

# Simultaneous faults diagnosis and prognostic in induction motor drives under nonstationary conditions

Ameur Fethi Aimer<sup>1,2</sup>, Ahmed Hamida Boudinar<sup>2,3</sup>, Mohamed El-Amine Khodja<sup>2,3</sup>, Azeddine Bendiabdellah<sup>2,3</sup>

<sup>1</sup>LDEE Laboratory, Department of Electrotechnics, University Tahar Moulay of Saida, Saida, Algeria

<sup>2</sup>Department of Electrotechnics, University of Sciences and Technology of Oran, Bir El Djir, Algeria

<sup>3</sup>LDEE Laboratory, University of Sciences and Technology of Oran, Bir El Djir, Algeria

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## ABSTRACT

In this paper, an auto regressive (AR) model-based approach is applied in the stator current analysis under non-stationary conditions (case of frequency variation due to variable speed operation). Under these conditions, the identification of fault signatures is almost impossible due the variation of the fundamental frequency using conventional analysis methods. Moreover, this approach is used in the diagnosis of multiple faults occurring simultaneously in induction motor drives. In this aim, the stator current signal is decomposed into short segments then the AR modeling approach is applied on each segment. This approach called short-time ROOT-AR is then applied to solve the problem of the non-stationarity of the stator current signal under variable speed operation. The efficiency of the short-time ROOT-AR approach is evaluated through experimental tests in the diagnosis of multiple faults occurring simultaneously in induction motor drive. Finally, the superiority of the proposed approach is highlighted in comparison with conventional techniques in terms of accuracy, computational time and robustness against the noise.

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## Corresponding Author:

Ameur Fethi Aimer

LDEE Laboratory, Department of Electrotechnics, University Tahar Moulay of Saida

BP 138 cité ENNASR 20000, Saida, Algeria

Email: ameurfethi.aimer@univ-saida.dz

## 1. INTRODUCTION

Induction motor represents a large part of the industrial machinery field, accounting for over 80% of installed machines. This is primarily due to its robustness, high power-to-weight ratio, and low manufacturing cost. However, diagnosing potential faults that may occur during the operation of an induction motor is essential to ensure continuous operation, improve efficiency, and minimize energy losses [1]–[4].

Furthermore, it is more common for several faults to occur simultaneously, making the process of identifying a single isolated fault ineffective. Therefore, it is more practical to design a diagnostic process that allows the monitoring of multiple faults at the same time. Indeed, several incipient faults, such as eccentricity, broken rotor bars, or scratches on bearing surfaces, can occur simultaneously but with a very low amplitude, making their detection almost impossible using conventional diagnostic methods [5]–[9].

Therefore, the use of high-resolution techniques is essential for better discrimination of the resulting frequency signatures, particularly in variable-speed applications where the static converter introduces harmonics that contaminate the signal, thus increasing the noise level. Moreover, these variable-speed applications introduce non-stationarity into the electrical signals due to the variation of the supply frequency.

This is particularly important since this frequency is crucial in the calculation of most fault-related frequency signatures [10]–[14]. To fix these problems, an improved auto regressive (AR) method called ROOT-AR is first introduced by improving two aspects on the AR modeling. The first one consists in processing the signal only on a limited frequency band where the signature of the faults is supposed to appear. This will reduce the samples number, and thus reduce the computation time. In addition, this solution allows the determination of the number of searched harmonics instead of its estimation. The second one provides a better display by representing the signal frequencies obtained using the ROOT-AR approach [15]. This approach is reliable in the case of stationary signals (constant frequencies). Nevertheless, it is limited in the case where the frequencies vary over time; this is the case of a load variation or a variable speed drive. In this case, the electrical signals become non-stationary (variable frequencies).

Several techniques address the problem of the analysis under non-stationary conditions. The basic technique in the analysis of non-stationary signals is the short time fourier transform (STFT) [16], [17] also known for its limited time-frequency resolution. Other techniques such as discrete wavelet transform (DWT) [18], Wigner-Ville distribution (WVD) [19], minimum norm spectral estimation technique [20], demodulation technique [21] or empirical mode decomposition (EMD) [22] present interesting results but with drawbacks related to the complexity of implementation and high computation time. Also, the resulting time-frequency spectrum is often difficult to read and to discuss. Moreover, several artificial intelligence (AI)-based diagnostic methods are presented in [23] in order to achieve a classification of multiple faults. Nevertheless, these AI techniques based on machine learning algorithms needs a large database necessary to the learning procedure.

To overcome these problems, the short time ROOT-AR approach is applied in the analysis of non-stationary signals. In this aim, the non-stationary signal is decomposed into short segments while applying the ROOT-AR approach on each segment, this adaptation aims to obtain a time-frequency spectrum where frequency variations over time can be observed. Indeed, since the proposed approach is based on the STFT principle, the window size width is fixed in order to reduce the complexity of the algorithm (in comparison with DWT for example). In the other hand, the fourier computation is replaced with ROOT-AR spectrum which improves the frequency resolution and the readability of the spectrum. Also, the analysis over a limited frequency band leads to a reduced computation time allowing a real-time diagnosis.

In addition, several faults operating simultaneously are identified in the case of non-stationary signals (with a variable fundamental frequency necessary for speed variation). Moreover, this variation is achieved using a pulse width modulation (PWM) inverter, which increases the harmonics in the stator current spectrum and, consequently, the noise. The distinctive feature of the short time ROOT-AR is the adaptation of the ROOT-AR method (robust against noise compared to fourier analysis: FT and STFT) in the analysis of non-stationary signals.

Finally, the resulting time-frequency spectrum is easy to read thanks to the robustness of the ROOT-AR against noisy signals (due to the PWM inverter). To verify the effectiveness of the SHORT TIME ROOT-AR in the analysis of signals in the presence of multiple faults under non-stationary operation cases, the diagnosis of bearing faults, eccentricity faults and broken rotor bars faults in variable speed induction motor is achieved through experimental tests.

## 2. FAULT DIAGNOSIS THEORY

Due to the rich information content of the stator current spectrum, several research studies have demonstrated that its analysis constitutes an effective tool not only for the detection, but also for the identification of faults affecting induction motors. This identification capability is essentially based on the precise monitoring of the frequency positions of certain harmonic components, as well as the analysis of their respective amplitudes, thus making it possible to identify the nature of the searched fault [24]. In this paper, multiple faults among most recurrent faults are investigated using experimental tests. These faults are presented in the following section.

### 2.1. Broken rotor bars

Manufacturing faults, porosity in materials, mechanical overloads, and gear damage are among the main causes of rotor bar breakage. When one or more rotor bars are broken, the electromechanical stresses applied on adjacent bars can lead to rapid propagation of the damage. In certain critical cases, this can lead to catastrophic motor failure, particularly if bar fragments detach from the cage during operation [25]. Thus, rotor bar breakage results in the occurrence of a series of frequencies calculated using (1).

$$f_b = (1 \pm 2ks)f_s \text{ with } k = 1,2,3 \dots \quad (1)$$

where:  $f_s$  is the supply frequency,  $f_b$  denotes the sideband frequencies associated with the rotor broken bar fault, and finally  $s$  represents the motor slip.

## 2.2. Eccentricity faults

In induction motors, residual eccentricity is inevitable, even when the motor is new. Eccentricity faults, caused by a variation in the air gap, cause vibrations and damage to the bearings, which can lead to rotor-stator contact. They are divided into three types: static, dynamic, and mixed.

In the presence of static eccentricity, the area of the smallest air gap remains fixed during rotation. This type of eccentricity generally results from improper rotor assembly or deformation of the stator core (ovalization). In contrast, dynamic eccentricity is characterized by a misalignment between the geometric center of the rotor and its axis of rotation, which causes the position of the minimum air gap point to vary during rotation. This phenomenon can be caused by factors such as resonance at a critical speed, rotor shaft deflection, bearing wear, or misalignment. If both static and dynamic eccentricity are present at the same time, a low-frequency component is formed near the main frequency, expressed by (2) [26].

$$f_{ecc} = f_s \cdot \left(1 \pm \frac{1-s}{p}\right) \quad (2)$$

## 2.3. Bearing faults

Bearings are designed as an electromechanical interface between the rotor and the stator of electric machines. In addition, they maintain the shaft of the machine in order to guarantee a proper rotation of the rotor. The rolling-element bearings consist of four parts: inner and outer races, balls and cage which guarantees an equidistant separation between balls. Bearing faults can be located on the stator current spectrum at the following frequencies [27].

$$f_{bear}[Hz] = |f_s \pm m \cdot f_v| \text{ with } m = 1,2,3 \dots \quad (3)$$

where  $f_v$  is the fault vibrational frequency corresponding to one of the faults that can be observed on bearings element (inner race, outer race, ball or cage), while  $f_s$  is the supply frequency. In this paper, the outer race fault is considered as the selected bearing fault. The characteristic frequency in the case of an outer race fault is given by the frequency  $f_o$ :

$$f_o = \frac{N_b}{2} f_r \left(1 - \frac{B_D}{C_D} \cos \beta\right) \quad (4)$$

where  $B_D$  and  $C_D$  respectively, are the ball and the cage diameters,  $N_b$  is the bearing balls number,  $\beta$  is a contact angle and  $f_r$  the mechanical rotor frequency.

## 3. AUTOREGRESSIVE MODEL OF STATOR CURRENT

The spectrum of stator current is composed of the following frequencies [15]:

- Supply frequency:  $f_s$
- Time harmonics caused by the supply pollution:  $(2k + 1) f_s$
- Harmonics due to eccentricity located around the fundamental
- Space harmonics due to non-sinusoidal distribution of windings

Therefore, the stator current can be presented as a sum of trigonometric functions given by:

$$i_s(t) = \sum_{i=1}^{N_H} I_i \cos(2\pi f_i t + \phi_i) + w(t) \quad (5)$$

where  $I_i$ ,  $f_i$ ,  $\phi_i$  are respectively, the magnitude, frequency and initial value of the  $i^{th}$  cosine phase,  $N_H$  being the number of harmonics,  $w(t)$  is the measurement noise.

Using the Euler's decomposition, the numerical expression of stator current of (5) can be presented as a sum of  $2 \cdot N_H$  complex exponentials given by:

$$i_s(n) = \sum_{i=1}^{2N_H} \frac{I_i}{2} \cdot e^{j\left(2\pi \frac{f_i}{f_e} n + \phi_i\right)} + w(n) \quad (6)$$

with  $n = 0,1,2, \dots, N - 1$  where  $N$  is the number of samples number and  $f_e$  is the sampling frequency.

As a matter of fact, the AR model is considered as an all-pole filter with a white noise as an input and a variance equal to  $\sigma_w^2$  [27]. The AR model of stator current is given by the following difference:

$$e(n) = i_s(n) - \hat{i}_s(n) = i_s(n) + \sum_{k=1}^L \hat{a}_k i_s(n - k) \tag{7}$$

Therefore, the transfer function of the system is expressed by:

$$H(z) = \frac{1}{1 + \sum_{k=1}^L \hat{a}_k z^{-k}} \tag{8}$$

where  $L$  represents the order of the AR model,  $e(n)$  the prediction error illustrated by a white noise and  $\hat{a}_k$  represent the filter coefficients obtained by minimizing the prediction error  $e(n)$ . The power spectral density (PSD) of the AR model given in (8), leads to:

$$PSD_{AR}(f) = \frac{\sigma_n^2}{\left| 1 + \sum_{k=1}^L \hat{a}_k e^{-j2\pi \frac{f}{f_e} k} \right|^2} \tag{9}$$

#### 4. PROPOSED SHORT-TIME ROOT-AR APPROACH

A non-stationary signal is characterized by frequency components varying over time. Consequently, the fault signatures, depending on the supply frequency, also vary over time, thus leading to an ineffective fault detection process. To solve this problem and to be able to introduce the notion of time into the resulting spectrum, the analysis must be shifted to a time-frequency plane. For this, the ROOT-AR approach is adapted to the analysis of non-stationary signals inspired from the STFT developed in our previous works. Furthermore, since the STFT is based on the calculation of the fourier transform, it presents problems related to limited time-frequency resolution (due to the Heisenberg-Gabor uncertainty principle) [16].

By applying the high-resolution approach ROOT-AR, a time-frequency approach superior in frequency resolution is applied. The idea is to introduce a sliding window through which we apply the ROOT-AR approach; this sliding window Figure 1 makes it possible to have portions or segments of the non-stationary signal where each portion of signal is considered stationary. These signal portions will then be analyzed by the ROOT-AR approach. The procedure of the proposed approach is given in the flowchart in the Figure 2. The resulting approach, called SHORT-TIME ROOT-AR or ST-AR, will allow us to observe the different signal components in a time-frequency plane.

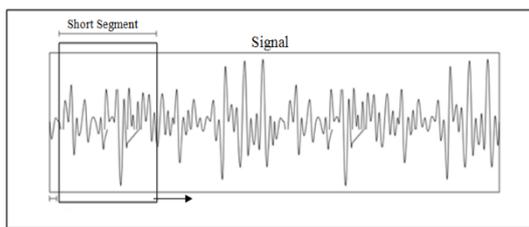


Figure 1. Sliding window analysis concept

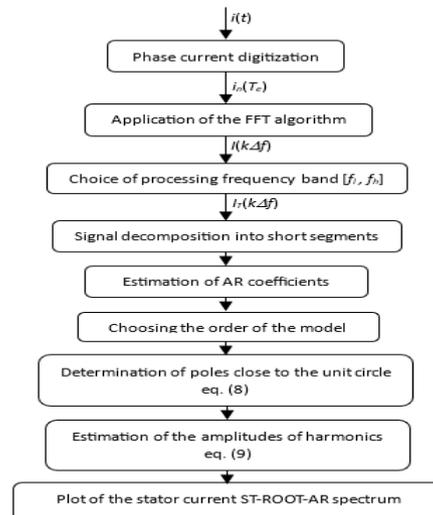


Figure 2. Flowchart of the short-time ROOT-AR

#### 5. EXPERIMENTAL VALIDATION OF THE SHORT-TIME ROOT-AR APPROACH

The experimental setup described in Figure 3 used for experimental tests is composed of a three-phase squirrel cage induction motor (3 kW, 7 A, 50 Hz, 1410 rpm, and 4 poles) coupled to a direct current (DC) generator associated to a resistive load. The stator current signals are measured using three Effect-Hall sensors and an anti-aliasing filter (in experimental tests, the cutoff frequency of the filter is equal to 400 Hz),

while the motor mechanical speed is measured using a tachometer. All acquisitions are obtained for an acquisition time of 40 s and a sampling frequency of 3 kHz. This leads to a frequency resolution equal to 0.025 Hz.

The entire set is connected to a computer for processing the measured signals and generating those necessary for the control of the PWM inverter. These control signals are obtained using a space vector PWM through a digital signal processing and control engineering (DSPACE) 1104 card. The bearing considered in this paper is a 6205-ZZ rolling-element bearing detailed in the Tables 1 and 2. For the fault diagnosis, an outer race fault is created artificially using a scratch of 2 mm width and 2 mm deep in the outer race. This configuration is illustrated in Figure 4.



Figure 3. Experimental setup description

Table 1. Induction motor parameters

Parameter	Value
Rated power	3 kW
Supply frequency	50 Hz
Rated voltage	380 V
Rated current	7 A
Rated speed	1440 rev/min
Number of rotor bars	28
Number of poles pairs	2

Table 2. Geometric parameters of rolling-element bearing “reference ZZ-6205 coupling opposite side”

Parameter	Value
Ball diameter $D_b$	7.835 mm
Cage diameter $D_c$	38.5 mm
Number of balls $N_b$	9
Contact angle $\beta$	0



Figure 4. Artificial bearing fault (outer race fault)

In experimental tests, the induction motor operates at a variable supply frequency from 30 to 50 Hz. The acquisition of the stator current during this variation makes the stator current non-stationary. Consequently, the frequency signatures of all considered faults (dependent on the supply frequency) vary

with the variation of the supply frequency. Indeed, the outer race fault signature for both supply frequencies 50 Hz and 30 Hz (for  $m = 1$ ) is determined from (3) and (4). These fault signatures are given in Table 3.

Table 3. Theoretical frequencies of bearing fault

Supply frequency	50 Hz	30 Hz
Theoretical frequency	$f_{bear}[Hz] =  f_s \pm m \cdot f_o $	
For $m = 1$	37.16 Hz	22.29 Hz

In the other hand, theoretical frequencies of broken rotor bars are given in Table 4 for both supply frequencies and for a motor slip equal to 4.6% corresponding to a measured speed of 1431 rpm in experimental tests. Also, theoretical frequencies of eccentricity fault calculated according to (4) are given in Table 5 for both supply frequencies. The purpose of the test is to show the ability and the efficiency of the proposed short-time ROOT-AR approach compared to the conventional method in the detection of multiple failures signatures when the frequency changes over time. For this aim, Figure 5 illustrates the stator current PSD using the periodogram technique for a supply frequency of 30 Hz, 50 Hz and when the supply frequency changes from 30 Hz to 50 Hz. This test shows the existence of two main frequencies observed at 30 Hz and 50 Hz frequencies.

Table 4. Frequency signatures of rotor fault (case of a motor slip of 4.6 %)

Sideband type	Lower sideband	Upper sideband
$f_b = (1 \pm 2ks)f_s$	$k = 1$	$k = 1$
Theoretical frequencies (for 30 Hz)	27.2 Hz	32.7 Hz
Theoretical frequencies (for 50 Hz)	45.4 Hz	54.6 Hz

Table 5. Frequency signatures of eccentricity fault (case of a motor slip of 4.6 %)

Sideband type	Lower sideband	Upper sideband
$f_{ecc} = f_s \cdot \left(1 \pm \frac{1-s}{p}\right)$	$k = 1$	$k = 1$
Theoretical frequencies (for 30 Hz)	44.3 Hz	15.7 Hz
Theoretical frequencies (for 50 Hz)	73.8 Hz	26.1 Hz

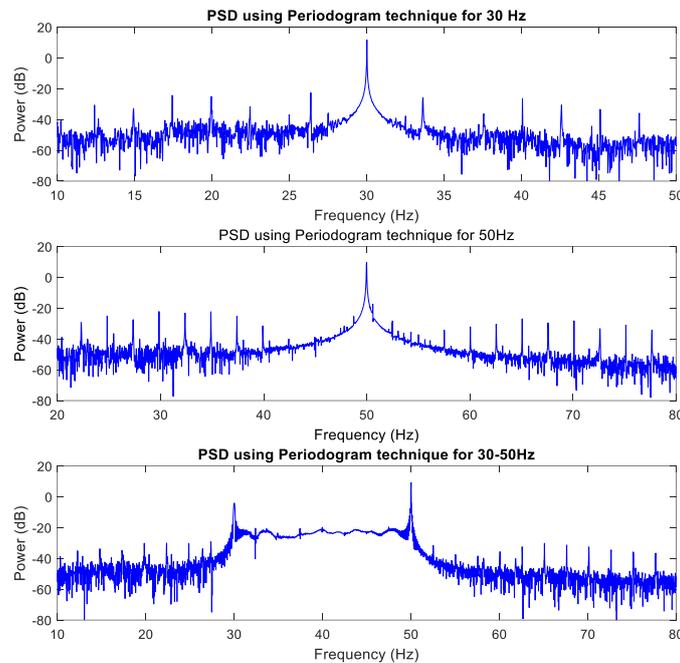


Figure 5. PSD using periodogram for a supply frequency of 30 Hz, 50 Hz and a variation from 30 to 50 Hz

In the first and second spectrum (stationary case), the searched harmonics related to the faults (Table 3 to 5) are visible but drowned in the other harmonics due to the PWM inverter. However, the identification of the fault signatures in the third spectrum (non-stationary case) is impossible. Indeed, it is impossible in this case to identify the rotor cage faults signature, for example, from the outer race fault signatures. In addition, this spectrum cannot indicate the initial supply frequency and the final one. This is the major drawback of this method of analysis using the PSD estimation by periodogram.

Figure 6 shows the time-frequency representation of the stator current obtained by the proposed short-time ROOT-AR approach. From Figure 6, the proposed approach is validated in the detection of the fundamental frequency, the rotor cage fault signature, the eccentricity fault signature and the outer race fault signature in both stationary and non-stationary conditions and especially in time-frequency plane. By comparing the spectrum of both approaches (periodogram and short-time ROOT-AR), the importance of introducing the notion of time in the analysis of non-stationary signals (variable frequency) and the amount of information lost in the absence the information of time in the spectrum are highlighted. In addition, Table 6 summarizes the main feature of each signal processing technique [28].

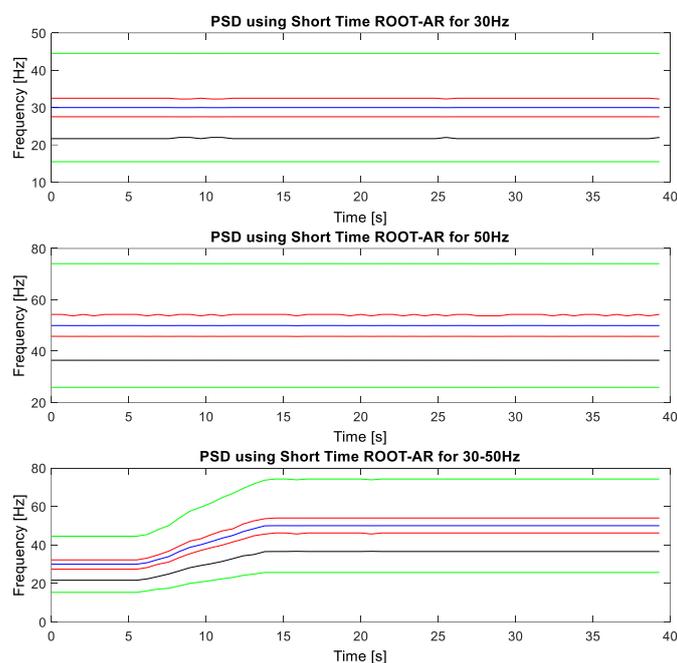


Figure 6. PSD using short time ROOT-AR approach for a supply frequency of 30 Hz, 50 Hz and a variation from 30 to 50 Hz

Table 6. Comparison between high resolution/time-frequency methods

Method	Frequency resolution	Noise robustness	Computation time	Complexity	Nonstationary analysis
Peridogram	Low	Low	Very low	Low	No
STFT	Low	Low	Low	Low	Yes
ROOT-music	Very high	High	High	High	No
ROOT-AR	Very high	High	Low	Low	No
Short time ROOT-AR	Very high	High	Low	Low	Yes

## 6. CONCLUSION

Through this paper, an experimental test setup of the induction motor fed with a PWM inverter for multiple faults diagnosis is presented. As a result, the effectiveness of the proposed approach and its superiority compared to the conventional periodogram based on fourier transform technique is highlighted. Moreover, in the aim of adapting the ROOT-AR approach to the analysis of non-stationary signals, a variant of ROOT-AR called short-time ROOT-AR is proposed. This approach has been applied in the detection of simultaneous faults in the case of a variation of the supply frequency (non-stationary signals). We were able to experimentally verify the effectiveness of the proposed approach and see its superiority compared to the classic periodogram method in the analysis of non-stationary signals. However, the proposed approach

focuses on the analysis over a well-defined frequency band in order to reduce the computation time. This frequency band is chosen depending on the searched faults. Therefore, it is interesting to develop an algorithm based on deep learning techniques in order to select the appropriate frequency band used in the analysis. This will be investigated in future works.

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### AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ameur Fethi Aimer	✓	✓	✓	✓	✓	✓		✓	✓					✓
Ahmed Hamida		✓		✓		✓		✓		✓	✓	✓		
Boudinar														
Mohamed El-Amine Khodja	✓		✓		✓		✓		✓		✓			✓
Azedine Bendiabdellah		✓		✓		✓	✓	✓		✓		✓		

C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

### CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

### INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

### DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author [Ameur Fethi Aimer]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions. Derived data supporting the findings of this study are available from the corresponding author [Ameur Fethi Aimer] on request.

### REFERENCES

- [1] "Report of Large Motor Reliability Survey of Industrial and Commercial Installations, Part I," *IEEE Transactions on Industry Applications*, vol. IA-21, no. 4, pp. 853–864, 1985, doi: 10.1109/TIA.1985.349532.
- [2] A. H. Bonnett and C. Yung, "Increased efficiency versus increased reliability," *IEEE Industry Applications Magazine*, vol. 14, no. 1, pp. 29–36, Jan. 2008, doi: 10.1109/MIA.2007.909802.
- [3] Y. Merizalde, L. Hernández-Callejo, and O. Duque-Perez, "State of the art and trends in the monitoring, detection and diagnosis of failures in electric induction motors," *Energies*, vol. 10, no. 7, p. 1056, Jul. 2017, doi: 10.3390/en10071056.
- [4] M. F. Yakhni *et al.*, "Variable speed induction motors' fault detection based on transient motor current signatures analysis: A review," *Mechanical Systems and Signal Processing*, vol. 184, p. 109737, Feb. 2023, doi: 10.1016/j.ymsp.2022.109737.
- [5] P. A. Delgado-Arredondo, D. Morinigo-Sotelo, R. A. Osornio-Rios, J. G. Avina-Cervantes, H. Rostro-Gonzalez, and R. de J. Romero-Troncoso, "Methodology for fault detection in induction motors via sound and vibration signals," *Mechanical Systems and Signal Processing*, vol. 83, pp. 568–589, Jan. 2017, doi: 10.1016/j.ymsp.2016.06.032.
- [6] M. B. Koura, A. H. Boudinar, A. F. Aimer, and M. E. A. Khodja, "Induction Motor Bearing Faults Diagnosis Using Stator Current and Vibration Analysis," *Periodica polytechnica Electrical engineering and computer science*, vol. 65, no. 4, pp. 344–351, Oct. 2021, doi: 10.3311/PPee.17284.
- [7] D. K. Soother and J. Daudpoto, "A brief review of condition monitoring techniques for the induction motor," *Transactions of the Canadian Society for Mechanical Engineering*, vol. 43, no. 4, pp. 499–508, Dec. 2019, doi: 10.1139/tcsme-2018-0234.
- [8] K. C. D. Kompella, N. S. Rongala, S. R. Rayapudi, and V. G. R. Mannam, "Robustification of fault detection algorithm in a three-

- phase induction motor using MCSA for various single and multiple faults,” *IET Electric Power Applications*, vol. 15, no. 5, pp. 593–615, May 2021, doi: 10.1049/elp2.12049.
- [9] M. Afshar, S. Abdi, M. Ebrahimi, and S. A. Mortazavizadeh, “Static Eccentricity Fault Detection in Brushless Doubly-Fed Induction Machines based on Motor Current Signature Analysis,” in *IECON Proceedings (Industrial Electronics Conference)*, IEEE, Oct. 2019, pp. 1369–1374, doi: 10.1109/IECON.2019.8926698.
- [10] P. Stoica and Y. Selén, “A review of information criterion rules,” *IEEE Signal Processing Magazine*, vol. 21, no. 4, pp. 36–47, Jul. 2004, doi: 10.1109/MSP.2004.1311138.
- [11] A. R. Muñoz, “Using an autoregressive model in the detection of abnormal characteristics of squirrel cage induction motors,” *Electric Power Systems Research*, vol. 55, no. 2, pp. 73–77, Aug. 2000, doi: 10.1016/S0378-7796(99)00101-7.
- [12] F. M. Garcia-Guevara, F. J. Villalobos-Piña, R. Alvarez-Salas, E. Cabal-Yepez, and M. A. Gonzalez-Garcia, “Stator Fault Detection in Induction Motors by Autoregressive Modeling,” *Mathematical Problems in Engineering*, vol. 2016, pp. 1–7, 2016, doi: 10.1155/2016/3409756.
- [13] E. Ayaz, “Autoregressive modeling approach of vibration data for bearing fault diagnosis in electric motors,” *Journal of Vibroengineering*, vol. 16, no. 5, pp. 2130–2138, 2014.
- [14] S. Haroun, A. N. Seghir, S. Hamdani, and S. Touati, “AR model of the torque signal for mechanical induction motor faults detection and diagnosis,” in *3rd International Conference on Control, Engineering and Information Technology, CEIT 2015*, IEEE, May 2015, pp. 1–5, doi: 10.1109/CEIT.2015.7232984.
- [15] A. F. Aimer, A. H. Boudinar, N. Benouzza, and A. Bendiabdellah, “Induction motor bearing faults diagnosis using Root-AR approach: simulation and experimental validation,” *Electrical Engineering*, vol. 100, no. 3, pp. 1555–1564, Sep. 2018, doi: 10.1007/s00202-017-0527-1.
- [16] M. Houili, M. Sahraoui, A. J. M. Cardoso, and A. Alloui, “Zero-Sequence Voltage Outperforms MCSA-STFT for a Robust Inter-Turn Short-Circuit Fault Diagnosis in Three-Phase Induction Motors: A Comparative Study,” *Machines*, vol. 13, no. 6, p. 501, Jun. 2025, doi: 10.3390/machines13060501.
- [17] Q. Yang, X. Li, Y. Wang, A. Ainapure, and J. Lee, “Fault diagnosis of ball screw in industrial robots using non-stationary motor current signals,” *Procedia Manufacturing*, vol. 48, pp. 1102–1108, 2020, doi: 10.1016/j.promfg.2020.05.151.
- [18] A. Bouzida, O. Touhami, R. Ibtouen, A. Belouchrani, M. Fadel, and A. Rezzoug, “Fault diagnosis in industrial induction machines through discrete wavelet transform,” *IEEE Transactions on Industrial Electronics*, vol. 58, no. 9, pp. 4385–4395, Sep. 2011, doi: 10.1109/TIE.2010.2095391.
- [19] M. Riera-Guasap *et al.*, “Diagnosis of induction machines under non-stationary conditions: Concepts and tools,” in *Proceedings - 2013 IEEE Workshop on Electrical Machines Design, Control and Diagnosis, WEMDCD 2013*, IEEE, Mar. 2013, pp. 220–231, doi: 10.1109/WEMDCD.2013.6525182.
- [20] T. A. Garcia-Calva, D. Morinigo-Sotelo, O. Duque-Perez, A. Garcia-Perez, and R. D. J. Romero-Troncoso, “Time-frequency analysis based on minimum-norm spectral estimation to detect induction motor faults,” *Energies*, vol. 13, no. 15, p. 4102, Aug. 2020, doi: 10.3390/en13164102.
- [21] T. A. Garcia-Calva, D. Morinigo-Sotelo, A. Garcia-Perez, D. Camarena-Martinez, and R. De Jesus Romero-Troncoso, “Demodulation Technique for Broken Rotor Bar Detection in Inverter-Fed Induction Motor Under Non-Stationary Conditions,” *IEEE Transactions on Energy Conversion*, vol. 34, no. 3, pp. 1496–1503, 2019, doi: 10.1109/TEC.2019.2917405.
- [22] D. Zhen, J. Guo, Y. Xu, H. Zhang, and F. Gu, “A novel fault detection method for rolling bearings based on non-stationary vibration signature analysis,” *Sensors (Switzerland)*, vol. 19, no. 18, p. 3994, Sep. 2019, doi: 10.3390/s19183994.
- [23] P. Pohakar, R. Gandhi, S. Hans, G. Sharma, and P. N. Bokoro, “Analysis of multiple faults in induction motor using machine learning techniques,” *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 12, p. 101007, Jun. 2025, doi: 10.1016/j.prime.2025.101007.
- [24] F. J. Villalobos-Pina, J. A. Reyes-Malanche, E. Cabal-Yepez, and E. Ramirez-Velasco, “Electric Fault Diagnosis in induction Machines using Motor Current Signature Analysis (MCSA),” *Time Series Analysis - Recent Advances, New Perspectives and Applications. IntechOpen*, Jan. 05, 2024, doi: 10.5772/intechopen.1004002.
- [25] R. Issa *et al.*, “Review of Fault Diagnosis Methods for Induction Machines in Railway Traction Applications,” *Energies*, vol. 17, no. 11, p. 2728, Jun. 2024, doi: 10.3390/en17112728.
- [26] S. K. Gundewar and P. V. Kane, “Condition Monitoring and Fault Diagnosis of Induction Motor,” *Journal of Vibration Engineering and Technologies*, vol. 9, no. 4, pp. 643–674, Jun. 2021, doi: 10.1007/s42417-020-00253-y.
- [27] Z. Wang, D. Shi, Y. Xu, D. Zhen, F. Gu, and A. D. Ball, “Early rolling bearing fault diagnosis in induction motors based on on-rotor sensing vibrations,” *Measurement*, vol. 222, p. 113614, Nov. 2023, doi: 10.1016/j.measurement.2023.113614.
- [28] M. Kouadria, A. Z. M. Chedjara, H. Ahmed, C. L. Su, M. Benbouzid, and J. M. Guerrero, “Inter-Turn Fault Diagnosis of Induction Motor Using a Root-Prony and Fuzzy Logic Method,” *IET Collaborative Intelligent Manufacturing*, vol. 7, no. 1, Jan. 2025, doi: 10.1049/cim2.70048.

## BIOGRAPHIES OF AUTHORS



**Ameur Fethi Aimer**    (IEEE M'15, SM'23) was born on August 23, 1983 in Saida, Algeria. He received his Engineer's degree in Electrical Engineering from the University of Saida in 2006, his Magister degree and his Doctor of Science degree in Industrial Control of Electric Drives and Diagnosis from the University of Sciences and Technology of Oran, Algeria in 2010 and 2018 respectively. He is currently an Associate Professor at the University of Saida. His research interests include: electric drives, control systems, signal processing as well as electric machines fault diagnosis. He is an IEEE senior member, a member of the IEEE/IES Electrical Machines Technical Committee EMTC, a member of the IEEE/PELS Power Electronics Society Technical Committee on Electrical Machines, Drives and Automation and a member of the Laboratory of Electrical Drives Development - USTO-Oran. Algeria. He can be contacted at email: fethi.aimer@yahoo.fr.



**Ahmed Hamida Boudinar**    (IEEE M'14) was born on September 10, 1969 in Oran, Algeria. IEEE Member; he received his Electronic Engineering degree, his Magister degree and his Doctorate degree with honors from the University of Sciences and Technology of Oran, (USTO-MB) Algeria, in 1992, 1997 and 2007 respectively. He is currently Professor and Researcher at the Electrical Engineering Department at the same university. His research interests are focused on condition monitoring and diagnosis of electrical machines and drives using numerical methods for signal processing. He can be contacted at email: boud\_ah@yahoo.fr.



**Mohammed El-Amine Khodja**    was born on June 12, 1990 in Oran, Algeria. He received his Master's degree and Ph.D. in Electrical Engineering with honors from the University of Sciences and Technology of Oran, (USTO-MB) Algeria, in 2013 and 2020, respectively. He is currently a Professor at the Department of Preparatory Classes at the National School of Built and Ground Engineering in Algiers and a Researcher and Laboratory of Electrical Drives Development LDEE at the University of Sciences and Technology of Oran, (USTO-MB). His research interests focus on condition monitoring and diagnosis of electrical machines and drives using advanced signal processing methods. He can be contacted at email: koudjamea@gmail.com.



**Azeddine Bendiabdellah**    (IEEE M'14) received his Bachelor Engineering degree (Honors class) in Electrical Engineering from the University of Sheffield, England, in 1980, and his Ph.D. degree from the same University in 1985. He is currently Professor Lecturer and Researcher in Electrical Engineering and the Director of both the LDEE laboratory and the Diagnostic Group at the University of Sciences and Technology of Oran (USTOMB), Algeria. His research interests include electrical machines and drives analysis and modelling, electrical machines and drives control, electrical machines and drives diagnosis and power converter detection fault and fault tolerance. He can be contacted at email: bendiazz@yahoo.fr.