this stage involves decision-making to assess the bearing's health.

Accurate feature extraction is essential, as poor-quality features may lead to false alarms (detecting a problem when none exists) or missed alarms (failing to detect a genuine fault).

There are multiple diagnostic approaches based on the nature of the signals, including:

- Acoustic analysis
- Temperature monitoring
- Lubricant condition assessment
- Electrical current analysis
- Vibration analysis
- Motor current signature analysis
- Sound-based diagnostics

Acoustic Emission (AE) is a prominent technique that detects transient elastic waves generated by the rapid release of energy due to structural changes, such as crack formation and propagation. This makes AE particularly useful for early fault detection in bearings.

Temperature monitoring is another effective method. Excessive heat often indicates bearing stress or failure. Therefore, keeping the temperature of bearing housings and lubricants within operational limits is critical. Specialized sensors can also detect metallic debris in lubricants, helping pinpoint the location and nature of wear-related issues.

Motor current analysis offers another layer of diagnostics. Mechanical changes in the machine often affect the electrical signal, allowing faults to be detected using proper signal processing techniques.

Vibration analysis remains the most widely used approach in industry. Bearings emit vibrations due to both structural defects and dynamic forces such as Hertzian contact deformation and radial clearances. Accurate diagnostics rely heavily on the interpretation of vibration frequency patterns.

Various techniques have been developed and studied for bearing fault detection, including:

- Vibration Signal Analysis
- Thermal Imaging
- Motor Voltage and Current Signature Analysis

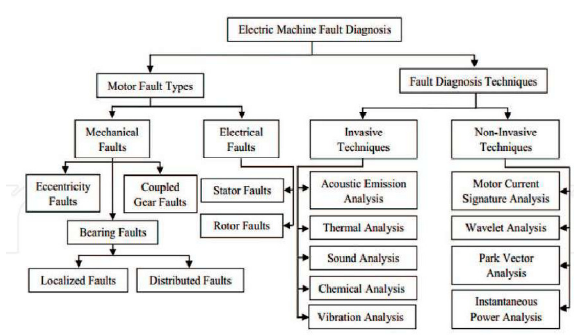
Advanced signal processing techniques such as:

- Fourier Transform (FT)
- Wavelet Transform (WT)
- Empirical Mode Decomposition (EMD)

are often employed—sometimes in combination—for enhanced feature extraction and diagnosis.

Given the increasing demand for precision and speed, real-time monitoring of roller bearings has become critical. Vibrations in the bearing cage can be captured by monitoring changes in the resonance frequency of an inductive coil coupled with a temperature-sensitive capacitor. An interrogator coil, placed near the bearing cage, detects these changes by measuring alterations in coupling and excitation frequency, which reflect bearing cage vibrations.

In the study presented, the author investigates bearing cage temperatures at varying RPMs. Vibration frequencies at each speed are recorded and compared to theoretical values derived from standard bearing frequency equations. A strong correlation is found between the experimental and calculated values, with an average deviation of just 2.8%. This includes key frequencies such as the Ball Spin Frequency, Fundamental Train Frequency, and Ball Pass Outer Race Frequency.



The structure representing various motor faults and fault diagnosis techniques.

Fig. Electric Machine Fault Diagnosis

II. INTRODUCTION

A. *The Significance of the Induction Motor:*

Induction motors are a fundamental component in industrial environments, where they power a diverse range of equipment such as pumps, compressors, conveyors, and fans. Their reliability is essential for maintaining operational efficiency and minimizing costly disruptions. The widespread use of induction motors across various industries is well justified by their robust construction, low maintenance requirements, and high efficiency. These attributes make them especially valuable in applications such as industrial automation, household appliances, and commercial systems, where consistent performance under different operating conditions is crucial. Their simple and durable design, combined with cost-effectiveness and the ability to operate directly from AC power without the need for complex control systems, enhances their appeal across a broad spectrum of uses. Additionally, energy-efficient models contribute to environmental sustainability, reinforcing the important role induction motors play in advancing modern electrical and mechanical systems.

B. *The Difficulty of Fault Diagnosis:*

Conventional fault diagnosis methods often rely on manual inspections and reactive repairs, which can lead to delays and the risk of further damage. Prompt detection and evaluation of issues are essential to prevent serious failures and ensure optimal system performance. The challenge of diagnosing faults is amplified by the increasing complexity of modern systems, where numerous components interact and many faults present in subtle, non-obvious ways. Frequently, the symptoms observed do not clearly indicate the underlying causes, necessitating thorough testing and analysis to accurately identify the problem. As technological systems continue to advance—particularly in sectors such as electronics, automotive engineering, and industrial automation—the need for sophisticated diagnostic tools and highly trained professionals becomes increasingly critical. This evolution underscores the importance of adopting advanced diagnostic technologies and developing specialized expertise to maintain reliability and efficiency in complex systems.

III. CAUSES/TYPES OFFAULTS OF BEARING INANINDUCTIONMOTOR

A. *Improper Lubrication and Fretting*

Inadequate lubrication may result in overheating and significant wear on bearings. Insufficient lubrication can also create fretting, which occurs when two unlike and dry surfaces rub against each other, leading to corrosion.

Fig Improper Lubrication and Fretting

B. *Corrosion and Contamination*

Substances like moisture, grit, soil, and chemicals can create numerous issues within bearing assemblies. As an example, they may wear down bearing surfaces or compromise the lubricant, both of which can result in early breakdown.

Fig. Corrosion and Contamination

C. Misalignment
Inconsistencies between the shaft and the bearing housing may arise from dirty parts, warped shafts, or misaligned locking nuts and shafts. Such issues can lead to significant vibrations and imbalanced load distribution, ultimately resulting in breakdowns.

D. Moisture
Wet or outdoor conditions may cause dampness to infiltrate your bearings. This establishes the perfect conditions for the formation of rust and corrosion, which can result in bearing malfunction.

E. High Temperatures
It's important to refer to your motor's operating guide for lubrication requirements and working temperature. Incorrect lubricant can bleed in even mild temperatures, resulting in a variety of lubricant-related problems. High temperatures can also decrease bearing hardness, leading to cracks.

Fig. High Temperature

F. Mistakes in Installation
Bearing malfunction can result from flawed installation and setup procedures. Typical errors during installation involve imbalance, faulty mounting, and misalignment or excessive shaft deviation.

G. Electrical Damage
When electrical currents flow through the bearing, it can result in electrical wear or arcing. This phenomenon can trigger a range of problems, such as the breakdown of lubricants, pitting harm to the rolling components and raceways, along with early bearing failure.

IV. METHODOLOGY
The proposed approach begins by capturing signals from a current sensor installed in one phase of the induction motor. These signals are then processed through Instrumentation Amplifiers and recorded using a Data Acquisition System, which enables efficient handling and transmission of the data to a computer for further organization and storage. The method proceeds with the measurement of current signals under both normal and fault conditions, followed by their characterization. This characterization involves computing the Cumulative Distribution Function (CDF) for each signal. The obtained CDFs are then compared to baseline CDFs corresponding to each motor state to determine the maximum deviation between them. Using this deviation, a reference p-value is calculated to evaluate whether the signal is likely associated with either the normal or fault condition. This assessment is conducted with a confidence level of $\alpha = 0.05$, allowing for statistically supported fault identification and condition monitoring of the motor.

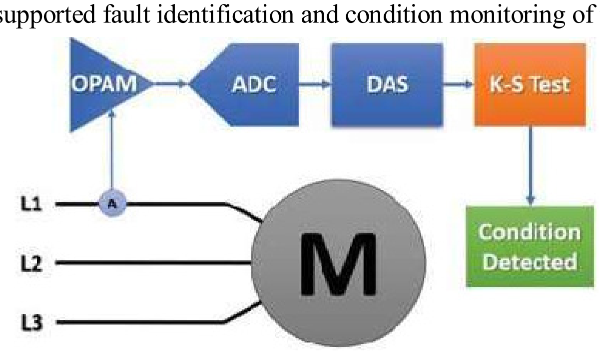


Fig. Block Diagram of Induction Motor

H. Representation

The bearing block can represent various types of bearings, such as ball bearings, roller bearings, or journal bearings, each serving the purpose of restricting the lateral movement of a shaft while allowing it to rotate along its axial axis within the bearing. In addition to supporting rotational motion, these bearings also introduce friction, which contributes to the overall torque within the mechanical system. This bearing friction can be modeled within a mechanical rotational framework either by connecting the bearing solely to port B or by integrating it with other system components using both ports B and F, depending on the desired configuration and level of complexity in the simulation or design.

A load, denoted as F, can be applied to the bearing and may be either constant or variable in nature. When the Radial load specification is set to Constant, the system utilizes the value defined in the Load on bearing parameter to represent the applied force. Conversely, if the Radial load specification is set to Variable, the block receives a physical signal input through the Load port. This input is then processed dynamically, allowing the bearing model to respond to changing load conditions during simulation or operation, enabling a more flexible and realistic representation of real-world scenarios.

$$F = (F_{2\,input} + F_{2\,Thr})$$

$$F_{2\,input} = \text{Load Port of Physical Signal}$$

$$F_{2\,Thr} = \text{Force Thresold}$$

The block calculates the torque due to friction such that

$T = \mu \cdot F \cdot r$,
μ = coefficient of friction.
Ff = friction force acting on the bearing.
r = **Bearing radius** parameter.

The method by which the block computes μ is influenced by the specific kind of bearing you are modeling.

V. MONITORING TECHNIQUES

A. Infrared Thermography

Mechanical issues are among the most frequently encountered failures in industrial induction motors, encompassing a broad range of problems such as bearing malfunctions, rotor imbalances, shaft misalignments, load-related discrepancies, gearbox faults, and transmission system defects. In industrial environments, vibration data analysis is the most commonly used method for diagnosing such mechanical problems. However, this technique has several limitations. It requires the installation of specialized vibration sensors, which may not be feasible for certain types of motors, including those that are enclosed or submersible. Additionally, vibration analysis can struggle to accurately differentiate between mechanical and electrical faults, or to distinguish motor-specific issues from those related to the load or transmission system. It may also fail to identify phenomena unrelated to actual faults.

Infrared thermography has emerged as a powerful alternative for detecting mechanical faults. Widely used for maintaining electrical equipment, this method captures infrared radiation emitted by objects, converts it into temperature data, and generates a detailed thermal image. One of its key advantages is the ability to provide high-resolution temperature mapping without requiring physical contact. This makes it especially useful for large induction motors, where it has proven effective in identifying bearing problems and cooling inefficiencies.

The types of mechanical faults that infrared thermography can detect include shaft misalignments, transmission system issues such as defective belts and couplings, and bearing failures that manifest through heat emissions—often due to lubrication problems or physical damage. For example, shaft misalignment typically results in localized temperature increases around the coupling area, which are easily visible in thermal images. Likewise, faults in transmission systems—like improperly tensioned or misaligned belts—can generate excessive heat, leading to uneven wear, shortened belt life, and potential mechanical failure. Over-tensioned belts may stretch and weaken, and even well-lubricated bearings can overheat under such conditions.

Infrared thermography is also effective in detecting a range of bearing defects. These include primary issues like wear, indentations, smearing, surface distress, and corrosion, as well as secondary faults such as flaking, cracks, and damage to the bearing cage.

By identifying these thermal anomalies, infrared thermography provides a reliable, non-invasive method for early detection and prevention of mechanical failures in industrial motors.

B. Sound Analysis

Identifying faults through sound is often an intuitive task for humans, even without technical expertise, as unusual noises can be clear indicators of mechanical problems. In industrial environments, machine operators frequently rely on abnormal sound patterns to detect equipment malfunctions. This ability is crucial, as a failure in a key component can lead to the shutdown of an entire facility.

In this context, sound analysis of electric motors is a valuable approach for fault detection. Sound, continuously produced during motor operation, acts as a key indicator of machine health. As faults develop, noise levels typically increase, making audio monitoring an effective diagnostic tool. Analyzing the sound spectrum—particularly harmonic amplitudes at various frequencies—can help identify issues such as bearing defects. Friction is often the primary source of high-frequency vibrations in bearings, and when faults occur, disruptions in the lubrication layer lead to shock pulses. These high-frequency sound signals are especially useful because they are largely isolated from noise generated by other components, making it easier to pinpoint the faulty bearing.

Bearing defects can result from improper installation, misuse, or overloading, and are typically classified into two categories: distributed defects (e.g., surface roughness, waviness, and race misalignment) and localized defects. To detect these faults, various sound detection instruments such as microphones, sound level meters, and electronic recorders are employed. Two widely used techniques for analyzing sound data are the MUSIC (Multiple Signal Classification) method and the Welch method.

The MUSIC algorithm applies Schmidt's eigen space analysis to estimate the pseudo spectrum from a signal or its correlation matrix. It is highly effective at identifying frequency components in signals composed of multiple sinusoids mixed with white Gaussian noise. Meanwhile, the Welch method estimates power spectra by dividing a time-domain signal into overlapping segments, computing the periodogram for each, and then averaging the results. This process reduces the influence of noise and allows for a clearer frequency analysis.

In the experiment, sound measurements were initially taken from an induction motor with a healthy rotor, followed by measurements using the same motor but with a faulty bearing. The analysis was carried out using MATLAB's Signal Processing Toolbox, along with the Data Acquisition Toolbox to collect sensor data and interface with external devices. Sound data was recorded using a laptop's built-in sound card, with a microphone and speaker serving as input and output devices.

The goal was to evaluate the motor's condition by applying WELCH and MUSIC analyses to its acoustic signals. These techniques proved effective in identifying faults, supporting the broader premise that sound-based diagnostic methods can be valuable tools for detecting both mechanical and electrical problems in motors. Ultimately, the study explored the feasibility of automating fault detection through sound analysis, aligning with existing research that supports the practicality of this approach for industrial applications.

C. Vibration Analysis

Surface irregularities and waviness in bearing components are typically a result of the manufacturing process, whereas discrete defects are linked to damage on the rolling surfaces caused by factors such as improper assembly, contamination, operational stresses, poor installation practices, or inadequate maintenance. Although these defects can be extremely small and difficult to detect, they can have a substantial impact—particularly on vibration-sensitive equipment—and can significantly reduce the bearing's operational lifespan. These flaws may appear in various forms, including indentations, longitudinal and transverse scratches, pitting, or the presence of foreign particles in the lubricant.

To detect such defects, bearing manufacturers often conduct basic vibration tests on finished products. However, the effectiveness of these tests is often limited by the bearing's size and type. For example, a typical vibration assessment used in quality control is shown in the accompanying figure.

In contrast to a bearing in good condition, localized damage—such as that occurring on the outer race—produces a distinct, impulsive vibration pattern. This pattern is characterized by a high peak-to-RMS (Root Mean Square) ratio, clearly indicating the presence of damage.

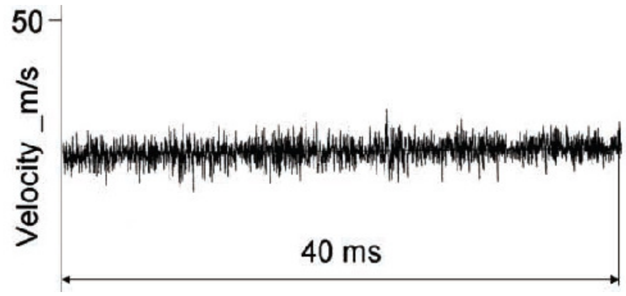


Fig. Good bearing signals

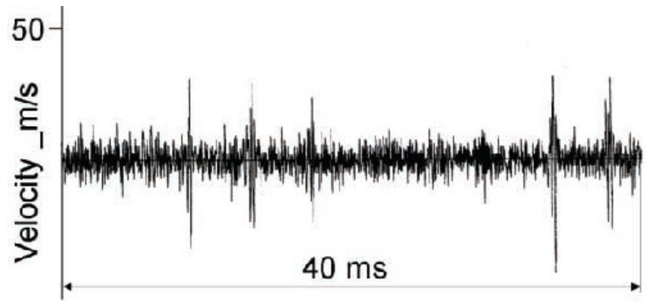


Fig. Fault bearing signals

In situations where numerous faults are present, distinct peaks are less pronounced; however, the RMS vibration measurement is significantly elevated compared to that typically found in a properly functioning bearing.

Parameter

$$f_{bpfo} = \left[\frac{n_b f}{2}\left(1-\frac{d}{D}\cos\theta\right)\right] \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_} (1)$$

$$f_{bpfi} = \left[\frac{n_b f}{2}\left(1+\frac{d}{D}\cos\theta\right)\right] \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_} (2)$$

$$f_{rf} = \left[\frac{Df}{d}\left(1-\left(\frac{d^2}{D^2}cos^2\theta\right)\right)\right] \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_} (3)$$

$$f_{cf} = \left[\frac{f}{2}\left(1-\frac{d}{D}\cos\theta\right)\right] \text{\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_} (4)$$

Example

Given Data:

n = no of balls = 6

d = ball diameter = 08mm

D = Pitch diameter = 40mm

θ = Contact angle = cos θ = 1

fr = Shaft Speed = 1800 RPM = 30 Hz

In equation (1)

$$f_{bpfo} = \left[\frac{6\times 30}{2}\left(1-\frac{8}{40}\cos 1\right)\right]$$

$f_{bpfo} = 72\ Hz$________Ball Outer Race Pass Frequency

In equation (2)

$$f_{bpfi} = \left[\frac{6\times 30}{2}\left(1+\frac{8}{40}\cos 1\right)\right]$$

$f_{bpfi} = 108\ Hz$________Ball Inner Race Frequency

In equation (3)

$$f_{rf} = \left[\frac{40}{8}\left(1-\left(\frac{8^2}{40^2}cos^2 1\right)\right)\right]$$

$f_{rf} = 4.8\ Hz$___________Ball Spin Frequency

In equation (4)

$$f_{cf} = \left[\frac{30}{2}\left(1-\frac{6}{40}\cos 1\right)\right]$$

$f_{cf} = 12.6\ Hz$______Fundamental Train Frequency

D. MCSA and Stator Current

Electrical machines are nearly universal in modern industrial environments, with induction motors being among the most commonly used drive systems. Their simple and robust design, however, makes the motor bearings particularly prone to damage. Studies show that approximately 40% of motor failures are caused by bearing issues. Detecting these faults involves capturing a clear signal and analyzing it to identify the source of the problem. When defects occur on the inner or outer race of a bearing, each time a rolling element passes over the damaged area, it generates a disturbance. These disturbances appear as a nearly periodic series of impulses, which vary depending on the bearing's geometry and the specific location of the defect. They can also trigger resonances within the bearing and the broader machine structure.

These impulses change in amplitude as the faulted area moves through the load zone and can be detected using appropriate sensors. The characteristics of these impulses depend on several factors, including the fault's location (inner race, outer race, or cage), the bearing dimensions, and the shaft speed (fr). From these signals, key bearing fault frequencies can be determined, such as the Ball Pass Frequency of the Outer Race (BPFO), Ball Pass Frequency of the Inner Race (BPFI), Fundamental Train Frequency (FTF), which relates to the rotation of the bearing cage, and the Ball Spin Frequency (BSF).

Motor Current Signature Analysis (MCSA) is a widely adopted method for diagnosing faults in induction motors because it can detect both electrical and mechanical issues. MCSA involves spectral analysis of the stator current, typically measured from one of the three supply phases. When a bearing fault is present, it causes irregularities in the motor's inductance due to uneven rotation, generating modulations in the stator current. These modulations appear at characteristic bearing frequencies (fC) such as BPFO and BPFI and are reflected in the frequency spectrum as sidebands, defined by the equation:

$fE = fs \pm k \cdot fC$,

where fE is the frequency component related to the fault, fs is the supply frequency, and k is an integer harmonic number (1, 2, 3, …).

It's important to consider that rotor inertia and stator winding inductance introduce an electromechanical filtering effect, which primarily allows low-frequency components to pass through to the stator current. An alternative approach to fault analysis is to simulate how a localized bearing defect influences stator current through changes in the air gap, known as air gap eccentricity. The resulting current spectrum is affected not only by fault-induced modulations but also by harmonic components typical of standard magnetic activity in induction motors.

One of the main challenges in implementing MCSA is accurately identifying and isolating the fault-related frequencies from the surrounding noise and other closely spaced spectral components, which often overlap. However, with high-resolution frequency and amplitude analysis and the use of advanced signal processing techniques, mechanical faults in induction motors can be effectively identified.

VI. RESULTS

Comparison Between Infrared Thermography, Sound Analysis, Vibration Analysis, MCSA, and Stator Current.

Technique	Primary Focus	Typical Use Cases	Contact/Non-contact	Real-time Monitoring	Fault Detection Types
Infrared Thermography	Surface temperature	Electrical hot spots, mechanical overheating	Non-contact	Yes	Overheating, insulation degradation
Sound Analysis	Acoustic emissions/sound	Bearing faults, cavitation, steam/gas	Non-contact (usually)	Yes	Leaks, mechanical

	patterns	leaks			defects
Vibration Analysis	Mechanical movement (vibration)	Unbalance, misalignment, bearing/wear issues	Contact (with sensors)	Yes	Mechanical faults, resonance issues
MCSA	Electrical current signal patterns	Rotor faults (broken bars), eccentricity, load issues	Non-contact (at motor leads)	Yes	Rotor bar faults, eccentricity
Stator Current Analysis	Current signature in stator windings	Similar to MCSA but focused on the stator side	Non-contact (at stator terminals)	Yes	Stator winding faults, harmonics

Table. Overview Table

Criteria	Infrared Thermography	Sound Analysis	Vibration Analysis	MCSA	Stator Current Analysis
Measurement Principle	Captures IR radiation (heat)	Analyses frequency/patterns of emitted sounds	Measures vibrations using accelerometers	Analyses motor current for fault-related patterns	Similar to MCSA, with a focus on the stator waveform
Type of Faults Detected	Overheating, insulation, and mechanical wear	Valve leaks, bearing cracks, and steam leaks	Shaft misalignment, bearing defects, looseness	Broken rotor bars, air-gap eccentricity	Winding faults, inter-turn shorts, harmonic issues
Tools Used	IR camera/scanner	Ultrasonic sensors, microphones	Accelerometers, vibration meters	Current sensors, data acquisition devices	Current transformers, oscilloscopes, and FFT analysers
Advantages	Fast scan, non-intrusive, good for electrical faults	Detects invisible issues (leaks, cracks)	Highly accurate for rotating equipment	No need for physical access to moving parts	Good for stator-related fault detection
Limitations	Surface only, influenced by the environment	Susceptible to background noise	Requires installation of sensors	Can be affected by load variations	Complex interpretation, sensitive to noise
Skill Required	Medium (interpreting images)	High (sound pattern interpretation)	High (signal processing and analysis)	High (requires signal processing knowledge)	High (requires electrical expertise)

Table. Detailed Comparison

VII. DISCUSSION

A three-phase, 3 kW induction motor was utilized in this research. Two fault scenarios were examined.

In Scenario 1, static eccentricity, fractured rotor bars, and outer-race bearing issues were applied at the same time. In Scenario 2, static eccentricity, fractured rotor bars, and inner-race bearing problems were put into action. During each experimental condition, both stator current and vibration data were captured.

Static eccentricity, broken rotor bars and outer-race bearing faults

Current Signals Analysis (Case 1)

The rates of specific harmonic elements linked to static eccentricity $fecn^{\circ}$ can be determined through

$fecn = fs \pm\ k\ .fr$ ____________________________ (1)

where,
fs - fundamental component
k - 1, 2, 3 and
fr - rotor (shaft) frequency.
The rates of specific harmonic elements associated with damaged rotor bars ($fbrb$) are detailed below.
$fbr\ b = (1 \pm 2ks) \cdot fs$______________________(2)
Where
s - the slip
Within the envelope spectrum, the distinct harmonic element associated with damaged rotor bars is determined by using $fs - fbrb$
The rates of distinctive harmonic elements related to bearing defects in the stator current signals are determined by utilizing
$f\text{bear} = |\, fs \pm k \cdot \text{BPFO}|$_____________________ (3)
where $k = 2, 3, 4$ and
BPFO - Ball Pass Frequency Outer (Outer-Race Failing Frequency).
The occurrence rate of distinct harmonic elements associated with the outer-race bearing defect is determined by employing
$\text{BPFO} = \frac{N_b}{2}.f.1 - \frac{B_d}{P_d}.\cos\varphi$_______________ (4)
where
Nb - quantity of balls
Bd - diameter of the balls
Pd - pitch diameter
φ - angle of contact for the balls
The details of the bearing (6206.C3) employed in the tests are presented in Table 7.2a.

Bearing number	$N_b(Qty)$	B_d(mm)	P_d(mm)	φ (°)
6206	9	9.525	46	0

Table. Data sheet of the 6206 bearing

The rate at which distinctive harmonic elements of the outer race bearing defect is determined in

$\text{BPFO} = \frac{9}{2}.f_r.1 - \frac{9.525}{46}.\cos 0 = 3.57.f$____________________ (5)
The table displays the relevant harmonic features associated with the current spectra of faults in outer-race bearings.

Load level (%)	Ball pass frequency of outer-race (Hz)	2nd current spectra harmonic (Hz)	3rd current spectra harmonic (Hz)	4th current spectra harmonic (Hz)
25	177.2	304	482	659
50	175	300	475	650
75	172.9	296	469	642
100	170.6	291	462	632

Table.Present spectra of distinctive harmonic elements related to outer-race bearing issues.

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The findings from the suggested technique implemented on the existing signals for Case 1 are displayed in Table and illustrated in Fig.

Load level (%)	f_r (Hz)	Broken rotor bars harmonic frequency (Hz)	1st harmonic component of static eccentricity (Hz)	Outer-race bearing fault 2nd harmonic component (Hz)
25	49.5	0.954	99.5	304
50	48.9	2.193	98.95	300
75	48.3	3.386	98.56	296
100	47.7	4.721	97.22	291

Table. The occurrence rates of distinct harmonic elements in the current evaluation

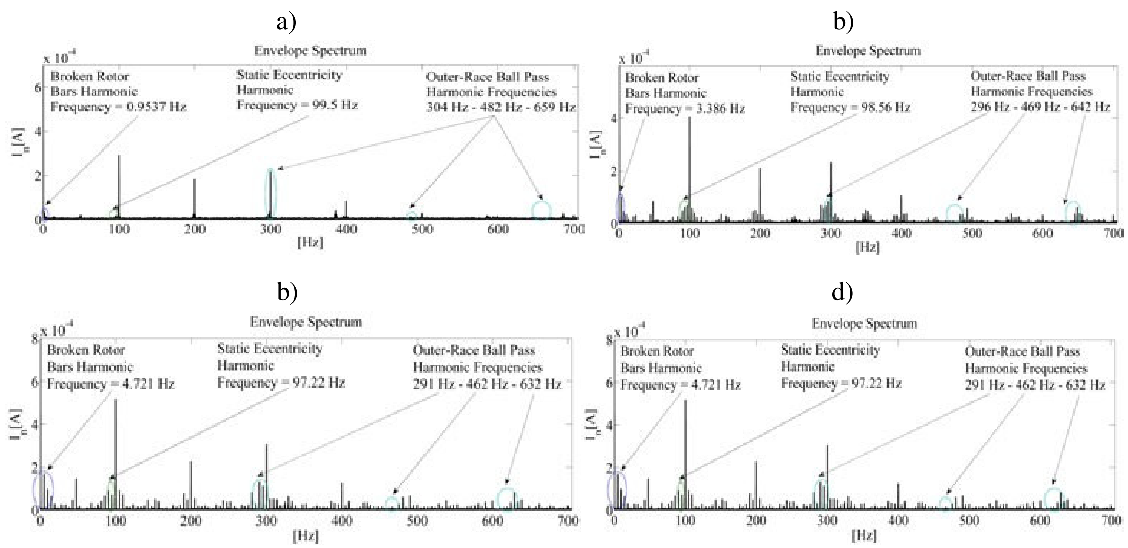

Fig. Characteristic harmonic components of current signal under a) 25% load, b) 50% load, c) 75% load, d) 100% load level of the induction motor.

In all diagrams, In indicates the magnitudes of normalized stator current signals. When employing the FFT technique, the distinct harmonic elements emerge in pairs as sidebands alongside the primary component. In contrast, the suggested approach identifies these distinct harmonic elements without needing to consider the primary component, particularly when various faults occur simultaneously. The subtle characteristic harmonic elements associated with damaged rotor bars shift within the 0–10 Hz range in the envelope spectrum. Thus, the suggested technique presents an effective method for addressing the challenges posed by overshadowing in prominent harmonic elements, as illustrated in Figure 7.2. Furthermore, the characteristic harmonic elements resulting from static eccentricity and outer-race bearing defects are effectively identified using the proposed method.

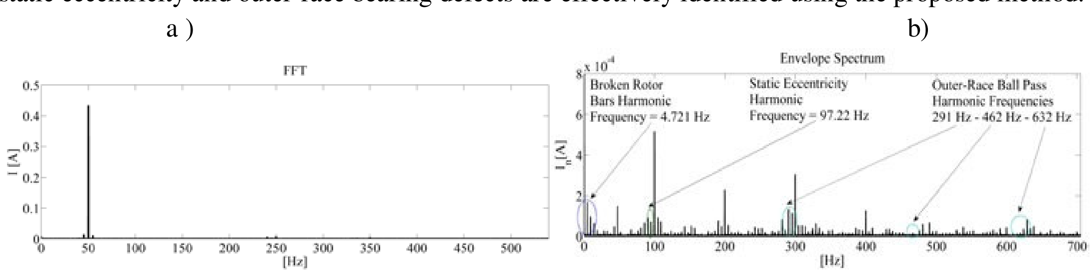

Fig. Analysis of the stator current signal at 100% load level of the induction motor using a) FFT method and b) Hilbert envelope analysis.

A.   Vibration Signals Analysis

The static eccentricity fault of the induction motor is detected by comparing the amplitudes of kfr characteristic harmonic components [33]. If the amplitude of 2 fr is greater than or equal to 1.5 fr, the static eccentricity fault is present.

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Traditional approaches determine the frequencies of specific harmonic elements related to fractured rotor bars ($fbrb$) as illustrated in (6). In contrast, Hilbert envelope examination emphasizes the $2ksfs$ harmonic elements.

$fbrb = fr \pm 2ksfs$____________________ (6)

The rate of the distinct harmonic elements related to the outer-race bearing defect is determined as shown in (7)

BPFO = $\frac{9}{2}.f_r.1-\frac{9.525}{46}.\cos 0 = 3.57.f$ ____________________ (7)

The outcomes of the suggested technique used on the vibration data for Scenario 1 are shown in Table 7 and Figure 7.

Loadlevel(%)	f_r (Hz)	Amplitude (2f_r)Amplitude(f_r)	Ballpassharmonicfrequency of theouter-race(Hz)	Broken rotor barsharmonicfrequency(Hz)
25	49.5	1.98	177.2	0.954
50	48.9	1.54	175.0	2.098
75	48.3	1.52	172.9	3.580
100	47.7	1.71	170.6	4.864

Table. The rates of distinct harmonic elements observed in vibration assessment

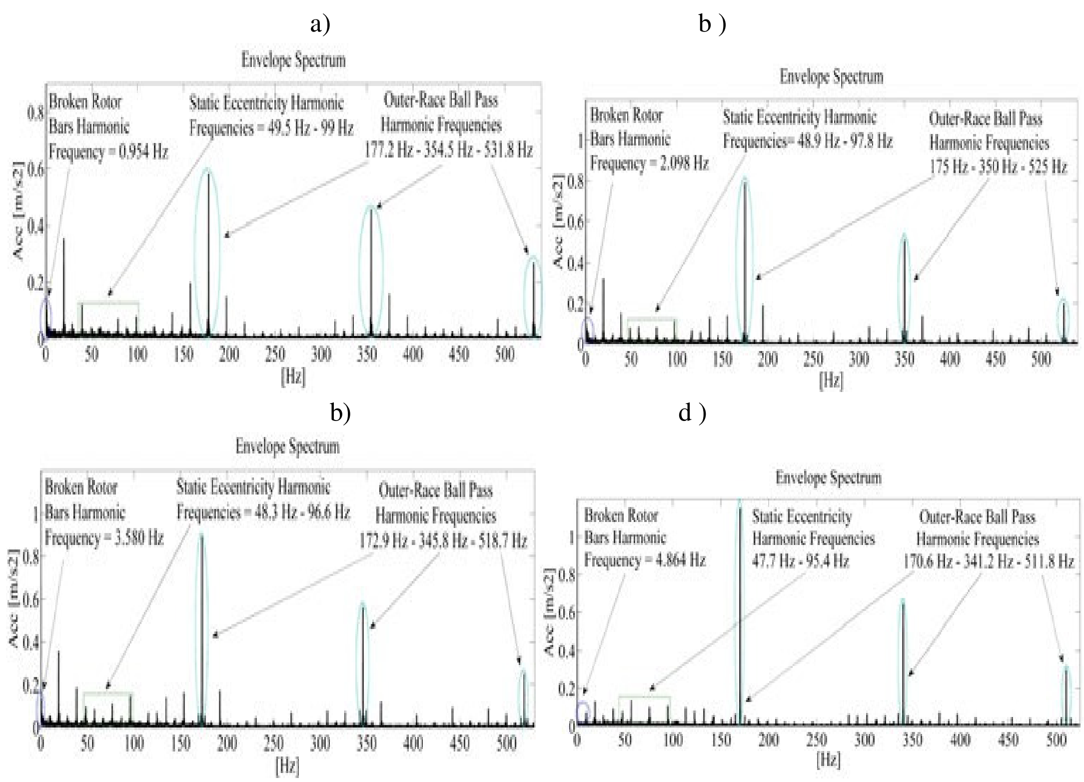

Fig. 7.2.1.2.a. Characteristic harmonic components of vibration signal under a) 25% load, b) 50% load, c) 75% load, d) 100% load level of the induction motor.

The figure illustrates that the suggested approach can identify distinct harmonic elements in vibration signals stemming from simultaneous faults under full load conditions just as efficiently as the FFT technique. The distinctive harmonic elements linked to static eccentricity and outer-race bearing defects are identified effectively, particularly at higher amplitudes when assessed against the FFT outcomes. Given that the harmonic elements associated with damaged rotor bars are moved into the 0 – 10 Hz frequency range, the proposed technique provides a viable resolution for challenges related to overshadowing within predominant harmonic elements, as shown in Fig.

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a) b)

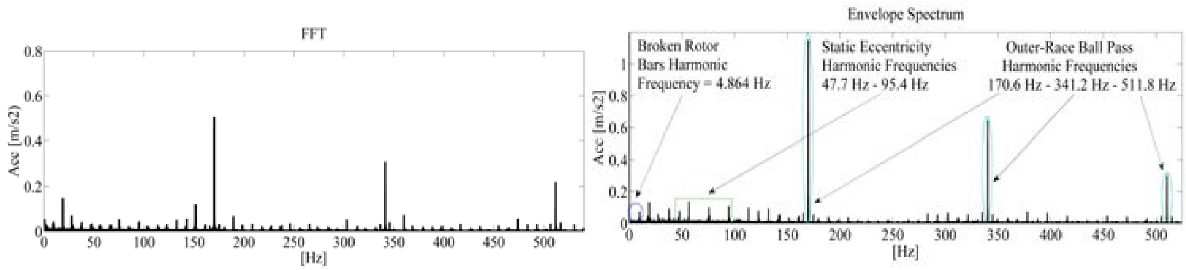

Fig. 7.2.1.2.b. Analysis of vibration signal at 100% load level of the induction motor using a) FFT method and b) Hilbert envelope analysis.

VIII. FUTURE SCOPE

Despite extensive research efforts in fault detection, the early identification and severity assessment of faults in induction machines (IMs) continues to present significant challenges. Most existing studies have focused on detecting faults during the machine's steady-state operation. As a result, investigating IM performance under varying operational conditions has become a natural and necessary next step. With the increasing use of inverters in industrial applications, there is also a growing need to develop advanced methods that can detect early-stage faults in inverter-driven IMs, particularly during transient operating states.

Although several techniques have been suggested to distinguish between load-induced oscillations and bearing race–ball (BRB) fault signals, the reliability of these methods in early fault detection under such external disturbances has yet to be fully validated. Both electrical signals (such as current) and mechanical signals (such as vibration) have been used in diagnostics, but the effectiveness of incorporating additional monitoring inputs remains an open area for further research.

To ensure dependable and accurate fault detection, it is crucial to account for a variety of real-world factors, including the presence of multiple simultaneous faults, typical wear and tear, and measurement inaccuracies commonly encountered in industrial environments. Recent trends highlight a growing interest in knowledge-based (KB) approaches, which—when integrated with advanced signal processing—offer promising new possibilities. These hybrid methods could significantly improve the accuracy and reliability of diagnostic systems.

There is also an urgent need for the development of new metrics to evaluate fault severity and extract meaningful diagnostic features, which would enhance fault classification and help estimate the remaining useful life of key components. Future methodologies must be capable of filtering out external noise while accurately quantifying the distinctive features of faults. Moreover, new approaches should consolidate the strengths of current detection techniques by offering reliable, low-complexity, portable, and online-capable solutions that can detect both individual and combined faults across a wide range of operating conditions.

IX. CONCLUTION

Fault detection in induction motors remains a major challenge for researchers and engineers, particularly in the area of motor current signature analysis, which continues to be a focal point of ongoing investigation. Most existing studies have concentrated on induction motors operating under constant speed conditions. In response to the growing complexity of modern motor systems, efforts are increasingly directed toward developing artificial intelligence-based diagnostic tools that leverage fuzzy logic, neural networks, and genetic algorithms. Additionally, the use of digital signal processors (DSPs) has shown promise in enhancing monitoring and diagnostic capabilities. However, there is still a significant gap when it comes to effectively diagnosing faults in induction motors driven by variable speed systems.

Recent research has primarily been based on experimental data obtained from laboratory tests using small-scale induction motors. While these studies offer valuable insights, applying the same diagnostic techniques to large industrial motors operating under real-world conditions introduces additional complexities. Nevertheless, advancements in fault detection are steadily progressing, and in the near future, diagnostic accuracy is expected to improve significantly—potentially paving the way for fault-tolerant drive systems.

This review highlights the latest developments in early fault detection for induction motors, categorizing them into two key operational modes: steady-state and transient-state. The majority of current research focuses on steady-state analysis, where fault severity assessment techniques demonstrate a high level of precision.

However, challenges such as diagnostic errors and limitations in accuracy still persist. The study also examines various algorithms that utilize different types of monitoring signals, each offering unique characteristics that contribute to fault identification.

Based on the literature, heuristic methods—often combined with advanced signal processing techniques—emerge as the most widely used strategies for detecting early-stage faults. These approaches are valued for their adaptability but are often limited by high computational requirements and the need to process large datasets. Despite significant research in this area, only a small fraction of studies address transient conditions, and even fewer explore fault detection in inverter-fed induction motors during such states. In terms of fault types, much of the existing work centers on the detection of partially broken rotor bars, indicating a need for broader investigation into other fault categories.

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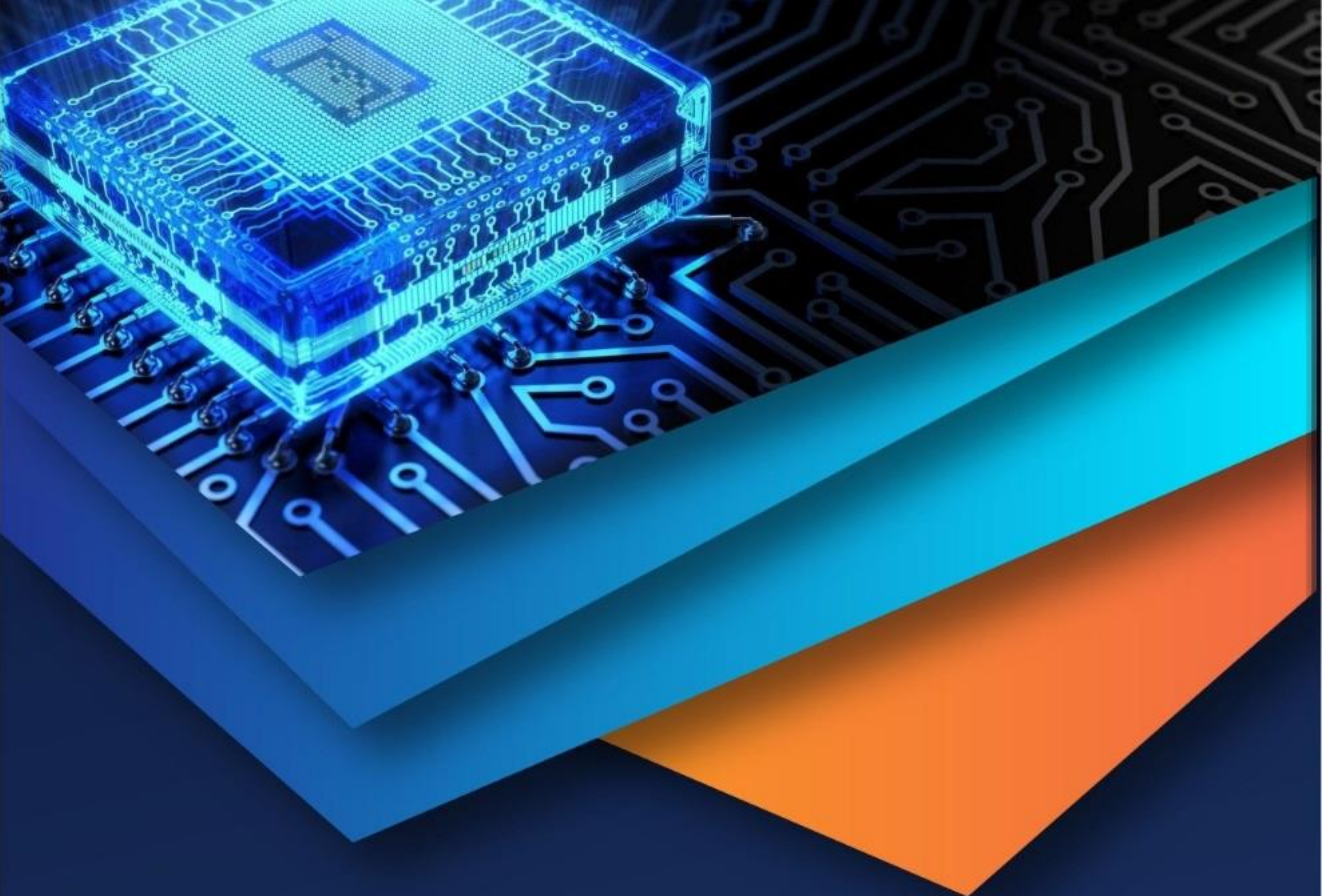

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