



RESEARCH ARTICLE

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ENHANCED BEARING FAULT DIAGNOSIS USING INTEGRATED ICEEMDAN-TKEO-ENVELOPE ANALYSIS UNDER VARIABLE LOAD CONDITIONS

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ABSTRACT

This study proposes a hybrid methodology for early bearing fault diagnosis in rotating machinery, particularly asynchronous motors. The approach combines three advanced techniques: ICEEMDAN (Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) to extract intrinsic mode functions from vibration signals, TKEO (Teager-Kaiser Energy Operator) to amplify fault-related impact characteristics, and envelope analysis to identify characteristic frequencies. Experimental validation was conducted using the Case Western Reserve University database with SKF 6205-2RS bearings exhibiting 7-mil single-point defects on inner race, outer race, and ball elements. Tests were performed under no-load (0 HP) and loaded (2 HP) conditions. The methodology involves decomposing the original signal using ICEEMDAN, selecting the most correlated IMF component, applying TKEO processing, and analyzing the envelope spectrum. This methodology provides a robust solution for clearly distinguishing healthy from faulty states and enables precise diagnosis of different bearing fault types under various load conditions.



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I. INTRODUCTION

Rolling bearings constitute one of the most essential components in rotating machinery and are crucial for maintaining overall system reliability. Extended operational periods inevitably lead to component deterioration, which generates various fault conditions that severely compromise machine operational integrity [1]. Consequently, implementing effective rolling bearing condition monitoring and achieving early fault identification are critical requirements [2]. Early fault detection in rolling bearings substantially mitigates production risks, optimizes maintenance strategies, and enhances the operational safety and reliability of industrial machinery. Vibration signal analysis for characteristic feature extraction serves as a fundamental approach in industrial fault diagnostics, enabling cost reduction and prevention of catastrophic failures resulting from bearing deterioration. Various approaches are presently available for the analysis and extraction of bearing fault characteristics. Empirical Mode Decomposition (EMD) represents an adaptive signal processing technique specifically designed for multiscale decomposition and time-frequency analysis of nonlinear and nonstationary signals. This method decomposes complex signals into a series of intrinsic mode functions (IMFs), each characterized by distinct local temporal scales [3]. However, the presence of mode mixing phenomena significantly compromises the quality of decomposition results [4]. Torres et al. [5] developed the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) algorithm, which incorporates adaptive white noise to enhance modal independence and facilitate the extraction of previously inseparable signal components. This methodology effectively mitigates mode-mixing phenomena while reducing residual noise contamination in reconstructed signals and minimizing computational requirements through reduced sifting iterations. Subsequently, Colominas et al. [6] introduced an enhanced variant termed Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN), which addresses inherent limitations in EMD's adaptive decomposition capabilities. This refined approach substantially diminishes residual artifacts within the IMF components, yielding superior reconstruction fidelity and providing further mitigation of mode-mixing issues [7].

In practical engineering machinery fault diagnosis, particularly during incipient bearing fault stages, fault signatures exhibit weak amplitude characteristics that are severely compromised by noise interference, making the extraction of periodic pulse features from composite signals extremely challenging. Consequently, the standalone ICEEMDAN methodology demonstrates limited effectiveness in achieving accurate bearing fault identification under such conditions. To address the limitations of standalone ICEEMDAN in noisy environments, the Teager-Kaiser Energy Operator (TKEO) provides a complementary solution. Originally developed for speech signal analysis, TKEO excels at tracking instantaneous energy variations with exceptional temporal resolution, requiring only three samples for computation [8]. This characteristic makes it particularly effective for amplifying transient fault signatures in bearing vibration signals. Additionally, envelope analysis has proven invaluable for extracting periodic impulse characteristics by demodulating high-frequency resonances excited by bearing defects, thereby revealing low-frequency fault signatures often obscured in raw signals. Contemporary research emphasizes hybrid methodologies that synergistically combine multiple signal processing techniques to overcome individual method limitations while maximizing fault information extraction. Despite advances in bearing diagnostics, significant challenges remain, including achieving robust performance under varying operational conditions, detecting incipient faults with low signal-to-noise ratios, and accounting for load variations that substantially influence vibration characteristics in industrial machinery. To address these challenges, this study proposes a hybrid methodology combining ICEEMDAN, TKEO, and envelope analysis for bearing fault diagnosis. The methodology employs ICEEMDAN for signal decomposition into IMF components, applies TKEO to the most correlated IMF for energy amplification, and uses envelope analysis to extract characteristic fault frequencies. This integrated approach aims to maximize fault signature extraction while overcoming individual technique limitations. This paper is organized as follows: Section 2 presents the theoretical background of ICEEMDAN and TKEO. Section 3 describes the experimental setup and database. Section 4 details the proposed methodology. Section 5 discusses results for different fault types under varying loads. Section 6 concludes with findings and future research directions. The novelty lies in the systematic integration of these techniques, validated using the Case Western Reserve University database for reproducibility and comparative assessment.

II. THEORETICAL REFERENCE

II.1 IMPROVED CEEMDAN WITH ADAPTATIVE NOISE FOR TIME SERIES

Empirical Mode Decomposition (EMD), introduced by Huang et al. [8], constitutes a multiscale decomposition methodology specifically designed for the analysis of nonlinear, non-stationary, and complex time series data. To mitigate the inherent mode mixing phenomenon, numerous researchers have proposed various enhancements to the original EMD framework, resulting in the development of advanced algorithms including Ensemble EMD (EEMD) by Wu and Huang [9] and Complete Ensemble EMD with Adaptive Noise (CEEMDAN) by Torres et al. [5]. Nevertheless, CEEMDAN continues to exhibit limitations related to residual noise contamination and the generation of spurious modes. In response to these persistent challenges, Colominas et al. [6] developed an enhanced variant known as Improved Complete Ensemble EMD with Adaptive Noise (ICEEMDAN), which addresses the aforementioned deficiencies of its predecessors. The implementation of ICEEMDAN follows a K-stage iterative computational protocol. The algorithmic procedure is structured as follows:

1. The intermediate signal is constructed by incorporating Gaussian white noise into the original dataset in accordance with the following expression: $x^i(t) = x(t) + \varepsilon_0 E_1(w^i(t))$, and the primary residual component r_1 was extracted through EMD-based decomposition employing local mean calculations on the resulting intermediate signal.

$$r_1 = \overline{M(x^i(t))} \quad (1)$$

2. Where $\varepsilon_0 = (\delta_0 \text{std}(x)) / \text{std}(E_1(w^i(t)))$, ε_0 is introduced at the initial stage for noise mitigation, where ε_0 represents the reciprocal of the anticipated signal-to-noise ratio between the initially added noise component and the signal under analysis. Here, i represents the number of times noise is added, std represents standard deviation, w^i represents the i -th set of added white noise, operator $E_j(*)$ represents the j -th IMF component of a signal's EMD decomposition, operator $M(*)$ represents the “local mean” of a signal [10]. “Local mean” is a crucial step in the computation of IMFs. The local mean is mathematically defined as the mean value of the upper and lower signal envelopes, which are derived by applying cubic spline interpolation to the respective local maxima and minima. This local mean serves as a representation of the signal's trend behavior. EMD employs an iterative procedure whereby the local mean is successively removed from the original signal, thereby decomposing it into constituent IMFs of varying frequency content until a final residual trend remains [11].

3. When $k = 1$, finding the first IMF component:

$$IMF_1(t) = x(t) - r_1(t) \quad (2)$$

4. The second-order residual and the second IMF component can be obtained by the average of the local mean of $r_1(t) + \varepsilon_1 E_2(w^i(t))$.

$$\gamma_2(t) = M(r_1(t) + \varepsilon_1 E_2(w^i(t))) \quad (3)$$

$$IMF_2(t) = r_1(t) - \gamma_2(t) \quad (4)$$

5. For the remaining stages $k = 3, \dots, k$ calculates the k -th residual and the k -th IMF component:

$$r_k(t) = \overline{M(r_{k-1}(t) + \varepsilon_{k-1} E_k(w^i(t)))} \quad (5)$$

$$IMF_k(t) = r_{k-1}(t) - r_k(t) \quad (6)$$

6. Repeat the above steps until all IMF components and residuals are obtained.

II.2 THE TKEO (TEAGER-KAISER ENERGY OPERATOR)

The Teager-Kaiser Energy Operator (TKEO) is a signal processing technique that was originally proposed for the analysis and processing of nonlinear speech signals. The TKEO was named after its originators, Teager and Kaiser, who developed this energy-based operator [12]. The TKEO is given for a continuous signal $x(t)$ by:

$$\psi(x(t)) = [\dot{x}(t)]^2 - x(t)\ddot{x}(t) \quad (7)$$

Who: $\dot{x}(t)$ et $\ddot{x}(t)$ correspond respectively to the first and second derivatives of $x(t)$. In the case of a discretized signal, the energy operator can be defined as follows:

$$\psi[x(n)] = [x(n)]^2 - x(n+1)x(n-1) \quad (8)$$

The energy operator can extract both amplitude modulation (AM) and frequency modulation (FM) from the signal. The TKEO has high temporal resolution since the operator requires only three samples for estimation [12-14]. This excellent temporal resolution enables the capture of energy fluctuations. Furthermore, this operator is very easy to implement. The AM-FM components of the signal are given by the following equations [15] [16]:

$$f(t) \approx \frac{1}{2\pi} \sqrt{\frac{\psi(\dot{x}(n))}{\psi(x(n))}} \quad (9)$$

$$|a(t)| \approx \frac{\psi(x(n))}{\sqrt{\psi(\dot{x}(n))}} \quad (10)$$

Who:

$f(t)$ and $|a(t)|$ represents the frequency and instantaneous amplitude of the signal, respectively.

III. MATERIALS AND METHODS

III.1 TEST BENCH DESCRIPTION

The vibration signals studied in this work were extracted from an experimental database developed by Case Western Reserve University (CWRU) [17]. This database comprises recordings from ball bearings, either in good condition or exhibiting various types of defects. The experimental platform includes a motor, a torque encoder, a dynamometer, an accelerometer, and other main components. The test bearings support the motor shaft and introduce different types of single-point faults at the drive end (DE) and fan end (FE) with varying fault diameters [18], including 7, 14, 21, and 28 mils. These faults result in single-point faults in the ball, inner race, and outer race. The rolling bearings used in the experiment are produced by SKF, with the specific model being 6205-2RS. The vibration signals from the rolling bearings were collected to acquire fault diagnosis experimental data. A total of three different single-point faults and one set of normal rolling bearing vibration signals were collected at sampling frequencies of 12 kHz and 48 kHz, with a total of 243,938 points per signal.

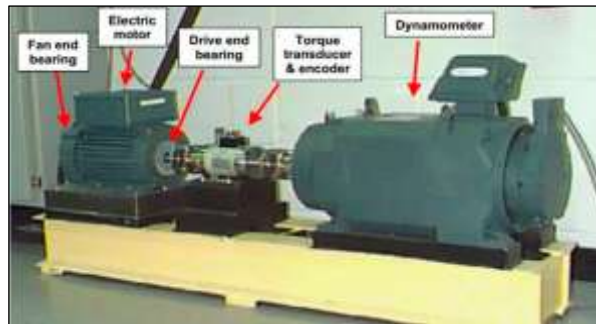


Figure 1: CWR University Test Bench.

Source: [17].

The data used in this study was collected on the experimental platform shown in Figure 1. The bearing data was acquired at the drive end (DE) under two operational conditions: no-load (0 HP) and loaded conditions (2 HP). The characteristic frequencies of the defects for both operational conditions are illustrated in the following table:

Table 1: Characteristics frequencies of the bearing.

Fault	Characteristic frequency	Value with $f_r = 1797 \text{ rpm}$	Value under load 2 HP with $f_r = 1750 \text{ rpm}$
Inner race	$f_{inner} = 5.415 \times f_r$	162.18 Hz	157.9 HZ
Outer race	$f_{outer} = 3.584 \times f_r$	107.34 Hz	104.50 HZ
Ball	$f_b = 4.7135 \times f_r$	140.74 Hz	137.44 HZ

Source: Authors, (2026).

III.2 THE ADOPTED APPROACH

In this study we are chose a vibratory signal that including single-point faults at the drive end (DE) with 7 mils fault diameter. Three bearing fault types were examined: inner raceway defect, outer raceway defect, and ball defect. The three fault types were analyzed under no-load conditions and load condition (2 HP). The methodology employed for bearing defect detection and characterization is illustrated in the flowchart below:

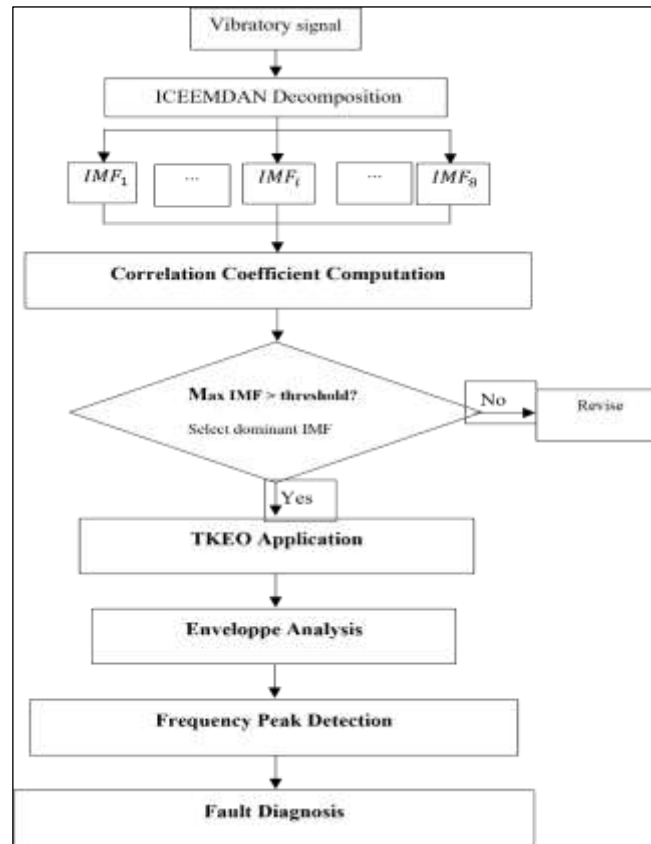


Figure 2: Bearing defect detection and diagnosis methodology.
Source: Authors, (2026).

III.3 EXPERIMENTAL STUDY

III.3.1 Healthy Bearing Under No Load And Under 2hp Load

Figure (3) illustrates the vibration signal measured for a healthy bearing under no-load conditions. This signal was decomposed into IMF components using the ICEEMDAN method (fig.5). Only the first components ($IMF_1 \sim IMF_8$) were retained for the analysis, as the remaining components represent low frequencies that are generally not significant for fault detection. The same procedure was applied to the healthy signal under a 2 HP load (fig. 4). The obtained IMFs are shown in Figure 6.

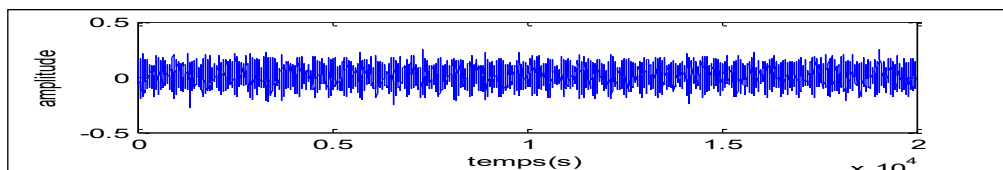


Figure 3: Healthy signal under no load.
Source: Authors, (2026).

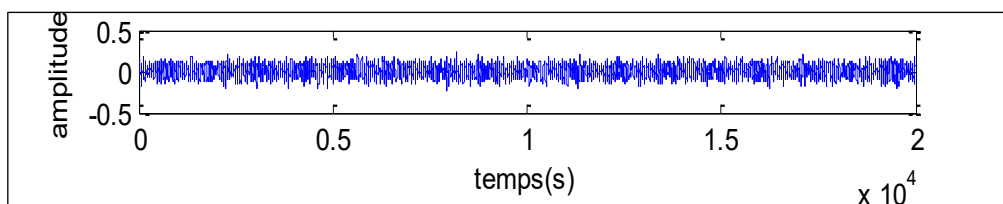


Figure 4: Healthy signal under 2 HP.
Source: Authors, (2026).

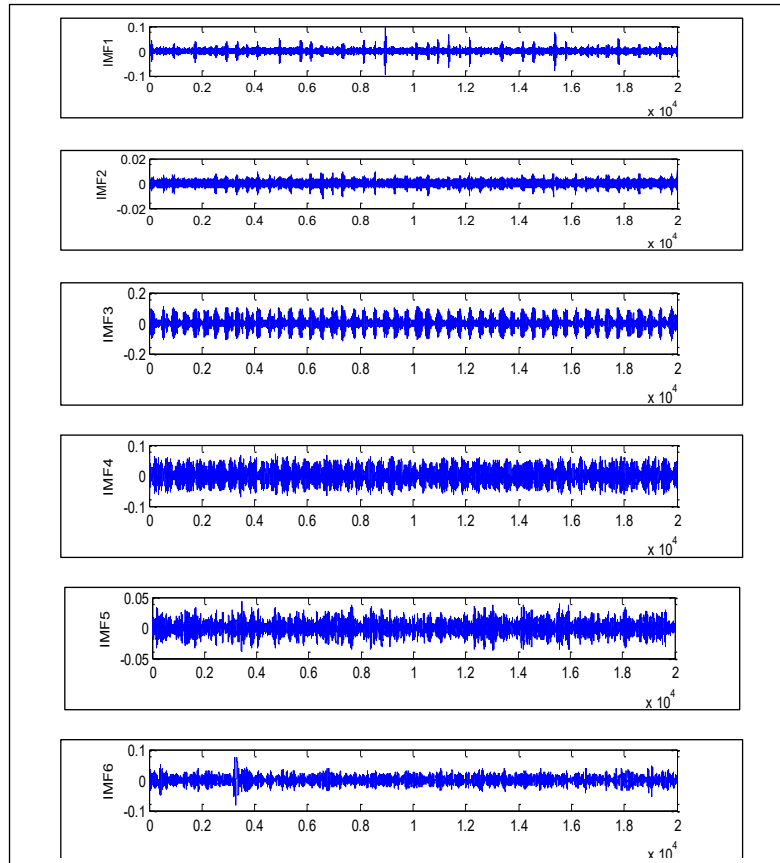


Figure 5: Decomposition with ICEEMDAN (0HP).

Source: Authors, (2026).

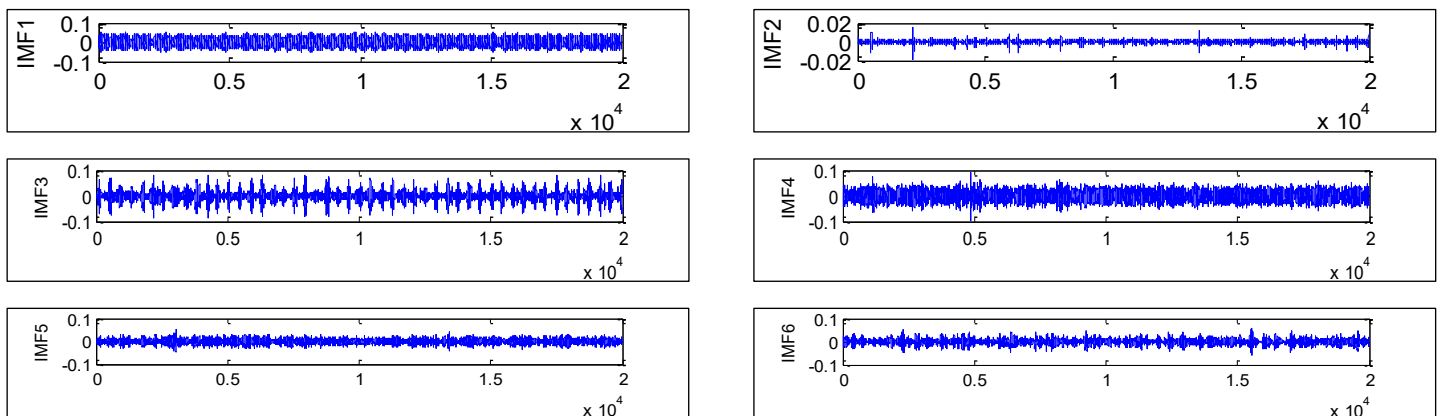


Figure 6: Decomposition with ICEEMDAN (2HP).

Source: Authors, (2026).

To identify the most representative IMF, the correlation coefficient between each IMF and the original signal was calculated for both operational conditions. Tables 2 and 3 present the correlation coefficients for the healthy bearing under no-load (0 HP) and 2 HP load conditions, respectively. Under no-load conditions (Table 2), IMF 3 exhibits the highest correlation coefficient, making it the most suitable component for subsequent analysis. Similarly, under 2 HP load conditions (Table 3), IMF 3 also demonstrates the highest correlation coefficient (0.6299), confirming its selection as the optimal component for both operational states. The selected IMF undergoes TKEO processing followed by envelope analysis to extract fault-related characteristics.

Table 2: Correlation coefficients between each IMF and the healthy signal under (0 HP).

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
0.5421	0.5808	0.7930	0.6630	0.3191	0.3122	0.3952	0.2055

Source: Authors, (2026).

Table 3: Correlation coefficients between each IMF and the healthy signal under (2 HP).

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
0.4758	0.5420	0.6299	0.5895	0.3460	0.3601	0.4700	0.4301

Source: Authors, (2026).

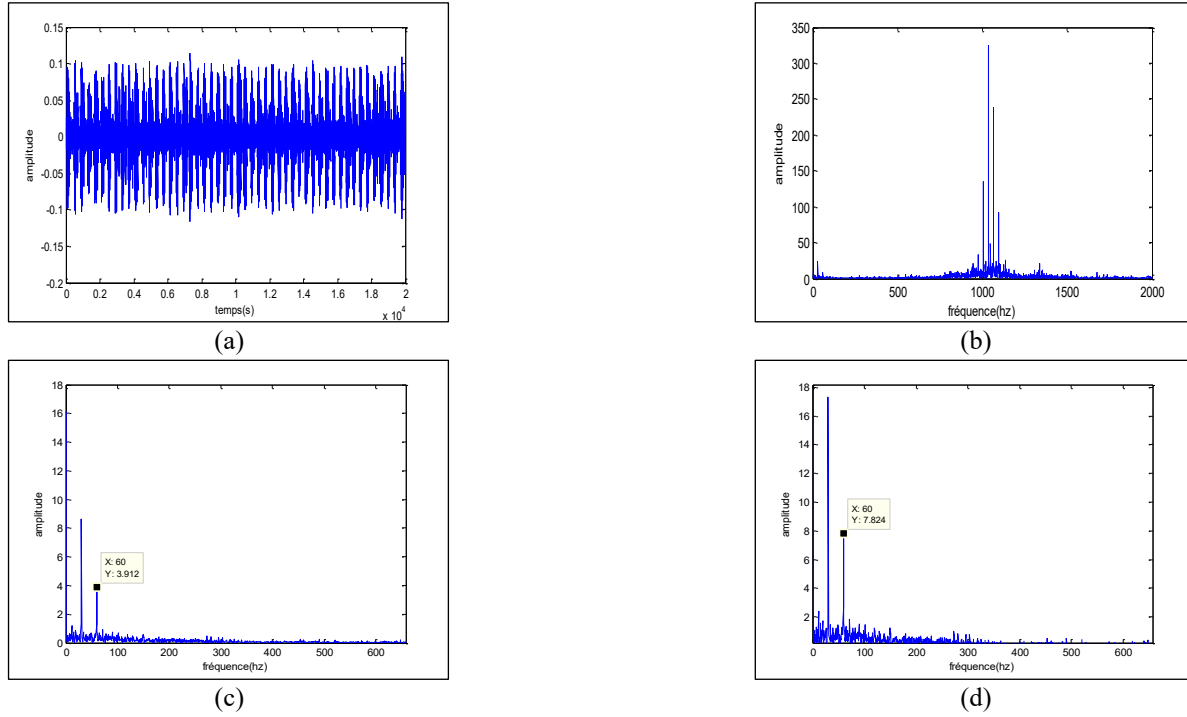


Figure 7: Healthy signal (0 HP): (a) Selected IMF, (b) IMF spectrum, (c) spectrum of TKEO, (d) envelope spectrum of TKEO.
Source: Authors, (2026).

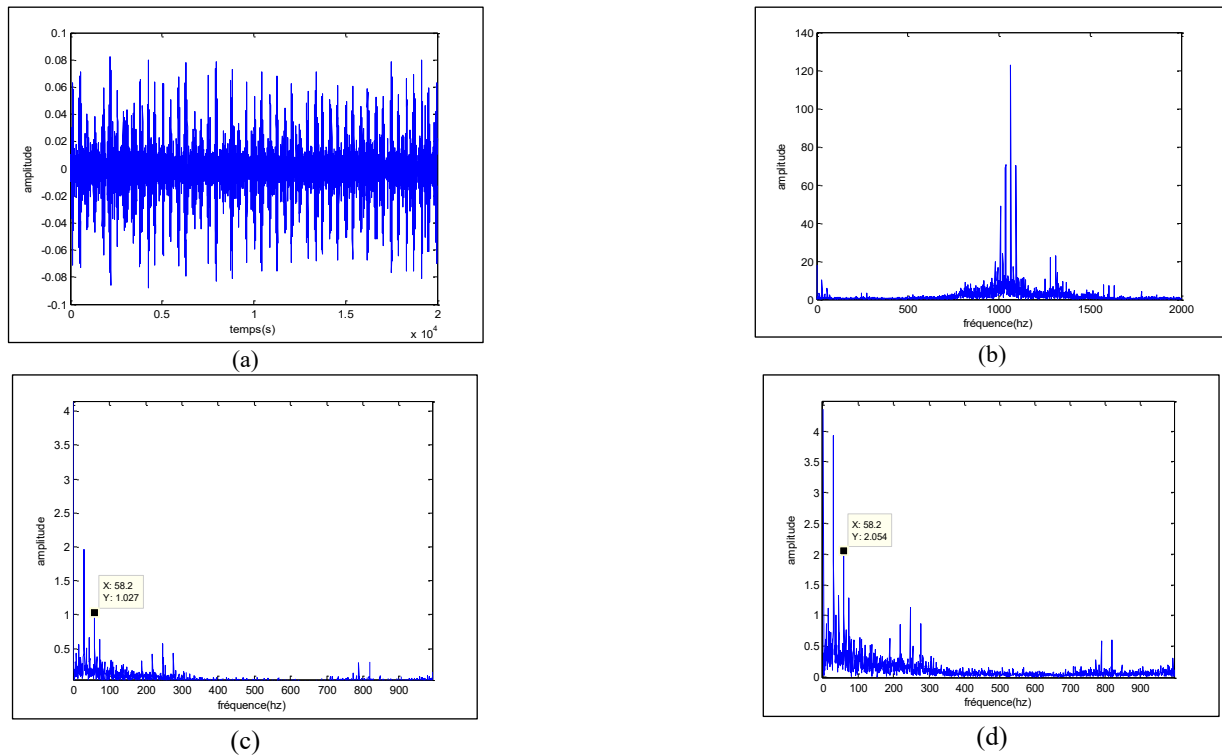


Figure 8: Healthy signal (2 HP): (a) Selected IMF, (b) IMF spectrum, (c) spectrum of TKEO, (d) envelope spectrum of TKEO.
Source: Authors, (2026).

Figures 7(c) and 7(d) represent the TKEO spectrum and its envelope spectrum under no-load conditions, respectively. A dominant peak is observed at 60 Hz with significant amplitude, indicating a stable and pronounced frequency component. In comparison, Figures 8(c) and 8(d) show the same spectra under a 2 HP load. In this case, the main peak is slightly shifted to 58.2 Hz, with a notable decrease in amplitude in the TKEO spectrum and a less pronounced attenuation in the envelope spectrum. This frequency and amplitude variation reflects a direct influence of operational conditions on the frequency signature of the signal. The observed evolution between these two operational states highlights the sensitivity of time-frequency analysis methods to changes in operating parameters, even in the absence of apparent faults.

III.3.2 Inner Race Bearing Analysis Under No Load And Under 2hp Load

Figures 9 and 10 illustrate the time-domain vibration signals for inner race bearing defects under no-load (0 HP) and 2 HP load conditions, respectively. Figures 11 and 12 present the ICEEMDAN decomposition results for the inner race fault signals under 0 HP and 2 HP conditions, respectively. Each decomposition yields eight IMF components (IMF1~ IMF8) arranged from highest to lowest frequency content. Under no-load conditions (Fig. 11), IMF1 captures the dominant high-frequency transient characteristics associated with the bearing fault, exhibiting clear impulsive patterns with well-defined amplitude peaks. The subsequent IMFs progressively extract lower frequency components, with diminishing amplitudes as the decomposition proceeds to higher IMF orders. Under 2 HP load (Figure 12), the ICEEMDAN decomposition reveals similar structural patterns, though with notable differences in amplitude distribution across the IMF components. IMF1 continues to contain the primary fault-related information, demonstrating consistent impulsive behavior indicative of inner race defects.

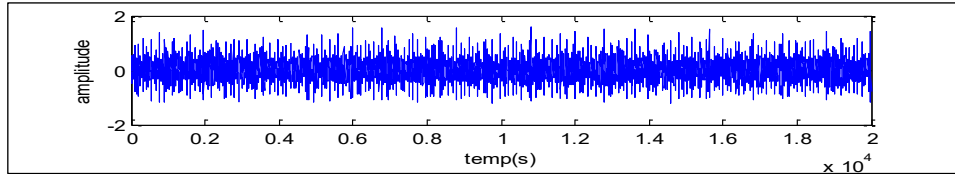


Figure 9: Signal with inner fault race (0Hp).

Source: Authors, (2026).

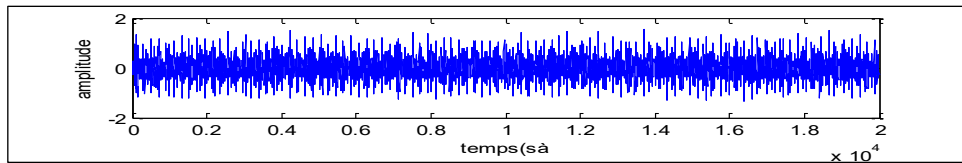


Figure 10: Signal with inner fault race (2Hp).

Source: Authors, (2026).

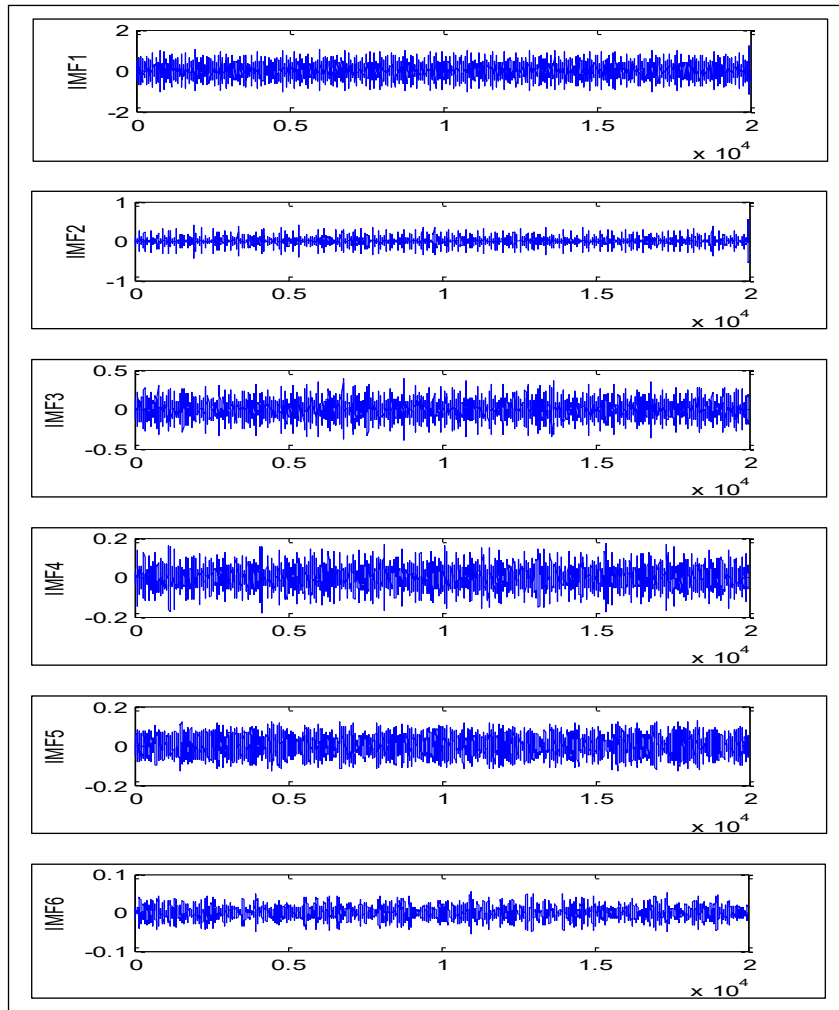


Figure 11: Decomposition with ICEEMDAN (0HP).

Source: Authors, (2026).

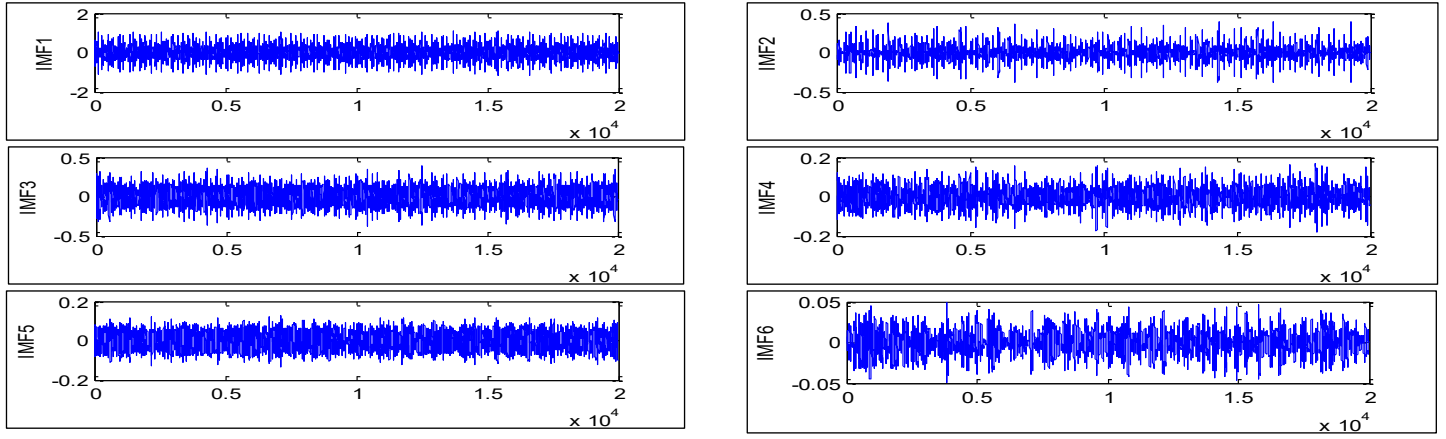


Figure 12: Decomposition with ICEEMDAN (2 HP).

Source: Authors, (2026).

Table 4: Correlation coefficients between each IMF and the healthy signal under (0 HP).

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
0.8538	0.3822	0.3790	0.2804	0.2018	0.0455	0.0387	0.0065

Source: Authors, (2026).

Table 5: Correlation coefficients between each IMF and the healthy signal under (2HP).

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
0.8585	0.4019	0.4057	0.2690	0.1929	0.0330	0.0371	0.0070

Source: Authors, (2026).

Tables 4 and 5 present the correlation coefficients between each IMF component and the inner race fault signal under no-load (0 HP) and 2 HP load conditions, respectively. The analysis reveals several significant observations. First, IMF1 demonstrates exceptionally high correlation coefficients under both operational conditions (0.8538 for 0 HP and 0.8585 for 2 HP), substantially exceeding all other IMF components. This indicates that IMF1 captures the predominant fault-related information and represents the most characteristic feature of the inner race defect. Based on these results, IMF1 is unequivocally selected for subsequent TKEO processing and envelope analysis, as it contains the maximum fault-related information necessary for accurate inner race defect diagnosis.

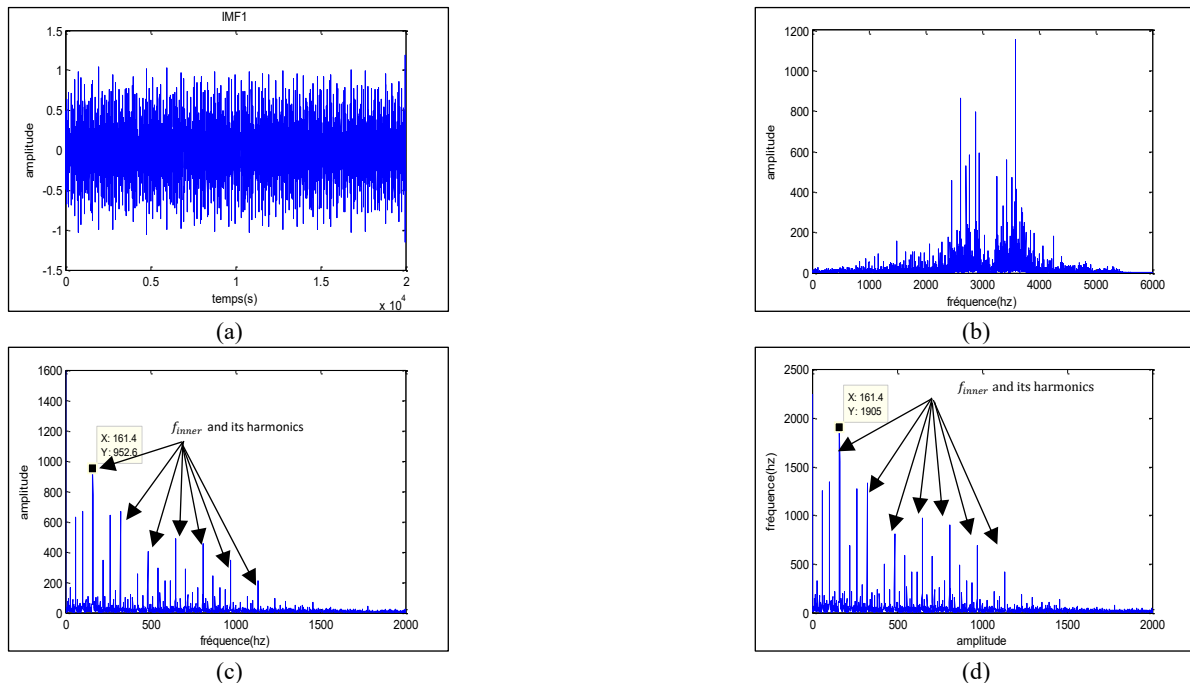


Figure 13: Inner race fault (0 HP): (a) Selected IMF, (b) IMF spectrum, (c) spectrum of TKEO, (d) envelope spectrum of TKEO.

Source: Authors, (2026).

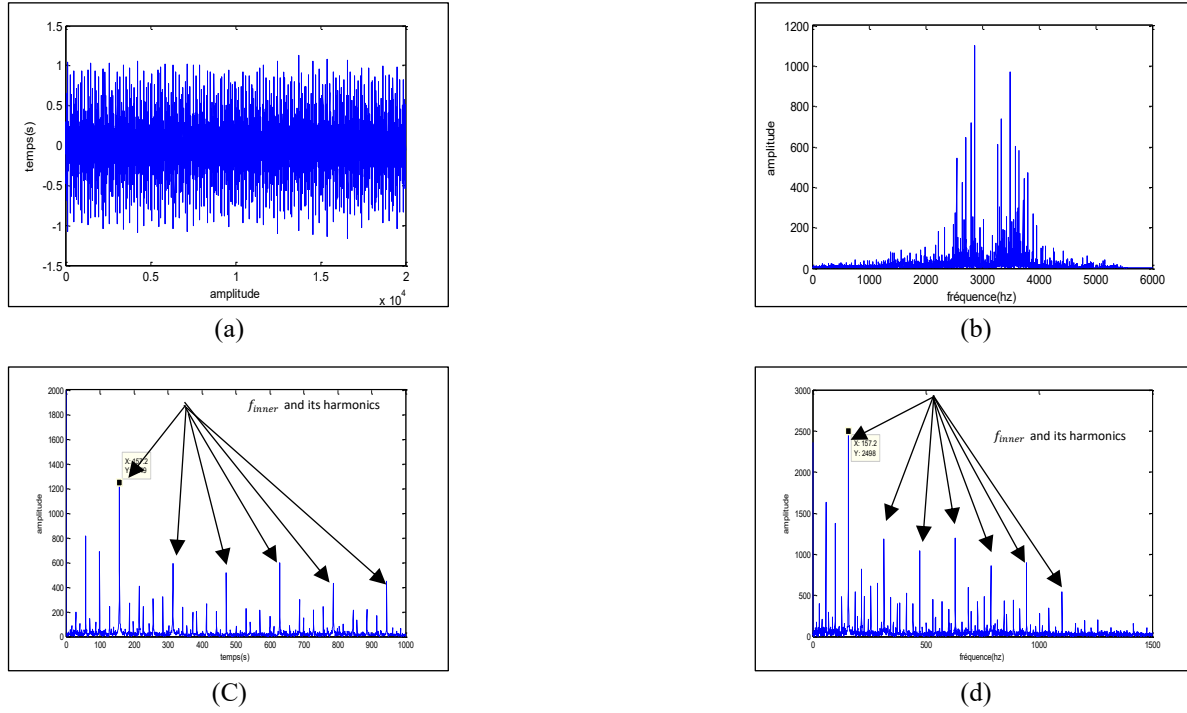


Figure 14: Inner race fault (2 HP): (a) Selected IMF, (b) IMF spectrum, (c) spectrum of TKEO, (d) envelope spectrum of TKEO.
Source: Authors, (2026).

Figures 13 and 14 present a comprehensive four-stage spectral analysis of the inner race fault under no-load (0 HP) and 2 HP load conditions, respectively, illustrating the progressive signal processing chain from IMF selection through envelope spectrum extraction. Under no-load conditions (Figure 13), subplot (a) displays the selected IMF1 in the time domain, exhibiting characteristic periodic impulsive patterns with approximately 0.06-second intervals, corresponding to the inner race defect frequency. The IMF spectrum (b) reveals dominant frequency content around 1000-1500 Hz, representing high-frequency resonances excited by fault-induced impacts. The TKEO spectrum (c) demonstrates successful demodulation, with the primary energy concentration shifted to lower frequencies, particularly around 161.4 Hz. Most significantly, the TKEO envelope spectrum (d) clearly reveals a dominant peak at 161.4 Hz with distinct harmonics at 322.8 Hz, 484.2 Hz, and higher multiples, confirming the inner race defect frequency calculated in Table 1 (162.18 Hz theoretical value). Under 2 HP load conditions (Figure 14), similar spectral evolution patterns are observed, though with notable differences. The selected IMF1 (a) shows enhanced impulsive characteristics with increased amplitude compared to the no-load case, indicating load-induced amplification of fault signatures. The IMF spectrum (b) maintains high-frequency content with slightly altered distribution. The TKEO spectrum (c) exhibits frequency shift with the primary peak appearing at 157.2 Hz, closely matching the theoretical inner race fault frequency under load (157.9 Hz from Table 1 with 1750 rpm). The envelope spectrum (d) displays a clear harmonic structure at 157.2 Hz and its multiples (314.4 Hz, 471.6 Hz), with significantly enhanced harmonic amplitudes compared to no-load conditions, indicating that the applied load amplifies the fault signature and intensifies the periodic impact characteristics associated with the inner race defect.

III.3.3 Outer Race Bearing Analysis Under No Load And Under 2hp Load

The time-domain analysis of the outer race bearing fault signal under no-load conditions is presented in Figure 15, while Figure 16 displays the corresponding signal under 2 HP load.

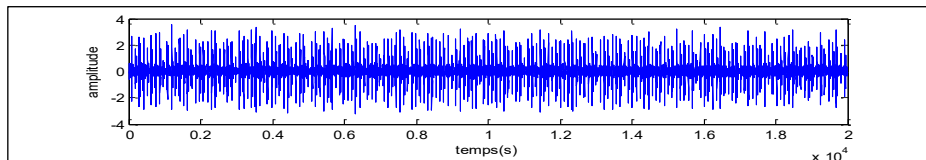


Figure 15: Signal with outer race fault (0HP).
Source: Authors, (2026).

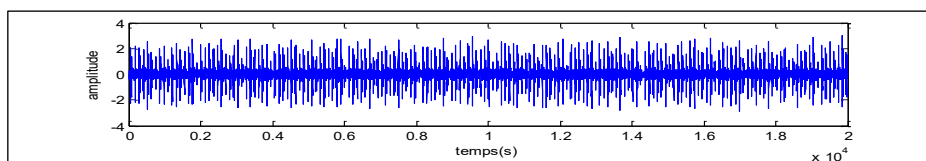


Figure 16: Signal with outer race fault (2HP).
Source: Authors, (2026).

Figures 17 and 18 present the ICEEMDAN decomposition results for the outer race fault signals under 0 HP and 2 HP conditions, respectively. Each decomposition yields eight IMF components (IMF1~ IMF8) arranged from highest to lowest frequency content.

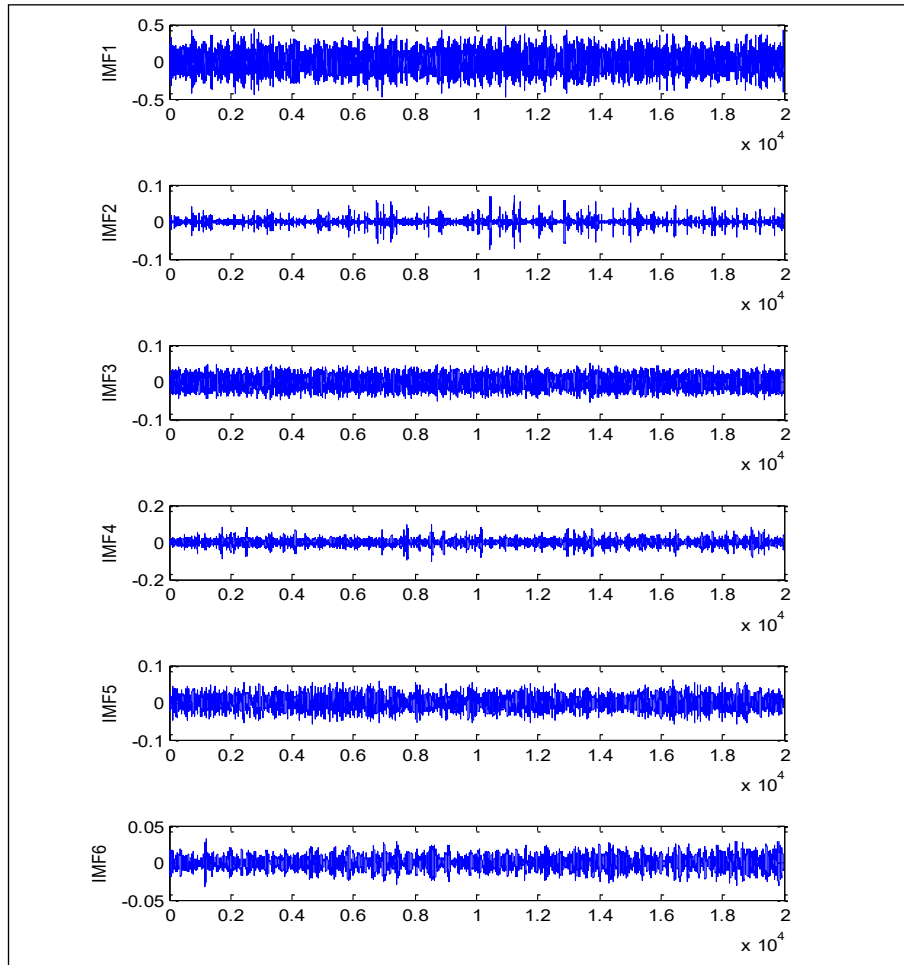


Figure 17: Decomposition with ICEEMDAN (0 HP).

Source: Authors, (2026).

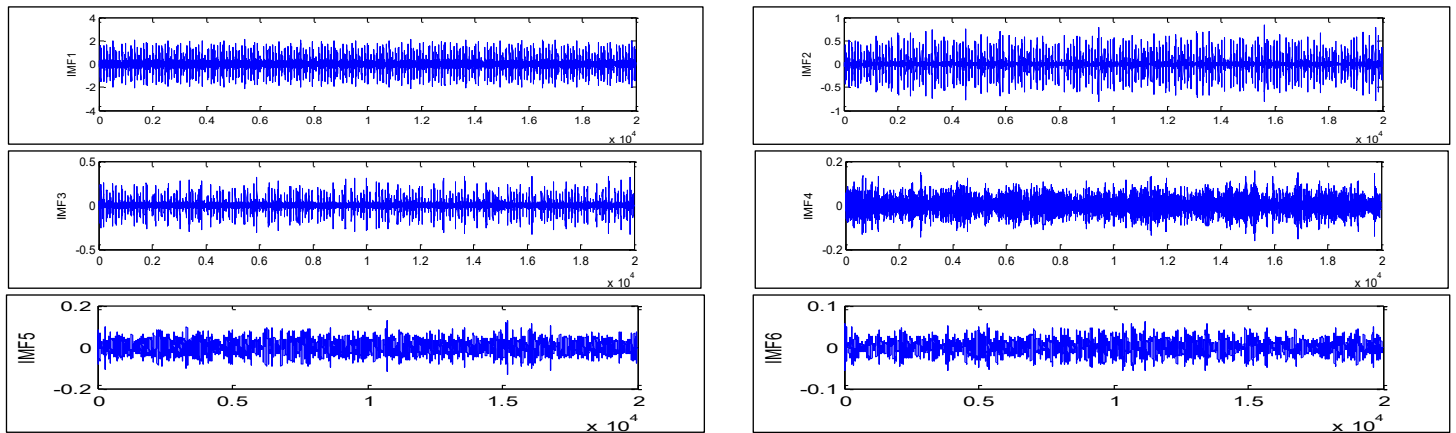


Figure 18: Decomposition with ICEEMDAN (2 HP).

Source: Authors, (2026).

Tables 6 and 7 present the correlation coefficients between each IMF component and the outer race fault signal under no-load (0 HP) and 2 HP load conditions, respectively. Under both operational conditions, IMF1 demonstrates exceptionally high correlation coefficients (0.9559 for 0 HP and 0.9551 for 2 HP), substantially exceeding all other IMF components. This indicates that IMF1 captures the predominant fault-related information and is therefore selected for TKEO processing and envelope analysis. Figures 19 and 20 display the resulting spectral analyses for both loading conditions. The envelope spectra reveal prominent frequency peaks at 107.4 Hz and its harmonics (214.8 Hz, 322.2 Hz, 429.6 Hz, and 537 Hz), which closely correspond to the theoretical outer race fault frequency presented in Table 1 (107.34 Hz for 0 HP and 104.50 Hz for 2 HP), thereby confirming the presence of an outer race defect.

Table 6: Correlation coefficients between each IMF and the outer fault signal under (0 HP).

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
0.9559	0.4295	0.0487	0.0549	0.0641	0.0211	0.01127	0.0020

Source: Authors, (2026).

Table 7: Correlation coefficients between each IMF and the outer fault signal under (2 HP).

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
0.9551	0.4333	0.0577	0.0740	0.057	0.0249	0.0114	0.0041

Source: Authors, (2026).

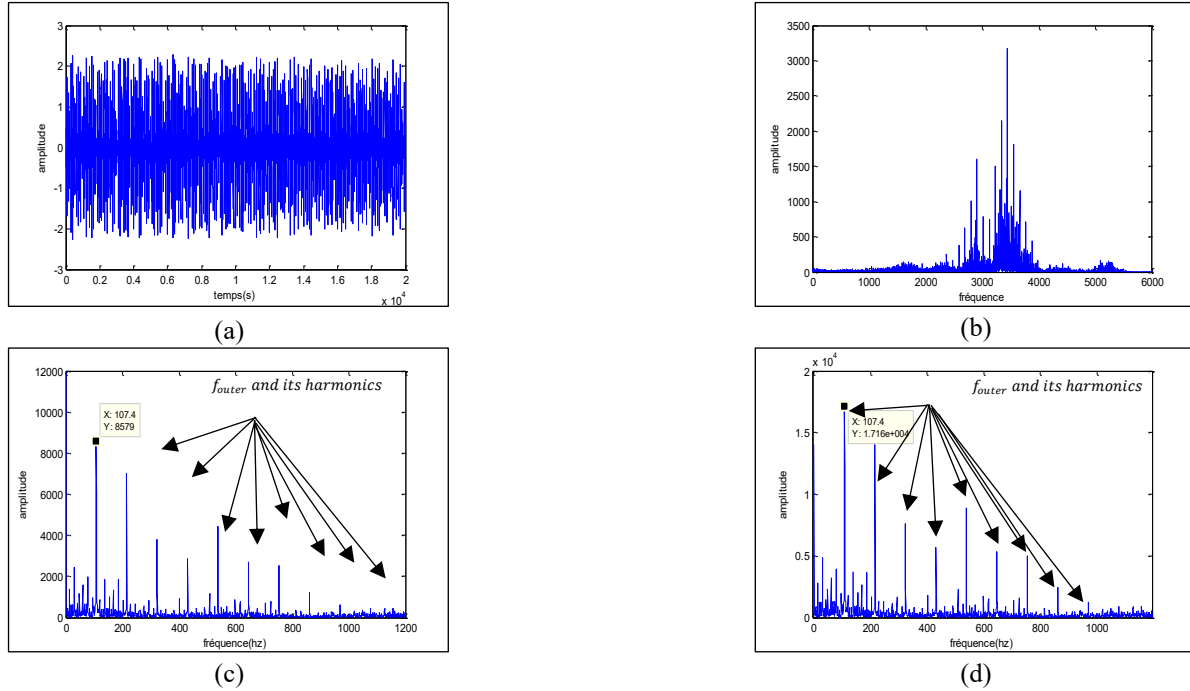


Figure 19: Outer race fault (0 HP): (a) Selected IMF, (b) IMF spectrum, (c) spectrum of TKEO, (d) envelope spectrum of TKEO.

Source: Authors, (2026).

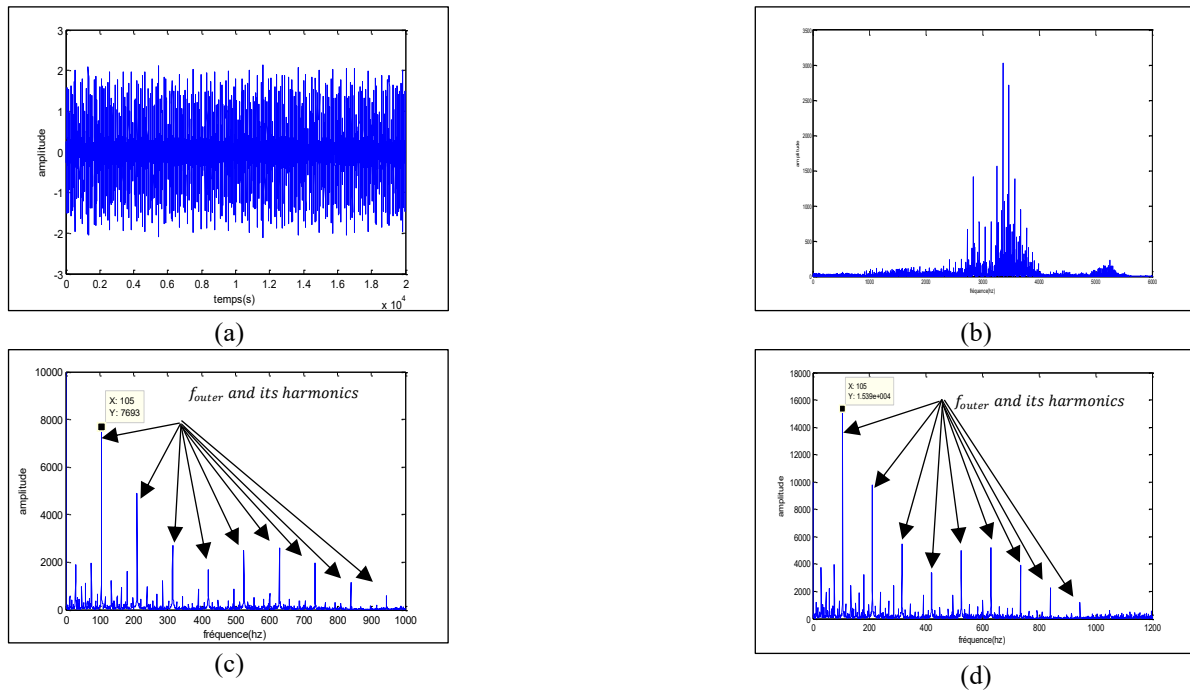


Figure 20: Outer race fault (2 HP): (a) Selected IMF, (b) IMF spectrum, (c) spectrum of TKEO, (d) envelope spectrum of TKEO.

Source: Authors, (2026).

III.3.4 Ball Fault Analysis

The time-domain analysis of ball bearing fault signals is presented in Figures 21 and 22 for no-load and 2 HP load conditions, respectively, with their corresponding ICEEMDAN decompositions shown in Figures 23 and 24.

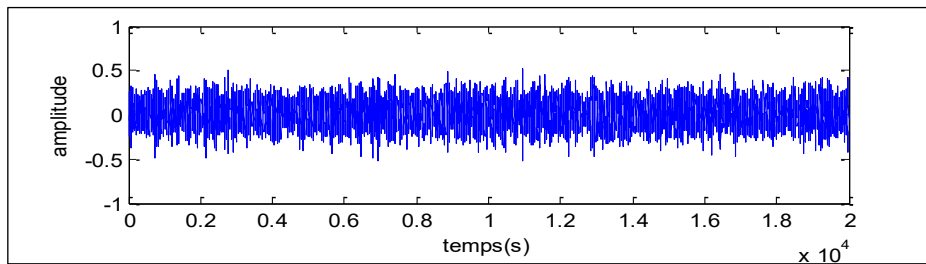


Figure 21: Signal with ball fault (0 HP).
Source: Authors, (2026).

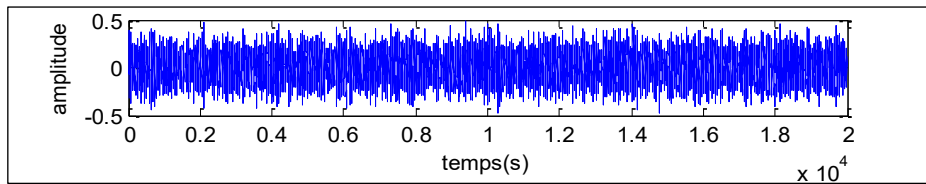


Figure 22: Signal with ball fault (2 HP).
Source: Authors, (2026).

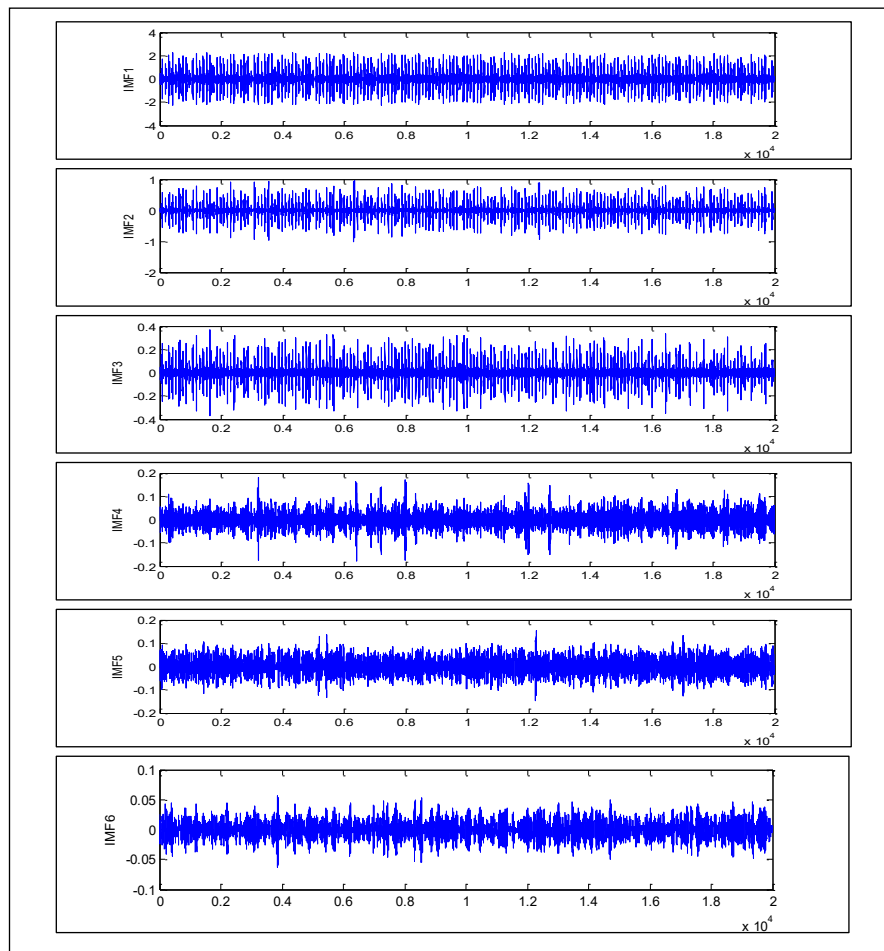
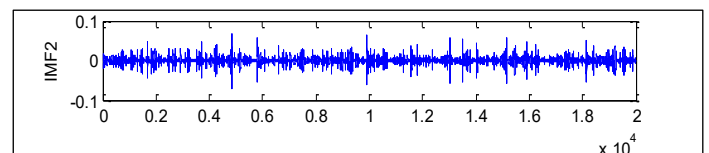
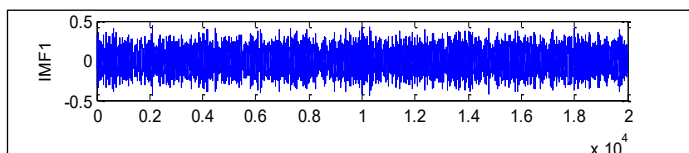


Figure 23: Decomposition with ICEEMDAN (0 HP).
Source: Authors, (2026).



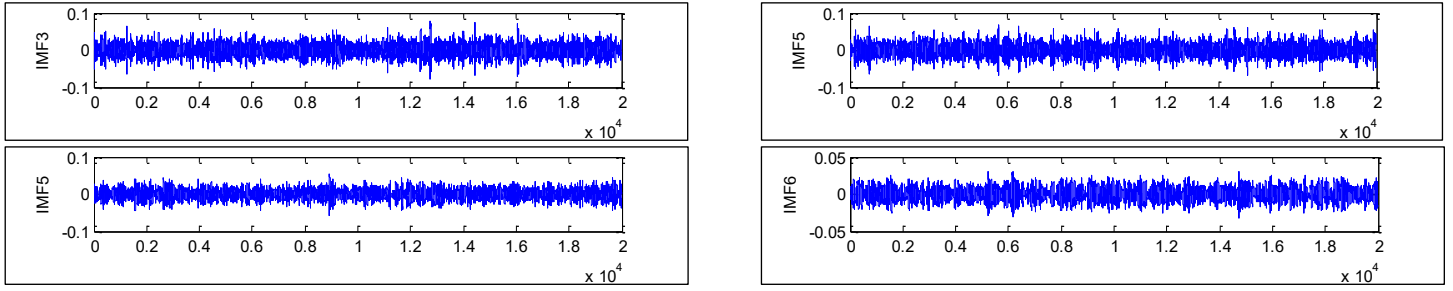


Figure 24: Decomposition with ICEEMDAN (2 HP).
Source: Authors, (2026).

Table 8: Correlation coefficients between each IMF and the ball fault signal under (0 HP).

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
0.9446	0.1563	0.1917	0.2341	0.2185	0.1120	0.0825	0.0166

Source: Authors, (2026).

Table 9: Correlation coefficients between each IMF and the ball fault signal under (2 HP).

IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
0.9609	0.1302	0.1723	0.1912	0.1535	0.0926	0.0631	0.0145

Source: Authors, (2026).

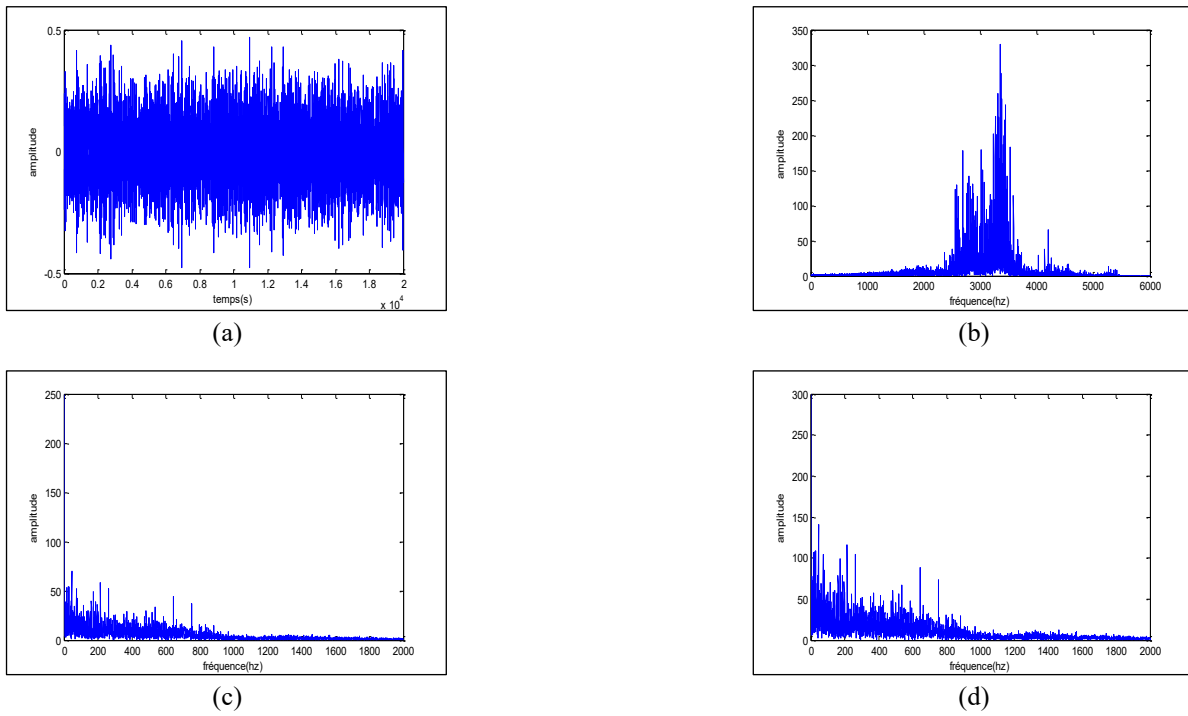
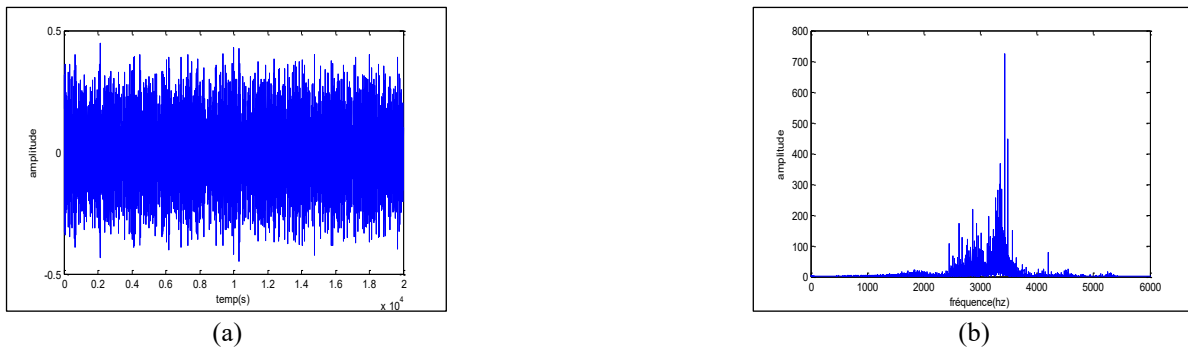


Figure 25: Ball fault (0 HP): (a) Selected IMF, (b) IMF spectrum, (c) spectrum of TKEO, (d) envelope spectrum of TKEO.

Source: Authors, (2026).



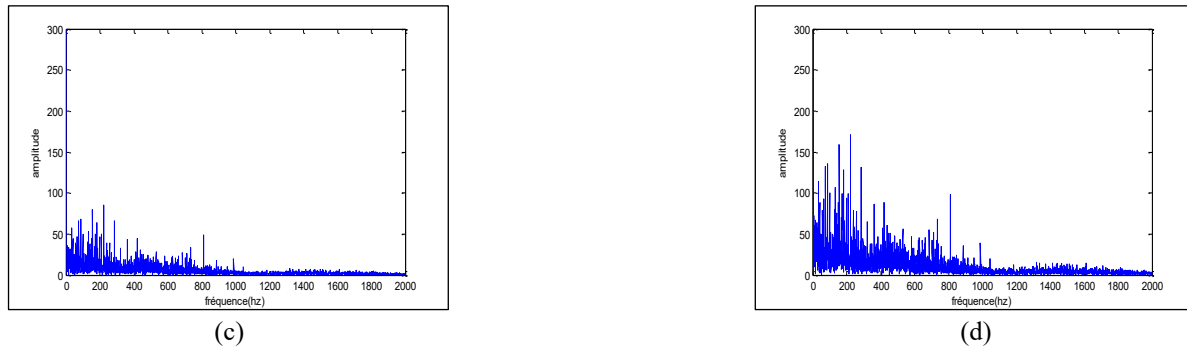


Figure 26: Ball fault (2 HP): (a) Selected IMF, (b) IMF spectrum, (c) spectrum of TKEO, (d) envelope spectrum of TKEO.
Source: Authors, (2026).

Tables 8 and 9 present the correlation coefficients between each IMF component and the ball fault signal under no-load (0 HP) and 2 HP load conditions, respectively. IMF1 demonstrates exceptionally high correlation coefficients under both operational conditions (0.9446 for 0 HP and 0.9609 for 2 HP), substantially exceeding all other IMF components. Notably, the correlation coefficient increases under load, suggesting enhanced fault signature prominence. The remaining IMF components (IMF2 through IMF8) exhibit significantly lower correlations (below 0.24), indicating minimal fault-related information content. Based on these results, IMF1 is selected for TKEO processing and envelope analysis. Figures 25 and 26 present the comprehensive spectral analysis of the ball fault under no-load and 2 HP load conditions, respectively. Under no-load conditions (Figure 25), the selected IMF1 (a) displays impulsive characteristics in the time domain. The IMF spectrum (b) reveals high-frequency content distribution. The TKEO spectrum (c) demonstrates successful demodulation with energy concentration in lower frequency bands. The envelope spectrum (d) exhibits frequency components around 140-141 Hz, corresponding to the theoretical ball fault frequency presented in Table I (140.74 Hz for 0 HP). Under 2 HP load (Figure 26), similar spectral patterns are observed with notable differences. The envelope spectrum reveals frequency peaks near 137-138 Hz, closely matching the theoretical ball fault frequency under load (137.44 Hz from Table 1). However, compared to inner and outer race fault analyses, the ball fault spectra present less distinct harmonic structures. This complexity in characteristic peak identification can be attributed to the inherent nature of ball defects, where the unstable rotational path and variable contact angle of the rolling element create irregular impact patterns. Unlike inner and outer race faults, which produce consistent periodic impacts at fixed locations, ball faults exhibit more complex kinematics due to the ball's combined rolling and spinning motion, resulting in less pronounced periodicity in the vibration signature.

IV. CONCLUSION

This study presented a hybrid diagnostic methodology that synergistically integrates ICEEMDAN, TKEO, and envelope analysis for early bearing fault detection in rotating machinery. The experimental validation using the Case Western Reserve University database demonstrated the effectiveness of the proposed approach in identifying and classifying three distinct bearing fault types—inner race, outer race, and ball defects—under both no-load and loaded operational conditions. The methodology's strength lies in its systematic integration of complementary techniques: ICEEMDAN effectively decomposes complex vibration signals, TKEO amplifies transient fault characteristics, and envelope analysis reveals characteristic fault frequencies. Correlation-based IMF selection consistently identified the most fault-representative components across all test scenarios. The detected frequencies demonstrated excellent agreement with theoretical predictions, validating the diagnostic accuracy of the proposed approach. Comparative analysis between operational conditions revealed load-dependent variations in fault signatures, with enhanced harmonic amplitudes under loaded conditions suggesting potential benefits for early fault detection. However, ball fault diagnosis presented greater complexity due to irregular impact patterns inherent to rolling element kinematics, indicating areas for future methodological refinement. Future work should focus on extending the methodology to multi-fault scenarios, integrating machine learning for automated classification, optimizing for real-time industrial implementation, and validating across diverse bearing types and operational conditions. The proposed ICEEMDAN-TKEO-envelope framework provides a robust foundation for enhancing predictive maintenance strategies and improving reliability in industrial rotating machinery systems.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Kabla aida and Asradj Zahir.

Methodology: Kabla aida and Asradj Zahir.

Investigation: Kabla aida and Asradj Zahir.

Discussion of results: Kabla aida and Asradj Zahir.

Writing – Original Draft: Kabla aida and Asradj Zahir.

Writing – Review and Editing: Kabla aida and Asradj Zahir.

Resources: Kabla aida and Asradj Zahir.

Supervision: Kabla aida and Asradj Zahir.

Approval of the final text: Kabla aida and Asradj Zahir.

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