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An Intelligent Optimization Algorithm's Evaluation and Comparison with the Evolutionary Algorithm for PD Denoising and Improved Convergence

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Abstract:

Introduction: Partial discharge (PD) signals measured in high-voltage systems are frequently affected by various forms of noise, which complicates accurate detection and analysis. Traditional denoising methods that rely on single-domain decomposition and basic optimization often fail to sufficiently remove noise while retaining critical PD details.

Objectives: The objective of this study is to design an advanced denoising strategy that effectively suppresses noise while preserving important PD characteristics to improve diagnostic reliability.

Methods: A hybrid denoising framework combining Variational Mode Decomposition (VMD), Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), and Singular Value Decomposition (SVD) is presented. The PD signal is decomposed into intrinsic mode functions (IMFs), and reconstruction is refined using power spectral entropy to discard noise-dominated components. Furthermore, an Improved Zebra Optimization Algorithm (IZOA) is integrated with the Whale Optimization Algorithm (WOA) to ensure an optimal balance between exploration and exploitation. The proposed method is assessed through simulation studies and compared with other optimization-based denoising techniques using multiple evaluation metrics.

Results: The proposed Evalutionary algorithm demonstrates superior noise removal capability, preserves essential PD features, and achieves significantly improved performance metrics compared to traditional denoising approaches.

Conclusions: The VMD–CEEMDAN–SVD hybrid denoising scheme supported by IZOA–IWOA optimization provides an efficient and robust solution for PD signal processing, improving the accuracy and dependability of high-voltage insulation condition monitoring.

Keywords: Partial discharge; hybrid decomposition; Variational Mode Decomposition; Complementary Ensemble Empirical Mode Decomposition; Singular Value Decomposition; Evolutionary Optimisation Algorithm; intelligent optimization; hybrid metaheuristics.

1.Introduction:

Partial discharges in high-voltage equipment are caused by insulation defects, surface charge migration, and field-dependent charging behaviors, which can lead to equipment failure [1]–[3]. Conventional methods, such as adaptive filtering and other traditional approaches, are commonly used for PD detection, but they often struggle with variable interference and inconsistent performance [4]-[5]. Singular value decomposition (SVD)[6] and empirical mode decomposition (EMD) [7] have been applied for denoising, yet they rely on threshold selection and suffer from mode mixing or boundary effects. Variational mode decomposition (VMD) introduced a variational optimization framework that effectively reduces mode mixing compared to EMD, but it requires careful parameter tuning of the number of modes and penalty factor, which limits adaptability in noisy environments [8]. Ensemble EMD (EEMD) and CEEMDAN further improve decomposition accuracy and reduce mode mixing, though they remain computationally intensive [9], [10].

Hybrid methods have been developed to improve PD signal denoising. Adaptive wavelet packet denoising reduces noise through wavelet decomposition and thresholding, but requires careful parameter selection [11]. The improved SVD–VMD method combines singular value decomposition with VMD to enhance noise suppression, yet tuning both components is necessary [12]. The empirical mode decomposition combined with wavelet transform (EMD-WT) has demonstrated strong adaptability in extracting partial discharge (PD) signals however, its performance may still be affected when the noise level is extremely high, leading to residual distortions [13]. VMD with wavelet thresholding suppresses white noise and narrowband interference, but its effectiveness relies on accurate settings [14]. Improved CEEMDAN with SVD enhances decomposition accuracy, yet it can be computationally demanding [15], [16]. Finally, adaptive VMD with improved thresholding adjusts decomposition parameters for varying noise conditions, though careful tuning is still required [17]. The SVD–EWT approach applies SVD to extract periodic interference and then uses empirical wavelet transform (EWT) to attenuate stochastic components, yielding better SNR but at the cost of parameter sensitivity [18]. Wavelet–SVD based methods have also been explored, where wavelet decomposition suppresses broadband noise and SVD filters structured components, yet their performance remains sensitive to the chosen wavelet basis and threshold settings, reducing robustness under varying noise conditions [19]. An intelligent denoising scheme based on improved zebra optimization (IZOA) has been proposed to adaptively select optimal denoising parameters for PD signals, effectively enhancing noise suppression while preserving signal features, though it does not incorporate hybrid decomposition and sometimes yields unsatisfactory metric values [20].

2.Objective

To address the limitations of previous approaches, this study introduces an advanced hybrid denoising framework that integrates variational mode decomposition (VMD)**,** complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN)**,** and singular value decomposition (SVD)**.** This multi-stage decomposition structure leverages the complementary strengths of each method—VMD for reducing mode mixing, CEEMDAN for producing stable intrinsic mode functions, and SVD for suppressing residual noise—thereby improving both denoising accuracy and preservation of PD features. Furthermore, to overcome the parameter sensitivity and performance instability issues seen in earlier techniques, the framework employs adaptive evolutionary optimization using improved zebra optimization (IZOA) [20] and improved whale optimization (IWOA) [21] to automatically tune the decomposition and threshold parameters. This combined strategy enhances denoising performance, achieves higher evaluation metrics, and offers robust adaptability under varying noise conditions.

Building on these state-of-the-art foundations, this paper delivers the following key innovations:

1. Section 3.1 presents the Generation of PD and realistic noise profiles.
2. Section 3.2 gives a comprehensive understanding of the systematic review of existing approaches for PD signal denoising.
3. Section 3.3 describes the hybrid algorithmic decomposition and noise-dominant IMF selection using Power spectral entropy for stronger mode extraction, residual noise suppression, and feature retention.
4. Section 3.4 presents a summary of various Optimisation techniques along with their mathematical representations.
5. Section 4 and 5 gives simulation analysis and a comparison between the Improved Zebra Optimisation algorithm, Whale Optimisation Algorithm and the Improved Whale Optimisation, and also comprehends the performance evaluation indices for IZOA+IWOA and the best optimised method among the listed ones.

6. Finally, Section 6 gives the conclusion.

This innovative framework positions itself as a robust blueprint for next-generation PD denoising under complex, real-world conditions.

3.methods

3.1 Generation of PD and realistic Noise signals:

Simulated partial discharge (PD) and noise signals follow validated physical models as prescribed in [20], ensuring a realistic representation of typical operating conditions. Representative time-domain waveforms for pure PD signals, noise, and their composite are depicted in Figure 1.

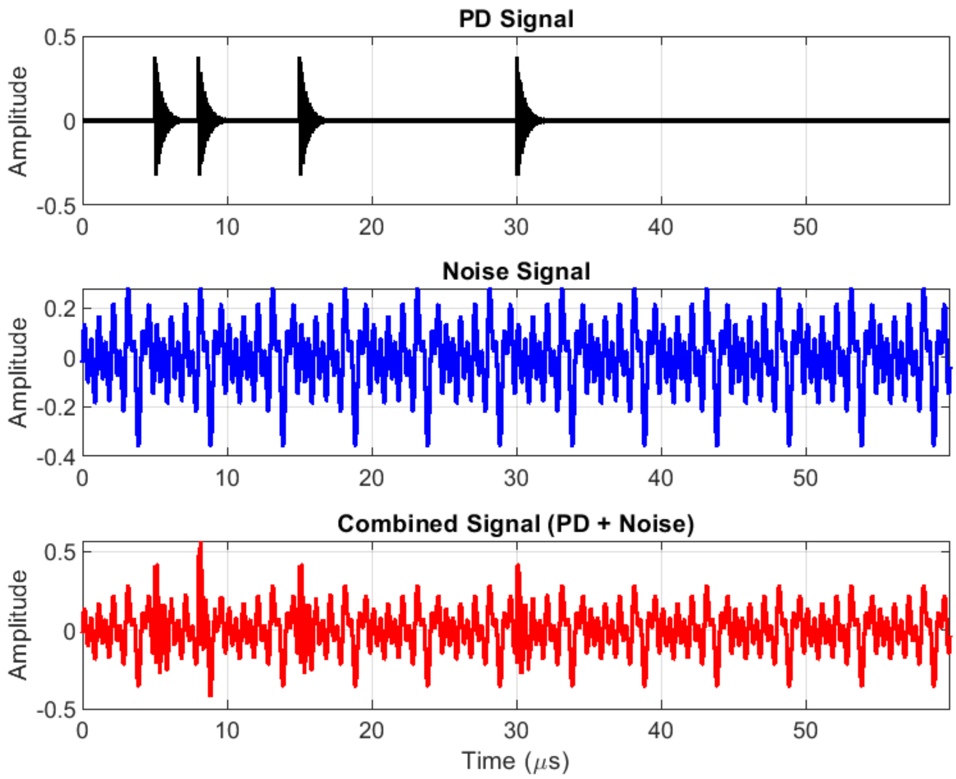

Figure 1: Simulated PD, noise, and combined signals

3.2 Existing Approaches for PD Denoising:

Research on PD denoising has advanced through three major categories: conventional single methods, hybrid decompositions, and intelligent optimization. Each category has contributed improvements but also carries inherent limitations.

A. Conventional Methods:

Traditional denoising relied on filtering and signal decomposition. EMD [7] was among the earliest adaptive techniques but suffers from mode mixing and endpoint effects**.** EEMD [9] introduced ensemble averaging to mitigate mixing, yet residual noise and computational cost remain. CEEMDAN [10] and ICEEMDAN [22] enhanced stability and accuracy, but at the expense of higher complexity and spurious modes. VMD [8] addressed mode mixing through variational optimization but is sensitive to the choice of mode number and penalty factor. Other approaches such as EWT [18] and SVD [6] also contributed, though both depend heavily on basis or threshold selection. Overall, conventional methods lack robustness and adaptability under multi-noise conditions.

B. Hybrid Decomposition Approaches:

To overcome single-method weaknesses, hybrid schemes combining multiple decompositions have been developed. SVD–VMD [12] improves noise suppression but requires careful tuning of both parameters. VMD combined with wavelet thresholding [14] enhances noise suppression yet is threshold dependent. SVD–EWT [18] exploits kurtosis-based IMF selection but relies on empirical criteria. Wavelet–SVD [19] improves broadband and structured noise removal but depends strongly on wavelet basis choice. More advanced combinations, such as SVD–ICEEMDAN [16]**,** offer stable decomposition accuracy but are computationally heavy. Similarly, VMD–EMD**,** EMD–CEEMDAN**,** and CEEMDAN–VMD [22][23][24] have been proposed to improve stability and feature retention, though they increase runtime, introduce redundancy, or demand higher computation. While hybrid methods outperform single approaches, their reliance on empirical thresholds and computational burden limits practicality.

C. Intelligent Optimization Approaches:

Since decomposition results are highly sensitive to parameter settings, intelligent optimization has been applied for adaptive tuning. The Improved Zebra Optimisation Algorithm (IZOA)[20] has been successfully implemented for PD denoising, adaptively selecting decomposition and threshold parameters to enhance noise suppression and feature preservation. Other algorithms, such as the Improved Whale Optimisation Algorithm (IWOA) [21] and Improved Moth–Flame Optimisation (IMFO) [25], have demonstrated strong global search and convergence properties in broader signal-processing tasks but have not yet been widely applied to PD denoising. Thus, while optimisation improves adaptability, its integration with decomposition in PD remains limited. Figure 2 gives a pictorial representation of existing advances in the area of Partial Discharge denoising.

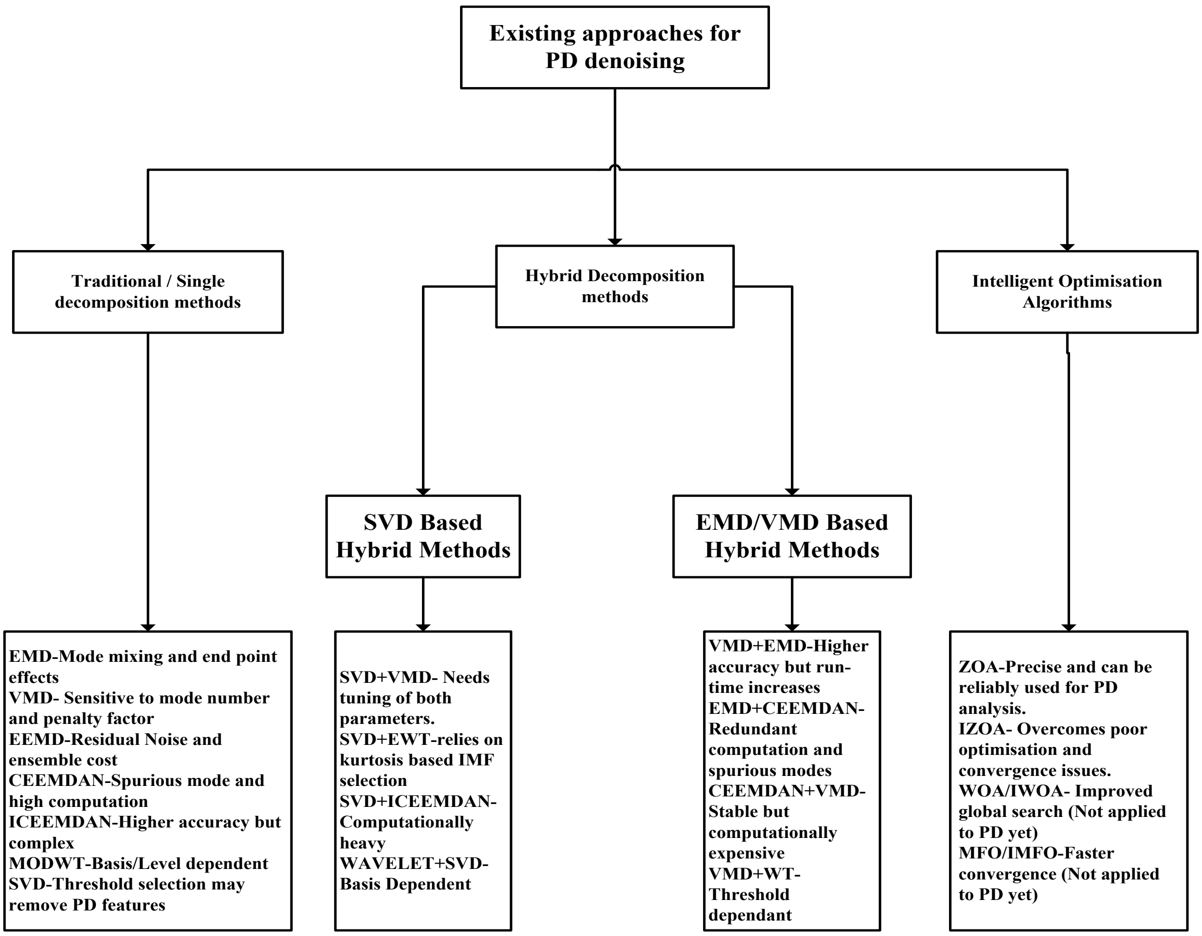

Figure 2. Existing Approaches

3.3 Proposed Hybrid Decomposition–Optimisation Framework

Accurately extracting partial discharge (PD) signatures from noisy backgrounds necessitates precise separation of signal and noise while faithfully retaining the intrinsic features of PD pulses. Conventional methods operating solely in a single domain—such as VMD, CEEMDAN, or SVD used independently—often falter in highly disturbed electromagnetic environments, resulting in sub-optimal denoising or loss of vital signal features.

To address these shortcomings, this research proposes a hybrid decomposition framework that synergistically integrates VMD, CEEMDAN, and SVD. This is complemented by entropy-driven selection of Intrinsic Mode Functions (IMFs) and an intelligent optimization scheme for adaptively tuning decomposition parameters to the characteristics of the measured signal.

A. Hybrid Decomposition Strategy:

The multi-stage decomposition process unites three advanced techniques to capitalize on their individual strengths:

I. **Variational Mode Decomposition (VMD):**

VMD decomposes the input signal y(t) into a series of N adaptively determined, band-limited modes. Each mode is centred around its own optimized frequency and captures distinct oscillatory components best suited to the underlying data. Unlike traditional EMD-based sifting methods, VMD [8] recasts signal analysis as a constrained variational problem, thereby exhibiting greater resilience to noise and reducing the risk of mode mixing.

$$y(t) \xrightarrow{VMD} \{u_n(t)\}, \quad n = 1,2,3,..,N$$

Here, N denotes the total number of decomposition modes, adaptively optimized according to signal complexity.

II. **Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN):**

An algorithm called CEEMDAN [10] was created using EEMD as its foundation. At each stage of signal decomposition, white noise is adaptively added, and the only residual is calculated to produce the IMFs. The reconstruction error is gradually removed in the iterative process by superimposing and cancelling the white noise added in each decomposition stage. This ensures the accuracy of the decomposition and significantly lowers the mode mixing. The decomposition steps involved in CEEMDAN include the generation of white noise sequences, which are then decomposed using the EMD algorithm. The IMF generated by the above-stated procedure is monitored, and the first-order IMF and its residue are deduced. Similarly, the I group signals are decomposed by the EMD algorithm, and average integration is performed to obtain the second-order IMFs and the k-th residue. This process is repeated until the residue cannot be further decomposed. Mathematical equations concerning this algorithm are discussed in detail in [8].

III. **Singular Value Decomposition (SVD):**

Finally, SVD[6] is applied to the CEEMDAN outputs to refine decomposition by eliminating redundant or low-energy modes. The signal matrix C can be expressed as:

$$\mathbf{C} \xrightarrow{SVD} C = U \sum V^T$$

where U and V are orthogonal matrices and Σ contains the singular values. The dominant singular values preserve the essential PD features, while smaller ones are associated with noise.

By cascading these three methods, the hybrid scheme leverages VMD's frequency adaptability, CEEMDAN's noise-assisted mode separation, and SVD's energy concentration capability, achieving a more reliable decomposition compared to individual techniques. The IMFs generated by hybrid decomposition method are further filtered for noise dominant IMFs using Power Spectral Entropy in this work.

B. Power Spectral Entropy-Based IMF Selection:

To further distinguish between PD signals and noise, an entropy criterion is leveraged for discriminative selection of the most representative Intrinsic Mode Functions (IMFs). Entropy measures such as power spectral entropy (PSE) [26], sample entropy (SampEn) [27], and permutation entropy

(PermEn) [28] quantify the degree of disorder in individual IMFs according to our requirement.

Low entropy values typically correspond to IMFs that possess structured, pulse-like, or quasi-deterministic features, which are characteristic of partial discharge events. High entropy values indicate increased randomness or complexity, commonly associated with noise-dominant components. This paper concentrates only on randomness obtained during power density calculations. For each IMF, the normalized entropy value E_k is calculated as:

$$E_k = -\sum_{i=1}^{M} P_{i,k} \log{(P_{i,k})}$$

where $P_{i,k}$ is the normalized power of the k-th IMF in the i-th frequency bin as defined by the spectral distribution.

IMFs whose entropy values fall below a dynamically set threshold (e.g., the mean or a percentile of all IMFs) are retained for PD reconstruction, while high-entropy IMFs are suppressed. This process ensures preservation of PD-related transients and removal of stochastic noise.To discriminate between PD-related and noise-dominated IMFs, the power spectral entropy (PSE) of each $c_{n,m}(t)$ is computed. The normalised spectral distribution is given by [26].

$p_{n,m}(k) = \frac{S_{n,m}(k)}{\sum_{k=1}^{L} S_{n,m}(k)}$, k = 1, . . ., L

Here, n,m are the IMFs generated by VMD and CEEMDAN, respectively and L is maximum number of IMFs The maximum number of modes in VMD used in this study is 7, and the maximum number of ensembles is 50, respectively

where $S_{n,m}(k)$ is the power spectrum of the IMF, and L is the number of discrete samples.

Also, to avoid singularity, the entropy is again calculated by [26].

$H_{n,m} = -\sum_{k=1}^{L} p_{n,m}(k) \log(p_{n,m}(k) + \epsilon)$,

where ε is a small constant to avoid a singularity. The flowchart demonstrating the flow of actions for the decomposition of the signal, along with the signal reconstruction to obtain the denoised signal, is shown in Figure 3.

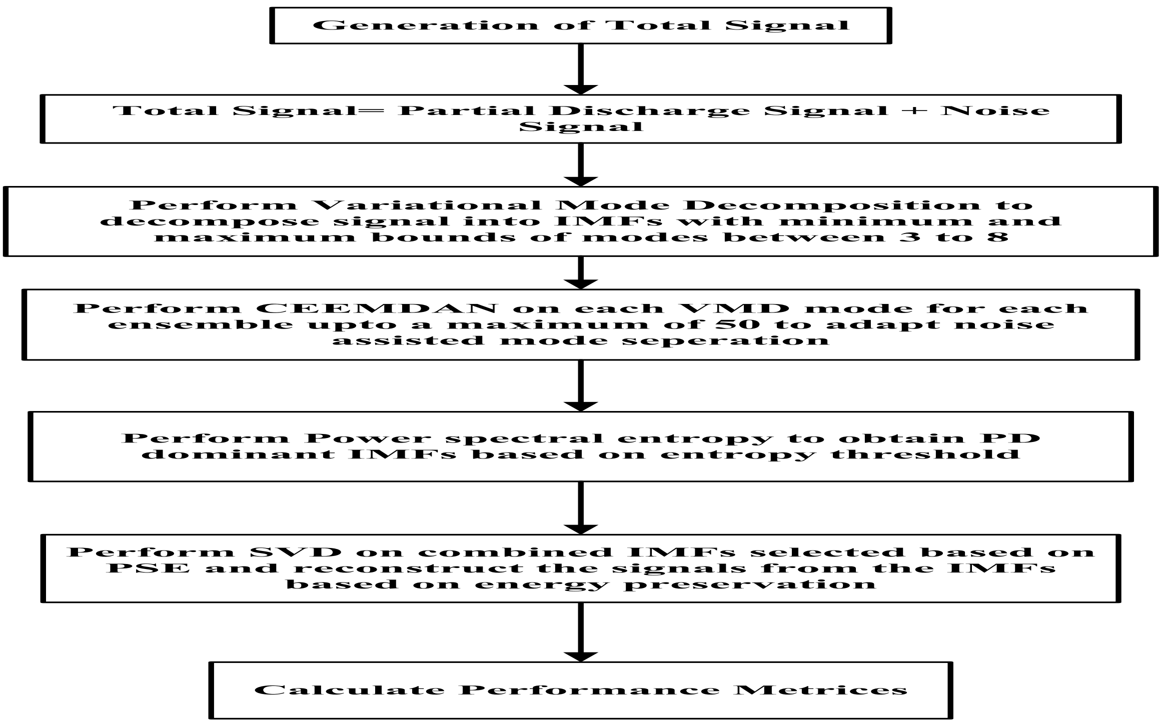

Figure 3: Proposed hybrid decomposition method.

3.4 Different Optimisation for Adaptive Parameter Selection:

Various intelligent optimization algorithms are employed to overcome several issues faced during the precise tuning of parameters obtained by the hybrid decomposition framework. Some of them are stated below:

1. The number of modes N in Variational Mode Decomposition (VMD),
2. The noise amplitude parameter in Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN),
3. The singular value threshold ψ in Singular Value Decomposition (SVD), and
4. The entropy threshold for selecting intrinsic mode functions (IMFs).

Empirically fixing these parameters can lead to either the suppression of important partial discharge (PD) signal components or the retention of excessive noise, compromising denoising performance. To mitigate these issues, this paper addresses advanced intelligent optimization algorithms—including the Improved Zebra Optimization Algorithm (IZOA)[20], Improved Whale Optimization Algorithm (IWOA)[21], to adaptively and systematically identify optimal parameter settings.

This adaptive tuning process maximizes denoising effectiveness by optimizing multiple objective functions that assess the trade-off between noise reduction and signal preservation. By incorporating the adaptive capabilities of IZOA+ IWOA the framework robustly enhances noise suppression while maintaining the distinctive impulsive characteristics of PD signals, thereby improving detection accuracy under varying signal conditions.

3.4.1 Improved Zebra Optimization Algorithm (IZOA) for PD Denoising:

In this paper, the Intelligent Zebra Optimisation Algorithm (IZOA) [20], was developed to address issues such as poor optimisation performance and premature convergence. To enhance exploration and exploitation capabilities, IZOA uses sophisticated techniques such as adaptive oscillation weights, nonlinear convergence factors, and Lévy flight. With these improvements, MZOA can more successfully traverse intricate search areas and produce superior optimisation outcomes. The flowchart demonstrating the intelligent Zebra Optimisation Algorithm is shown in Figure 4, and its integration to denoise the PD signal is pictorially shown in Figure 5.

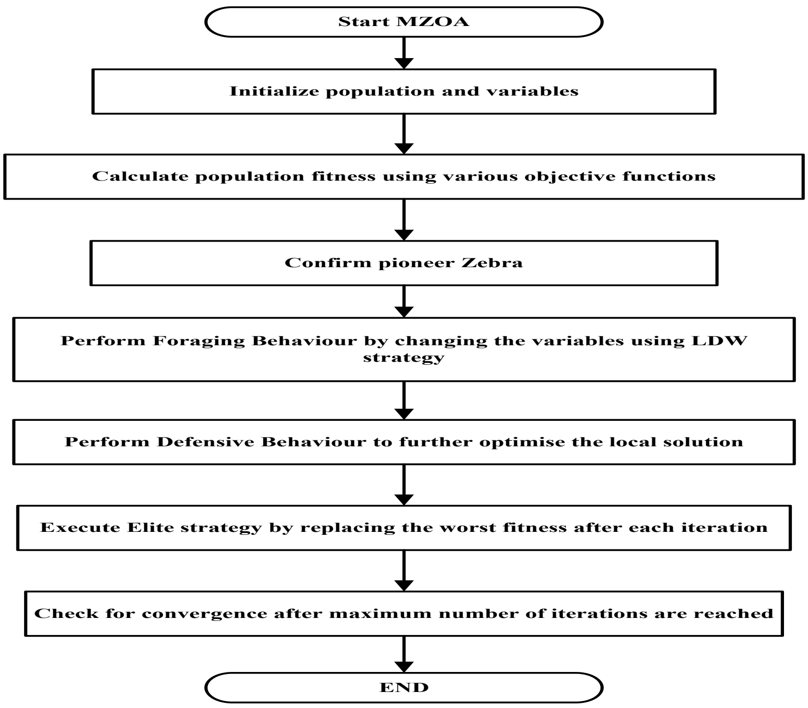

Figure 4: IZOA Algorithm

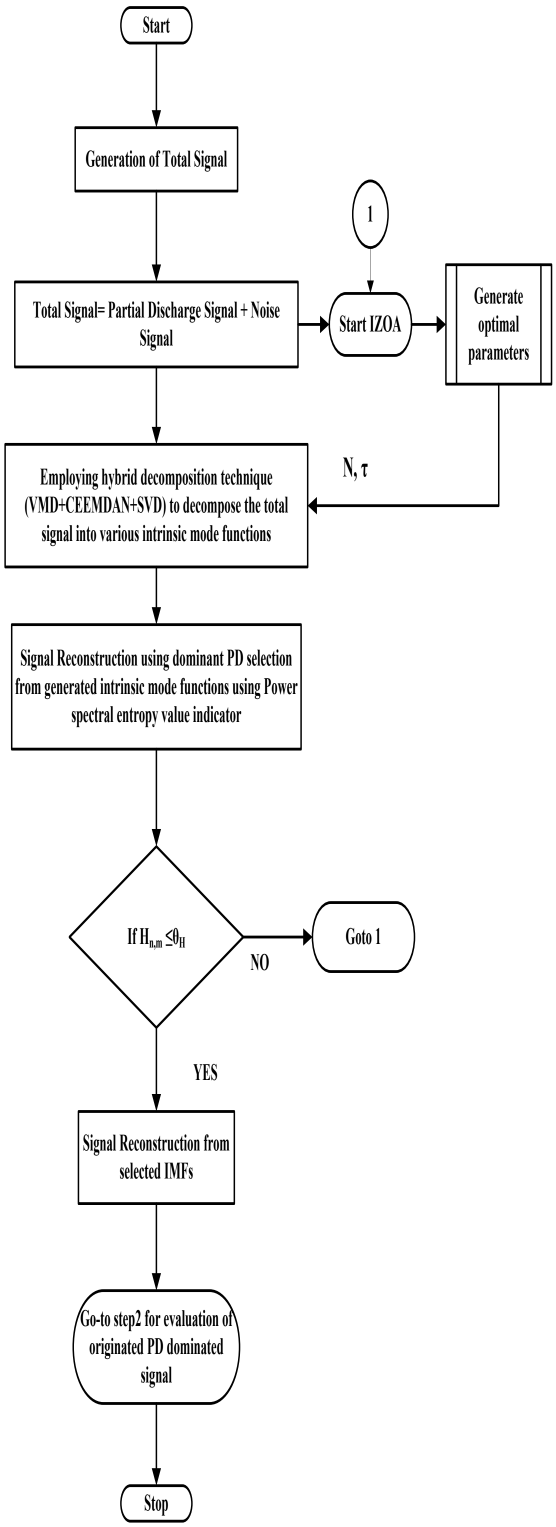

Figure 5: IZOA based hybrid decomposition

Various steps shown in Figure 4 are defined in this paper as follows:

Step 1: Initialise variables to be optimised and the population of zebras. The variables to be optimised are modes of VMD and the threshold value obtained through SVD.

The maximum and minimum bounds for each variable are defined as follows: N: 3and 8, τ: 0.9 and 0.999.

The set of variables is defined as ω, with m as the label of the variables. y_{min} and y_{max} are the minimum and maximum values of the defined set of variables, respectively, and n is the number of iterations.

$$\omega\left(y_m^{(n)}\right) = \{N, \tau\}$$

$$y_{mmin} \le y_m^{(n)} \le y_{mmax}, \quad \text{Where } m = 1,2,3,4$$

To generate a population with a size equal to 20 individuals, the mathematical relation given by [20]

$$y_{im}^{(n)} = y_{mmin} + (y_{mmax} - y_{mmin}).rand, \quad subject\ to\ i \in [1, popsize]$$

Where
$y_{im}^{(n)} is\ the\ i^{th}\ zebras\ m^{th}\ variable\ in\ n^{th}\ iteration.$

Step 2: Calculate population fitness using various objective functions. The various fitness-controlled objective functions discussed in this paper are the signal-to-noise ratio, normalised correlation coefficient, the sum of absolute error, the mean square error and the noise reduction ratio. Each one of these evaluation parameters is defined below:

a. Signal-to-noise ratio (I_{SNR}): This evaluation metric is used to evaluate how much a denoising algorithm improves the quality of a signal. A higher ISNR indicates better denoising, suggesting superior noise suppression and clearer signal clarity. Positive I_{SNR} values indicate an improvement in signal quality. If I_{SNR} is zero or negative, the denoising either had no effect or made the signal worse.

Mathematically, the signal-to-noise ratio is given by [20]

$$I_{snr}(y(n)_k) = 10log_{10}\left(\frac{\sum_{i=1}^{I} f^2(t_i)}{\sum_{i=1}^{I}[f'(t_i) - f(t_i)]^2}\right)$$

$f(t)$ *is denoised signal and* $f'(t)$ *is pure PD signal*

(i)

b. Normalised Correlation Coefficient (I_{NCC}): It measures the similarity between the original noisy signal and the denoised signal. Ideally, I_{NCC} is approximated to one. If I_{NCC} lies within 0.7 to 1, it suggests that similarity is between a good and acceptable range. If I_{NCC} lies within 0.4 to 0.7, it suggests moderate correlation.

(ii)

Mathematically ,

$$I_{ncc}(y(n)_k) = \left(\frac{\sum_{i=1}^{I} f'(t_i) f(t_i)}{\sqrt{[\sum_{i=1}^{I} f^2(t_i)].[\sum_{i=0}^{I-1} f'^2(t_i)]}}\right)$$

c. Sum of Absolute Error (I_{SAE}): It is the absolute difference between the pure signal and the denoised signal. Mathematically, this evaluation metric is given by [20].

$$I_{sae}(y(n)_k) = \sum_{i=1}^{I}[|f'(t_i) - f(t_i)|]$$

d. Noise Rejection Ratio (I_{NRR}): The degree to which a denoising algorithm eliminates noise from a signal while maintaining its original characteristics—such as partial discharge pulses—is gauged by the Noise Rejection Ratio (NRR). It is calculated using the noise component's energy or power reduction.

Mathematically, the Noise Rejection ratio is given by [20]

$$I_{nrr}(y(n)_k) = 10log_{10}\left(\frac{\|noisy\ signal - pure\ signal\|^2}{\|denoised\ signal - pure\ signal\|^2}\right)$$

All the above evaluation indices contribute to the overall fitness function, φ which is given by [20]

$$\varphi[\omega(y_m^{(n)})] = \sum_{i=1}^{N} k_1.I_{snr}(i) + k_2.I_{ncc}(i) + \frac{k_3}{I_{sae}(i)} + k_4.I_{nrr}(i),$$

Here N is the total input signal.

Step 3: Once initialisation is complete with various objective function values, each member in ZOA is updated using two phases, as illustrated below in Step 3.

Foraging behaviour, which makes use of elite and linear momentum weight strategies.
Defensive behaviour against bad solutions is used.

Numerical representation for foraging behaviour is given by [20]

$$y_{m\_new}^{(n)} = y_m^{(n)} + rand(y_m'^{(n)} - l_{dw} y_m^{(n)})$$

Here $y_m'^{(n)}$ is the best solution, l_{dw} is the linear weight momentum strategy [20]

$$l_{dw} = w_0 - n\left(\frac{w_0 - w_1}{n_{max}}\right)$$

N is the present iteration, n_{max} is the maximum iteration.

Further refining process is carried out based on $[y_{m\_new}^{(n)}]$ equation using Defensive behaviour, which has two strategies: (a) Escape strategy, and (b) Herd Movement

Numerical representation of the above two stated strategies is

$$y_{m\_new}^{(n)} = \begin{cases} y_m^{(n)} + R\ .(2rand - 1)\left(1 - \frac{n}{n_{max}}\right) y_m^{(n)}\ , P_s \leq 0.5 \\ y_m^{(n)} + rand(y_m'^{(n)} - l_{dw} y_m^{(n)}), P_s > 0.5 \end{cases}$$

$$y_{m\_new}^{(n)} = min\left\{y_{m\_new}^{(n)}, y_{mmax}\right\}$$

$$y_{m\_new}^{(n)} = max\left\{y_{m\_new}^{(n)}, y_{mmin}\right\}$$

Step 4: Improved ZOA employs the Elite strategy, which suggests substituting the individual with the worst fitness after each search to accelerate convergence speed.

Step 5: Once the maximum number of iterations is reached, the optimisation algorithm provides the optimised output and terminates.

3.4.2 Improved Whale Optimization Algorithm (IWOA)

Another optimization algorithm used in this research is Whale Optimisation Algorithm[21], which was opted in order to improve the convergence speed and signal quality and produce accurate and effective denoising of partial discharge (PD) signals, sophisticated optimisation techniques are necessary. Among the many bio-inspired metaheuristic algorithms, the Whale Optimization Algorithm (WOA), first presented by Mirjalili and Lewis in 2016, has drawn a lot of interest because of its robustness, simplicity, and capacity to strike a balance between local exploitation and global exploration. The WOA draws inspiration from humpback whales' communal hunting strategies, especially their bubble-net feeding behavior, in which the whales encircle their food and follow spiral paths in an attempt to catch it. In order to create an optimization strategy that can successfully penetrate complex and multifaceted search spaces, this natural phenomenon is mathematically expressed.

However, the traditional WOA may occasionally experience loss of diversity and premature convergence during iterations, which can limit the effectiveness of its global search. The Improved Whale Optimization Algorithm (IWOA), an improved version, is suggested as a solution to these problems. To enhance the algorithm's exploration and exploitation balance, the IWOA adds techniques including dynamic coefficient adjustment, adaptive convergence control, and nonlinear parameter tuning. These improvements accelerate convergence towards the global optimum, preserve population diversity, and avoid early stagnation. As a result, IWOA outperforms the conventional WOA in terms of optimisation accuracy, stability, and convergence efficiency, which makes it better suited for feature optimisation and PD signal denoising applications.

The various steps involved in the whale Optimisation Algorithm are shown in figure 6.

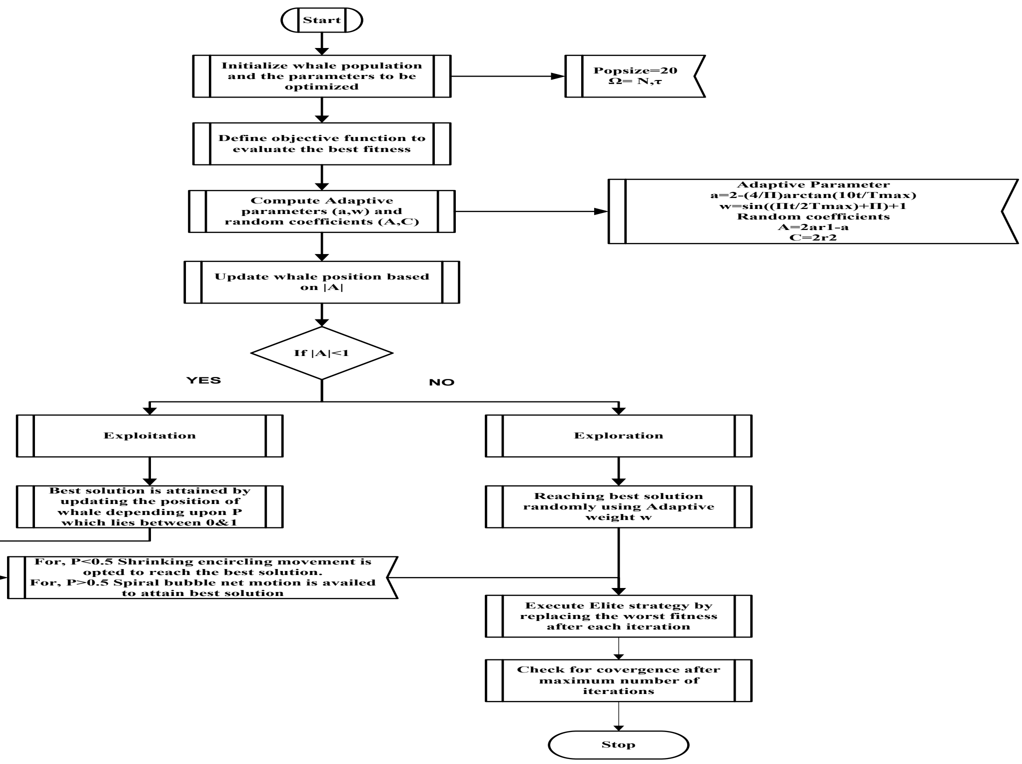

Figure 6: IWOA Algorithm

3.4.3 Evolutionary Optimization Technique:

This paper presents an evolutionary optimisation approach to get the best denoised signal. In theory, IZOA and algorithms like as GWO, DWOA, IWOA, MFO might work together cooperatively. For example, IZOA could be guided by IWOAs' best prey search or a GWO population could be started using IZOA's output. In other fields, similar hybrids have shown promise [29] (for example, a PSO–GWO hybrid fared better than single algorithms on reliability optimisation tasks). The goal is to balance exploration and exploitation by mixing algorithms, even if specialised PD-focused IZOA hybrids are not yet widely available in the literature. To attain a fine-tune, fast-converging, refined local search and to avoid premature convergence, IWOA is incorporated after running IZOA to investigate the search space in general in this research paper. Compared to using either approach alone, this method is seen to produce more accurate results. The pictorial representation of the metaheuristic optimisation technique is shown in Figure 7.

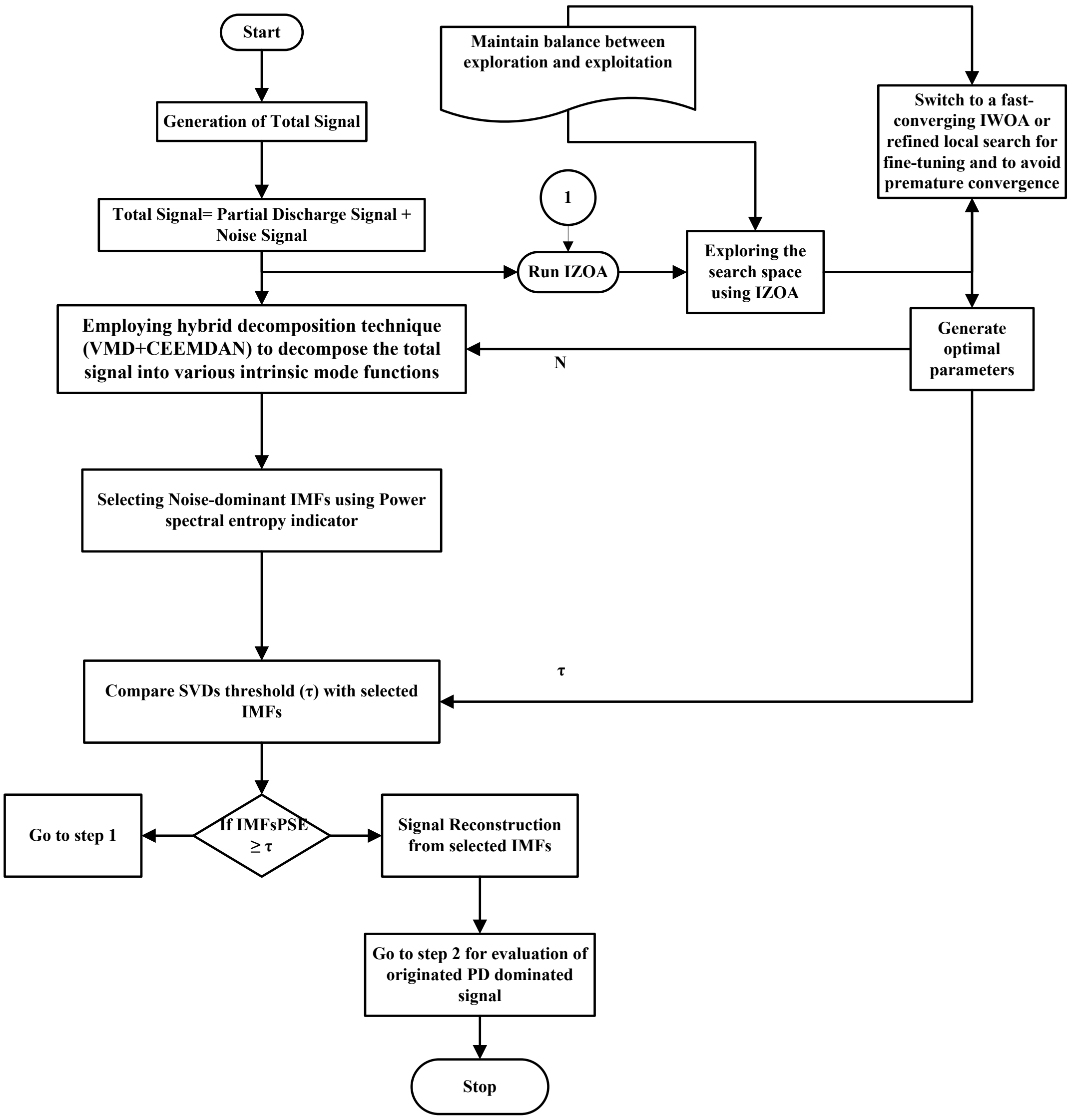

Figure 7: Evolutionary algorithm based hybrid decomposition

The efficient development of ideal parameters utilising both IZOA and IWOA is shown in Figure 4, where the search space is first explored using IZOA before switching to IWOA to achieve a precise and quick convergence using the best prey selection method.

4.Results

1. Analysis of various Simulation Cases:

The mathematically generated partial discharge signal is shown in Fig. 1 along with the noisy signal. This paper presents an integrated decomposition technique in which IMFs are generated using VMD+CEEMDAN initially. The result obtained through simulation, demonstrating 3D IMFs, an absolute error plot, is shown in Figures 8,9, respectively.

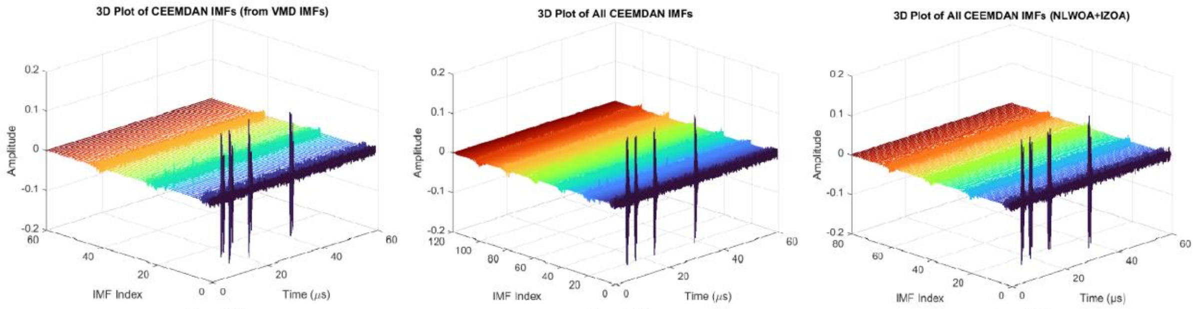

Figure 8(a) Figure 8(b) Figure 8(c)

Figure 8: 3D IMFs plot for various optimisation- 8(a) WOA, 8(b) IWOA, 8(c) IZOA+IWOA

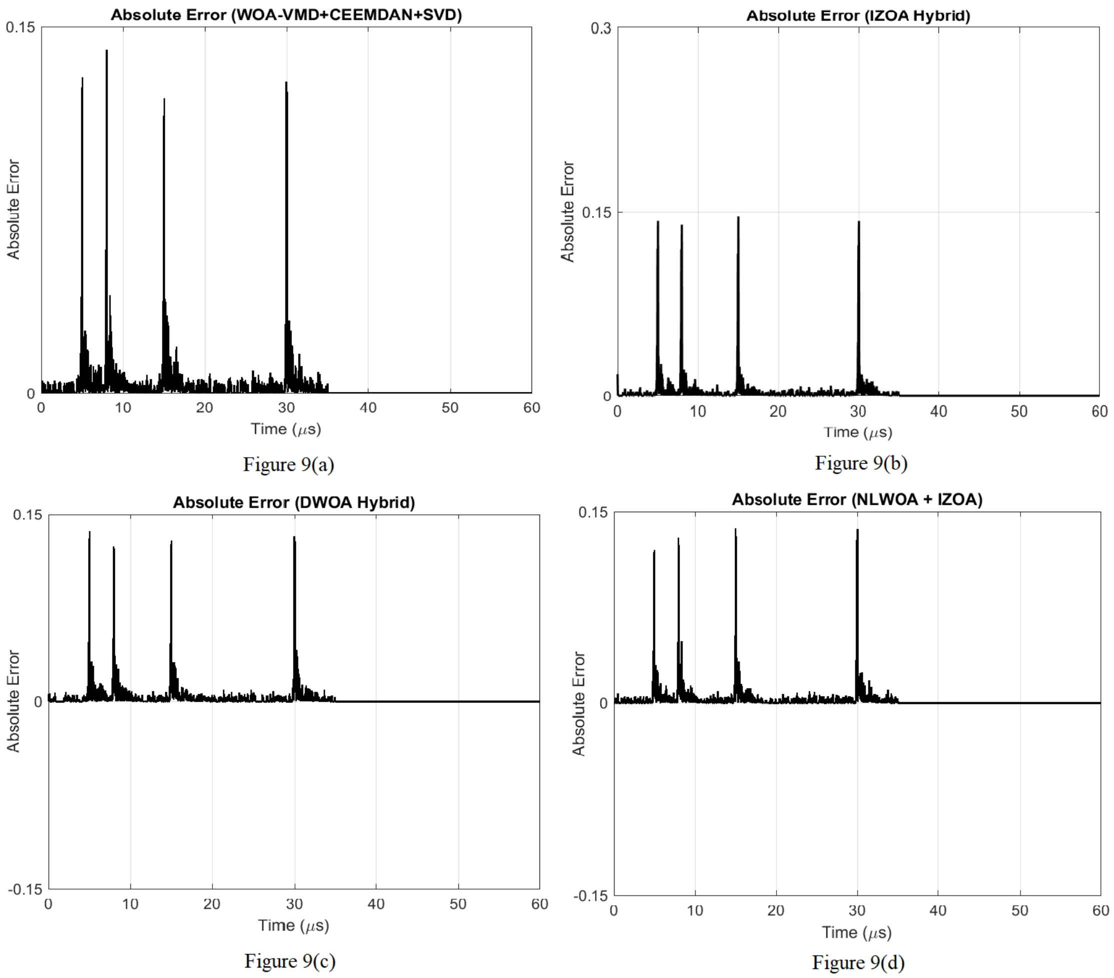

Figure 9(a) Figure 9(b) Figure 9(c) Figure 9(d)

Figure 9: Absolute error plot for various optimisation- 9(a) WOA, 9(b) IZOA, 9(c) IWOA, 9(d) IZOA+IWOA

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Though the optimisation technique guarantees the presetting of various parameters to enhance its applicability to different types of signals, the traditional method of denoising using various hybrid decomposition techniques and entropy criteria for signal reconstruction has also proven to be accurate. However, the performance index for the evolutionary optimisation technique, which is a gauge of how well the PD signal is denoised, is found to be best when compared to traditional methods. Also, the fitness curve is shown in Figure 10, which indicates that the IZOA+IWOA gives the highest fitness factor of 512when compared to others.

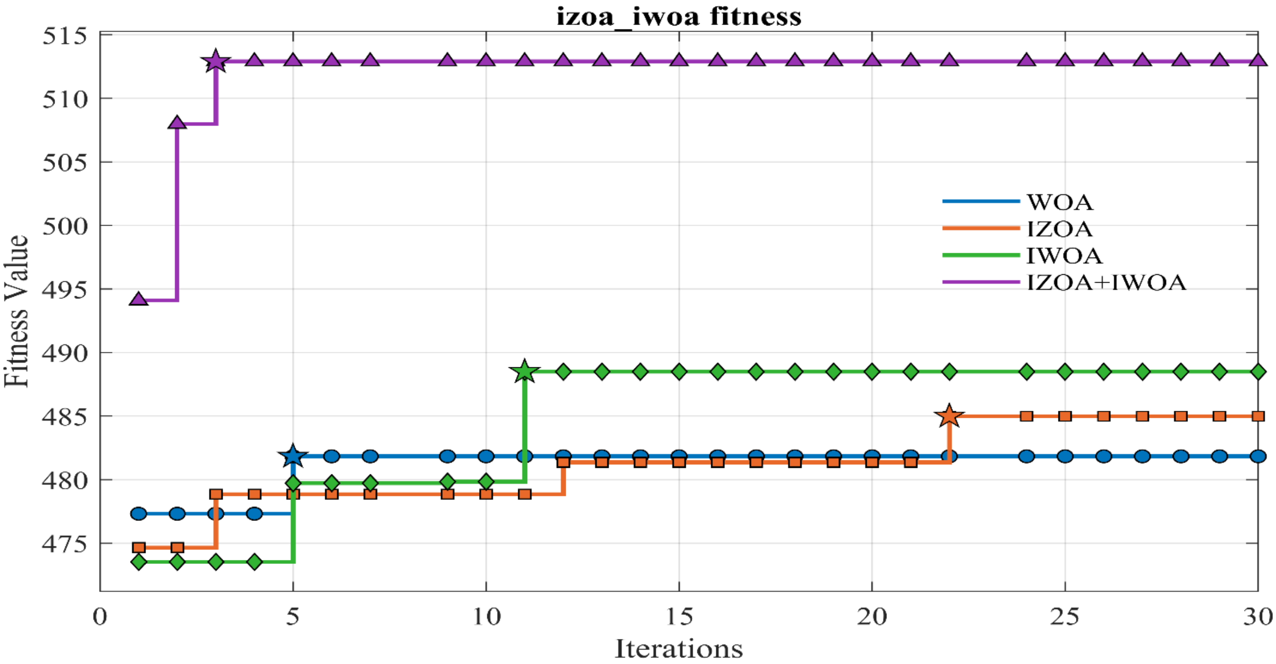

Figure 10: Fitness comparison plot for various optimisation

The simulated results of the reconstructed signal and the denoised signals is shown in Figure 11 and 12

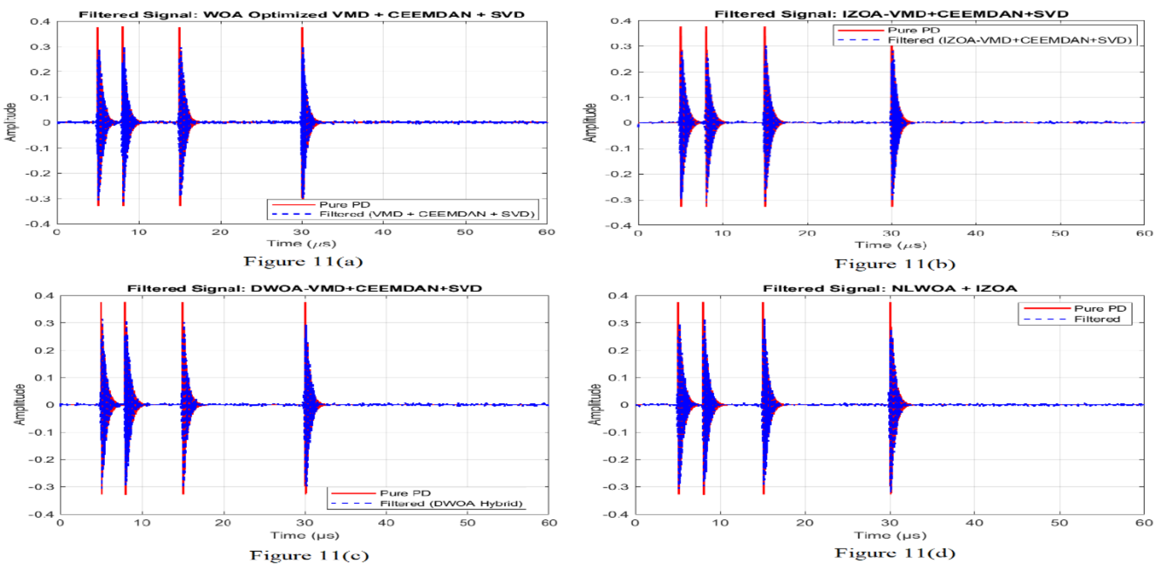

Figure 11: Filtered and pure PD signal for various optimisation- 11(a) WOA, 11(b) IZOA, 11(c) IWOA, 11(d) IZOA+IWOA

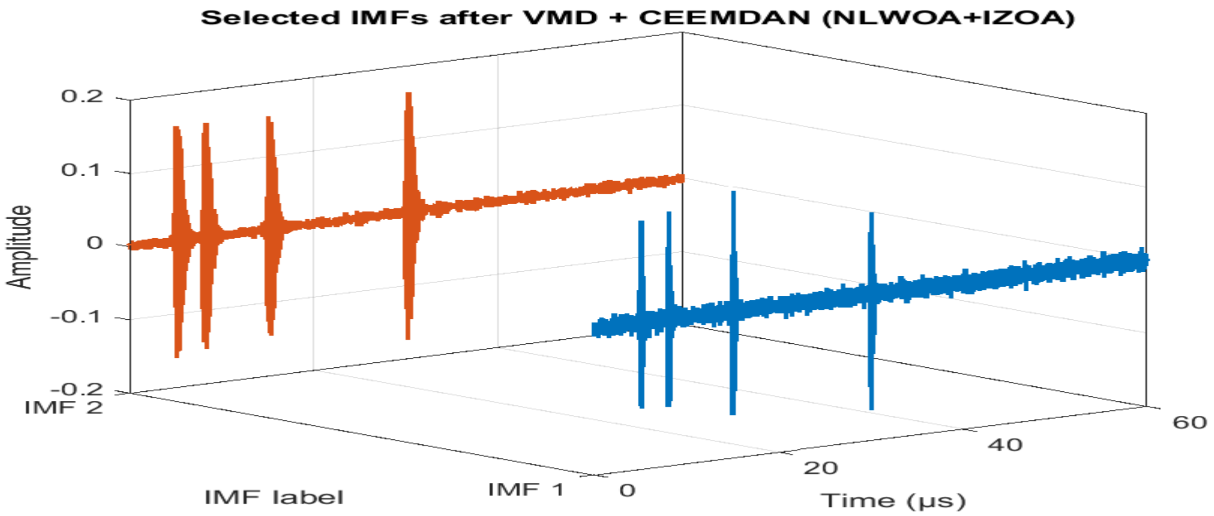

Figure 12: Selected IMFs plot for signal reconstruction using IZOA+IWOA

TABLE 1: Comparioson of performance indices for various algorithms

Algorithm	Best (N)	Best (τ)	SNR (dB)	NCC	SAE	NRR (Db)	Max AbsErr	Mean AbsErr
Hybrid Decomposition	NA	NA	9.02	0.944	1.00	11.331	0.1559	0.0033
With WOA	3	0.900	11.596	0.960	0.547	11.422	0.1404	0.0026
With IZOA	7	0.990	11.647	0.960	0.552	11.489	0.1391	0.0025
With IWOA	3	0.900	11.678	0.960	0.553	11.510	0.1390	0.0024
With Evolutionary algorithm	4	0.900	11.780	0.963	0.543	11.625	0.1370	0.0023

NA- Not Applicable

The Table [1] demonstrates performance indices for each optimisation along with the integrated one.

5.Discussion

5.1 Observations from the Performance Metrics:

I. Signal-to-Noise Ratio: Signal-to-noise ratio determines the amount of noise present over the total PD signal. After denoising, a higher SNR indicates a cleaner signal. As per the table 1, the SNR is found to be 11.78 dB for the evolutionary algorithm, which shows how effectively the noise signal has been reduced compared to the conventional and intelligent schemes.The evolutionary algorithm shows 30.5% improvement when compared to conventional method(hybrid decomposition).

II. Normalised-Cross Correlation: Since NCC measures the similarity between the original and noise signal, the results tabulated above clearly reveal that all the methods give approximately equal performance results since all the algorithms have results close to one

III. Sum of Absolute Error: SAE gives the difference between the original and the noisy signal. The lesser the difference, the better the performance and as per Table 1, the IZOA+IWOA optimisation showed a lesser difference, revealing a greatly decreased error and indicating improved reconstruction accuracy.

IV. Noise Rejection Ratio: The rate at which the noise is rejected while retaining the original signal is defined as NRR. The higher the percentage of NRR, the better the signal denoised, and the integrated algorithm shows 2.5% increased performance when compared to conventional and 1.7% improvement when compared to intelligent schemes , thereby enabling good noise reduction.

V. Maximum Absolute Error: The performance statistics that are used to estimate the greatest absolute difference between the pure and noisy signal are known as Maximum Absolute Error. From Table 1**,** the maximum absolute error is found to be the least in the case of IZOA+IWOA, revealing a very minute difference between the original and noisy signal.

VI. Mean Absolute Error: A frequently used metric to calculate the average size of errors between the original (actual) signal and the reconstructed or estimated signal, without taking account of their direction, is called mean absolute error, or MAE. In terms of MAE**,** Table 1 displays the best outcome for IZOA+IWOA when compared to all others.

6. Conclusion:

By combining two intelligent optimisation techniques, IZOA and IWOA, this study offers the best and most efficient denoising method. Along with their mathematical deductions, a number of optimization strategies are explained in depth, including the Whale Optimization Algorithm, Improved Zebra Optimization Algorithm, and Improved Whale Optimization Algorithm. The findings from the IOAs mentioned above show that

1. It may be difficult to apply a particular decomposition technique to break down the original signal into many intrinsic mode functions for various signal types, and precise results might not be achieved. Therefore, depending on the type of PD signal, optimization methods make the process easier and more application-oriented while producing denoising results that are more accurate and efficient.
2. In comparison to IZOA and WOA alone, EOA (IZOA+IWOA) effectively denoises the PD signal.
3. SNR, NCC, MSE, SAE, and NRR are some of the factors that determine how precisely the noisy signal is filtered out of the original PD signal. However, EOA demonstrated the best performance across all evaluation matrices.
4. The Evolutionary Optimisation Algorithm also has a greater rate of convergence at each step of identifying the optimal parameters.

According to [Figure 10], using the Evolutionary Algorithm results in an 6.2% improvement in the fitness curve when compared to WOA, an 5.7% improvement with IZOA, and an 4.9% with IWOA. Therefore, a new integrated optimisation Algorithm, which is thought to be the best optimisation method available, is presented in this study.

Additionally, future research in this field can use other optimization algorithms like Moth Flame, in which the population size is greatly reduced by eliminating the worst condition in every iteration, thereby enabling much higher convergence. Also, combination of other decomposition methods can yield better results thereby improving noise removal while maintaining the essential characteristics of the PD signal. This will improve the system's performance even in realistic noisy environments.

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Declaration of Conflicting Interest:
The Authors declare that there are no known competing financial interests or personal relationships that could influence the work reported in this paper.