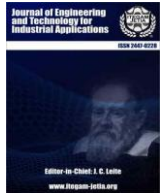




ISSN ONLINE: 2447-0228

ITEGAM-JETIA

Manaus, v.12 n.59, p.07-18. May/June, 2026.
DOI: <https://doi.org/10.5935/jetia.v12i59.2719>



RESEARCH ARTICLE

OPEN ACCESS

FAULTS DIAGNOSIS OF ROTATING MACHINERY USING MULTISCALE ENTROPY AND PRINCIPAL COMPONENT ANALYSIS BASED ON MOTOR CURRENT SIGNATURE ANALYSIS

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ARTICLE INFO

Article History

Received: September 20, 2025

Reviewed: January 20, 2026

Accepted: April 6, 2026

Published: May 29, 2026

Keywords:

Misalignment,
Bearing,
Fault diagnosis,
Motor current signature analysis,
Multiscale entropy (MSE),
Principal component analysis (PCA).

ABSTRACT

In this experimental paper, we propose a method for identifying misalignment and bearing faults, as well as their combined fault, from phase currents measured on a variable-speed induction motor. For this purpose motor current signature analysis (MCSA) technique successfully distinguishes healthy states from faulty states. In order to optimise the identification of correlations in the signals on several time scales, we propose a new fault detection tool based on multiscale entropy (MSE) algorithm SampEn applied to extract detailed features, dimensionality and isolating fault relevant variations are reduced through principal component analysis (PCA) and the comparison of the measured values with those predicted by our model built from the nominally healthy data. Finally, we used the squared prediction error (SPE) analysis to improve the fault detection capability and ensure a more comprehensive analysis of the induction machine condition, the combination of these techniques aims to provide early and accurate fault diagnosis. The experimental results obtained show that the proposed method is efficient, accurate and reliable for extracting characteristic frequencies from the current signal, and that it provides a powerful tool for fault diagnosis and condition monitoring.



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1. INTRODUCTION

As key components in various rotating machinery, induction motors (IMs) are used extensively to ensure smooth operation processes. They have played a significant role in industrial applications due to their numerous benefits, which stem from their stability, reliability, robustness, and efficiency. However, like all rotating machinery, induction motors (IMs) are harmed by many failures resulting from various issues, which can lead to reduce the reliability, minimise the productivity, and increase the operation and maintenance (O&M) costs. Many factors may lead to malfunction and be a major cause of various electrical and mechanical faults that occur on motors during their normal function, including stator faults, rotor faults, bearings, eccentricities, and broken rotor bar faults [1]. In recent years, huge focuses and wide examples of condition monitoring systems for induction motors have been used over the last decade to detect faults in the early stages to prevent the main components from catastrophic failures through an accurate and quick diagnosis of these faults for the purpose of identifying the specific failure and ensuring the safe and effective operation process. To assure a thorough inspection of faults, numerous analysis approaches have been applied and investigated to identify the defects [2]. Those methods can be reflected by vibration analysis, ultrasonic analysis, thermography, motor current signature analysis (MCSA), and others [3]. For years, the motor current signature analysis (MCSA) method has been well-known as a cornerstone approach for pinpointing the presence of faults in induction motors [4]. This method offers important advantages due to its low cost and ability to detect mechanical and electrical faults at an early stage, thus preventing unexpected breakdowns. However, its accuracy and reliability are significantly dependent on numerous signal processing methods, whether in the time domain, frequency domain, and time-frequency domain [5].

Among these, signal processing methods in time-frequency domain analysis techniques such as wavelet transform (WT), short-time Fourier transform (STFT), empirical mode decomposition (EMD), and Hilbert-Huang transform (HHT) [6], [7]. However, discrete wavelet transform (DWT) is an interesting approach, and a specific implementation of wavelet transform (WT) has been presented through numerous research papers. Its development has been crucial to the advancement of signal processing approaches [8]. In other cases, the application of entropy has been a popular choice in temporal signal analysis fields. The entropy approaches are based on calculating and contrasting between values of statistical indicators to distinguish healthy from unhealthy states of the rotating machinery. Therefore, several types of entropy have been utilised and shown great efficacy, such as sample entropy (SE), fuzzy entropy (FuzzyEn), dispersion entropy (DE), and multiscale entropy (MSE) [9], [10]. Our study addresses research by focusing on two approaches for detecting anomalies within induction motors with the aim of reaching more accurate knowledge and a more thorough diagnostic viewpoint. To achieve this goal, the proposed methods are based on fault detection.

Both the faults, including bearing and misalignment, are identified by using the suggested methodology; the first approach centres on the use of motor current signature analysis (MCSA) in an induction motor and the energy analysis method on the basis of a discrete wavelet transform. Furthermore, within the article, the second methodology integrates MCSA in conjunction with the multiscale entropy (MSE) method and principal component analysis (PCA). The combination of these techniques aims to provide early and accurate fault diagnosis, thereby prolonging operational machinery lifespans and reducing maintenance costs. Despite the fact that signal processing techniques are well known, each writer needs to analyse and adapt how they are structured to achieve an effective diagnostic result. This work is structured as follows: the first section is dedicated to the introduction, then, the definitions of the faults that have been researched, along with the theoretical underpinnings of the suggested diagnosis techniques, are thoroughly discussed in the second section. Next, the experimental part and the data acquisition are both covered in the third section. Readers of this paper will encounter in the fourth section the discussion of results obtained under both normal and faulty conditions. Lastly, the conclusion of the paper is provided in the fifth section.

II. THEORETICAL BACKGROUND

II.1 MOTOR CURRENT SIGNATURE ANALYSIS (MCSA)

Monitoring stator current, also known as motor current signature analysis has been one of the most significant diagnosis methods that have been applied in current research throughout the last years. Motor current signature analysis has been considered an effective, powerful, and trustworthy tool for monitoring health and identifying the existence of faults in electrical machines. Several problems that may be effectively detected by monitoring stator currents, which show clear fault patterns. This method assures on going condition monitoring through offering a non-intrusive method for consistently and regularly assessing the state of health [11]. Misalignment and bearing faults considered the most commonly observed disturbance sources in rotating systems; the careful exploration of the instantaneous stator current of the rotating machinery is a very important contribution to the detection of mechanical faults. It has been proven in [12], [13] that misalignment and bearing damage to the actuator oscillations causes the load torque which, consequently, will change the variation of the stator current of the rotating machinery.

II.2 THE DISCRETE WAVELET TRANSFORMS (DWT)

The discrete wavelet transform (DWT) can be considered an analytical method that makes it possible to analyse data by way of transforming signals from the time domain to the time and frequency domain in order to process signals and obtain a good result. By following the decomposition process of an original signal (S) through the use of two complementary filters, we are able to obtain high pass (H) and low pass (L), one of which reflects the detail signal (d) that corresponds to the high frequencies content of the signal and the other the approximation signal (a) that corresponds to the low frequencies content of the signal [14]. In each level, the detail and approximation coefficients are determined by the following expression:

$$s(t) = \sum_i \alpha_i^n \cdot \Psi_i^n(t) + \sum_{j=1}^n \sum_i \beta_i^n \cdot \varphi_i^j(t) = a_n + d_n + \dots + d_1 \quad (1)$$

Where, α , β represent scales and coefficients of the wavelet, Ψ^n , φ^j represent the decomposed function at level n and the wavelet function at level j respectively, n is the decomposition level a_n , d_n are respectively the approximation signal the detail signal at level n . These decompositions are limited by the maximum number of levels to which a signal can be broken down; this limit is determined based on the currents sampling frequency and the fundamental frequency. This limit number of levels is provided by the following relation:

$$N = \text{int} \left(\frac{\log \left(\frac{f}{f_s} \right)}{\log(2)} \right) + 2 \quad (2)$$

Where, N is the number of decomposition levels, f is the currents sampling frequency, f_s is the fundamental frequency.

II.3 ENERGY OF DECOMPOSITION IN WAVELETS

For more comprehensive diagnostics, the energy analysis technique on the basis of discrete wavelet transform (DWT) is an extremely efficient diagnostic process, which can be used to compare the energy characteristics of signals in both healthy and anomalous conditions by calculating the energy related to each level of wavelet decomposition detail [15]. The energy value can be identified at each level through the following expression:

$$E_j = \sum_{n=1}^N |d_j(n)|^2 \quad (3)$$

Where, j is the level of decomposition, N is the total sample number of the signal, d_j is the detail signal at discrete point j .

II.4 MULTISCALE ENTROPY (MSE)

Multiscale entropy (MSE) is an effective tool designed to quantify the complexity data from time series over several time scales. Unlike single-scale analyses, this method permits revealing hidden complexities and capturing underlying patterns that appear at various levels of resolution [16], [17]. A coarse-grained data sequence $y(s)$ should be obtained by a coarse-grained process, this process begins with coarse-graining, which simplifies the time series at each scale. For a scale factor τ , and a time series $x = \{x_1, x_2, x_3, \dots, x_N\}$, the coarse-grained series $y(\tau)$ is calculated as [18]:

$$y_j(\tau) = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x(i), \quad 1 \leq j \leq \frac{N}{\tau} \quad (4)$$

Where τ represents a scale factor and $j = 1, 2, \dots, \frac{N}{\tau}$. When $\tau = 1$, the coarse-grained time series is the same as the original time series. As the value of τ increases, the length of the coarse-grained time series decreases. Figure 1 shows the process of dividing the original time series into coarse-grained time series for scale factor $\tau = 2$ and $\tau = 3$.

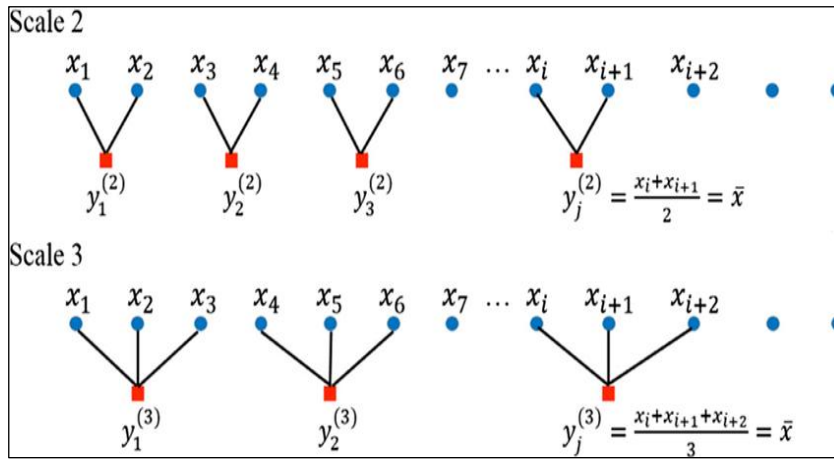


Figure 1: A representation of the coarse-graining process.
Source: Authors, (2026).

II.5 PRINCIPAL COMPONENT ANALYSIS (PCA)

The principal component analysis (PCA) is particularly a powerful statistical procedure when dealing with a large number of variables. This dimensionality reduction approach is used to simplify complex datasets while preserving as much variance as possible, facilitating analysis and visualisation by transforming the dataset with high dimensions into one with lower dimensions [19].

II.6 THE SQUARED PREDICTION ERROR (SPE)

The Squared Prediction Error (SPE) is a statistical metric used to evaluate the effectiveness of a predictive model by squaring the difference between the actual observed and the predicted values for a dataset. Regarding fault detection and diagnosis, SPE is often applied in conjunction with other metrics such as Mean Squared Error (MSE) to provide a comprehensive understanding of the performance of a model [20]. A high SPE indicates deviations that can be indicative of anomalous conditions or faults. The basic definition of SPE is expressed as:

$$SPE = \sum_{i=1}^k (X_{ij} - Y_{ij})^2 \quad (5)$$

Where X_{ij} represents the observed feature value, Y_{ij} represents the predicted value.

III. MATERIALS AND METHODS

The experimental tests were successfully carried out on the machinery fault simulator of Mines and metallurgy research unit (URMM/CRTI-Annaba); Figure 2 illustrates the test bench that has been used to conduct our study in order to validate the efficacy of the proposed method in the detection of numerous faults affecting the induction machine.

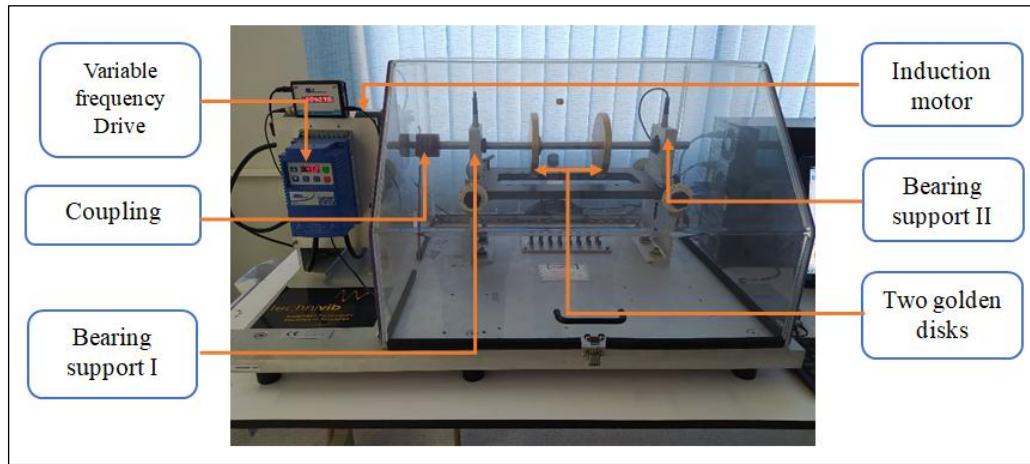


Figure 2: Experimental test bench.

Source: Authors, (2026).

In this investigation, a mechanical system has been used consisting of an induction motor, shaft, coupling, and bearing as shown in Figure 3. The induction motor used throughout this work was a three-phase model of 0.5 HP. The parameters of the main motor utilised in the study at a line frequency of 50 Hz are given in Table 1.

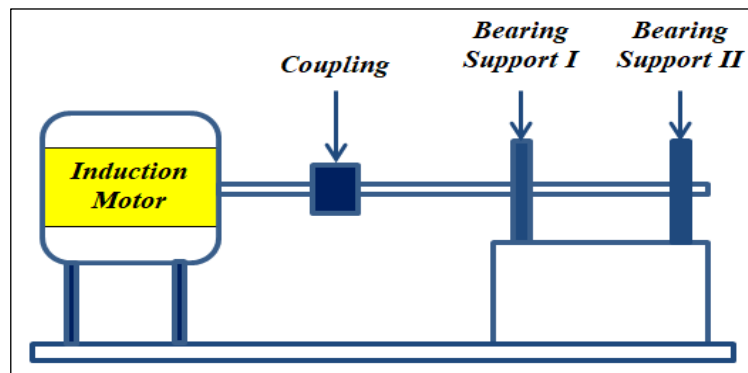


Figure 3: Experimental setup.

Source: Authors, (2026).

Table 1: Machine details.

Name plate details	Rating
Rated power	0.25 KW
Ratted current	1.92 A
Rated speed	2850 RPM
Norminal voltage	380 V
Norminal frequency	50 Hz

Source: Authors, (2026).

The material required to measure, collect, and interpret the three stator phase currents (I_A , I_B , and I_C) consists of a current sensor, an oscilloscope, and a computer. The three stator phase currents were measured by the use of a current sensor type: PAC 12 connected to a numerical oscilloscope HAMEG507 equipped with an acquisition card and connected to a PC, while the acquired data processing is carried out using MATLAB software for signal analysis. The experiments were performed under various operation conditions, which are given as:

- Healthy state,
- Inner race bearing defect,
- Motor fault with misaligned rotor,
- Combined defects (Motor fault with misaligned rotor and Inner race bearing defect).

In each condition, the stator currents are obtained at a sampling frequency of $f_s = 1$ KHz for three different speeds: 15, 30, and 50 Hz.

IV. RESULTS AND DISCUSSIONS

Figure 4 shows the temporal signals of the stator currents for three phases I_A , I_B , and I_C under different working conditions, including healthy state, misaligned rotor, inner race bearing fault, and combined faults, at a rotational speed of 2850 rpm.

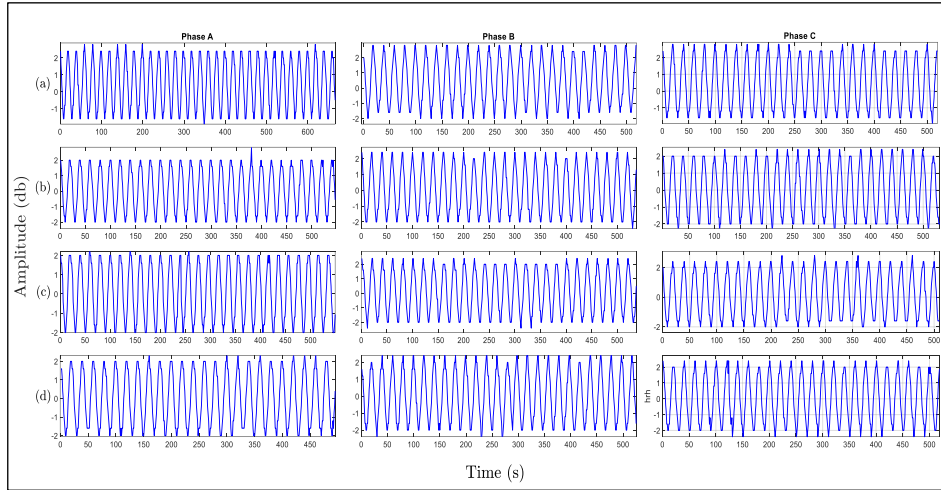


Figure 4: The temporal signal under different operating condition: (a) healthy, (b) Motor fault with misaligned rotor, (c) inner race bearing fault, (d) combined faults.

Source: Authors, (2026).

The decomposition levels in the DWT analysis are using Equation (2) with a frequency of 50 Hz and sampling frequency of 1 kHz. There are 6 levels of decomposition; Table 2 shows the frequency bands for each detailed decomposition level and the sixth approximation level.

Table 2: Frequency bands of detail signals.

Levels	Frequency Band
d_1	500 – 1,000 Hz
d_2	250 – 500 Hz
d_3	125 – 250 Hz
d_4	62.5 – 125 Hz
d_5	31.25 – 62.5 Hz
d_6	15.625 – 31.25 Hz
a_6	0 – 15.625 Hz

Source: Authors, (2026).

Figures 5 show a detailed representation of the discrete wavelet transform (DWT) decomposition applied to stator current for phase A under healthy and faulty states on the machine at an operating speed of 50 Hz. This analysis covers forth different operational conditions, including healthy case, misaligned rotor, inner race bearing fault, and combined defects. These figures offer a granular view of the decomposition process, presenting the detailed coefficients from levels d_1 to d_6 , as well as the approximation level at the sixth level (a_6).

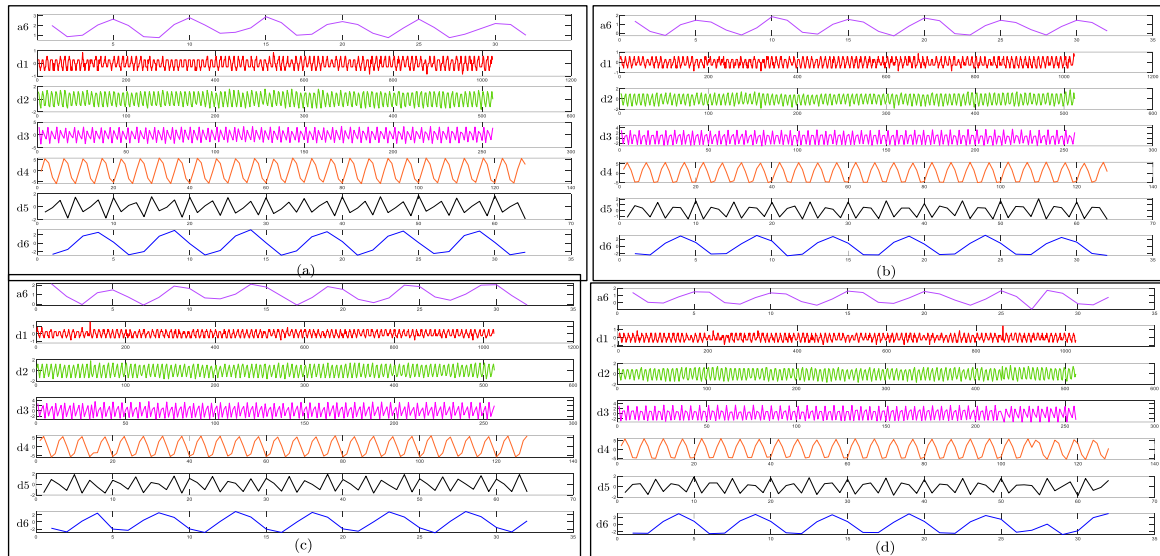


Figure 5: Wavelet decomposition of stator current signal for Phase A at different operating condition: (a) healthy state, (b) misaligned rotor, (c) inner race bearing fault, and (d) combined fault.

Source: Authors, (2026).

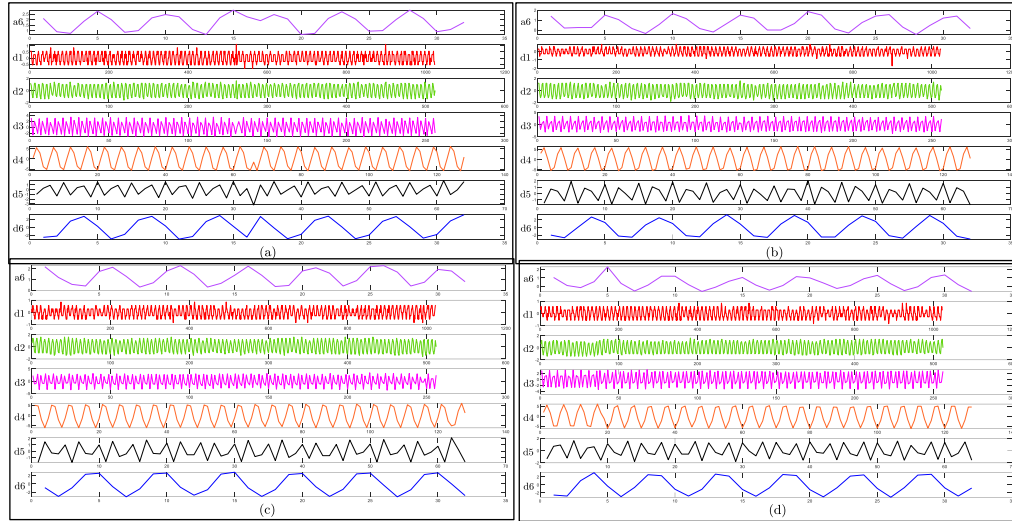


Figure 6: Wavelet decomposition of phase B stator current signal in four operating conditions: (a) healthy state, (b) misaligned rotor, (c) inner race bearing fault, and (d) combined fault.

Source: Authors, (2026).

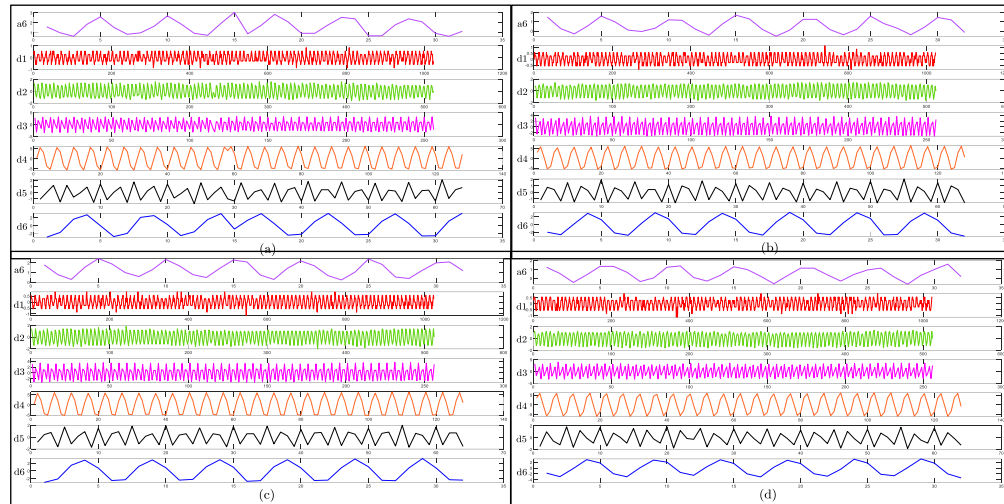


Figure 7: wavelet decomposition of phase C stator current at different working conditions: (a) healthy state, (b) misaligned rotor, (c) inner race bearing fault, and (d) combined faults.

Source: Authors, (2026).

Figure 6, and 7 demonstrates a thorough analysis of the stator current signals for IB and IC within the time-frequency domain through the discrete wavelet transform (DWT) technique for case of a healthy machine and three other states including inner race bearing fault, misaligned rotor, and combined faults. Through a visual comparison, there is hardly any distinction between healthy and faulty states of the stator current signal for phase A (Figure 5), phase B (Figure 6), and phase C (Figure 7). However, we observe in each phase that the fifth and sixth detail levels of the signal in the defective states show a remarkable variation in contrast to the healthy state. These noticeable shifts among the original signal in the healthy and the faulty states reflect the impact of machine failures. Tables 3 and 4, respectively, highlight the energy values of detail coefficients (d1 to d6) from the phase A and phase B stator current under various working conditions. The energy values of phase C at six decomposition levels across healthy and different fault states are presented in Table 5.

Table 3: Energy values of phase A at different decomposition levels.

Wavelet level	Energy value			
	healthy	Misaligned rotor	Inner race bearing fault	Combined faults
D1	2.73	3.06	3.12	3.17
D2	9.57	9.14	9.39	9.14
D3	29.43	30.29	29.89	30.13
D4	50.74	51.45	51.30	51.61
D5	1.76	2.01	1.98	1.88
D6	3.26	3.23	3.09	3.30

Source: Authors, (2026).

Table 4: Energy values of phase B at different decomposition levels.

Wavelet level	Energy value			
	healthy	Misaligned rotor	Inner race bearing fault	Combined faults
D1	3.20	2.93	2.86	3.07
D2	9.58	9.71	9.93	9.69
D3	28.80	30.42	29.17	30.12
D4	50.56	51.15	50.96	51.33
D5	2.15	2.02	2.05	1.94
D6	3.23	3.30	3.27	3.35

Source: Authors, (2026).

Table 5: Energy values of phase C at different decomposition levels.

Wavelet level	Energy value			
	healthy	Misaligned rotor	Inner race bearing fault	Combined faults
D1	2.74	3.05	3.11	2.99
D2	9.34	9.52	9.84	9.21
D3	29.70	30.36	29.75	30.34
D4	50.82	51.22	50.42	51.65
D5	1.88	1.89	1.99	1.90
D6	3.27	3.38	3.29	3.37

Source: Authors, (2026).

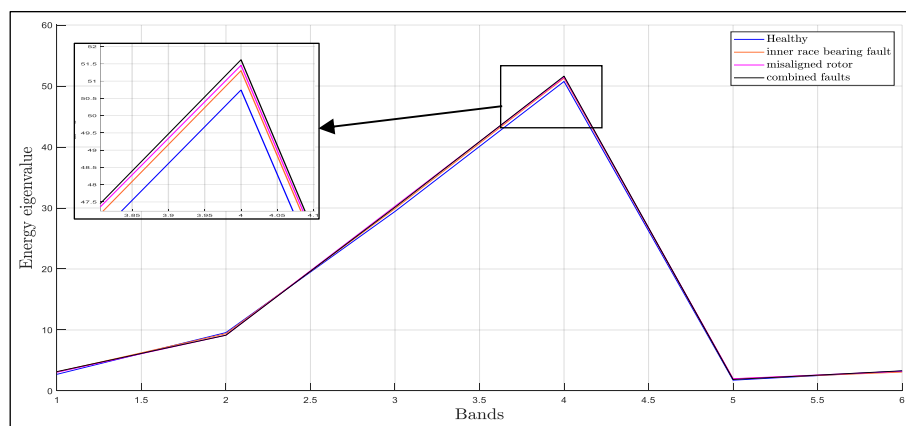


Figure 8: Energy levels of the phase A stator current under different operating conditions.

Source: Authors, (2026).

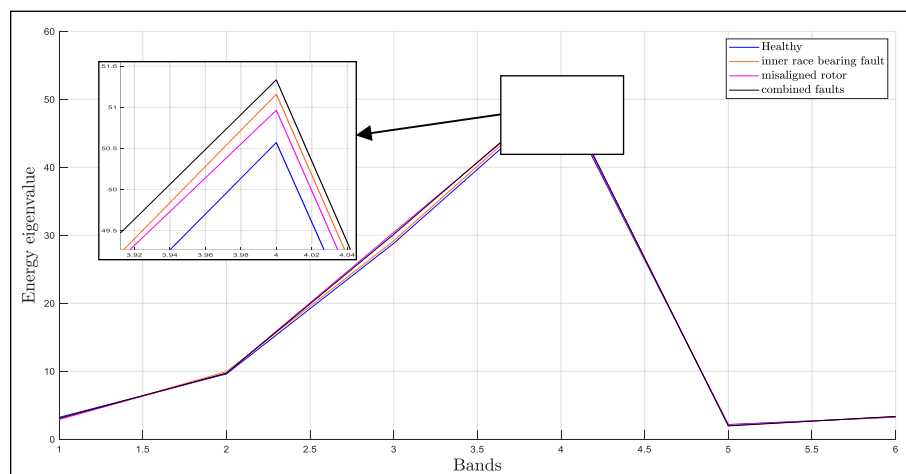


Figure 9: Energy levels of the phase B stator current under different operating conditions.

Source: Authors, (2026).

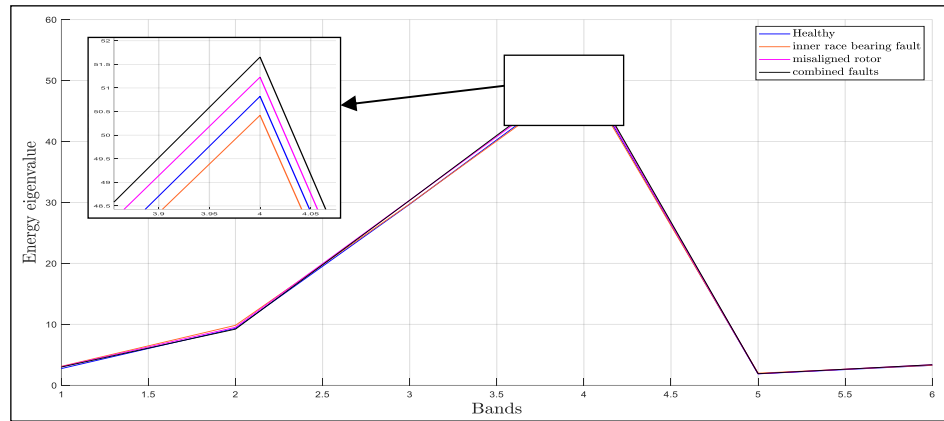
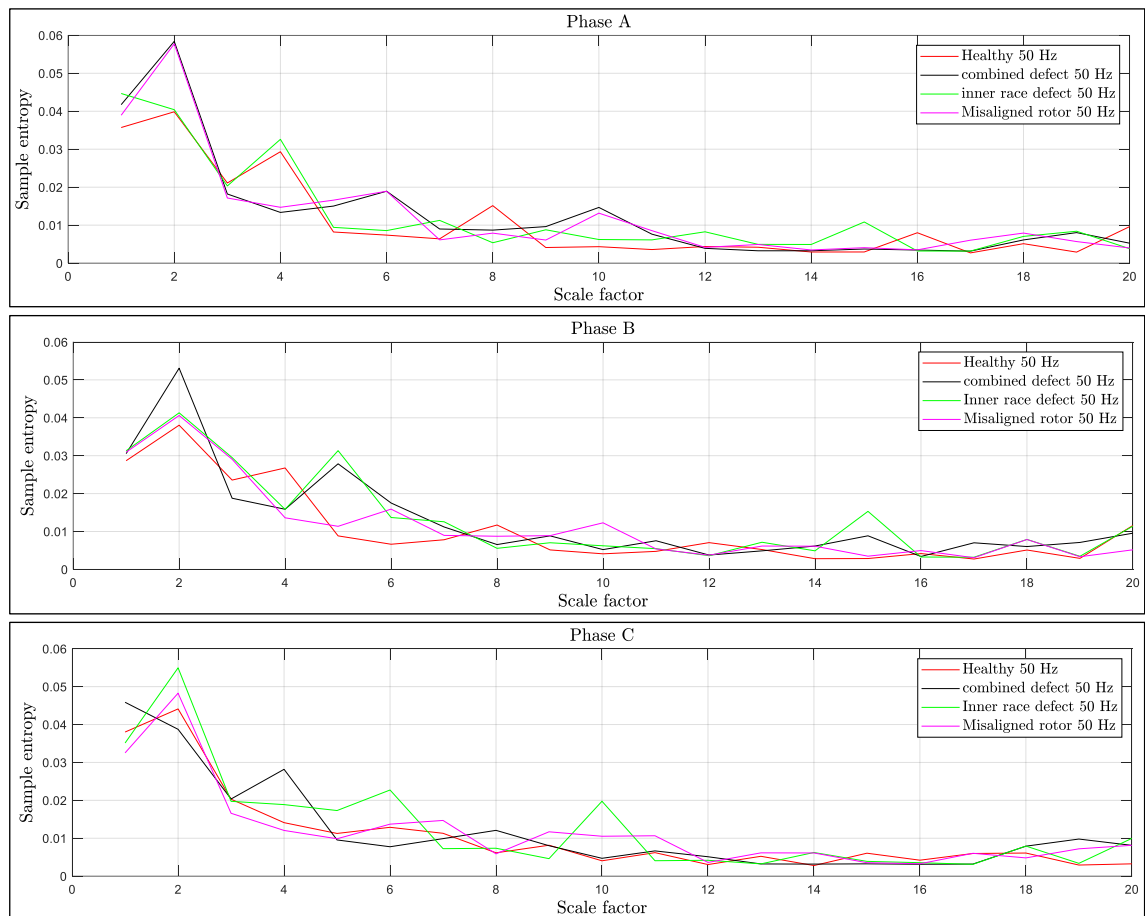


Figure 10: Energy levels of the phase C stator current under different operating conditions.

Source: Authors, (2026).

The graph in Figure 8 illustrates the variation in the energy values of the current signal in phase A for different decomposition levels in the state of a healthy machine and with different defect conditions. Figure 9 shows the change in the energy of I_B stator current across different signal decomposition levels. As to the variation in energy of the stator current signal in phase C for different decompositions of signal levels across healthy and faulty working states, it is also given in Figure 10. Upon close examination of the provided figures, a notable variation within the energy values at different detail levels is revealed. According to tables 3 and 4, along with figures 8 and 9, a comprehensive analysis of the obtained results reveals that there is a notable distinction in energy values in diverse decomposition levels for I_A and I_B stator current, especially for the fourth decomposition level, which exhibits that there is a significant rise in energy for the faulty signals in contrast to the healthy signal. As for phase C, it becomes evident that distinct energy values occur between healthy and misaligned and combined faults at the fourth detail level, whereas bearing fault energy shows a lower value than the healthy case, unlike the two other phases. This sort of conduct may arise in certain cases due to several factors. However, the increase differs based on the severity of the default at the machine. It can be seen that the distinction among the healthy and the faulty states is very clear, and the rise of energy varies according to the degree of the default.

Figure11: Multiscale sample entropy over 20 scales of the corresponding stator current signal I_A , I_B and I_C .

Source: Authors, (2026).

Figure 11 illustrate the sample entropy for phase A of stator current across 20 time scales for four working condition at an operating speed of 50 Hz. In the SampEn for phase's current, we clearly observe differences in entropy patterns; sample entropy values are lower and more consistent across different scales for healthy operating condition in contrast to other faulty states, which exhibit a noticeable deviation for sample entropy values.

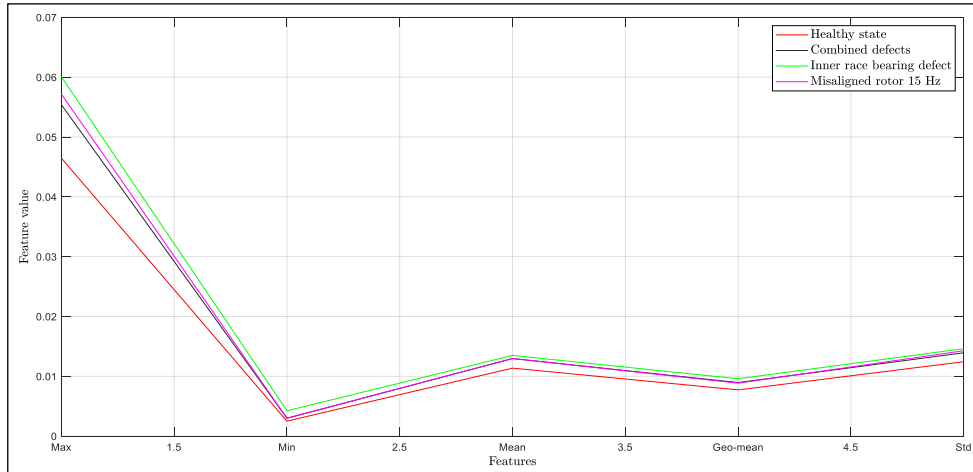


Figure 12: Five statistics over multiscale sample entropy of the phase current signal I_A .

Source: Authors, (2026).

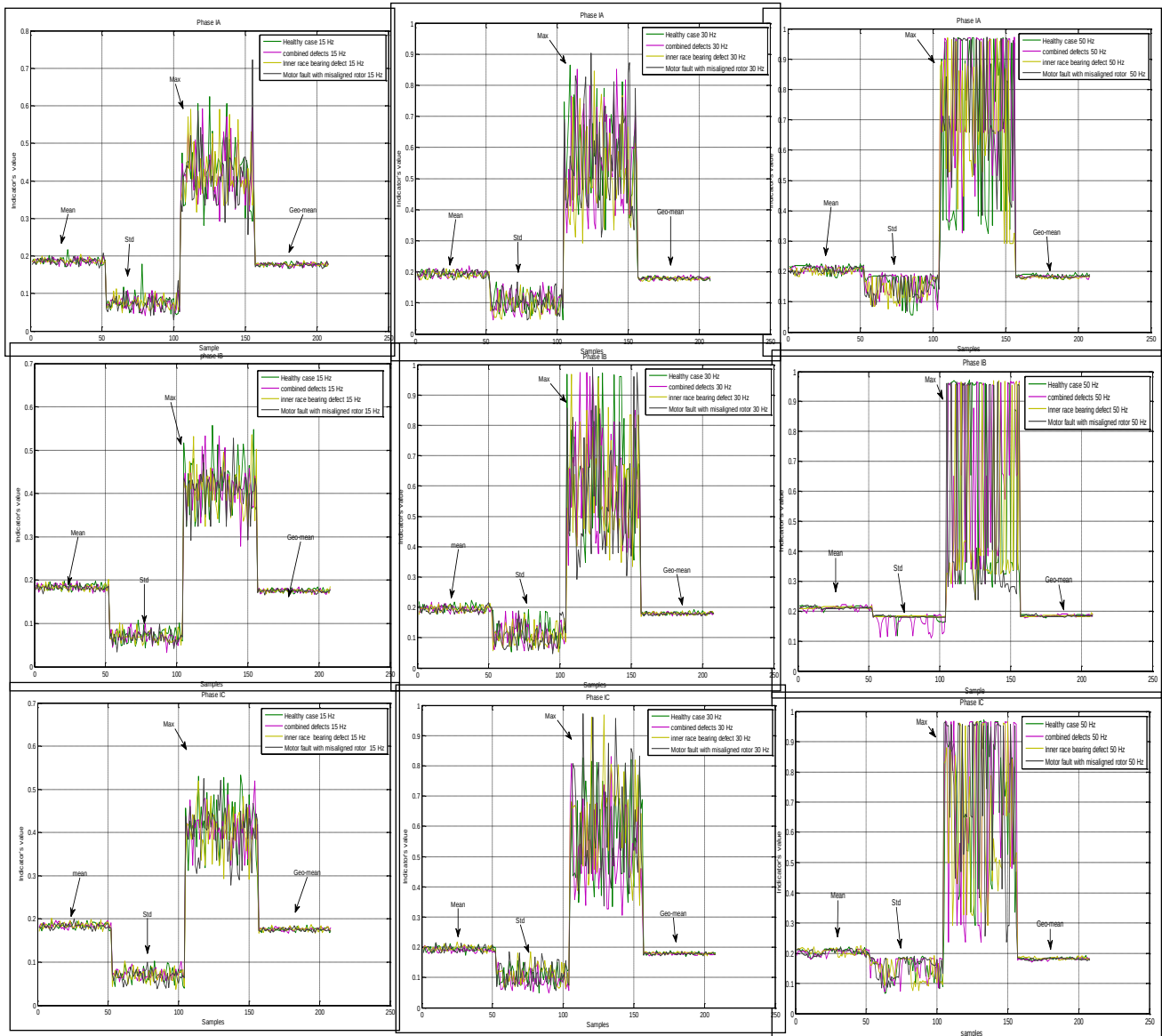


Figure 13: Four statistics over Multiscale sample entropy of phase current signal I_A , I_B and I_C with various speeds (15 Hz, 30 Hz and 50 Hz).

Source: Authors, (2026).

Figure 12 shows five feature statistics: the maximum SampEn value (max), minimum value (min), geo-mean of SampEn value (geo-mean), standard deviation of SampEn value (std), and arithmetic mean of SampEn value (mean) that are extracted from the Multiscale entropy (MSE) of current stator phase A at the speed of 15 Hz. Figure 13 displays the evolution of four statistical features (mean, max, geo-mean, std) over the MSE under different operating speeds (15 Hz, 30 Hz, 50 Hz). Figure 13 shows the four statistical features across the MSE for IA, IB and IC, respectively. By comparing the healthy state with defect conditions, these figures reveal a significant rise in all fault feature values in contrast with the healthy case, which exhibit a stable and consistent feature over time. These feature statistics are compared across four operating conditions, including healthy, inner race bearing fault, misaligned rotor, and combined faults.

Figure 14 illustrates the squared prediction error (SPE) of the phase current IA over time for fourth operation conditions, demonstrating how the SPE values are low and stable in healthy cases compared to when defects are revealed; the SPE values deviate significantly with noticeable fluctuations. This deviation corresponds to the type and severity of defects. Figure 15 offers a more detailed analysis of the SPE for the same four working conditions as in Figure 14 by decomposing it into four statistical features (mean, STD, max, and geo mean) extracted from the Multiscale entropy (MSE) of the phase current signals, demonstrating how the SPE fluctuates as faults develop from a healthy condition to higher levels of severity. In the healthy state, the SPE values for all features remain consistently low. In contrast, faulty conditions exhibit distinct increases in the SPE, and peaks begin to appear as defect severity progresses. Among the features, Geo-mean shows the highest sensitivity to faults, demonstrating the largest SPE peaks, while the other features display moderate but noticeable fluctuations. These results highlight the ability of SPE for progression monitoring and fault detection.

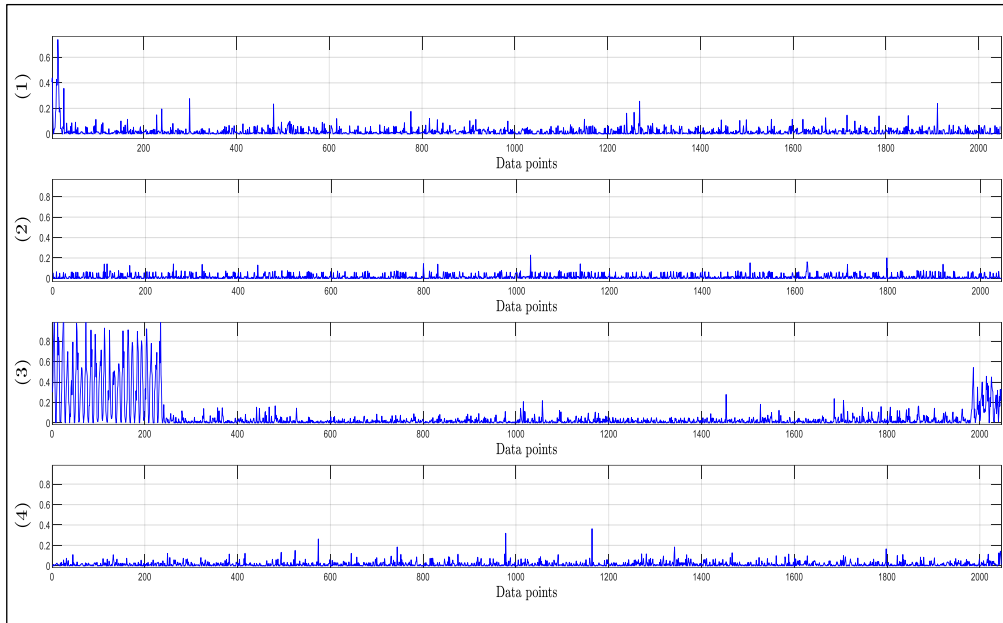


Figure 14: Evolution of the SPE for: **(1)** healthy case; **(2-4)** defects in different cases.

Source: Authors, (2026).

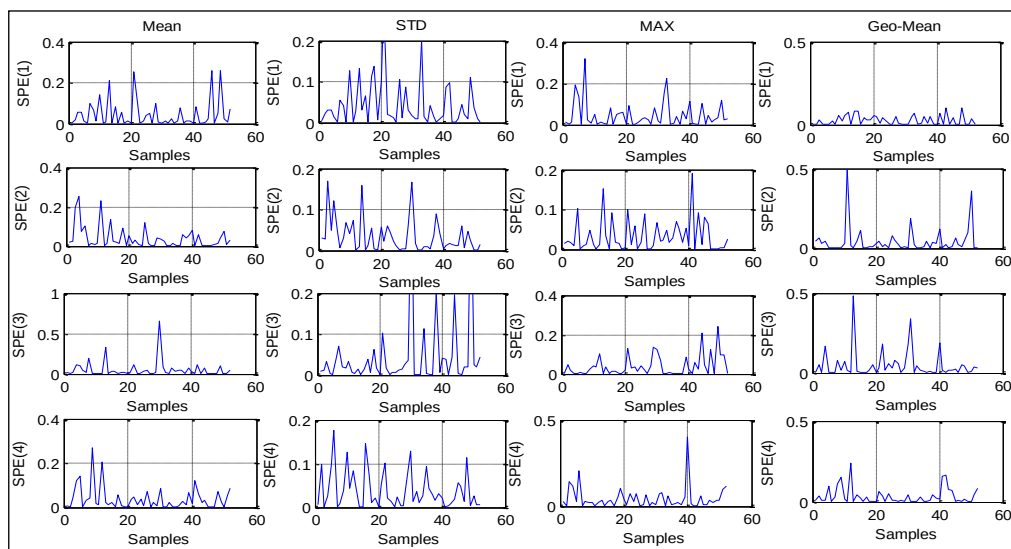


Figure 15: Evolution of the SPE for four statistics over multiscale sample entropy of the phase current signals for: **(1)** healthy case, **(2-4)** defects in different cases.

Source: Authors, (2026).

V. CONCLUSIONS

In summary, this research paper highlights two successful approaches to pinpointing and detecting various faults affecting induction motors, utilising the motor current signature analysis (MCSA). The first approach applies the MCSA technique with DWT energy analysis, while the second approach involves the application of the MCSA on the three-phase induction motor combined with multiscale entropy (MSE) and principal component analysis (PCA). The DWT energy analysis technique provides valuable information to identify the multifunction operating conditions. Through these results, we can observe clearly that the energy level increases with the presence of the fault. Conversely, in a healthy state, the energy levels are always at their lowest. These findings validate the accuracy and reliability of these combined approaches for fault diagnosis, which exhibit notable improvements in identifying and addressing inner race bearing fault, misalignment rotor, and combined defects.

The second experimental results from a three-phase induction motor demonstrate the ability of the proposed method in addressing challenges in early fault detection. This approach successfully distinguishes healthy from faulty states by analysing stator currents, particularly for localised defects. MSE is applied to extract detailed features while dimensionality and isolating fault relevant variations are reduced through PCA. The squared prediction error (SPE) analysis enhances the fault detection ability and assures more comprehensive analysis of the induction machine health. The SPE effectively confirms these findings by highlighting anomalies and deviations from healthy conditions, with increasing peaks and fluctuations that correspond to the severity of faults. Future studies should focus on expanding the approaches to different industrial conditions, including advanced methods of machine learning to enhance fault classification and optimising the algorithms for applications in real time. Overall, this research not only improves the detection of induction motor faults but also contributes to enhancing motor reliability, reducing unplanned downtimes, and leading to more effective industrial operations.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Hamdane Housseem, Bouras Abdelkarim and Aouabdi Salim.

Methodology: Hamdane Housseem, Bouras Abdelkarim and Aouabdi Salim.

Investigation: Hamdane Housseem and Aouabdi Salim.

Discussion of results: Hamdane Housseem, Bouras Abdelkarim and Aouabdi Salim.

Writing – Original Draft: Hamdane Housseem, Bouras Abdelkarim and Aouabdi Salim.

Writing – Review and Editing: Bouras Abdelkarim and Aouabdi Salim.

Resources: Aouabdi Salim.

Supervision: Bouras Abdelkarim and Aouabdi Salim.

Approval of the final text: Hamdane Housseem, Bouras Abdelkarim and Aouabdi Salim.

VII. REFERENCES

- [1] O. AlShorman, et al., "Advancements in condition monitoring and fault diagnosis of rotating machinery: A comprehensive review of image-based intelligent techniques for induction motors," *Engineering Applications of Artificial Intelligence*, vol. 130, p. 107724, 2023. doi: 10.1016/j.engappai.2023.107724.
- [2] L. H. Wang, X. P. Zhao, J. X. Wu, Y. Y. Xie, and Y. H. Zhang, "Motor fault diagnosis based on short-time Fourier transform and convolutional neural network," *Chinese Journal of Mechanical Engineering*, vol. 30, pp. 1357–1368, 2017. doi: 10.1007/s10033-017-0190-5.
- [3] C. Li, R. V. Sanchez, G. Zurita, M. Cerrada, D. Cabrera, and R. E. Vásquez, "Gearbox fault diagnosis based on deep random forest fusion of acoustic and vibratory signals," *Mechanical Systems and Signal Processing*, vol. 76–77, pp. 283–293, 2016. doi: 10.1016/j.ymssp.2016.02.007.
- [4] A. Bouras, S. Bouras, and S. Kerfali, "Prediction of the mass unbalance of a variable speed induction motor by stator current multiple approaches," *Turk. J. Elec. Eng. & Comp. Sci.*, vol. 26, pp. 1056–1068, 2018. doi: 10.3906/elk-1702-58.
- [5] L. Valladares and O. Baute, "Automation engineering service for corn steeping and wet milling processes, in factory of glucose and corn derivatives (GYDEMA)," *ITEGAM-JETIA*, vol. 6, no. 22, pp. 04–10, Apr. 2020.
- [6] H. Sun, Q. Si, N. Chen, and S. Yuan, "HHT-based feature extraction of pump operation instability under cavitation conditions through motor current signal analysis," *Mechanical Systems and Signal Processing*, vol. 139, p. 106613, 2020. doi: 10.1016/j.ymssp.2019.106613.
- [7] S. Halder, S. Bhat, D. Zychma, and P. Sowa, "Broken rotor bar fault diagnosis techniques based on motor current signature analysis for induction motor: A review," *Energies*, vol. 15, p. 8569, 2022. doi: 10.3390/en15228569.
- [8] E. Akbari and M. S. Shadlu, "An intelligent ANFIS-based fault detection, classification, and location model for VSC-HVDC systems based on hybrid PCA-DWT signal processing technique," *Computers and Electrical Engineering*, vol. 120, p. 109763, 2024. doi: 10.1016/j.compeleceng.2024.109763.
- [9] Z. Wang, L. Yao, and Y. Cai, "Rolling bearing fault diagnosis using generalized refined composite multiscale sample entropy and optimized support vector machine," *Measurement*, vol. 156, p. 107574, 2020. doi: 10.1016/j.measurement.2020.107574.
- [10] M. Rostaghi, M. R. Ashory, and H. Azami, "Application of dispersion entropy to status characterization of rotary machines," *Journal of Sound and Vibration*, vol. 438, pp. 291–308, 2018. doi: 10.1016/j.jsv.2018.08.025.
- [11] A. Bouras, S. Bouras, and S. Kerfali, "Prediction of the mass unbalance of a variable speed induction motor by stator current multiple approaches," *Turkish Journal of Electrical Engineering & Computer Sciences*, vol. 26, pp. 1056–1068, 2018. doi: 10.3906/elk-1702-58.
- [12] J. Lee, Y. Lee, and N. Kim, "Detection and analysis of shaft misalignment in application of production and logistics systems using motor current signature analysis," *Expert Systems with Applications*, vol. 217, p. 119463, 2023. doi: 10.1016/j.eswa.2022.119463.
- [13] K. K. C. Deekshit, M. V. G. Rao, and R. S. Rao, "DWT-based bearing fault detection in induction motor using noise cancellation," *Journal of Electrical Systems and Information Technology*, vol. 3, pp. 411–427, 2016. doi: 10.1016/j.jesit.2016.07.002.

- [14] V. B. Bal, N. F. Kotelenets, and M. Deeb, "Discrete wavelet transform for stator fault detection in an induction motor," *Power Technology and Engineering*, vol. 57, pp. 175–185, 2023. doi: 10.1007/s10749-023-01639-0.
- [15] N. Benamira, A. Dekhane, A. Bouraiou, and I. Atoui, "Exploring the effects of overvoltage unbalances on three-phase induction motors: Insights from motor current spectral analysis and discrete wavelet transform energy assessment," *Computers and Electrical Engineering*, vol. 117, p. 109242, 2024. doi: 10.1016/j.compeleceng.2024.109242.
- [16] W. T. Thomson and R. J. Gilmore, *Motor Current Signature Analysis to Detect Faults in Induction Motor Drives—Fundamentals, Data Interpretation, and Industrial Case Histories*. Tulsa, OK, USA: Electrical Apparatus Service Association (EASA), 2003.
- [17] S. Aguayo-Tapia, G. Avalos-Almazan, and J. de Jesus Rangel-Magdaleno, "Entropy-based methods for motor fault detection: A review," *Entropy*, vol. 26, p. 299, 2024. doi: 10.3390/e26040299.
- [18] K. W. Mukanda, M. N. Waswa, and L. Ouma, "Radiological risk assessment of ^{238}U , ^{232}Th and ^{40}K in the top soils of Ahero paddy fields of Kisumu County, Kenya," *ITEGAM-JETIA*, vol. 8, no. 36, pp. 32–36, 2022.
- [19] A. H. Bonnett and G. C. Soukup, *Cause and Analysis of Stator and Rotor Failures in Three-Phase Squirrel-Cage Induction Motors*. Piscataway, NJ, USA: IEEE Press, 1992. doi: 10.1109/IEEESTD.1992.106933.
- [20] S. Aouabdi, M. Taibi, S. Bouras, and N. Boutasseta, "Using multiscale entropy and principal component analysis to monitor gears degradation via the motor current signature analysis," *Mechanical Systems and Signal Processing*, vol. 90, pp. 298–316, 2017. doi: 10.1016/j.ymssp.2016.12.027.