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Sensors Applied to Bearing Fault Detection in Three-Phase Induction Motors: A Review†

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Abstract: TIMs are widely applied in industries. Therefore, there is a need to reduce the operational and maintenance costs since their stoppages can impair production lines and lead to financial losses. Among all the TIM components, bearings are crucial in the machine operation once they couple rotor to the motor frame. Also, they are constantly subjected to friction and mechanical wearing. Consequently, they represent around 41% of the motor fault, according to IEEE. In this context, several studies have sought to develop monitoring systems based on different types of sensors. Therefore, considering the high demand, this article aims to present the state of the art of the past five years concerning the sensing techniques based on current, vibration, and infra-red analysis, which are characterized as promising tools to perform bearing fault detection. The current and vibration analysis are powerful tools to assess damages in the inner race, outer race, cages, and rolling elements of the bearings. These sensing techniques use current sensors like hall effect-based, Rogowski coils, and current transformers, or vibration sensors like accelerometers. The effectiveness of these techniques is due to the previously developed models, which relate the current and vibration frequencies to the origin of the fault. Therefore, this article also presents the bearing fault mathematical modeling for these techniques. The infra-red technique is based on heat emission, and several image processing techniques were developed to optimize bearing fault detection, which is presented in this review. Finally, this work is a contribution to pushing the frontiers of the bearing fault diagnosis area.

Keywords: bearing fault; induction motors; fault detection; review

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1. Introduction

Nowadays, the development of monitoring systems applied to electrical machines is a challenge for industry and science. The goal is to avoid stoppages in industrial processes with punctual and planned maintenance. In this context, Three-Phase Induction Motors (TIMs) are the main focus of maintenance plans since they are widely applied as a mechanical source in the industrial process [1–4].

Among all TIMs components, bearings are crucial in the machine operation once they allow the rotary motion of the rotor while keeping it fixed to the motor structure. Due to their high degree of mobility, they are subject to different types of mechanical flaws [1,2,5]. According to [6], the TIM failures can be distributed in the bearings, rotor, stator, shaft coupling, external conditions, and other types of fault. Charts prove that the bearings are the components with the highest fault percentage (41%) in induction motors (Figure 1).

Bearings can be divided into four parts: outer ring, inner ring, cage, and balls (Figure 2) [7]. All parts are subject to degradation due to several factors, including operation, maintenance, handling, design, poor lubrication, and manufacturing. These factors are further detailed in Figure 3 [8]. Also, these conditions can compromise the integrity of the device, increasing the vibration pattern of the machine, generating eccentricity in the rotor, and elevating the supply current [7]. Due to their relevance, bearings are the focus of predictive, preventive, and corrective maintenance.

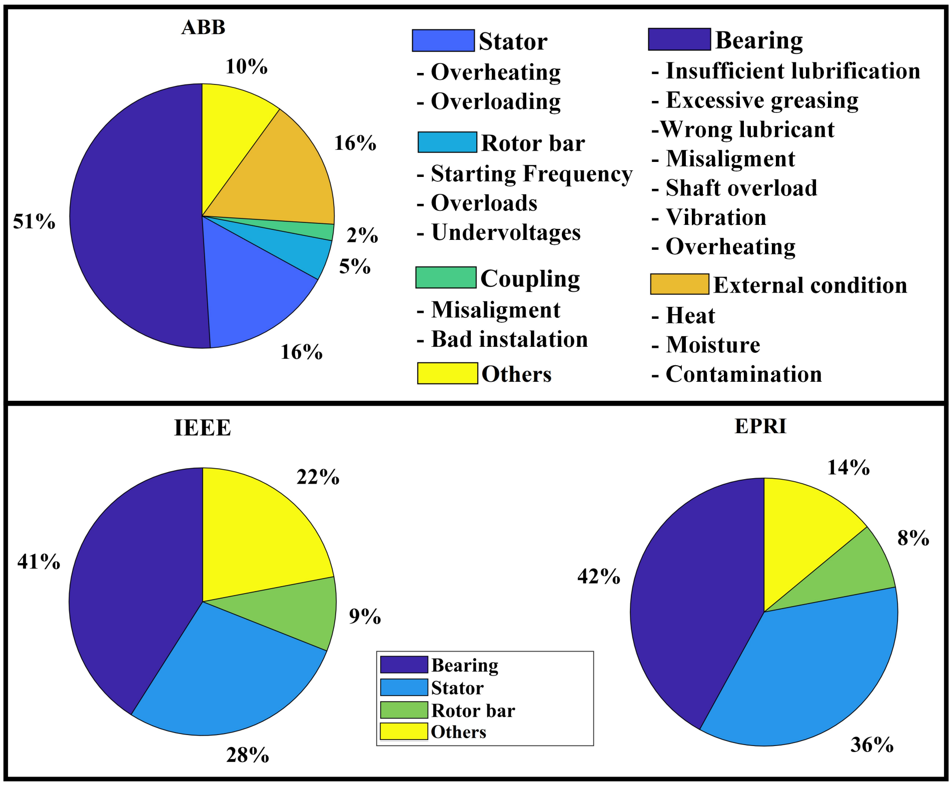


Figure 1. Faults in induction motors [6].

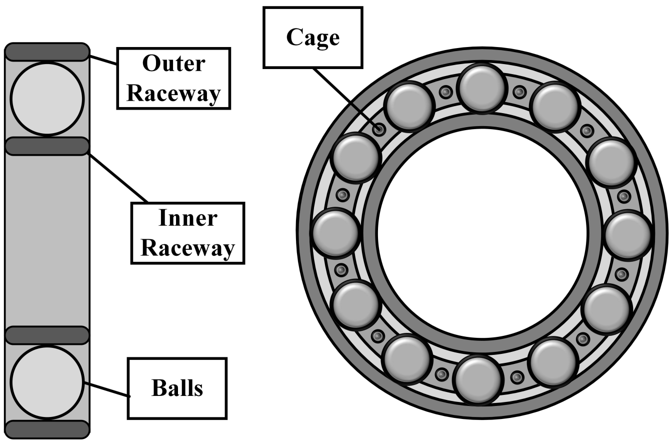


Figure 2. Bearing parts [7].

Therefore, this work presented the principal approaches for bearing fault detection: vibration, current, and thermal analysis. Additionally, the following sections describe the dynamic model of the faults for vibration and current signals. And, finally, the most recent works in this field were introduced and discussed.

Lubrication	Not enough lubricant	**Handling and mounting**	Inappropriate storage conditions
	Too much lubricant		Exposure to vibration during transport
	Viscosity too low		Wrong clearance or preload setting
	Inappropriate additives or thickener		Wrong radial or axial preload
	Oxidized lubricant		Misalignment
	Solid contaminants in the lubricant		Damage during mounting
	Lubricant contaminated by water	**Design and adjacent parts**	Geometrical form errors of shaft or housing seat
Operating conditions and maintenance	Static or dynamic load too high		Inconsistent support of rings
	Insufficient load		Inappropriate fits and tolerances
	Speed too high		Ineffective seal
	Speed too low		Worn seals
	Rapid changes in direction of load or rotation		Insufficient heat removal
	Exposure to vibration		Difficult assemby due to design
	Current passage, current leakage	**Bearing manufacturing**	Material, heat treatment
	External heat / insufficient cooling		Machining and assembly
	Oil filter clogged / internal contamination		Handling

Figure 3. Possible causes for faults in bearings [8].

2. Bearing Fault Detection by Vibration Analysis

The nominal operation of TIM produces vibrations that are proportional to its rotational speed. However, the existence of non-conformities can change the vibration patterns of the machine. Therefore, vibration analysis stands out as a tool for fault diagnosis and is carried out by applying acceleration sensors [7,9,10].

2.1. Mathematical Models

Based on the constructive elements of the bearings, the failures in this device can be found on the balls, cage, outer raceways, and inner raceways. Just as other types of faults, bearing faults are modeled from sidebands of the rotating frequency of the TIM, i.e., the frequency imposed by the angular velocity of the rotor [9,10].

Considering D_B the diameter of a ball, D_{COB} the distance between the centers of two opposite balls, f_r the rotational frequency of the rotor, and *theta* the contact angle between the spheres and the raceways; the sidebands regarding to faults in balls (f_b), cages (f_c), outer raceways (f_{or}), and inner raceways (f_{ir}) are determined by the following equations [9,10]:

$$f_b = \frac{D_{COB}}{2.D_B}.f_r.\left(1 - \frac{D_B^2.cos^2(\theta)}{D_{COB}^2}\right) \tag{1}$$

$$f_c = \frac{1}{2}.f_r.\left(1 - \frac{D_B.cos(\theta)}{D_{COB}}\right) \tag{2}$$

$$f_{or} = \frac{N_B}{2}.f_r.\left(1 - \frac{D_B.cos(\theta)}{D_{COB}}\right) \tag{3}$$

$$f_{ir} = \frac{N_B}{2}.f_r.\left(1 + \frac{D_B.cos(\theta)}{D_{COB}}\right) \tag{4}$$

where N_B is the number of balls.

2.2. Recent Studies

Recent studies indicates that a critical issue to perform damage detection in bearings is the speed variation, once the mathematical model depends on the velocity of the machine.

In this scenario, Tang et al. (2020) [11], proposed an approach in which the nonstationary vibration signal was converted from the time domain into a stationary signal in the angle domain with computed order tracking to eliminate speed fluctuations [11]. Multiple bearing faults under no-load and full-load and a combination of bearing and rotor bar faults are diagnosed with Rational Dilation Wavelet Transforms (RDWT) in [9]. Ref [12] proposed an intelligent system based on k-nearest neighbour (kNN) for diagnosing bearing defects. Hilbert Transform-based enveloping, principal component analysis (PCA), and sequential floating forward selection (SFFS) techniques were used for elimination of the redundancies, selecting the relevant features to perform bearing fault diagnosis. These selected features were the input of the kNN system.

3. Bearing Fault Detection by Current Analysis

Due to the operation and architecture of the TIMs, bearing faults influence the motor supply currents. Therefore, current signature analysis is a widely explored technique in recent studies for fault diagnosis.

3.1. Mathematical Models

As mentioned, bearing failures can be modeled according to dynamic equations. As observed in the last section, a faulty element introduces harmonics into the vibration spectrum of the machine. Additionally, any change in the vibration pattern will proportionally affect the current frequency components [7,13].

Considering the vibration fault frequencies f_b, f_c, f_{or} and f_{ir}, as the frequency f_v, the respective fault frequency for current signals (f_I) is given by the equation below [13]:

$$f_I = |f \pm k.f_v| \tag{5}$$

where f is the electrical supply frequency.

Although the frequency f_I is essentially related to the multiple harmonics k of the vibration fault frequency f_v, the use of vibration sensors is not always feasible in practice. The application of current sensors is usually more simple, cheap, and non-invasive when compared to accelerometers.

3.2. Recent Studies

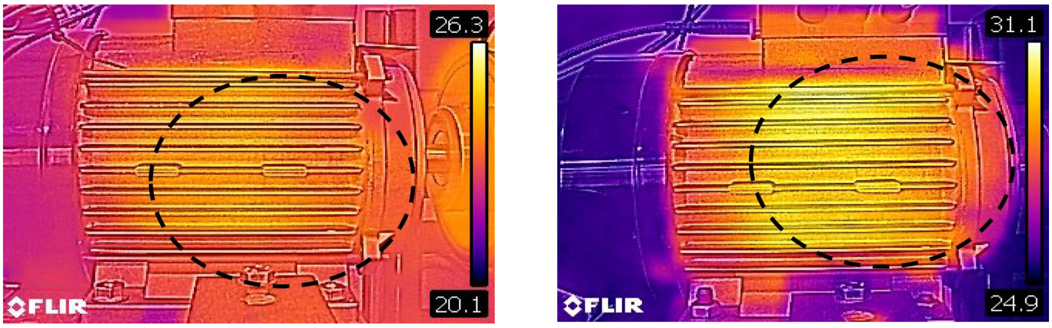
Despite being a simple methodology, the current analysis may be subject to harmonics. Also, overload operation can impair the capabilities of the methodology to identify the frequencies amplitudes and, consequently, the bearing faults. In this sense, several works try to improve the efficiency of current analysis by proposing signal processing methods.

In this context, [14] proposed a new approach to estimate the bearing fault severity based on the air-gap displacement profile. This profile was reconstructed from the mutual inductance variation, which is estimated from a quantitative electrical model that takes the stator current as input. A superposition of multiple Fourier series was used to estimate the severity of the bearing flaw [14].

Toma et al. (2020) [10] used a Genetic Algorithm and Machine Learning classifiers to perform bearing fault detection based on current analysis. Multiple characteristic vibration frequencies modulated in the current was investigated in [15], which proposed a new mathematical model considering the geometry of the damages. A remote monitoring system combined with frequency analysis was proposed by [13]. Corral et al. (2021) [16] studied three types of goodness-of-fit (GoFT) tests for current analysis to detect three types of bearing fault.

4. Bearing Fault Detection by Infrared Thermal Cameras

Since bearing failures are inherently related to high temperatures, thermal analysis is frequently applied to monitor this equipment. Although its feature extraction is not as effective as other methods, its simplicity and reliability make it a widely used tool [17]. The basis of this method is to detect the infrared wavelengths emitted by bearing failures. Figure 4 illustrates an image of a TIM with a faulty bearing captured by a thermal camera.



(**a**) (**b**)

Figure 4. (**a**) Thermal image of a healthy TIM, (**b**) Thermal image of a TIM subjected to a outer raceway bearing fault.

4.1. Recent Studies

One of the most common issues in Infrared Thermal Analysis is the noise caused by the environment, which impairs the capabilities of distinction of heat spots. Therefore, recent studies focus on improving signal processing techniques to distinguish the heat emitted by the faults from background noise.

In [6], the discrete wavelet transform was applied for denoising the images captured from different bearing conditions under different speeds and loads. After that, Principal component analysis and Mahalanobis distance (MD) criteria were applied to perform better classification accuracy and less training time compared to conventional algorithms. Thus, PCA-MD method has been used to obtain the optimal feature set as a training classifier for bearing fault detection.

Ammar et al. (2020) [18] proposed a new approach to improve the capabilities of thermal analysis by proposing a new color model namely Hue, Saturation and Value (HSV). Five segmentation methods (Sobel, Prewitt, Roberts, Canny and Otsu) were used for segmenting the Hue region aiming to highlight the hottest area in the thermal image. After that, the Mean, Mean Square Error, Peak Signal to Noise Ratio, Variance, Standard Deviation, Skewness and Kurtosis were applied to select bearing fault conditions [18].

In [19] a histogram-based approach was used to classify the bearing condition under temperature variation. Shao et al. (2021) proposed a rotor-bearing diagnosis under rotating speeds using two-stage parameter transfer [20]. This imaging processing was based on a scaled exponential linear unit (SELU) and a modified stochastic gradient descent (MSGD), which were applied to construct an enhanced convolutional neural network.

5. Conclusions

Three Phase Induction Motors are widely applied in several industrial processes. One of the most important components of this electrical machine are bearings, which couple the housing to the motor.

As previously mentioned, the bearings are essential elements for the operation of electrical machines. Their role is to decrease the friction between the shaft and the supports and align the rotor with the stator. This device represents around 41% of the TIM failures, and, in this context, several approaches have been proposed to monitor bearing flaws. Therefore, this article introduces a literature review of bearing fault detection using different types of sensing techniques. In this review, state-of-the-art approaches were presented to assist future works to further enhance these systems, and expand the borders of fault detection technology.

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