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COMBINED ROTOR FAULTS DIAGNOSIS IN INDUCTION MOTORS USING MVSA AND INTRA-MODE VARIATIONAL MODAL DECOMPOSITION (IM-VMD)

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Abstract

In modern industry, constant production and operation without stoppages is viewed as being vital in ensuring competitiveness and efficiency. To maintain continuity in production, industries make use of advanced diagnostic measures by using of different performance measures such as reliability and risk assessment. In addition, within the context of Industry 4.0, there are also smart devices and Internet of Things (IoT) that can be used to enhance monitoring and optimize production processes intelligently. In such a context, this study seeks to examine the problem of detecting combined faults in three-phase induction machines via vibration signals. The purpose of this research is to diagnose fault signatures as early as possible even in the presence of multiple interactions between the faults. To achieve this objective, an intra-mode variational mode decomposition (IM-VMD) approach that employs an embedded source separation strategy was applied for decomposing vibration signals into multiple intrinsic modes. Using this framework, it became possible to isolate those vibration components associated with faults and increase interpretability of signals in terms of time and frequency domains. The outcomes demonstrated an effective identification of fault signatures; the extracted vibration frequency components match the theoretical frequencies of the defects. More precisely, the coefficient of correlation between extracted frequency components and theoretically calculated ones equals 0.95 to 1. This finding suggests that the proposed algorithm provides reliable results that can be applied in practice for detecting combined faults in three-phase induction machines. It is also possible to highlight that by utilizing the introduced method, it becomes possible to detect fault signatures at the earliest stage of their appearing.

Keywords: induction motor, fault diagnosis, vibration analysis, signal processing, blind source separation, broken rotor bar, eccentricity, combined faults

List of Symbols/Acronyms

FFT – Fast Fourier Transform;
BSS – Blind Source Separation;
BRB – Broken Rotor Bar;
DFT – Discrete Fourier Transform;
EESC – São Carlos Engineering School;
EWT – Empirical Wavelet Transform;
FastICA – Fast Independent Component Analysis;
IEEE – Institute of Electrical and Electronics Engineers;
IM – Induction Machine ;
IM-VMD – Intra-Mode Variational Mode Decomposition ;
IoT – Internet of Things;
JADE – Joint Approximate Diagonalization of Eigen-matrices;
LMS – Least Mean Squares;
MVSA – Motor Vibration Signature Analysis;
RMS – Root Mean Square;
SANC – Smart Adaptive Noise Cancellation;
SNR – Signal-to-Noise Ratio;
USP – University of São Paulo;
VMD – Variational Mode Decomposition.

1. INTRODUCTION

Induction motors (IMs), also known as asynchronous motors, are a cornerstone of mechanical energy conversion systems. Their widespread use in industrial applications is primarily due to their simple design, high durability, and favorable cost-effectiveness. For example [1], highlights that squirrel-cage induction motors are widely used in industry due to their reliability, low maintenance requirements, and economic benefits. Also, [2] emphasizes their widespread use as primary actuators in industrial systems, where reliability and cost-effectiveness are key factors.

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These machines are used in multiple industrial sectors, thanks to their reliability and operational continuity that are critical to maintaining productivity. Despite their proven durability, induction machines may experience an internal degradation because of their exposure to thermal, mechanical, and electromagnetic stresses. Broken rotor bar (BRB) faults, represent a significant defect because of their impact on electromagnetic symmetry and torque production [3]. These faults are caused by cyclic mechanical stresses, thermal expansion effects, or manufacturing imperfections. Their severity increases over time if not detected at an early stage. As the defect spreads, it may generate torque pulsations, speed oscillations, abnormal vibration patterns, and localized temperature rise. Rotor arcing phenomena can occur in advanced stages, bringing to the scene an acceleration of structural deterioration and a reduction of the overall system efficiency. Detecting BRB faults at an early stage is challenging because the associated fault signatures are weak and depend strongly on operating conditions such as load variation and supply fluctuations [4, 5]. Environmental noise, structural resonances, and electromagnetic interactions impact vibration signals. This results in a challenging extraction of relevant diagnostic features. Therefore, the effectiveness of traditional signal processing techniques is limited, especially when fault-related components overlap with dominant mechanical frequencies. Motor vibration signature analysis (MVSA) becomes a widely used condition monitoring technique due to its non-invasive nature, low cost, and compatibility with online monitoring systems [6]. However, vibration signals collected in practical environments usually contain multiple interacting components: mechanical and electromagnetic sources. These components make accurate fault isolation difficult, especially under varying load and high noise levels. To overcome these limitations, advanced signal processing approaches have been investigated, including adaptive filtering, blind source separation (BSS), and signal decomposition techniques. Although these methods have demonstrated potential in improving diagnostic performance, they remain subject to certain constraints. BSS-based approaches lean on statistical assumptions such as source independence, that may not be satisfied in real industrial systems. In parallel, classical decomposition methods may experience mode mixing, parameter sensitivity, and reduced robustness under non-stationary operating conditions. These challenges highlight the need for an adaptive and a stable diagnostic framework capable of enhancing weak fault signatures while preserving physical interpretability. In this paper, an Intelligent Mode–Variational Mode Decomposition (IM-VMD) framework is proposed for an early detection of broken rotor bar faults. The proposed methodology combines the intrinsic mode extraction capability of VMD with enhanced filtering and intelligent mode selection strategies, to improve fault-related component isolation. The effectiveness of the approach is evaluated through simulation-based experiments, using a realistic induction machine model. The results show that the IM-VMD framework enhances detection sensitivity and robustness, especially under low-severity fault conditions, thereby improving condition monitoring and preventive maintenance of induction motor systems [7].

2. PROPOSED APPROACH AND EXPERIMENTAL SETUP

2.1. Motor Vibration Signature Analysis

Motor Vibration Signature Analysis (MVSA) is a common method used to detect problems in electric motors, especially rotor bar faults in squirrel-cage induction machines. It works by studying the axial and radial vibration signals produced during motor operation [8]. When a rotor bar is damaged or broken, the rotor loses its electromagnetic balance. This creates specific frequency components in the vibration spectrum. These components come from torque oscillations and the mechanical imbalance caused by the fault. By looking at these features, it becomes possible to see the difference between a healthy motor and a faulty one. This is particularly useful in closed-loop systems, where motor current analysis may not detect early rotor defects. Because it is non-invasive and reliable, MVSA is widely used for monitoring the condition of induction motors and supporting maintenance decisions [9, 10].

2.2. Rotor Faults Description

Broken rotor bar faults do not happen often in industrial motors. This is because most rotors are strong and can handle normal stress. Many motors also work under moderate load, so they are not exposed to heavy conditions that could damage the bars. Even if the fault is rare, it can still cause serious problems. When a rotor bar breaks, the rotor becomes unbalanced. This can create extra vibration, reduce efficiency, and lead to mechanical wear if no action is taken [9, 10]. Over time, the machine may become less stable and less reliable. The early signs of the fault are often weak, which makes detection difficult. A broken bar changes the magnetic field inside the machine. This creates small changes in vibration and current signals. The motor may show slight speed variations, stronger torque pulses, and sideband components around the main stator frequency. In MVSA, these faults are found by looking for specific frequencies that do not appear when the motor is healthy [11] which depend on the slip and the supply frequency. However, these components are usually close to the main frequency. Envelope analysis is often used to make them easier to see [12]. Nevertheless, using MVSA helps detect broken rotor bars earlier and reduces the risk of major failures:

$$f_d = (1 \pm 2.k.g)f_s \qquad (1)$$

- f_d : Fault frequency (Hz)
- f_s : Supply frequency (Hz)
- g: Slip
- $k = \{1, 2, 3, \ldots, n\} \in N$

Eccentricity faults in induction machines are classified into two categories: static and dynamic. The first type refers to situations where there is a misalignment between the rotor and the axe of the stator, with the rotor remaining stationary. This creates a constant and irregular air gap. In contrast, dynamic eccentricity refers to situations where the rotor rotates around an axis that does not coincide with the axe of the stator, creating a periodic variation in the air gap. This defect can be identified by specific characteristics in the vibration and current spectra [13]. Eccentricity causes a periodic force, creating characteristic vibrations at certain frequencies:

$$f_{exen} = n * f_{rotation} \qquad (2)$$

- f_{exen} : Fault frequency (Hz)
- f_r: the machine rotation frequency (Hz).
- $n = 1$ ➔ Static eccentricity
- $n = \{2, 3, \ldots, n\} \in N$ ➔ Dynamic eccentricity

This study focuses primarily on dynamic eccentricity, characterized by multiple harmonic components (n ≥ 2), which are more representative of actual operating conditions and provide more detailed diagnostic information.

2.3. Experimental Testbed and Dataset Acquisition

This study is based on a dataset for the detection and diagnosis of broken rotor bar faults of the induction machine supplied by the IEEEDataPort certified site. The testbed is located on the premises of the São Carlos Engineering School (EESC) of the University of São Paulo (USP) in Brazil, more specifically in the Laboratory of Intelligent Automation of Processes and Systems (LAIPS) and the Laboratory of Intelligent Control of Electrical Machines (LACIME) [14].

The three-phase induction machine used is WEG's standard model W22, 220V/380V, 3.02A /1.75A, 4 poles, 60 Hz, with a rated torque of 4.1 N.m and a rated speed of 1715 rpm. The rotor is of the squirrel-cage type, with 34 bars. The vibration sensors used were Vibrocontrol uniaxial accelerometers, model PU 2001, with a sensitivity of 10mV/mm/s, a frequency range of 5 to 2000Hz and a stainless-steel housing, which provides the time-integrated acceleration signal, i.e. it provides the vibration velocity measurement. Currents were measured using Yokogawa model 96033 AC current probes, precision meters with a capacity of up to 50 A RMS, and an output voltage of 10 mV/A. Voltages were measured directly at the terminals using oscilloscope voltage probes also manufactured by Yokogawa.

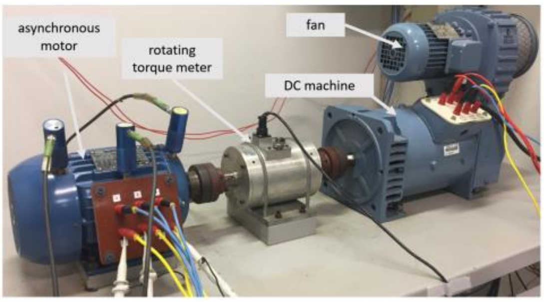

Fig. 1. The testbed [14]

The data used for this induction machine contains several types of vibration data. These include axial, radial and angular vibration measurements, as well as basic motor data. Analysis of vibration signals from different directions helps to identify fault signatures, such as those generated by broken bars. Axial and radial vibrations have proved particularly useful for detecting bar defects, with each type of vibration providing additional information on the condition of the machine. The IM-VMD algorithm developed was implemented in Python. Parametric studies were conducted for establishing the ideal number of decomposition modes. Several tests were performed, and the criteria used included the capability of the technique to identify frequencies corresponding to faulty rotors.

The database consists of data from normal and abnormal operating conditions. Rotor faults were simulated using the drilling of the rotor bars to obtain the broken bars type fault condition. There were many severities considered, such as a single, two, three, and four broken rotor bars.

3. EXPERIMENTAL RESULTS ANALYSIS

3.1. Experimental Results Analysis

Before starting the experimental part, it is important to distinguish between the respective contributions of axial and radial vibration signals. Axial vibration signals are often more sensitive to broken rotor bar faults. They capture the mechanical changes caused by the loss of electromagnetic balance inside the rotor [11]. These changes appear as variations in axial force. They are linked to torque pulses and the imbalance of the magnetic field. Because of this, axial vibration is very useful for detecting the fault at an early stage. Indeed, the axial forces caused by these faults result in more pronounced frequency components in axial signals, even under closed-loop control conditions, where signal damping can attenuate faults in radial vibrations. Radial vibrations, on the other hand, although more sensitive to mechanical imbalances and inter-bar currents, are less robust for the direct detection of broken bars. Thus, the combined analysis of both types of signal or radial vibration signals provides a more complete picture of the engine's condition, with each direction providing additional information on the nature and severity of faults. To study broken bars faults as a first check, we analyzed the signals, and the figures below show the spectra of the faulty state (a single broken bar).

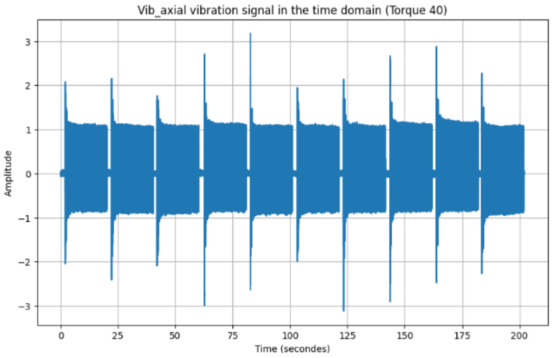

Fig. 2. Vibration spectrum in the time domain - on load 4 Nm. - faulty state

Note that there are no components around the fundamental frequency, while there are two lines in the spectrum, indicating the presence of a fault. What are these faults? And how can we identify them? It's very important to eliminate noise and transient phase from the signal before proceeding with frequency analysis, as these affect the quality of the signal.

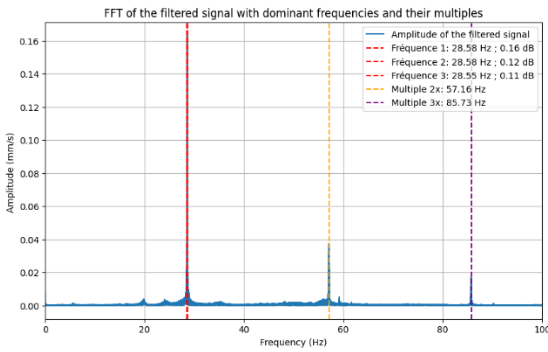

Fig. 3. Vibration spectrum in the frequency domain - on load 4 Nm. - faulty state

3.2. Signal Denoising Methods

In this study, three filtering methods were applied to improve the signal-to-noise ratio (SNR) of an original signal: the Least Mean Squares (LMS) filter, spectral subtraction, and wavelet decomposition. These techniques are commonly used to attenuate noise in signals while preserving as far as possible the characteristics of the original signal.

First, the LMS filter is an adaptive filtering technique in which the filter coefficients are progressively adjusted to minimize the mean square error between the desired signal and the filter output. The adaptation process depends on the error signal. This signal is the difference between the reference input and the estimated output of the filter. At every step, the filter coefficients are updated using a gradient-based rule. This update lets the filter react to changes in the signal and keep good tracking performance under different operating conditions [14]. The method aims to minimize the cost function $J(\omega) = E[e^2(n)]$, where $e(n) = d(n) - y(n)$ is the error between the desired signal d(n) and the filter output $y(n) = \omega^T x(n)$. Here, ω represents the filter coefficients and x(n) is the noisy input vector. The coefficients are updated according to the rule:

$$\omega(n+1) = \omega(n) + 2\mu e(n)x(n) \quad (3)$$

Where μ the learning is step and $x(n)$ is the input vector. This technique is effective when the noise is correlated with the signal.

The Least Mean Squares (LMS) algorithm is widely used because it is simple and does not need any prior knowledge about the noise. This is useful in vibration analysis, where signals often contain non-stationary and unpredictable disturbances. When the noise has some correlation with the measured signal, the LMS filter can estimate and reduce these unwanted components while keeping the information needed for machine monitoring. However, the performance of the LMS algorithm depends on the choice of its parameters, especially the learning step. If the step is too large, the filter may become unstable. If it is too small, the convergence becomes slow. A good balance is needed to get both fast and accurate filtering results. Even with these constraints, the LMS algorithm remains a reliable and common method for improving fault-related features in noisy vibration signals [15].

Second, the spectral subtraction is a noise reduction technique, that operates in the frequency domain. The method relies on estimating and subtracting undesired noise spectrum from the noisy signal, to improve the signal of interest while minimizing distortion. The principle consists in subtracting the estimated spectrum from the noise |N(k) of the noisy signal spectrum $|N(k)|$, obtained via discrete Fourier transform (DFT) [15]. The filtered signal is then reconstructed using the following equation:

$$|X_f(k)| = \max(|X(k)| - |N(k)|, 0) \quad (4)$$

Where $|X_f(k)|$ is the amplitude spectrum of the filtered signal. This method relies on good noise estimation and can introduce distortions if the noise is not correctly estimated.

Finally, the wavelet decomposition is a frequency filtering technique that decomposes the signal into several frequency sub-bands using a wavelet basis. Each sub-band is then processed separately by applying a threshold to reduce noise [15, 16]. Soft thresholding is applied to the wavelet coefficients d via the formula:

$$\hat{d} = sign(d) \max(|d| - \lambda, 0) \quad (5)$$

Where λ the threshold applied. The signal is then reconstructed after filtering, effectively reducing noise at different frequency scales.

After applying these three filters, the results showed that the SANC filter obtained the best SNR, with a value of 37.18 dB The SANC signal power after filtering was close to that of the original signal, at 1.01, while the residual noise power was reduced to 1.01e-02, indicating excellent filter efficiency. In conclusion, the LMS filter proved to be the most effective method for this case, closely followed by wavelet decomposition, while spectral subtraction did not produce satisfactory results, probably due to incorrect noise estimation.

Table 1. Comparison of filter's results in terms of SNR, signal power and noise power

Filters	Spectral subtraction	Wavelet decomposition	Adaptive Noise Cancellation
Filtered signal power	1.85e-01	9.53e-01	1.01
Noise power	4.68e-01	8.46e-04	1.01e-02
SNR	-4.03 dB	30.52 dB	37.18 dB
Accuracy	Low	Proper separation	Excellent

4. APPLICATION

The aim of this research work is to develop a real-time monitoring and diagnostic approach for induction machines, based on advanced signal processing and artificial intelligence algorithms, within the framework of emerging Industry 4.0 technologies. These techniques, grouped under the name of intelligent predictive maintenance or maintenance 4.0, aim to detect the presence of faults, whether single or combined, as well as to precisely locate these anomalies in systems. In parallel, the framework also aims to limit unplanned machine stops and improve scheduled maintenance. By using Blind Source Separation (BSS) algorithms, it becomes easier to extract the fault-related components from complex signal mixtures. This improves machine reliability, lowers maintenance costs, and supports better operation in modern industrial systems, which now include higher levels of connectivity and intelligent control.

4.1. Blind Source Separation

Separating sources inside mixed signals is still a major challenge in signal processing. This is especially true in industrial environments, where signals are affected by noise, interference, and overlapping frequency components. In real applications like vibration analysis and machine monitoring, the measured signal rarely comes from one source. It is usually a mix of mechanical, electromagnetic, and environmental contributions. This makes it difficult to isolate the parts of the signal that are linked to a fault. Blind Source Separation (BSS) methods help address this problem. They extract useful components without needing information about the original sources or the mixing process. Fast Independent Component Analysis (FastICA) is one of the common methods. It assumes that the sources are statistically independent and uses higher-order statistics to separate them quickly. JADE follows a similar idea but works with fourth-order cumulants, which gives good performance when dealing with non-Gaussian sources. In parallel, Variational Mode Decomposition (VMD) has become a flexible tool for breaking a signal into a set number of band-limited modes. Compared to classical empirical methods, VMD handles noise better and reduces mode mixing. By isolating hidden components related to different physical effects, these BSS-based techniques make signals easier to interpret and support the extraction of useful features for fault diagnosis. Their ability to suppress interference and reveal weak fault signatures makes them particularly suitable for noisy and non-stationary operating conditions, where classical analysis approaches often reach their limitations.

4.2. Proposal approach & Experimentation

The proposed fault detection approach for induction motors is based on a well-defined processing chain comprising four main steps: data acquisition, signal denoising, decomposition of the acquired signal, and fault analysis. Specifically, vibration signals will first be acquired from the induction motor using a sensor; then, adaptive noise reduction methods will be used to attenuate the noise present in the obtained vibration signals.

While previous approaches to fault diagnosis do not include any additional steps beyond signal decomposition, the proposed approach incorporates a preprocessing phase during which the acquired signals undergo noise removal to further improve the signal-to-noise ratio. Subsequently, the processed signal undergoes a variational mode decomposition (VMD); furthermore, a nested VMD decomposition will be applied to the selected modes.

This approach will allow us to account for the complexity of the vibration signals generated by the induction motor, particularly when these signals are disrupted by high levels of noise and non-stationary operating conditions. In such cases, faults present in the system may become undetectable due to their partial overlap with other components of the signal.

Finally, the decomposed signal will undergo a frequency analysis to extract the characteristic frequencies associated with a rotor defect.

To justify the choice of the proposed decomposition method, a comparison with blind source separation techniques is provided.

JADE, FastICA and VMD differ in their approach to the dimensionality of the data they process. JADE and FastICA, both used for independent source separation, require multidimensional data, which means that they need several input signals to be able to identify and separate the different sources mixed in the observations. These algorithms exploit the statistical

Table 2. Different algorithm uses in this application

Algorithm		Equation
FastICA [17, 18]	The FAST ICA algorithm is a blind source separation method that aims to extract independent signals from a mixture of observed signals, assuming that the original sources are statistically independent of each other.	Separation criteria: $J(Y) = \mathrm{G}(Y_{gauss}) - G(Y)$ $G(Y) = -\int p(y) logp(y) dy$
JADE [19, 20]	The JADE (Joint Approximate Diagonalization of Eigenmatrices) algorithm is used for blind source separation by jointly diagonalizing a set of fourth-order cumulant matrices.	Calculating cumulative matrices: $J(y) = \sum_{i1,i2,i3=1}^{N} \lvert Cum[x_{i1}, x_{i2}, x_{i3}] \rvert^2$ Joint diagonalization: $D(H;M) = \sum_{m=1}^{M} \sum_{i=1}^{N} \lvert (H^T M(m) H)_{i,j} \rvert^2$
VMD [21, 22]	The Variational Modal Decomposition (VMD) method is a signal analysis technique that allows a complex signal to be decomposed into several intrinsic modes with good separation of the frequency components.	$f(t) = \sum_{k=1}^{K} u_k(t)$

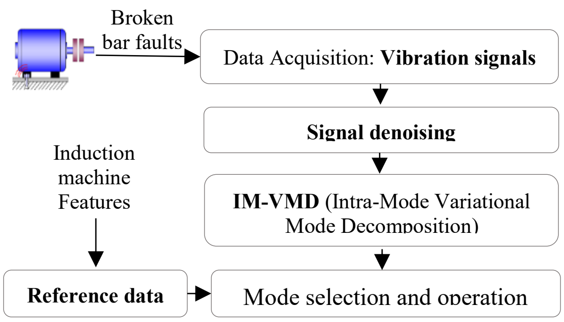

Fig. 4. Proposed architecture for broken bar fault detection with VMD

independence of the signals to accomplish this task. In contrast, the VMD algorithm is more flexible in terms of dimensionality. It is primarily designed to decompose a one-dimensional signal, such as a signal from a single sensor, into several distinct oscillatory modes. However, VMD can also be applied to multidimensional data when multiple signals need to be decomposed simultaneously.

In our work, the data is one-dimensional, coming from a single sensor, which makes the VMD approach particularly relevant. In summary, JADE and FastICA require multidimensional data for source separation, while VMD is equally suited to one-dimensional and multi-dimensional signals. The VMD problem is formulated as a variational optimization. The objective is to decompose a signal $f(t)$ into several modes $u_k(t)$, each with a frequency band centered around a frequency ω_k. Mathematically, this can be expressed as shown in table 3. Where $u_k(t)$ is mode centered around a frequency ω_k. The cost function to be minimized is given by:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\delta(t) + \frac{j}{\omega_k} \right] u_k(t) \right\|_2^2 \right\} \tag{6}$$

The optimization process is iterative. VMD starts with an initial estimate of the modes and center frequencies, then progressively adjusts them to minimize the cost function. At each iteration, the modes $u_k(t)$, and frequencies $\omega_k$are refined until a point is reached where the cost function is minimized [23].

In summary, the main strength of the suggested IM-VMD model is that it can analyze a single-channel vibration signal, and therefore it is highly applicable in the real-world industrial environment where only one sensor is used. Contrary to the blind source separation techniques such as JADE and FastICA algorithms that require multiple sources to perform source separation, this approach provides an effective and practical solution for extracting fault-related information from single channel signals.

4.3. Results and discussion

The mode extraction process was successful, and the vibration signal was thus decomposed into eight distinct modes. In the first decomposition phase, the first three modes contain most of the important information regarding the machine's dynamic behavior. In a second step, the IM-VMD method performs a nested decomposition on certain modes selected in the previous step, providing more refined modes containing useful information about faults. Consequently, the modes to be analyzed will be those corresponding to the refined modes obtained previously, each corresponding to specific frequency bands of the original signal. Since a mode corresponds to a specific frequency band, any component associated with a fault can also be detected in another mode, depending on its spectral properties. This means that a given fault is not necessarily present in lower-order modes and may also exist in higher-order modes, or even in refined modes. As a result of the previous analysis steps, modes 3 and 5 were identified as those containing information about broken rotor bars and other possible defects.

Table 3. Broken-bar faults and eccentricity faults frequencies

Faults	Frequencies Faults	Values
Broken bars	$f_d = (1 \pm 2.k.g)f_s$	22.92 Hz
		34,25 Hz
Eccentricity	$f_{exen} = \mathrm{n} * f_{rotation}$	28.58 Hz
		57.17 Hz
		85.75 Hz
		114.34 Hz

The characteristic fault frequencies shown in Table 3 were derived from well-established analytical expressions using the nominal parameters of the induction motor, namely the supply frequency, rotational speed, and slip. They are then used as reference indicators to evaluate and compare the performance of the different signal processing and fault detection methods applied in this study, examining their ability to extract physically meaningful spectral components consistent with the expected fault signatures.

For fault identification in this study, the correlation metric based on frequency proximity is used to indicate the gap between the dominant frequency component of the IM-VMD mode and the calculated fault frequency. Using this index makes it possible to evaluate the relevance of modes based on their correspondence with the fault signature. It should be noted that the correlation index takes values between 0 and 1, its use therefore allows for the selection of the most relevant modes. Although it does not account for signal energy or other waveform properties, it remains effective for identifying dominant frequencies.

$$Correlation = 1 - \frac{|f_{mode} - f_{default}|}{f_{default}} \tag{7}$$

where f_{mode} is the dominant frequency of the extracted mode and f_{defaut} is the theoretical fault frequency.

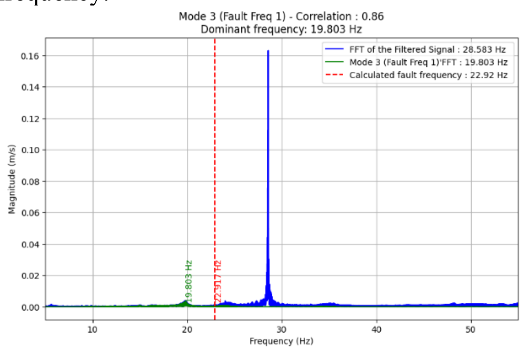

Fig. 5. The 3rd mode correlates with the broken bar's fault frequency 1 (22.917 Hz) with a correlation of 0.86.

The 3rd and 5th modes were identified as representing the broken bars fault, displaying two dominant frequencies of 19.80 Hz and 35.94 Hz, obtained by applying nested VMD or IM-VMD. These frequencies show a strong correlation with the specified defect frequencies, namely $fm\text{-}2sf$ at 22.92 Hz and $fm\text{+}2sf$ at 34.25 Hz, with correlations of 0.85 and 0.79 respectively. These results underline the importance of this mode in the analysis of the machine's structural integrity.

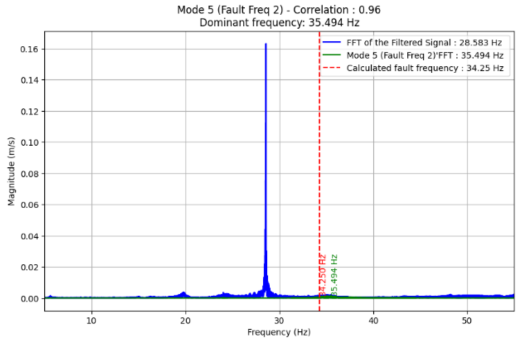

Fig. 6. The 5th mode correlates with the broken bar's fault frequency 2 (34,250 Hz) with a correlation of 0.96

The difference between the theoretical and experimental frequency values of the faults can be explained by the fact that the components responsible for generating the faults depend on slip and higher-order harmonics. In practice, their values vary depending on the load and operating mode. As research based on the RMF principle has shown, the breakage of a rotor bar generates several harmonic components. Consequently, their frequency cannot be considered constant and varies depending on the operating mode of the machine. [24].

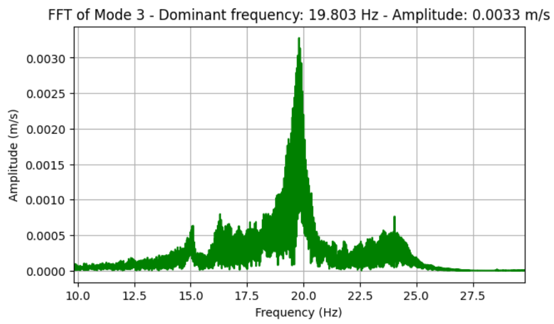

Fig. 7. The 3rd mode's Amplitude at the broken bar's fault frequency 19,803Hz (22,91Hz)

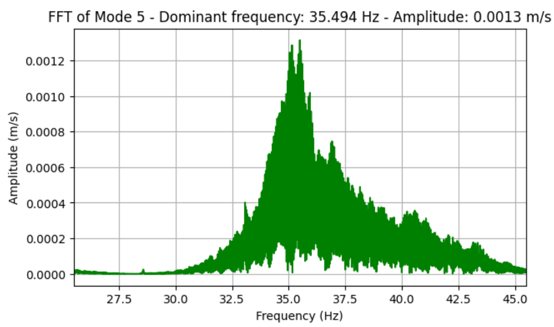

Fig. 8. The 5th mode's Amplitude at the broken bar's fault frequency 35,494Hz (34,25Hz)

Interpretation of the amplitudes of the lines detected in the broken-bar fault [0.0033, and 0.0013] m/s as the onset of a fault:

- Low but significant values: Although these values are low, they could represent the first signs of the fault. In this first stage, the fault is non-critical yet because it generates only small disturbances in the vibratory system.
- If these values progressively over time, this could indicate that the fault is beginning to worsen. In this case, further analysis or a preventive maintenance plan would be useful.
- If they remain stable, this could confirm that these vibrations are merely background noise, with no major impact on the machine.

To further evaluate the effectiveness of the proposed approach, a comparison with the high-resolution ZMUSIC method is discussed below. The ZMUSIC algorithm is an efficient spectral estimation technique based on subspace decomposition, enabling accurate extraction of closely spaced frequency components. However, its performance strongly depends on noise conditions and requires careful selection of parameters, such as the number of sources. In contrast, the IM-VMD approach provides a more physically interpretable representation of the signal by decomposing it into intrinsic modes without prior assumptions. This facilitates the analysis of non-stationary signals and improves the identification of fault-related components [25].

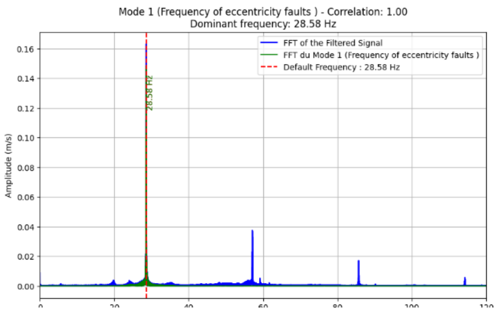

Fig. 9. The 1st modes correlate with the eccentricity's fault frequency

Mode analysis revealed a perfect correlation between several modes and the characteristic eccentricity fault frequencies. The 9nd mode is perfectly aligned with the eccentricity fault frequency f_r at 28.58 Hz, with a correlation of 1.00, indicating that this mode accurately captures the initial eccentricity.

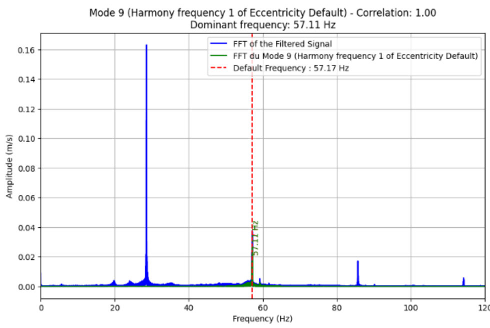

Fig. 10. The 9th Mode correlate with the first harmony of the eccentricity's fault frequency.

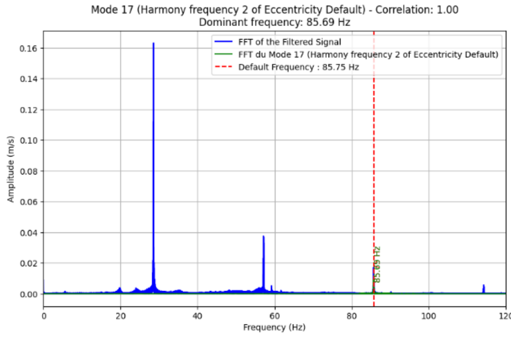

Fig. 11. The 17th Modes correlate with the second harmony of the eccentricity's fault frequency.

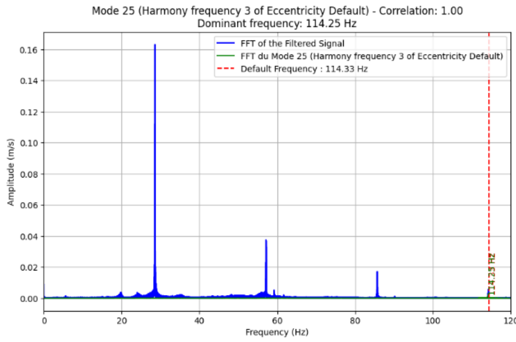

Fig. 12. The 25th Modes correlate with the third harmony of the eccentricity's fault frequency.

Furthermore, the 9th mode correlates with the first harmonic of this fault at 57.17 Hz, while the 17th mode corresponds to the second harmonic at 85.75 Hz. Finally, the 25th mode captures the third harmonic at 114.33 Hz.

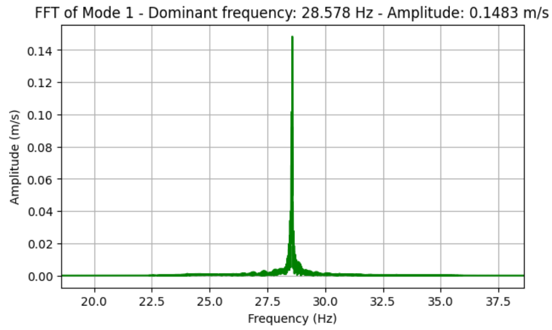

Fig. 13. The 1st mode's amplitude at the eccentricity's fault frequency 28.58Hz

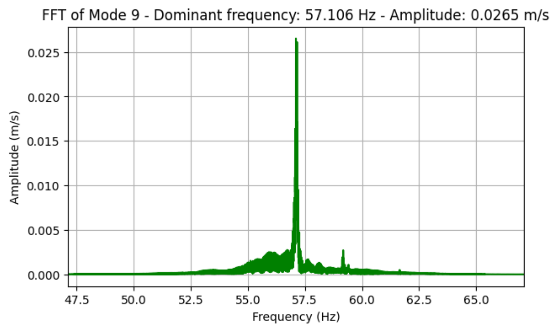

Fig. 14. The 9th mode's amplitude at the 1st harmony of the eccentricity's fault frequency

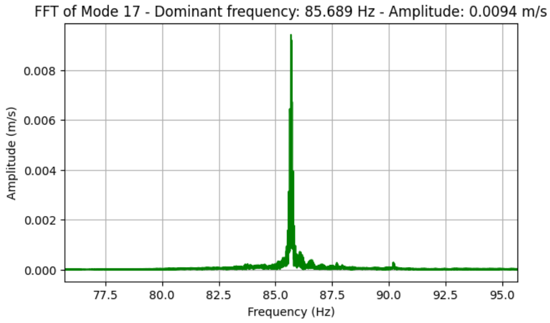

Fig. 15. The 17th mode's amplitude at the 2nd harmony of the eccentricity's fault frequency

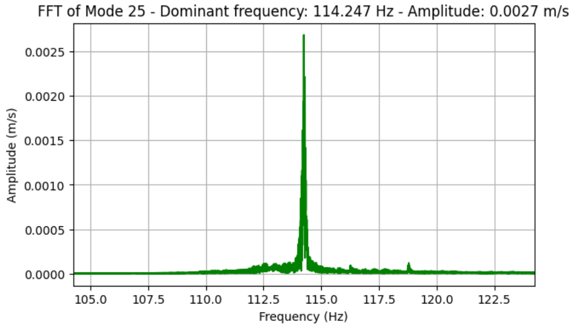

Fig. 16. The 25th mode's amplitude at the 3rd harmony of the eccentricity's fault frequency

Figure 13, 14, 15 and 16 clearly illustrates the vibration behaviour of the first mode at the characteristic frequency of the eccentricity (28.58 Hz). As observed, the dominant spectral component is directly reflecting the impact of the defect on machine operation. This response indicates that the fault influences the dynamic behaviour of the system. To assess and contextualize the evolution of the associated harmonic components, Table 4 presents the measured amplitudes and corresponding power levels. This structured representation enables clearer interpretation of the results and facilitates comparison of vibration levels linked to the defect.

Table 4. Amplitudes and power of the eccentricity fault and its 3 first harmonics

n	Frequency (Hz)	Amplitude (m/s)	Power (m/s^2)
0	28.587	0.148	0.2131
1	57.105	0.0265	0.0142
2	85.689	0.0094	0.0014
3	114.247	0.0027	0.0001

The values obtained for the 1st mode, with a dominant frequency of 28.578 Hz, an amplitude of 0.1483 m/s, and a power of 0.2131, indicate a dynamic eccentricity defect well present in the machine. The main vibration frequency matches the rotational frequency. As a result, it demonstrates the presence of rotor eccentricity and confirms that the rotor is not centered inside the stator. This condition creates periodic mechanical forces and keeps the vibration level high. The measured amplitude of 0.1483 m/s is above normal limits, which means the imbalance is strong enough to cause noticeable mechanical disturbance. If the issue is not addressed, the vibrations can speed up the wear of key parts especially rolling bearings which gradually reduce the system's reliability. therefore, maintenance actions focused on rotor realignment is necessary to avoid further mechanical damage. The match between the extracted modes and the harmonic components linked to eccentricity, supports the reliability of the diagnosis. The alignment of these spectral elements shows that eccentricity features are clearly visible in the frequency analysis of the decomposed modes. This confirms that the signal processing method works well.

It should be noted, however, that conventional approaches using stator current as the basis for analysis, as described in [26], focus primarily on sidebands with high amplitudes that appear when the fault reaches a sufficiently critical level. In the case of developing faults, these signals may be too weak to be detected, as they are masked by certain disturbances or by changes in the system's operating conditions. This is why these techniques lack sensitivity to the early symptoms of the eccentricity problem in its initial stages. In contrast, the proposed method, which uses adaptive decomposition, allows for more effective identification of low-amplitude components arising from different modes.

Table 5 presents a qualitative comparison of the considered methods based on literature analysis and experimental observations:

- Fast Fourier Transform (FFT),
- Variational Mode Decomposition (VMD),
- The Park's vector approach
- Blind source separation methods such as JADE and FastICA.

This comparison gives a clear overview of their characteristics and diagnostic abilities.

Table 5. Comparative table of defect separation and analysis methods

Method	Mode separation capability	Noise robustness	Sensitivity to incipient faults	Ability to detect multiple faults
FFT	None	Noise sensitive	Limited sensitivity	Weak (signature overlap)
EWT	Very good	Moderate	Good	Good
VMD	Good	Moderate	Good	Moderate
Fast ICA	Very good	Moderate	Moderate	Good
The Park's vector	None	Medium	Poor sensitivity	Limited
IM-VMD	Very good	Very good	Very good	Excellent

The qualitative terms used in the table are defined as follows:

The terms used for qualitative evaluation (e.g., "Good," "Very Good," and "Excellent") are defined based on several performance criteria, including faults detection accuracy, noise immunity, and the effectiveness of signal decomposition in separating overlapping defect components. The use of the FFT algorithm alone is not sufficient to accurately identify defects under difficult conditions without quantitative analysis or the separation of overlapping frequency bands. The 96.8% accuracy rate claimed by the FFT for fault detection cannot be validated using the FFT alone, but only in combination with ICA, which demonstrates the inadequacy of the FFT when used on its own [27]. More advanced signal processing approaches have been proposed to overcome these limitations. For instance, the reviewed paper [28] suggests a fault diagnosis approach integrating EWT with a Duffing oscillator. Here, EWT is employed to provide adaptive analysis based on frequency segmentation of the vibration signals to achieve empirical modes separation and separate different types of faults into various modes. Subsequently, each mode is examined using a Duffing oscillator. Faults are detected through alterations in the system's dynamic characteristics. From the presented results, we may conclude that such an approach outperforms other methods (such as EMD and wavelets) in terms of mode decomposition accuracy due to lower mode-mixing errors. Nevertheless, this method is quite sensitive to spectral segmentation errors, and some parameters should be chosen carefully during analysis, specifically in the oscillator part. Similarly, the VMD method improves the process by limiting the contribution of each mode to a defined frequency range, so it's more stable and gives a more accurate representation of the spectrum. That said, the success of this technique depends on how you set the parameters, like the number of modes and the penalty parameter, among others [26]. Current-based diagnostic methods, such as Park's vector approach, have also demonstrated effectiveness in detecting stator and rotor faults under industrial conditions. The main challenge lies in the difficulty of detecting faults early and establishing a reliable diagnosis in the presence of power supply asymmetry and complex interactions between faults. To overcome this, the authors develop an algorithm that analyses the geometric characteristics of the Park vector, such as ellipticity and thickness (ΔIp), to identify short circuits between turns in the stator winding and structural faults in the rotor. The results demonstrate the proposed system's ability to simultaneously monitor multiple machine components and estimate fault severity, even under non-ideal power supply conditions, making it suitable for practical industrial implementation. However, this approach remains limited by the global nature of the indicator, its sensitivity to operating conditions, and the difficulty of interpretation, particularly under no-load conditions or in the presence of complex and combined fault scenarios [29,30]. While there is a large variety of existing diagnostic methods, most approaches remain limited when it comes to handling complex operating conditions, noise, and overlapping fault signatures, particularly in the case of combined faults. These limitations highlight the need for more robust and adaptive techniques capable of accurately separating and identifying the multiple components of a fault.

In this context, the proposed approach, based on IM-VMD (Intra-Mode VMD), aims to address these challenges by offering improved signal decomposition and better fault detection under realistic industrial conditions. This approach enables the separation of the different vibration sources and reveals clear spectral signatures linked to each fault type. Despite these promising results, detecting more than two faults at the same time is still difficult, especially when several rotor bars are broken. Handling such situations needs stronger decomposition methods and a deeper study of how these faults interact. Extending the current framework to cover these complex cases could improve predictive maintenance and reduce unplanned machine stoppages. The experimental tests support the results. They show a strong match between the extracted modes and the frequencies linked to the studied defects, which confirms the relevance of the IM-VMD method under controlled conditions. However, when the signals contain a lot of noise or when many defects are present, especially several broken bars, the diagnosis becomes harder. In these cases, classical frequency-domain tools, including correlation-based methods, lose efficiency, and the interpretation of the modes becomes less clear. Deep learning methods offer a promising alternative here. With training on simulated and real data, these models can learn complex fault signatures created by the interaction of multiple defects, even when noise masks part of the information. Combining deep learning with the IM-VMD framework could lead to more automated, robust, and industry-ready diagnostic systems able to work under realistic conditions.

5. CONCLUSION AND FUTURE WORK

This work focuses on separating induction machine faults using axial vibration signals. The approach uses two main steps. First, an Adaptive Noise Cancellation filter based on the LMS algorithm removes noise from the signal. Then, a nested VMD procedure extracts and analyses the modes. Together, these steps help isolate the fault-related components from complex and noisy measurements. From a research point of view, the method can be linked to the Frascati criteria. The novelty of this work lies in the development of a unified diagnostic framework that integrates adaptive filtering and advanced signal decomposition within a single process. This combination offers an effective and innovative way to process complex vibration signals, particularly under challenging operating conditions. Unlike conventional methods, which focus primarily on single-fault scenarios, this framework improves the separation of overlapping vibration signatures, optimize early detection of rotor faults [30]. The second criteria concern uncertainty. Industrial vibration signals often contain random noise and change with load and speed. The LMS-based filter helps reduce this uncertainty. This makes the extracted modes more stable and reliable. The third criteria concern a structured and systematic procedure. The method follows a clear sequence of steps, which makes it reproducible and easy to apply to other fault types or similar electromechanical systems. The filtering and decomposition stages work together to support clear interpretation of the diagnostic results. The framework also shows a certain level of transferability. It is not limited to one machine. With small adjustments, such as changing the number of modes or the filter settings, the method can be adapted to machines working under different speeds or load levels. Even if each machine has its own vibration behaviour, the combination of nested VMD and adaptive denoising can handle part of this variation. Experiments show that the method can detect at least two fault types under the tested conditions. This confirms its diagnostic value.

Despite being a proven solution for fault detection, the suggested approach can be costly in terms of computation and time needed for execution. It is a downside that can be noted from current research. Future investigations will consider enhancing computation and decreasing time consumption through the application of machine learning algorithms.

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