Journal of Engineering and Technology for Industrial Applications

ITEGAM-JETIA

Manaus, v.11 n.52, p. 165-172. March./April., 2025.
DOI: https://doi.org/10.5935/jetia. v11i52.1569

ISSN ONLINE: 2447-0228

RESEARCH ARTICLE OPEN ACCESS

COMBINATION OF MINIMUM ENTROPY DECONVOLUTION METHOD AND VAN CITTERT ALGORITHM FOR FEATURES EXTRACTION OF BEARINGS

Nesrine Gouri[1], Hocine Bendjama [2], Mohamed Larbi Mihoub [3]

[1,3]Mathematical Modeling and Numerical Simulation Research Laboratory, Badji Mokhtar University, Po. Box 12, Annaba 23000, Algeria
[2]Research Center in Industrial Technologies CRTI, P.O.Box 64, Cheraga Algiers, Algeria

[1]https://orcid.org/0009-0007-4344-8920, [2]https://orcid.org/0000-0001-6221-028X, [3]https://orcid.org/0000-0001-7230-7165

Email: gou.nesrine@gmail.com, nesrine.gouri@univ-annaba.org, h.bendjama@crti.dz, mihoubmedlarbi@yahoo.fr

ARTICLE INFO

Article History
Received: January 17, 2025
Revised: February 20, 2025
Accepted: March 15, 2025
Published: April 30, 2025

Keywords:
Fault diagnosis,
Rotating machine,
Bearing vibration signal,
Deconvolution,
Iterative algorithm.

ABSTRACT

Rolling bearings functionality has a primary importance for the correct operation of the rotating machines. In this paper, a monitoring technique based on deconvolution approach is proposed to restore the impulsive shape from the measured vibration signal. This latter is obtained from a convolution of real impulse signal and transmission function. The proposed procedure consists of two major steps; firstly, using the minimum entropy deconvolution (MED) to obtain the inverse filter, secondly introducing the iterative deconvolution algorithm to go back to the initial problem that is mathematically described by the convolution process to restitute the impulsive signal. The proposed procedure is applied to bearing diagnosis, and its effectiveness is validated by simulated and experimental data acquired from operational bearings. Moreover, the monitoring obtained results are satisfactory.

I. INTRODUCTION

Due to the complexity of mechanical system, multiple faults may co-exist in rotating machinery, especially in one of their most important component rolling element bearings. Therefore, the requirement for fault diagnosis has grown and proves that it is extremely essential task in process monitoring; it provides operators with the process operation information. Early diagnosis of process faults like rolling bearing faults can help to avoid abnormal event progression, and to reduce productivity loss in order to ensure the safe running of machines. Several monitoring methods for this purpose have been developed, including dynamics, tribology, nondestructive methods and vibration [1-3].

The vibration signal analysis has been widely used over the past decade, as it provides valuable information about the health condition of mechanical equipment. Vibration signals from rolling bearings are particularly important for fault diagnosis due to their critical role as mechanical components. However, these signals often contain significant noise because of their sensitivity to various faults. In the presence of background noise, the useful information can be obscured. Therefore, to extract the effective information, various feasible and effective techniques need to be applied. Numerous researches for this goal are available in the literature.

From a mathematical perspective, the bearing vibration signal is viewed as the result of a convolution process involving periodic impacts caused by faults and the response of mechanical components. This work builds on this concept, aiming to restore the original impulsive signal from the measured one. There has been a considerable amount of research into the creation of different restoration techniques during the last decades. Among the many proposals found in the scientific literature, there are: wavelet transform [4],[5], Variational Mode Decomposition (VMD) [6],[7], Empirical Mode Decomposition (EMD) [8],[9], Blind Separation Sources (BSS) [10],[11] and the Minimum Entropy deconvolution) (MED) [12- 15] etc.

MED has been shown to be a successful deconvolution method, it was proposed by Wiggins [16] to enhance the excitation component in the fault vibration signal. This technique is based on the maximization of the kurtosis by finding an inverse filter while considering that the initial excitation was impulsive. After that, Endo and Randall [17] applied MED to detect faults in rotating machines diagnosis, more precisely in gears. Then, [18], [19] adopted this technique to enhance the detection of bearings faults. In [20] combined a monostable stochastic resonance with minimum entropy deconvolution based on time-delay feedback for fault diagnosis of rolling bearings. In [21] suggested rolling bearing condition monitoring technique based on the envelope spectrum and MED. Recently, many researchers such as: [22-25], … etc. employed different deconvolution methods as an important step in an effective strategy in order to restitute the informative impulse. Unfortunately, unless the development of those different researches, the results are limited.

As mentioned previously, the vibration signal of rolling bearings is often contaminated by significant noise due to their sensitivity to various faults, leading to many difficulties in extracting useful information. Although different studies have been conducted to isolate the impulse signal and eliminate unwanted sources. Unfortunately, the results remain insufficient to overcome these difficulties. For this purpose, we propose a novel strategy in this paper, combining MED with iterative algorithms to restore the impulsive components present in the bearing signal.

Firstly, an investigation by applying the deconvolution techniques and adopting the MED method to optimize the finite impulse response (FIR) filter that eliminates the effect of the transmission path through inverse filtration to get a signal closer to the original impulse, this useful information corresponds to the convolution process of the generated impulses and the transmission path of the mechanical component. Although the MED filter has been estimated as a first step, this latest leads a solution of an appropriate ill-posed problem and it requires the result to be regularized, hence this typically referred to operates it in combination with other signal processing techniques in order to overcome these limitations. For this reason, we present in the second step of this procedure, an estimation of the original impulses by applying iterative algorithms regularized by Tikhonov-Miller (TM) based on integrated a priori model of solution.

The rest of this paper is structured as follows: section 2 describes in detail the proposed method. Section 3 contains the theoretical background of MED, iterative algorithm and TM Regularization. In section 4, verification of the suggested procedure's efficacy utilising simulated bearing signal and the experimental data collected from bearing test rig. Section 5 discussed the obtained results. Finally, the conclusions are drawn in Section 6.

II. THEORETICAL BACKGROUND:

II.1 MINIMUM ENTROPY DECONVOLUTION (MED)

Deconvolution is defined as the opposite process of convolution. In fact, the measured signal may be seen as result of a convolution operation of the original signal and the transmission path. Figure (1) illustrates the convolution/deconvolution process in which the signals *g(k)* and *x(k)* represent respectively the original impulse and the measured output, *h(k)* represents the effect of the transmission path, *f(k)* is the finite impulse response (FIR) filter, *n(k)* represents the noise and * denotes the convolution.

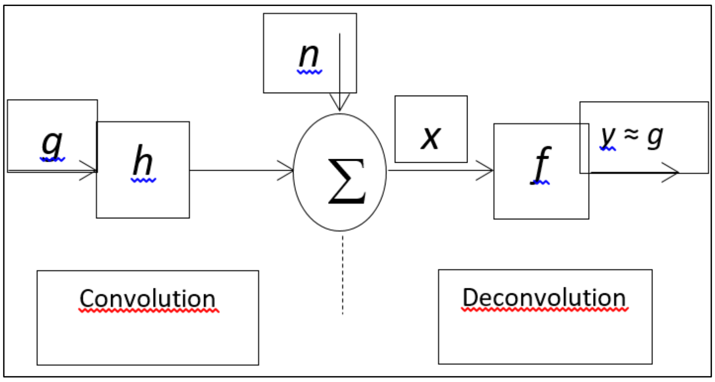


Figure 1: Convolution/deconvolution basic process.
Source: Authors, (2025).

As mentioned previously different deconvolution techniques are employed to restore the original impulses. In this work we present the MED method, which has been recently introduced to the machine monitoring domain. Wiggins [16] was the first to suggest it in the area of blind convolution, and it was effectively used in seismic treatment.

The fundamental idea of applying the MED technique is to construct an inverse filter in order to eliminate the effect of the transmission path from the measured signal. Thus, the filtered output signal y_k produced by the input signal (measured signal) x_k ($k=1, 2 \ldots N$) and the building inverse filter $f=[f_1, f_2, \ldots, f_L]$ with L coefficients, as follows:

$$y(k) = f(k) * x(k) = \sum_{i=1}^{L} f(i)x(k-i) + n_k \tag{1}$$

Such that:

$$x(k) = g(k) * h(k) + n_k \tag{2}$$

The figure (2) illustrates the basically process of MED, this process is implemented for calculating the optimal set of filter coefficients by maximizing the kurtosis of y*(k).]*

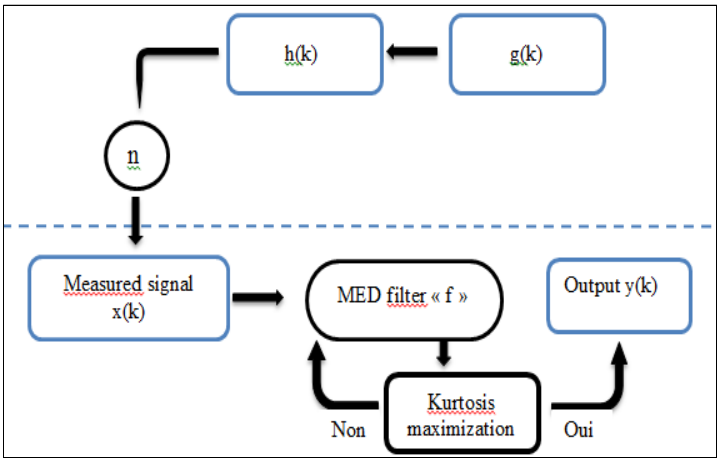


Figure 2: MED process.
Source: Authors, (2025).

Hence, the kurtosis of an output signal y is given by:

$$k = \frac{E(y^4)}{(E(y^2))^2} - 3 \tag{3}$$

$$y = fx + b \tag{4}$$

Unfortunately, the challenge of reconstructing x from equation (4) leads to an ill-posed problem; in other words, the solution x of equation (4) may not be unique, may not exist, or may not depend continuously on the data. It is clear that these limitations must be overcome by introducing stability criteria; more precisely regularizing this ill-posed problem, and through adopting a deconvolution algorithm.

II.2 ITERATIVE ALGORITHM AND TIKHONOV-MILLER REGULARIZATION

II.2.1 VAN CITTERT ALGORITHM

Iterative algorithms are used to inspect the solution more precisely than when calculating in a single operation, in other words they generally have the advantage of not imposing the direct calculation of inverse operators.

Van Cittert algorithm [26] serves as a foundational tool for many iterative deconvolution methods. This approach is a fixed-point [27], its iterative formula is given by:

$$\begin{cases} x_{n+1} = x_n + (y - f x_n) \\ x_0 = y \end{cases} \tag{5}$$

The vector x_n represents an intermediate solution that lies between the initial estimate x_0 and the final solution x_∞. It can be demonstrated that the Van Cittert algorithm converges to a solution x_∞ that is equivalent to that derived from direct inversion (Equation 6).

$$x_\infty \longrightarrow f^{-1} y \tag{6}$$

This property underlines the effectiveness of the algorithm in reconstructing signals. But unfortunately the Van Cittert algorithm does not consider the presence of noise in the measured signal. This leads from a mathematical point of view to an unstable solution if the problem is ill-posed. Therefore, it is essential to incorporate an effective regularization in order to achieve a reliable solution.

II.2.2 TIKHONOV-MILLER REGULARIZATION

When the problem is poorly conditioned, it can lead to an unstable solution. Therefore, it is necessary to use a regularization method to obtain a desirable solution. Different regularization methods have been proposed and discussed [28-30].

Tikhonov regularization is regarded as one of the most widely used methods for addressing ill-posed problems and solving inverse problems. It is accomplished by choosing a solution that does not only reconstructs a signal close to the measured one but also aligns with prior knowledge of the original signal [31-34]. From mathematical perspective, this method consists of redefining the concepts of inversion and solution such that the regularized solution depends continuously on the data and remains close to the exact solution. In other words, it reduces the sensitivity of the solution to errors in the data.

This regularization method is based on a quadratic criterion (least squares between the measured data and the reconstructed signal), so this quadratic quantity is required to be lower than the noise energy$\|y - f\hat{x}\|^2 \leq \|b\|^2$. According this method, the stabilization of the estimated solution is achieved generally by differentiating a functional to be minimized:

$$\Delta = \|y - f\hat{x}\|^2 + \alpha \|D\hat{x}\|^2 \tag{7}$$

Where $\alpha > 0$ and D is a stabilizing operator; D measures the degree of regularity of the solution such that$\|D\hat{x}\|^2 \leq r^2$. It is chosen according to the treatment context and some previous information about the original signal. D is typically used to smooth the estimated signal, followed by the selection of a gradient or discrete Laplacian. Its spectrum functions as a high-pass filter, for more details, refer to [32],[35] and [36]. The minimization of D proposed by Tikhonov is given as follow:

$$\hat{x} = argmin(\|y - f\hat{x}\|^2 + \alpha(\|D\hat{x}\|^2 - r^2)) \tag{8}$$

Such that, *argmin* represents the argument that minimizes the expression between brackets, and α is the regularization parameter. This latest controls the trade-off between data-fidelity and regularization term. It is a challenging task to find the regularization parameter α that provides the best balance between signal smoothing and feature preservation, see [28],[37]. The previous minimization problem can be solved by the system below:

$$(f^T f + \alpha D^T D)\hat{x} = f^T y \tag{9}$$

The regularized solution has the following form:

$$\hat{x} = (f^T f + \alpha D^T D)^{-1} f^T y \tag{10}$$

Where

$$f^+ = \hat{x} = f^T f + \alpha D^T D \tag{11}$$

The generalized matrix f^+ is more conditioned that is why it replaces the matrix H, which described the deconvolution process before regularization. The system becomes more stable by the modification of the eigenvalues of H.

The regularization operator D selection should not present any issues as long as the eigenvalue modification criterion is followed, and the regularization value α must be chosen optimally in order to achieve reconstruction quality. In fact, the matrix H is not as well-conditioned when this parameter is estimated poorly, thus, the solution is degenerated. By replacing the iterative resolution of $y = fy$ by that of

$$f^T y = (f^T f + \alpha D^T D)x \tag{12}$$

The Van Cittert algorithm with Tikhonov-Miller regularization is written as follows:

$$\begin{cases} x_{n+1} = x_n + [f^T y - (f^T f + \alpha D^T D)x_n] \\ x_0 = f^T y \end{cases} \tag{13}$$

III. THE PROPOSED PROCEDURE

This paper proposes a novel deconvolution procedure in order to effectively restore the original periodic impulses from faulty bearing vibration signals. The bearing vibration signal acquired from an accelerometer sensor is considered as measured signal, this later is a convolution between periodical impulses signal and a transmission path.

A suitable combination between MED and iterative algorithm based on a priori model of solution is adopted as a deconvolution procedure to extract the original signal from the measured signal.

In the first step, MED is employed to determine a deconvolution filter by maximizing the kurtosis of the output. This involves finding the optimal inverse filter to counteract the effects of the transmission path. The filter coefficients can be computed using a second-order iterative Kurtosis algorithm based on the Hessian matrix. With the known source, the coefficients of the mixing matrix f can be estimated. The filter coefficients $f_{m,n}(l)$ are estimated using the following formula:

$$f_{k,l}(l)=\frac{E(x(k)y(k-l))}{E(y(k)^2)}, \quad k=1,2,\dots,N, \quad l=1,2,\dots,M \qquad (14)$$

Unfortunately, the obtained inverse filter cannot directly reflect the convolution relationship between source features and the transmission path. In other words, restoring the original impulses using the resulting inverse filter involves solving an ill-posed problem, where noise prevents the solution from being unique or stable. Therefore, in the second step, we propose to solve this ill-posed problem by introducing the Van Cittert algorithm, based on Tikhonov-Miller regularization, using an a priori model of the solution. The detailed strategy of this method is summarized in Figure 3.

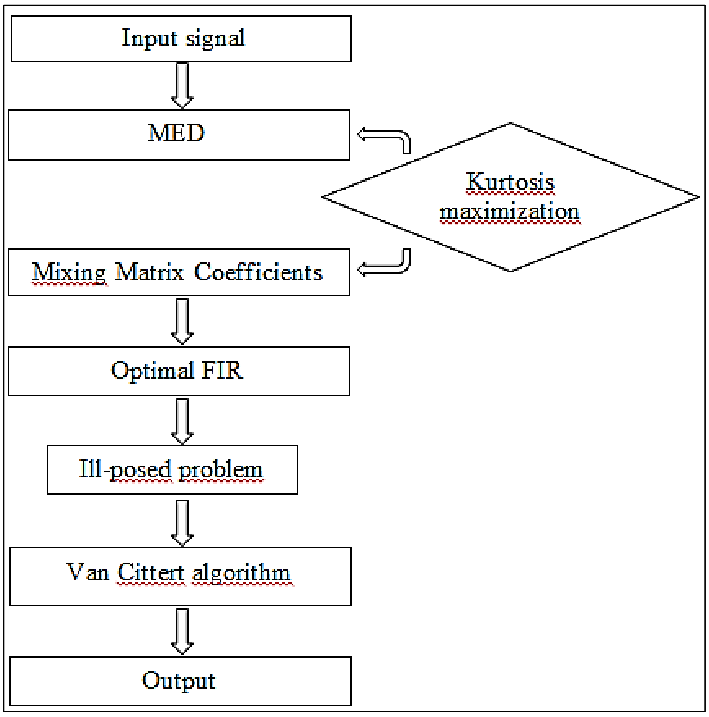


Figure 3: The flowchart of the proposed strategy.
Source: Authors, (2025).

IV. NUMERICAL SIMULATION AND EXPERIMENTAL VALIDATION

IV.1 NUMERICAL SIMULATION

In this part, a numerical simulation is presented to evaluate the effectiveness of the proposed procedure. This investigation demonstrates the importance of the two steps in the proposed strategy. We have chosen a model that simulates the impulse response derived from a pulse train. The model modulates each pulse with two harmonic frequencies, with exponential decay occurring. Hence, the impulse response could serve to model the modulated signal of a bearing system, and is presented as follows:

$$x(t) = e^{-\varepsilon\tau}(\sin(2\pi f_1 t) + 3\times\sin(2\pi f_2 t)) \qquad (15)$$

With

$$\tau = mod\left(t, \frac{1}{f_d}\right) \qquad (16)$$

Where ε, f_1, f_2, and f_d represent, respectively, the frequencies of decay, resonance, and defect (modulation).

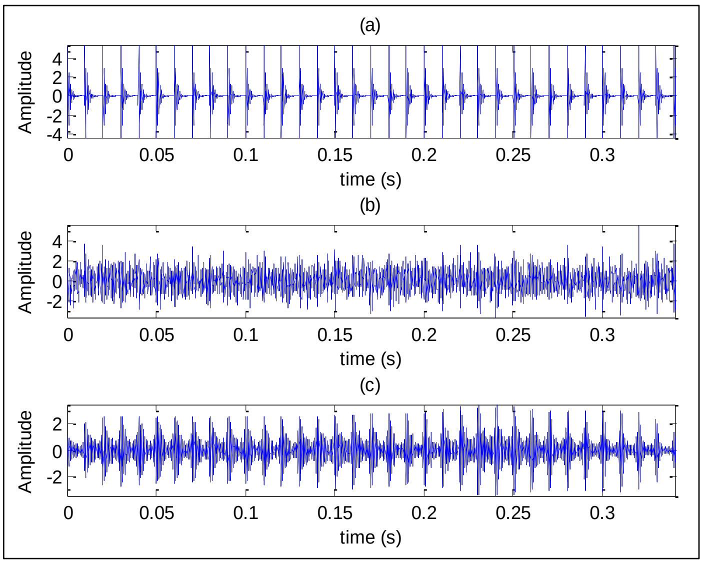
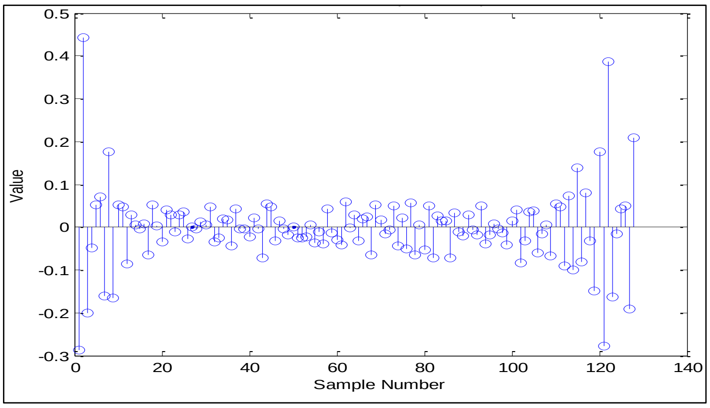
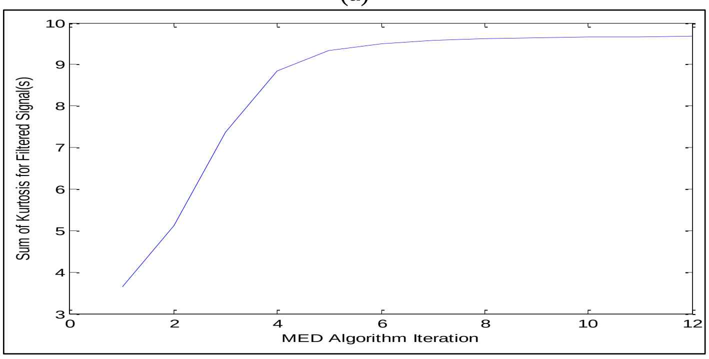


Figure 4: **a)** Simulated signal without noise, **b)** Signal with noise and **c)** Filtered signal.
Source: Authors, (2025).



(a)



(b)

Figure 5: **a)** Final Filter, Finite Impulse Response, **b)** Kurtosis maximization during MED Algorithm iteration.
Source: Authors, (2025).

The simulated vibration signal obtained from Equation 15 is displayed in Figure 4a with Gaussian noise and in Figure 4b without it. A comparison of Figures 4a and 4b shows that the periodic impulses in Figure 4b are not clearly visible in the time domain. It is important to note that the main advantage of the proposed procedure is its ability to detect periodic effects, enabling the extraction of useful information. The inverse filter constructed using the MED technique is shown in Figure 5a, while the kurtosis maximization during MED Algorithm iteration is illustrated in Figure 5b. After applying the Van Cittert algorithm as a second step, the filtered signal is obtained by maximizing kurtosis to extract the impulsive signal from bearing vibration.

Figure 4c illustrates the resulting signal from the proposed procedure. The impulsive shape of the signal is more clearly visible, with a kurtosis value of 3.96 compared to the input signal's value of 3.67, indicating effective noise reduction while preserving key impulsive features. Although the improvement in the kurtosis value is slight, it is clearly visible in Figure 2, reflecting the enhancement in the clarity of the impulsive features after processing.

IV.2 EXPERIMENTAL VALIDATION

Vibration measurement used for defect diagnosis and condition monitoring imposes various kinds and degrees of equipment and methods selected according to the available resources, skills and knowledge.

In this study, we present the experimental measurements utilized entirely from the vibration data acquired at the Case Western Reserve University Bearing Data Center [38]. As illustrated in Figure 6, the vibration data were obtained using accelerometers mounted on the housing with magnetic bases. The measurement unit is mm/s² (gravity).

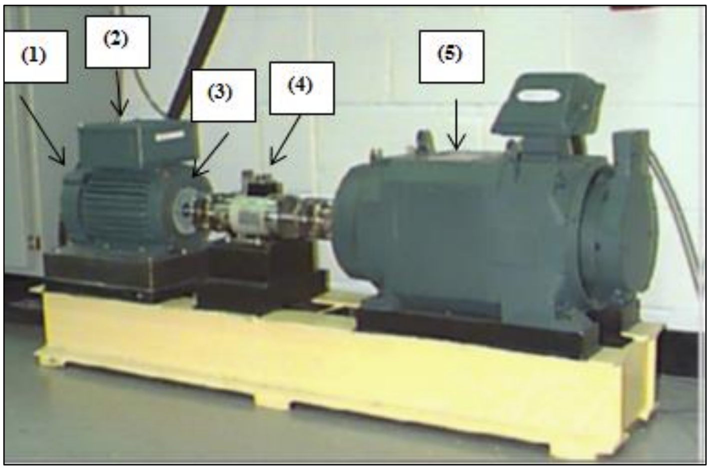


Figure 6: Bearing test rig.
1- Fan end bearing, 2-induction motor, 3-Drive end bearing, 4-Torque transduce, 5-Load Motor
Source: Authors, (2025).

The vibration signals were obtained from four various bearing conditions: (1) Bearing without fault i.e. Normal state (NS); (2) Bearing with Outer Race Fault (OrF); (3) Bearing with Ball Fault (BF) and (4) Bearing with Inner Race Fault (IrF). The vibration signals were sampled at a rate of 12000 Hz.

Deep groove ball bearings were used in the experiments, with the following specifications: ball diameter = 7.94 mm; pitch diameter = 39.04 mm; number of balls = 9; and contact angle = 0. The electro-discharge machining (EDM) technique created faults in the test bearings, using varying diameters: 0.1778 mm, 0.28 mm and 0.5334 mm. The bearings were tested at four rotational speeds (ranging from 1797 to 1730 rpm) and under four different loads (ranging from 0 to 4 horsepower (hp)) using a dynamometer.

In this study, the motor speeds considered are 1797 rpm and 1750 rpm, corresponding to 0 hp and 2 hp, respectively. The defect sizes in both the inner and outer races are recorded at 0.1778 mm and 0.5334 mm. Since there are many samples in every signal, choosing sample numbers that spans a sufficient amount of full rotations is necessary to reduce computing time. For the two rotation speeds considered in this study, selecting 4096 samples provides approximately 12 full rotations that is enough for analysis. While preserving the essential system information.

Vibration signals collected from defective bearings, with IrF, BF and OrF, at speeds of 1797 and 1750 rpm, are plotted in Figure 8. From these plots, Impulse responses are not directly identifiable, aside from OrF cases, in which they are noticed along with background noise. Overall, the signals obtained from the experiments are contaminated by noise, which introduces various frequency components and can lead to inaccurate conclusions during interpretation.

The proposed procedure processes the measured signals to extract periodic impulses, thereby revealing the fault information. Because there were so many findings, we have chosen to display just a few. The filtered signals are displayed in Figures. 9b, 10b, and 11b. Compared with the input (measured) signal, it is clear that the bearing impulses show periodically over time to evaluate the quality of the signals produced by the proposed procedure, Table (1) presents the calculated kurtosis values. The optimal filter size, determined as 64, was selected based on kurtosis maximization, as illustrated in Fig. 7 this analysis was performed using the vibration signal of a bearing with IrF of diameter 0.5334 mm.

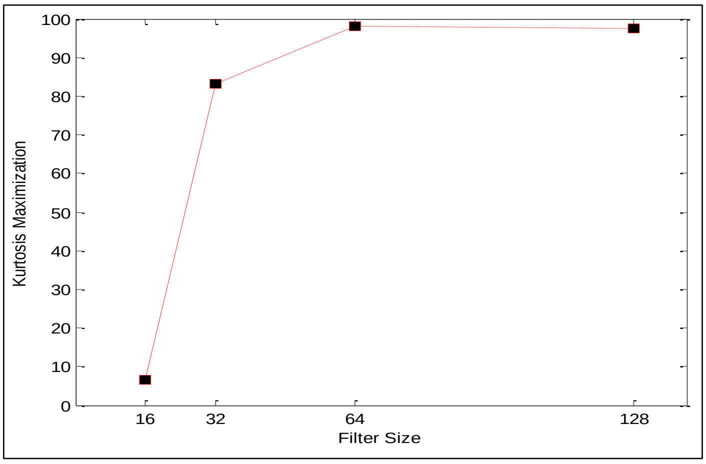


Figure 7: Effect of filter size on Kurtosis maximization.
Source: Authors, (2025).

The results demonstrate that the extracted signal, which exclusively represents the rolling bearing fault characteristics, is accurately reconstructed.

Table 1: Comparison of Input and Filtered Signals for Bearing Faults with different Fault Sizes.

Bearing faults	IrF	OrF	BF
Fault size	0.5334 mm		0.1778 mm
Input signal	6.8718	4.4488	2.6767
Filtered signal	98.1651	5.5134	102.9748

Source: Authors, (2025).

The results in the table confirm a significant difference between the input signal and the resulting one for the two rotational speeds examined (1797 and 1750 rpm), suggesting that the extracted signals include more defect-related information. The chosen characteristics are then rebuilt for every rotation speed (Figure 9 , 10 and 11), especially in Figure 9 and 11, which show the bearing signals with an IrF and BF measured at different rotational speeds of 1797 rpm and 1750 rpm. In these figures, periodic impulses are seen in the time domain. These impulses occur when the balls make contact with the defect, clearly showing peaks associated with the fault.

The combined approach shows better results regarding residual noise removal and fault identification effectiveness. The achieve outcomes demonstrate that the suggested method might be successfully utilized to extract utility characteristics from bearing vibration signals, as evidenced by a comparison with previous studies. However, accurately identifying fault features in both the time and frequency domains remains challenging due to interference from rotating components. To address this issue, the suggested procedure first constructs the inverse filter using the MED technique, followed by the application of the Van Cittert algorithm to recover the most relevant features that contain the key fault information.

The results indicate that our strategy successfully identifies the fault characteristic frequencies of damaged bearings, outperforming methods from previous research, such as those cited in [10], [37], [39-41]. While these studies applied different methods to extract useful information directly from the measured signal through filtering, our approach introduces a crucial step before filtration: the extraction of the inverse filter. The results presented here validate the effectiveness of this additional step in improving fault detection and feature extraction.

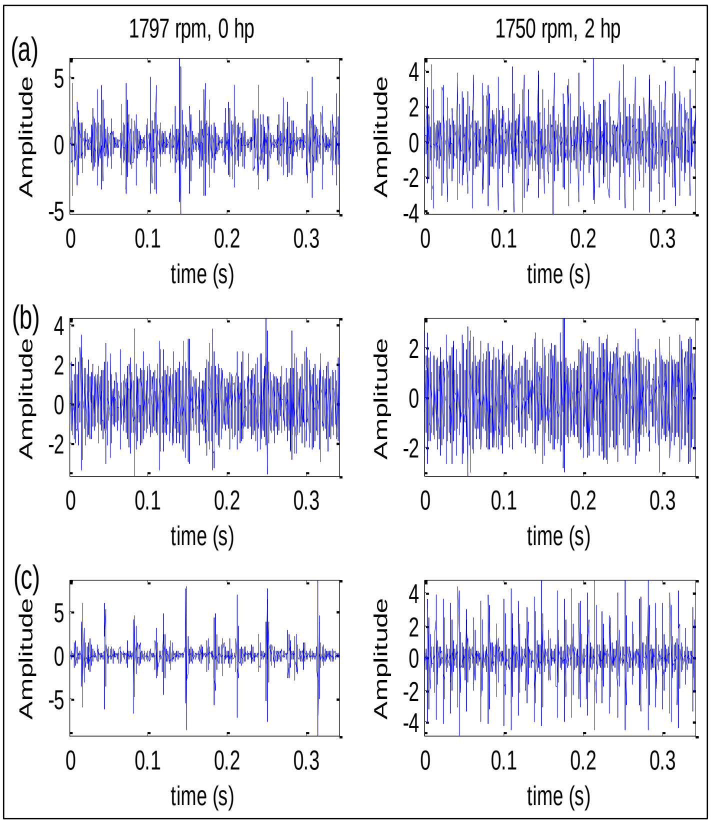


Figure 8: Vibration signals in time domain of bearing with: **a)** IrF, **b)** BF and **c)** OrF.
Source: Authors, (2025).

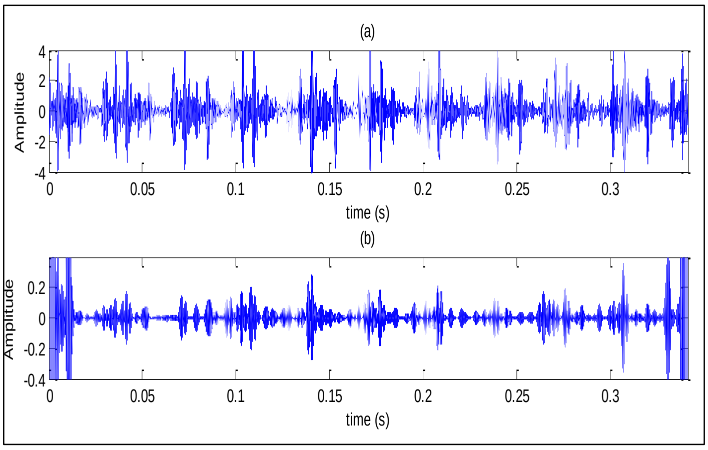


Figure 9: Bearing with IrF of diameter 0.5334 mm: **a)** Measured signal, **b)** filtered signal.
Source: Authors, (2025).

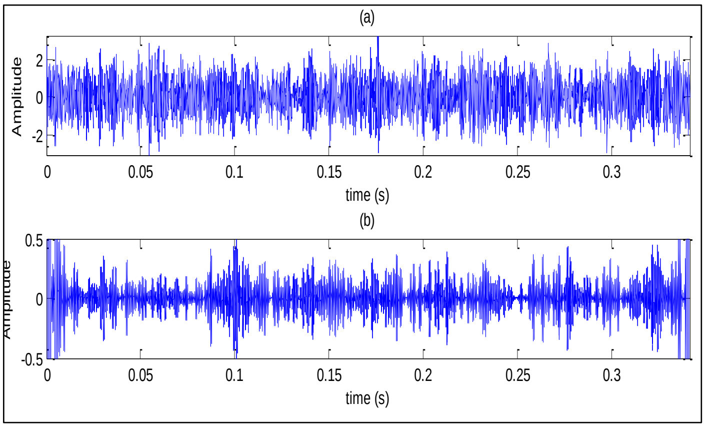


Figure 10: Bearing with BF of diameter of 0.1778 mm: **a)** Measured signal, **b)** filtered signal.
Source: Authors, (2025).

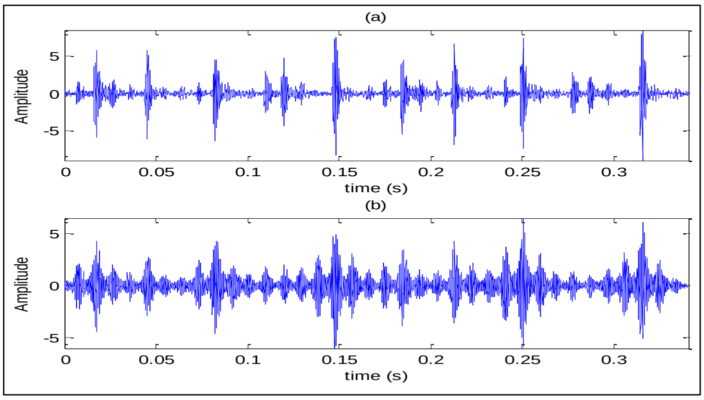


Figure 11: Bearing with OrF of diameter 0.5334 mm: **a)** Measured signal, **b)** filtered signal.
Source: Authors, (2025).

V. CONCLUSIONS

This work presents an effective method for diagnosing bearing faults by reconstructing a signal that closely approximates the original one. First, the measured signal was processed using the Maximum Entropy Deconvolution (MED) technique to design an optimal inverse filter, effectively offsetting the influence of the transmission path. The restoration of the original impulses through this inverse filter corresponds to solving an inherently ill-posed problem.

To address this challenge, the Van Cittert algorithm was employed as a second step, working in tandem with MED to iteratively refine the reconstructed signal. This combination ensures a stable solution by suppressing noise while retaining crucial diagnostic information embedded in the fault-induced impulses. The iterative nature of the Van Cittert algorithm enables the process to progressively approximate the original signal, achieving a balance between noise reductions and preserving the true signal characteristics.

The proposed approach has proven effective in enhancing the visibility of fault-related impulse components, even in the presence of significant noise. This methodology highlights the significance of integrating advanced deconvolution techniques with regularization algorithms for reliable signal restoration in fault diagnosis, offering a competitive alternative to existing methods in the field.

VI. AUTHOR’S CONTRIBUTION

Conceptualization: Nesrine Gouri, Hocine Bendjama.
Methodology: Nesrine Gouri, Hocine Bendjama and Mohamed Larbi Mihoub.
Investigation: Nesrine Gouri, Hocine Bendjama and Mohamed Larbi Mihoub.
Discussion of results: Nesrine Gouri, Hocine Bendjama and Mohamed Larbi Mihoub.
Writing – Original Draft: Nesrine Gouri, Hocine Bendjama.
Writing – Review and Editing: Nesrine Gouri, Hocine Bendjama.
Resources: Hocine Bendjama.
Supervision: Hocine Bendjama and Mohamed Larbi Mihoub.
Approval of the final text: Nesrine Gouri, Hocine Bendjama and Mohamed Larbi Mihoub.

VIII. REFERENCES

[1] X. Zhu, C. Zhong, J. Zhe, ”Lubricating oil conditioning sensors for online machine health monitoring–a review”, Tribol. Int., vol. 109, pp. 473-484, 2017, doi: 10.1016/j.triboint.2017.01.015.

[2] A. Choudhary, T. Mian, and S. Fatima, “Convolutional neural network based bearing fault diagnosis of rotating machine using thermal images”, Measurement, vol. 176, 2021, doi: 10.1016/j.measurement.2021.109196.

[3] H. Bendjama, “Bearing fault diagnosis based on optimal morlet wavelet filter and teager Kaiser Energy operator”, J. Braz. Soc. Mech. Sci. Eng., vol. 44, no. 9, pp. 392, 2022, doi: 10.1007/s40430-022-03688-4.

[4] J. Chebil, G. Noel, M. Mesbah, and M. Deriche, “Wavelet decomposition for the detection and diagnosis of faults in rolling element bearings’’, Jordan j. mech. ind. eng., vol. 3, no. 4, pp. 260-267, 2009.

[5] H. Bendjama, and M. S. Boucherit, “Wavelets and Principal Component Analysis Method for Vibration Monitoring of Rotating Machinery,’’ J. theor. appl. mech., vol. 54, no. 2, pp. 659-670, 2016, doi: 10.15632/jtam-pl.54.2.659.

[6] X. An, L. Pan, and F. Zhang, “Analysis of hydropower unit vibration signals based on variational mode decomposition,” JVC, vol. 3, no. 12, pp. 1938–1953, 2015, doi: 10.1177/1077546315605240.

[7] J. Zhang, J. Wu, B. Hu, J. Tang, “Intelligent fault diagnosis of rolling bearings using variational mode decomposition and self-organizing feature map”, JVC, vol. 26, no. 21-22, pp. 1886-1897, 2020, doi: 10.1177/1077546320911484.

[8] Y. Damine, N. Bessous, R. Pusca, A. C. Megherbi, R. Romary, and S. Sbaa, “A new bearing fault detection strategy based on combined modes ensemble empirical mode decomposition, kmad, and an enhanced deconvolution process”, Energies, vol. 16, no. 6, 2023, doi: 10.3390/en16062604.

[9] H. Bendjama, “Feature extraction based on vibration signal decomposition for fault diagnosis of rolling bearings”, Int. J. Adv. Manuf. Technol., vol. 130, no. 1, pp. 821-836, 2024, doi: 10.1007/s00170-023-12710-5

[10] A. Had, and K. Sabri, “A two-stage blind deconvolution strategy for bearing fault vibration signals”, Mech. Syst. Signal Process., vol. 134, 2019, doi: 10.1016/j.ymssp.2019.106307

[11] M. L. Cherrad, H. Bendjama, and T. Fortaki, “Combination of single channel blind source separation method and normal distribution for diagnosis of bearing faults”, Jordan j. mech. ind. eng., vol. 16, no. 4, pp. 493-502, 2022.

[12] B. Peng, Y. Bi, B. Xue, M. Zhang, and S. Wan, “A survey on fault diagnosis of rolling bearings”, Algorithms, vol. 15, no 10, p. 347, 2022, doi: 10.3390/a15100347.

[13] Y. Cheng, N. Zhou, Z. Weihua, Z. Wang, “Application of an improved minimum entropy deconvolution method for railway rolling element bearing fault diagnosis”, J. Sound Vib., vol. 425, pp. 53-69, 2018, doi: 10.1016/j.jsv.2018.01.023.

[14] Z. Zhang, M. Entezami, E. Stewart, C. Roberts,” Enhanced fault diagnosis of roller bearing elements using a combination of empirical mode decomposition and minimum entropy deconvolution”, Proc. Inst. Mech. Eng., Part C, vol. 231, no. 4, pp. 655-671, doi: 10.1177/0954406215623575.

[15] Z. Liao, J. Xu, M. Jin, Y. Cao, D. Hou, and P. Huang, “An improved adaptive minimum entropy deconvolution method in bearing fault detection”, Fourth International Conference on Mechanical, Electronics, and Electrical and Automation Control (METMS 2024), SPIE, pp. 1841-1848, 2024.

[16] R. A. Wiggins, “Minimum entropy deconvolution”, Geoexploration, vol. 16, no. 1–2, pp. 21–35, 1978, doi: 10.1016/0016-7142(78)90005-4.

[17] H. Endo, R. B. Randall, “Enhancement of autoregressive model based gear tooth fault detection technique by the use of minimum entropy deconvolution filter”, Mech. Syst. Signal Process, vol. 21, no. 2, pp. 906-919, 2007, doi: 10.1016/j.ymssp.2006.02.005.

[18] N. Sawalhi, R. B. Randall, H. Endo, “The Enhancement of Fault Detection and Diagnosis in Rolling Element Bearings Using Minimum Entropy Deconvolution Combined with Spectral Kurtosis”, Mech. Syst. Signal Process, vol. 21, no. 2, pp. 2616-2633, 2007, doi: 10.1016/j.ymssp.2006.12.002.

[19] T. Barszcz, and N. Sawalhi, ”Fault detection enhancement in rolling element bearings using the minimum entropy deconvolution”, Arch. Acoust., vol. 37, no. 2, pp. 131-141, 2012, doi: 10.2478/v10168-012-0019-2.

[20] J. Li, M. Li and J. Zhang, “Rolling bearing fault diagnosis based on time-delayed feedback monostable stochastic resonance and adaptive minimum entropy deconvolution”, J. Sound Vib., vol. 401, pp. 139-151, 2017, doi: 10.1016/j.jsv.2017.04.036.

[21] R. Jiang, J. Chen, G. Dong, T. Liu, and W. Xiao, “The weak fault diagnosis and condition monitoring of rolling element bearing using minimum entropy deconvolution and envelop spectrum”, Proc. Inst. Mech. Eng., Part C, vol. 227, no. 5, pp. 1116–1129, 2013, doi: 10.1177/0954406212457892.

[22] A. Had, K. Sabri, “A two-stage blind deconvolution strategy for bearing fault vibration signals”, Mech. Syst. Signal Process., vol. 134, 2019, doi: 10.1016/j.ymssp.2019.

[23] Y. Cheng, B. Chen, and W. Zhang. “Adaptive multipoint optimal minimum entropy deconvolution adjusted and application to fault diagnosis of rolling element bearings”, IEEE sensors journal, 2019, vol. 19, no. 24, pp. 12153-12164, doi: 10.1109/JSEN.2019.2937140

[24] J. Zhang, M. Zhong, J. Zhang, “Detection for weak fault in planetary gear trains based on an improved maximum correlation kurtosis deconvolution”, Meas. Sci. Technol, vol. 31, no. 2, 2019, doi: 10.1088/1361-6501/ab43ed.

[25] B. Chen, W. Zhang, D. Song, and Y. Cheng, “Blind deconvolution assisted with periodicity detection techniques and its application to bearing fault feature enhancement”, Measurement,vol.159,2020,doi:10.1016/j.measurement.2020.107804.

[26] P. H. Van Cittert, “Zum einfluss der spaltbreite auf die intensitätsverteilung in spektrallinien. Ii’’, Z. Physik, vol. 69, no. 5, pp. 298-308, 1931, 10.1007/BF01391351.

[27] G. Speranza, “Application of the Van Cittert Algorithm for Deconvolving Loss Features in X-ray Photoelectron Spectroscopy Spectra”, Materials, vol. 17, no. 3, p. 763, 2024, doi: 10.3390/ma17030763.

[28] C. R. Vogel, “Computational methods for inverse problems”. Society for Industrial and Applied Mathematics, 2002.

[29] X. Xiong, X. Xue, and Z. Qian, “A modified iterative regularization method for ill-posed problems”, Appl. Numer. Math, vol. 122, pp. 108-128, 2017, doi: 10.1016/j.apnum.2017.08.004

[30] M. Singhal, M. Goyal, and R. K. Singla, “A review of regularization strategies and solution techniques for ill-posed inverse problems, with application to inverse heat transfer problems”, Rev. Math. Phys., vol. 36, no. 01, 2024, doi: 10.1142/S0129055X23300078.

[31] Y. Teng, Y. Zhang, H. Li, and Y. Kang, “A convergent non-negative deconvolution algorithm with Tikhonov regularization ”, Inverse Problems, vol. 31, no. 3, 2015, doi: 10.1088/0266-5611/31/3/035002.

[32] E. Pantin, J. L. STARCK, and F. MURTAGH, “Deconvolution and blind deconvolution in astronomy”, Blind Image Deconvolution, 2017, pp. 301-340, doi: 10.1201/9781420007299

[33] X. Xiong, J. Li, and J. Wen, “Some novel linear regularization methods for a deblurring problem’’, *Inverse problems and imaging*, vol. 11, no. 2, pp. 403-426, 2017, doi: 10.3934/ipi.2017019.

[34] H. Pan, Y. W. Wen, and H. M. Zhu, “A regularization parameter selection model for total variation based image noise removal”, App. Math. Model., vol. 68, pp. 353-367, 2019, doi: 10.1016/j.apm.2018.11.032.

[35] M. Boulakroune and D. Benatia, “Multi-Scale Deconvolution of Mass Spectrometry Signals”, Advances in Wavelet Theory and Their Applications in Engineering, Physics and Technology, pp. 125-152, 2012, doi: 10.5772/37772.

[36] M. Boulakroune, “Reliability of multiresolution deconvolution for improving depth resolution in SIMS analysis”. Appl. Surf. Sci., vol. 386, pp. 24-32. 2016, doi.org/10.1016/j.apsusc.2016.05.164

[37] O. San, and P. Vedula, “Generalized deconvolution procedure for structural modeling of turbulence”, J. Sci. Comput., vol. 75, pp. 1187-1206, 2018, doi: 10.1007/s10915-017-0583-8.

[38] K. A. Loparo. Bearing vibration dataset, Case Western Reserve University, 2016 Available at: www.eecs. case.edu/laboratory/bearing.

[39] F. B. Abid, and A. Braham, “Advanced signal processing techniques for bearing fault detection in induction motors”, 15th International Multi-Conference on Systems, Signals & Devices (SSD), IEEE, pp. 882-887, 2018, doi: 10.1109/SSD.2018.8570403.

[40] G. Manjunatha, H. C. Chittappa and D. Kumar, “Fault Detection of Bearing using Signal Processing Technique and Machine Learning Approach”, J. Mines Met. Fuels, vol. 70, no. 10a, pp. 380-388, 2022, doi: 10.18311/jmmf/2022/32937.

[41] P. Yu, J. Zhang, B. Zhang, J. Cao, Y. Peng, “Research on small sample rolling bearing fault diagnosis method based on mixed signal processing technology”. Symmetry, vol. 16, no 9, p. 1178, 2024, doi.org/10.3390/sym16091178.