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An improved approach for denoising acoustic signals of subsea gas pipeline leak using hybrid algorithms

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Abstract: Detecting leaks in subsea gas pipelines is a complex challenge because ambient noise often compromises the accuracy of detection. Effective noise removal from pipeline leak signals is essential for improving the precision of leak identification in subsea pipelines. In this study, a hybrid intelligent algorithm is designed to enhance the denoising capability of subsea gas pipeline leak signals. The key parameters of the Variational Mode Decomposition (VMD) were optimized using the Archimedes Optimization Algorithm (AOA) to ensure efficient and accurate signal decomposition. The optimized VMD decomposes a noisy signal into multiple Intrinsic Mode Functions (IMFs), each containing distinct signal components. These IMFs were filtered by calculating their correlation with the original signal. The principal components of the leak signal retained after this screening process were reconstructed. The Wavelet Transform (WT) was applied to further eliminate residual noise and enhance the signal quality. The results demonstrate that the optimized VMD significantly improves the decomposition accuracy and efficiency compared to traditional parameter selection methods. Furthermore, the joint AOA-VMD-WT denoising algorithm outperformed the other methods across common denoising metrics, showing superior noise reduction performance.

One sentence summary: This study presents a novel approach to subsea leak signal processing, showing that AOA-VMD-WT boosts acoustic quality, simplifying preprocessing and making reliable signal analysis accessible for real-time pipeline monitoring.

Keywords: Subsea gas pipeline leak; acoustic signals; denoising; VMD; AOA

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1 Introduction

Effective signal processing is critical for ensuring the reliability of subsea natural-gas pipeline leak detection. However, background noise and environmental interference often obscure the acoustic signals generated by pipeline leaks, thereby creating significant challenges in extracting key leak features. Without effective denoising, these signals can blend with noise, resulting in false alarms or missed detections. To address these issues, various detection techniques have been developed, including distributed fiber-optic sensing, negative pressure wave detection, and acoustic methods (Madabhushi et al., 2023; Ma et al., 2023; Li et al., 2019). These advancements have collectively driven substantial progress in the development of leaking-detection technologies. Among these techniques, acoustic methods have gained considerable attention for subsea pipeline leak detection owing to their noncontact operation, high sensitivity, and extended detection range. However, acoustic signals in marine environments are often accompanied by complex noise interference, which can degrade the Signal-to-Noise Ratio (SNR) and obscure pipeline leak characteristics, potentially resulting in false alarms or missed detection. To address this challenge, this study focuses on effectively denoising and preprocessing acquired leak signals to improve the accuracy of subsea natural gas pipeline leak detection.

Numerous signal processing methods have been developed. Empirical Mode Decomposition (EMD), an adaptive signal decomposition technique based on envelope features, is widely used (Huang et al., 1998). However, the performance of a single algorithm is often limited, particularly when dealing with complex signals containing noise or non-stationary components. These limitations stem from issues such as mode mixing, poor frequency separation, and inability to adapt effectively to varying signal characteristics. To address these challenges, some studies integrated EMD with other methods to enhance its effectiveness. For example, Zhang et al. (2017) improved the denoising capability of vibration signals in flood-delivering structures by integrating WT with EMD under low SNR conditions. Similarly, Liu et al. (2023) applied a cross-correlation method to EMD to adaptively extract leak features and improve the accuracy of pipeline leak detection. Under high SNR conditions, Zhou et al. (2019) reconstructed denoised signals by extracting information from multiple EMD layers, whereas Dao et al. (2019) developed an adaptive modulation interval thresholding algorithm to enhance the reception of frequency-modulated signals. Despite these advancements, EMD remains hindered by challenges such as mode mixing and boundary effects, which can lead to waveform distortion and reduce its ability to preserve the essential signal features. As an adaptive and nonrecursive signal processing technique, VMD addresses these limitations by reducing mode mixing and boundary effects (Dragomiretskiy & Zosso, 2013). Its integration with the negative pressure wave method has demonstrated strong performance in urban pipe network detection (Jiang et al., 2023). Furthermore, when combined with permutation entropy or detrended fluctuation analysis, VMD shows significant potential for processing noisy signals, thereby enabling accurate signal identification and reconstruction (Zhang et al., 2022; Liu et al., 2016). These findings underscore the continuous advancements in signal processing techniques and their potential for improving the accuracy and reliability of complex signal analyses.

However, the practical effectiveness of Variational Mode Decomposition (VMD) is limited by the sensitivity of its parameter selection. The core of the algorithm lies in the reasonable setting of two key parameters: number of modes K and penalty coefficient α. Parameter K needs to be accurately identified through spectral cliff analysis; low values of K can lead to modal aliasing residuals, while high values may trigger spurious modal components. Parameter α controls the balance between component fidelity and noise immunity, with lower values favoring narrowband retention and higher values enhancing noise rejection.

To address these challenges, various optimization algorithms, such as Particle Swarm Optimization (PSO), Whale Optimization (WO), and Sailfish Optimization (SO), have been integrated with VMD to enhance its denoising and feature extraction capabilities for handling complex signals. These strategies effectively suppress noise interference while preserving the essential signal information (Long et al., 2017; Zhou et al., 2021; Nassef et al., 2021). To eliminate the need for manual parameter tuning, Li et al. (2021) developed the Improved Adaptive Variational Mode Decomposition (IAVMD) algorithm, which autonomously adjusts K and α based on signal characteristics. Additionally, Li et al. (2020) improved the VMD adaptability by introducing a signal clarity parameter, enabling automatic mode selection for reconstructing pipeline leak signals under unknown noise conditions. Hybrid optimization methods have demonstrated superior performance in this domain. For instance, Gai et al. (2020) combined VMD with Hybrid Grey Wolf Optimizer (HGWO) for fault diagnosis applications, whereas Cheng et al. (2018) employed the Firefly Algorithm to optimize K and α using thoronol low peaks as the optimization objective. Kumar et al. (2021) developed a Genetic Algorithm (GA) model based on the kernel based mutual information (KEMEI) fitness function for rapid defect detection under varying speeds. Yan and Jia (2019) presented a Cuckoo Search Algorithm-Variational Mode Decomposition (CSA-VMD) approach to adaptively decompose multicomponent signals into IMFs. Despite significant progress in VMD-based methods, several issues remain unaddressed.

- Although the existing parameter optimization schemes can suppress some background noise, some high-frequency noise and random impulse interference remain in the decomposition results. This residual noise can contaminate the critical feature bands and lead to erroneous judgements by subsequent fault identification algorithms.
- A strong correlation exists between the number of modal decompositions and bandwidth constraints. Subtle parameter changes may trigger modal aliasing and invalid component generation, which often requires time-consuming manual debugging.
- The decomposition process of the traditional fixed-parameter model cannot follow the change in the signal characteristics over time. When the monitoring is under pressure fluctuation or a sudden change in the flow rate, it may miss the early characteristics of a sudden leak.

The purpose of this study is to develop an improved denoising approach for acoustic signals of subsea gas pipeline leaks using hybrid intelligent algorithms, which are employed to optimize the parameters of VMD, enhance decomposition accuracy, and eliminate the need for manual tuning. Additionally, the WT was utilized to reduce the noise in the decomposed components. This hybrid method effectively retains key signal features while mitigating noise interference, thereby rendering a robust solution for accurate and reliable subsea pipeline leak detection.

The rest of this paper is organized as follows. Section 2 presents a brief introduction of the AOA, VMD, and WT methods. Section 3 presents the implementation procedure for the subsea gas pipeline leak signal denoising. Section 4 illustrates this approach by using a case study. Finally, section 5 summarizes the conclusions of this study.

2 Method

Fig. 1 illustrates the implementation procedure for denoising the acoustic signals of subsea gas pipeline leaks using a hybrid algorithm. This approach enhances the effectiveness of signal decomposition by optimizing the parameters of VMD with AOA and incorporating WT denoising to improve the accuracy of the signal processing. The primary stages of this approach are as follows.

- Subsea gas pipeline leak signal acquisition;
- Establishment of denoising model of pipeline leak signals;
- Reconstructing acoustics signals of pipeline leak;
- Signal noise reduction.

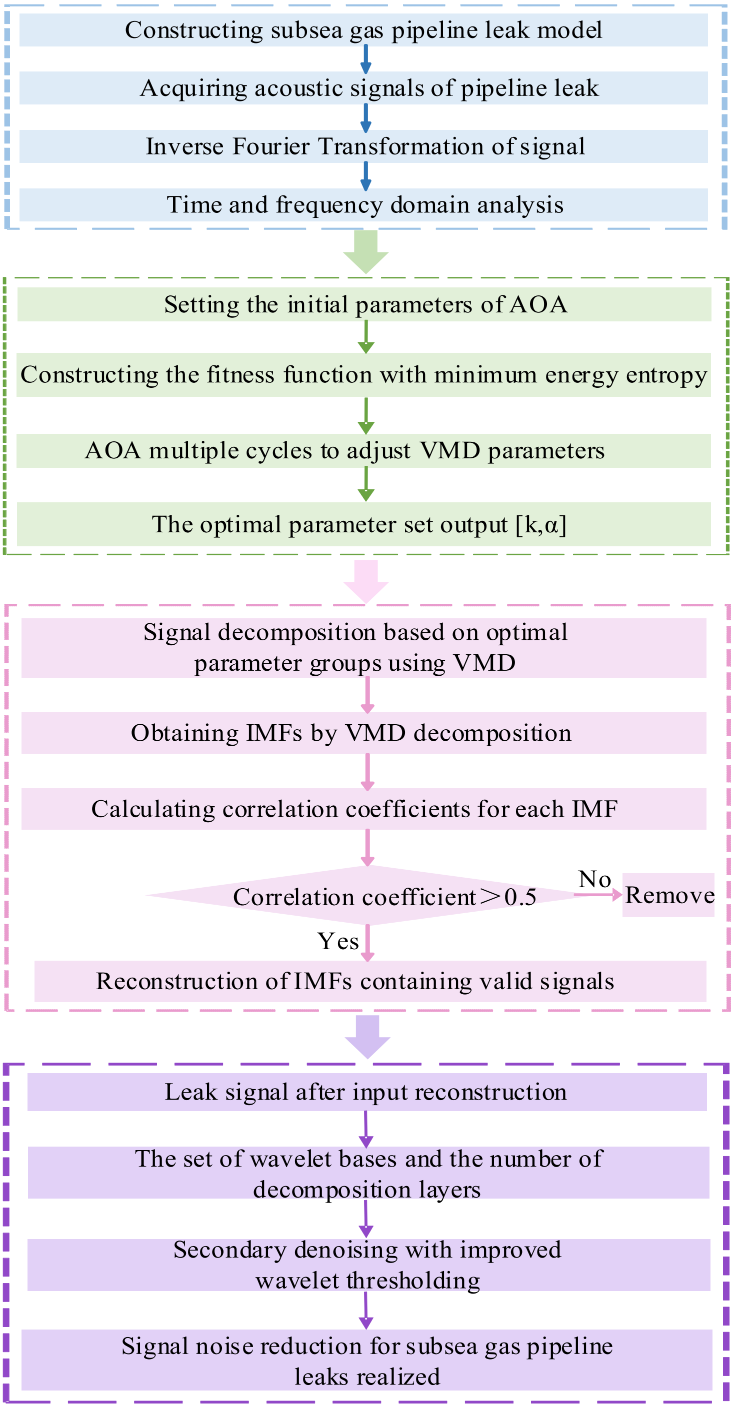


Figure 1. Flowchart of denoising signals of subsea gas pipeline leak

2.1 Acquisition of subsea gas pipeline leak signal

The acquired acoustic signals were composed of leak signals and background noise. The VMD method traditionally relies on manually setting modal quantities K and penalty factors α, which often fail to adequately adapt to the characteristics of different signals, leading to insufficient signal separation. To address this limitation, an AOA was employed to optimize the key parameters of the VMD to improve the signal separation accuracy. The AOA algorithm achieves optimal solutions by modeling the Archimedean leverage principle and combining a global search with local optimization strategies. In this study, AOA was used to optimize the number of modes K and penalty factor α, enabling VMD to adaptively adjust its decomposition parameters based on the unique characteristics of the signals. This adaptive optimization facilitates the accurate separation of leak signals from background noise, effectively reducing noise interference, and enhancing the extraction of leak signal features. Compared to manual parameter selection, AOA not only improves the decomposition accuracy but also enhances the flexibility and adaptability of signal processing. The specific optimization procedure for the AOA is detailed in Li et al. (2021). By incorporating AOA, the VMD model can dynamically adjust its decomposition parameters, ensuring the precise separation of leak signals from background noise. This optimization process significantly enhances the feature extraction and improves the reliability of leak detection in subsea pipelines.

2.2 Establishment of denoising model

The acquired acoustic signals were composed of leak signals and background noise. The VMD method traditionally relies on manually setting modal quantities K and penalty factors α, which often fail to adequately adapt to the characteristics of different signals, leading to insufficient signal separation. To address this limitation, an AOA was employed to optimize the key parameters of the VMD to improve the signal separation accuracy. The AOA algorithm achieves optimal solutions by modeling the Archimedean leverage principle and combining a global search with local optimization strategies. In this study, AOA was used to optimize the number of modes K and penalty factor α, enabling VMD to adaptively adjust its decomposition parameters based on the unique characteristics of the signals. This adaptive optimization facilitates the accurate separation of leak signals from background noise, effectively reducing noise interference, and enhancing the extraction of leak signal features. Compared to manual parameter selection, AOA not only improves the decomposition accuracy but also enhances the flexibility and adaptability of signal processing. The specific optimization procedure for the AOA is detailed in Li et al. (2021). By incorporating AOA, the VMD model can dynamically adjust its decomposition parameters, ensuring the precise separation of leak signals from background noise. This optimization process significantly enhances the feature extraction and improves the reliability of leak detection in subsea pipelines.

2.3 Reconstructing acoustic signals of pipeline Leak

Using the optimized parameters, the VMD decomposes the original signal into intrinsic mode functions (IMFs), each corresponding to a specific frequency band. VMD, proposed by Dragomiretskiy and Zosso (2013), is an adaptive signal decomposition technique that preserves the key features of leaked signals while isolating noise. During the decomposition process, the optimized parameter K determines the number of IMFs, whereas the penalty factor α controls the bandwidth distribution and central frequency of each IMF. Low-frequency IMFs primarily contain leak signal components, whereas high-frequency IMFs mainly contain background noise. This optimized decomposition ensures effective separation of leak signal frequencies from noise. The detailed steps of the VMD computation are outlined by Liu et al. (2025).

Following VMD, this study selects and reconstructs the obtained IMFs. The correlation coefficient between each IMF and the original signal was calculated, and IMFs containing the effective signal components were selected using the following equation:

$$R = \frac{cov(IMF_i, X)}{\sigma IMF_i \cdot \sigma_X} \tag{13}$$

where $cov(IMF_i, X)$ is the covariance between the i-th IMF and the original signal, and σIMF_i and σ_X are the standard deviations of the i-th IMF and original signal, respectively. The value range of R was [-1, 1]. The closer R is to 1, the more original signal features that the IMF retains. When closer R is to 0, the IMF is primarily a noise component.

Based on the correlation results, the IMFs with higher correlation coefficients were retained, whereas those dominated by noise components were discarded. The selected IMFs are then reconstructed to obtain the denoised leak signal, preserving the essential features of the leak while minimizing noise interference.

2.4 Signal noise reduction

Although the optimized VMD effectively separates most of the noise components, some residual high-frequency noise may remain in the reconstructed signal. This residual noise can compromise the purity of the signal and reduce the accuracy of subsequent analysis. To address this issue, WT denoising was introduced in this study. The WT denoising method effectively separates the low-frequency components of the signal from high-frequency noise through wavelet transformation. Although traditional hard and soft threshold functions are widely used, they have inherent limitations: the hard threshold function exhibits discontinuity at the threshold point, and the soft threshold function introduces estimation bias. Both these issues can adversely affect the denoising outcome. To overcome these limitations, this study adopts the improved threshold function proposed by Qiao et al. (2021), which achieves a higher denoising precision and better preservation of signal features. The specific expression for the improved threshold function is as follows.

$$W_{j,k} = \begin{cases} sgn(\omega_{j,k}) \times \left| |\omega_{j,k}| - \frac{\lambda}{\sqrt[p]{|\omega_{j,k}|^p - |\lambda|^p + 1}} \times \frac{1}{e^{\sqrt[q]{[\omega_{j,k}] - |\lambda|}}} \right| & |\omega_{j,k}| \geq \lambda \\ 0 & |\omega_{j,k}| < \lambda \end{cases} \tag{15}$$

where $\omega_{j,k}$ represents the wavelet decomposition coefficients corresponding to the noisy signal after wavelet transformation and $W_{j,k}$ denotes the estimated wavelet coefficients after threshold processing. This method incorporates two adjustable parameters (p and q) for the threshold functions. By varying the values of these parameters, an effective signal energy retention can be achieved, thereby addressing the constant error issue inherent in traditional soft-threshold functions.

3 Results

3.1 Obtaining acoustic signals of pipeline leaks

In this study, numerical simulation was employed to generate subsea pipeline leak signals as an alternative to field data acquisition. Compared to field data, simulations offer a cost-effective and efficient solution, enabling the controlled generation of representative leak signals while circumventing the complexities and high costs associated with field data collection. Additionally, the simulation provides flexibility in controlling environmental variables, ensuring the acquisition of consistent and reliable data for validation purposes.

A numerical model of a subsea natural gas pipeline was developed to facilitate the validation of the pipeline leak detection methods. As shown in Fig. 2, the calculation domain includes the interior of the pipeline, the leakage region, and the leak jet region. The inner part of the pipeline is a cylinder with a length of 1000 mm and an inner diameter of 320 mm. The leak area is a cylinder with a height of 600 mm and a diameter of 800 mm, and the leak jet area is located in the center of the pipeline with a wall thickness of 8 mm and a diameter of 60 mm. To ensure the accuracy of the calculation, the mesh at the leakage hole was encrypted, and the total mesh number of the model was 834,126. The gas inlet at the left end of the pipeline was set as the pressure inlet, the gas outlet at the right end and the sea surface were set as the pressure outlet, the leak port was set as the internal surface, and the water tank, pipe wall and leakage hole wall were set as non-slip walls. The working pressure of the pipeline was set to 3.5MPa, and the signal acquisition time was 1 s.

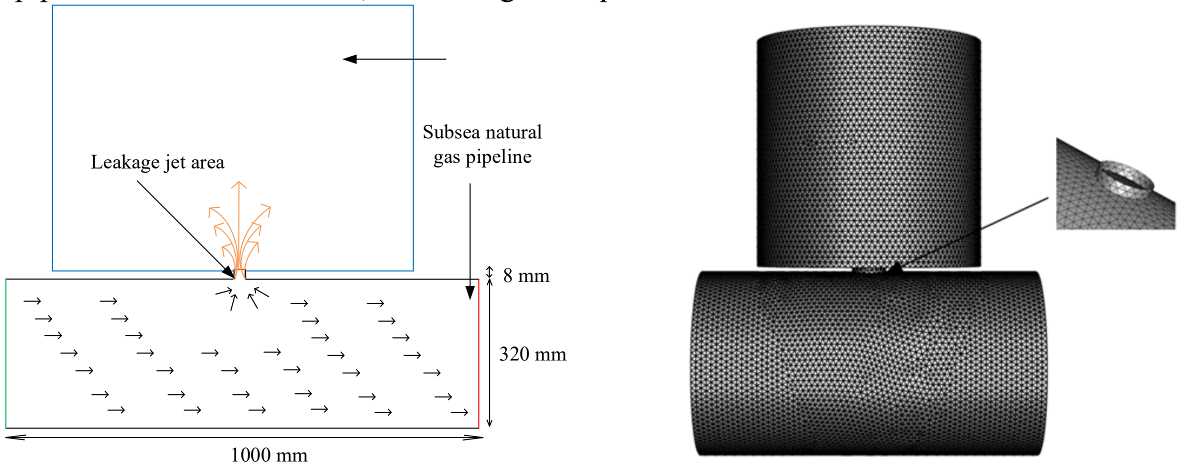
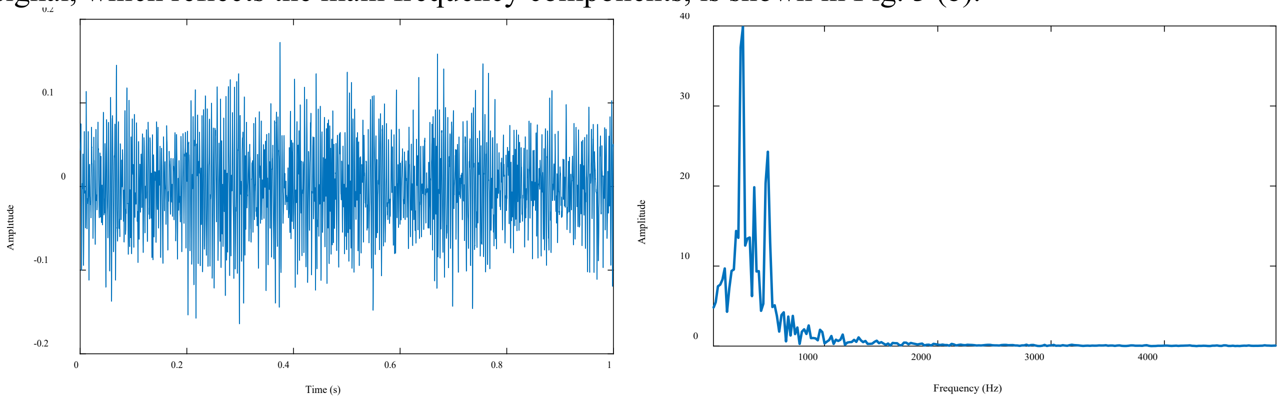


Fig.2 Acoustic signal model of subsea natural gas pipeline leaks

As shown in Fig. 3, the leakage signals obtained through the model were analyzed in both the time and frequency domains. The time-domain waveform of the leakage signal is shown in Fig. 3 (a), which shows the overall trend of the acoustic leakage signal. The frequency spectrum of the leakage signal, which reflects the main frequency components, is shown in Fig. 3 (b).



(*a*) Time domain signal (*b*) Frequency domain signal

Fig. 3 Acoustic signals of subsea natural gas pipeline leak

3.2 Development of denoising model

The noise reduction performance of the AOA-VMD optimization model was evaluated based on pipeline leak signals generated by numerical simulations. As shown in Fig. 3, these signals have nonlinear and non-stationary characteristics, and are accompanied by noise interference. To optimize the signal decomposition process, an AOA optimization algorithm was introduced to adaptively adjust the control parameters of the VMD algorithm. During this process, the minimum energy entropy is adopted as the fitness function to ensure the effective concentration of energy in the signal decomposition process.

According to the nonlinear and non-stationary characteristics and noise background of the pipeline leak signal, the parameter search range combined with the time-frequency distribution characteristics and energy concentration degree of the signal provides reasonable constraints required for optimization. During the optimization process, the AOA algorithm adjusts the VMD parameters through an iterative search, including the number of decomposition layers K and quadratic penalty coefficient α. As shown in Fig.4, the convergence curve of the fitness function becomes stable after the sixth iteration, and the final value is 0.0169, which indicates that the optimization determines the optimal solution with fast convergence and high computational efficiency. The optimization results show that the optimal decomposition layers for K=6, the effective separation of leakage signal main ingredients and noise; when the quadratic penalty coefficient is α=2666, the stability of decomposition can be guaranteed, and mode aliasing can be suppressed.

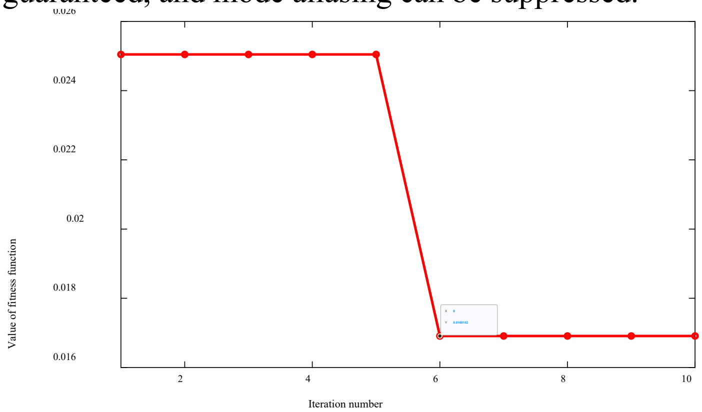


Fig. 4 Convergence curve of the fitness function of AOA based pipeline leak signals

To evaluate the feasibility of the recommended method, the GA and Grey Wolf Optimization (GWO) were used to optimize the VMD parameters under the same conditions. All optimization methods use the minimum energy entropy as a fitness function. The convergence curves of GA and GWO are shown in Fig. 5 and Fig. 6, respectively.

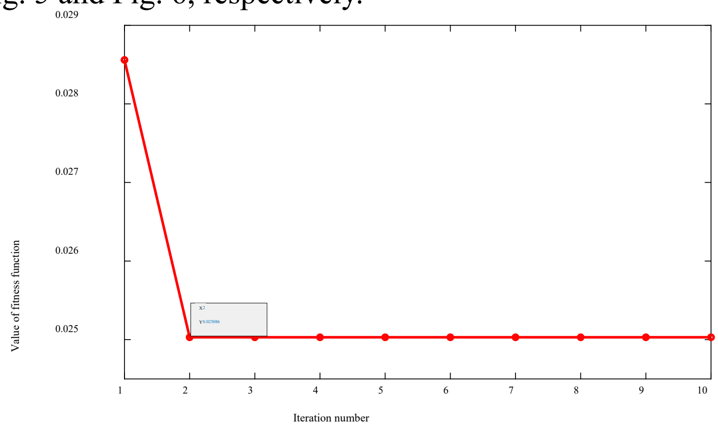


Fig. 5 Convergence curve of GA fitness function

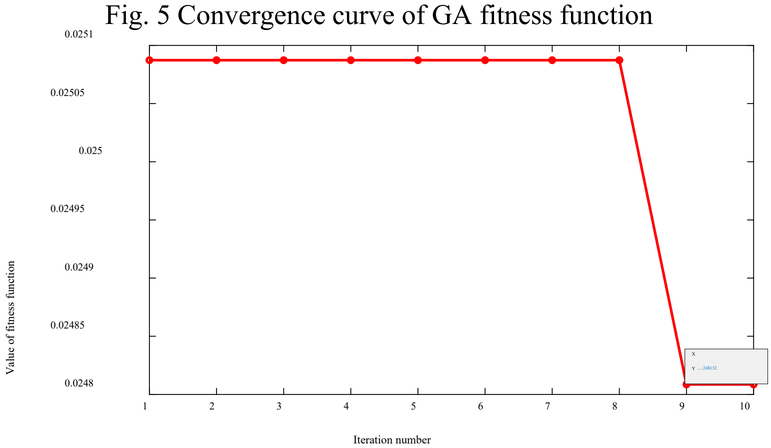


Fig. 6 Convergence curve of GWO fitness function

From the figures, it can be observed that GA-VMD exhibits rapid convergence and is stabilized by the second iteration. However, it is susceptible to being trapped in local optima, which limits its ability to further explore the search space. In contrast, GWO-VMD demonstrates a better global search capability but experiences slower convergence, particularly for complex signal decomposition tasks. Therefore, the developed method of AOA-VMD is effective in balancing global exploration and local refinement and optimizing VMD parameters with greater efficiency, thus reducing the risk of local optima and providing more accurate parameter combinations.

3.3 Decomposition and Reconstruction of Pipeline Leak Acoustic Signals

The pipeline leak signals were decomposed into six IMFs using the VMD algorithm with optimized parameters, K=6 and α=2666, determined through AOA-based optimization. The decomposition results are illustrated in Fig. 7, which reveals that each IMF corresponds to a distinct frequency component of the original signal. For instance, IMF1 has a center frequency of approximately 200 Hz, whereas IMF2 is centered near 700 Hz. These frequency components reflect the characteristics of the original signal, suggesting that the decomposition process effectively captures key signal features. Notably, this high-frequency IMF is considered to primarily contain noise, which can be directly extracted from the leak signals, effectively reducing noise and improving signal clarity for subsequent analysis.

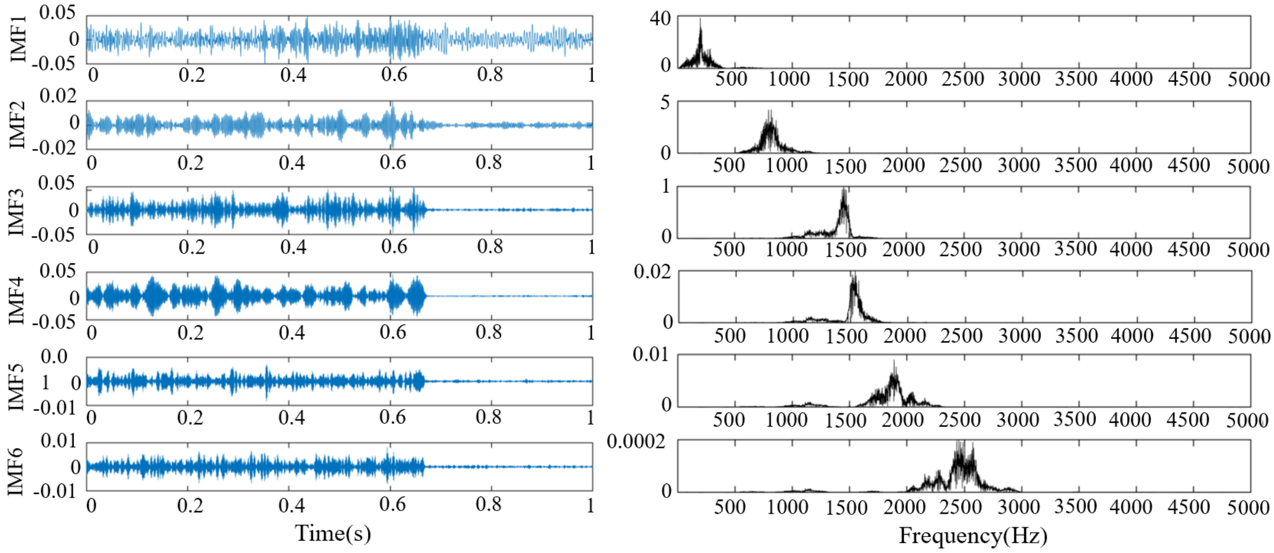


Fig. 7 Signal decomposition based on AOA-VMD method

To assess the accuracy of the selected K values, a comparative analysis of the decomposition results obtained using AOA-VMD, GA-VMD, and GWO-VMD was conducted. As illustrated in Fig. 8, the GA-VMD method results in significant over-decomposition when K=9, with IMF2 displaying frequency aliasing, where both 200 Hz and 700 Hz components are present simultaneously. Furthermore, the decomposition from IMF7 to IMF9 excessively fragmented the signal, leading to the loss of critical frequency details and misrepresentation of the original signal. In contrast, GWO-VMD, as shown in Fig. 8, offers better decomposition of the low-frequency components, but exhibits mode copying at higher frequencies, particularly around 2000 Hz, as shown in Fig. 9. This mode of copying leads to redundant representations of high-frequency components across multiple IMFs, thereby compromising the precision of the decomposition. These findings indicate the limitations of both GA-VMD and GWO-VMD in achieving optimal decomposition of complex signals, such as those from subsea natural-gas pipeline leaks.

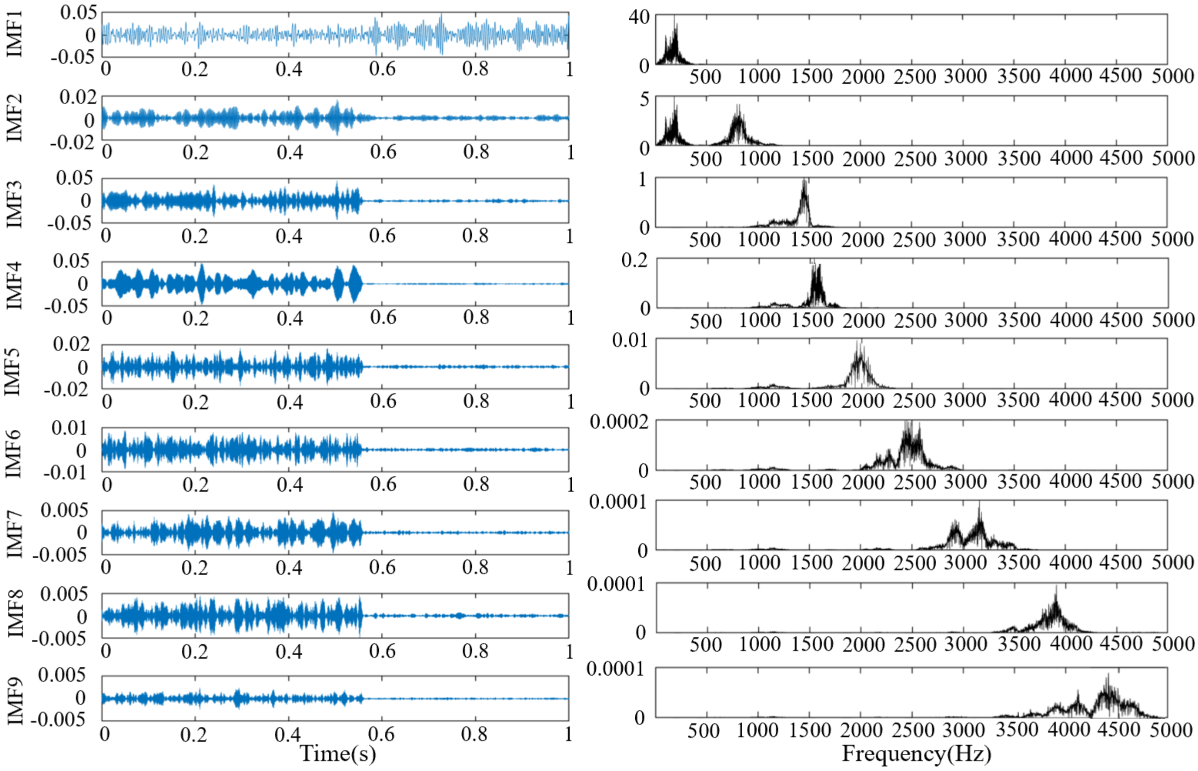


Fig. 8 Signal decomposition based on GA-VMD method

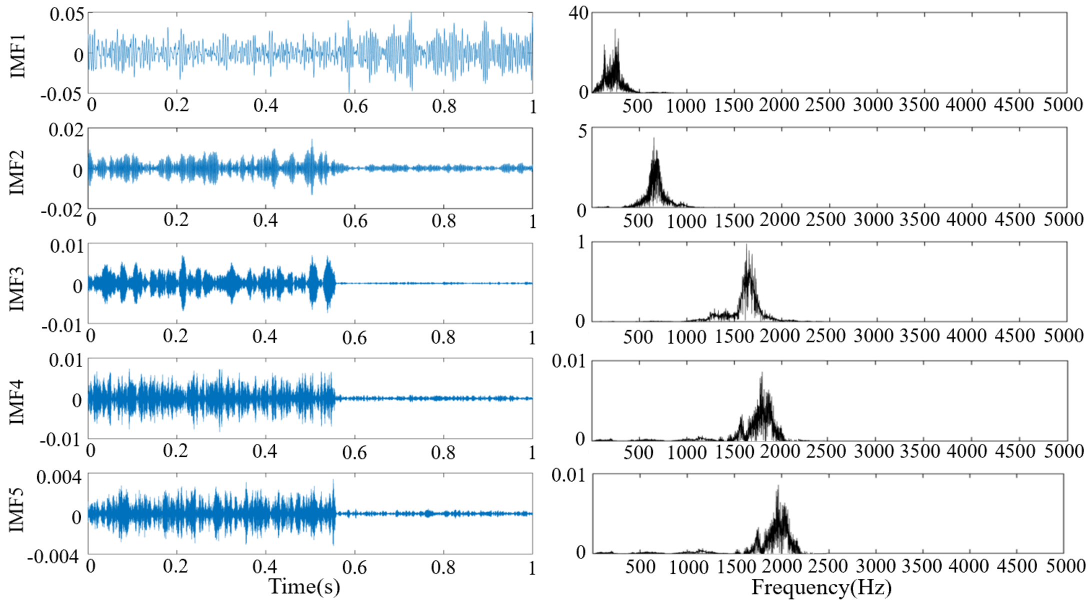


Fig. 9 Signal decomposition based on GWO-VMD method

The performance of GA-VMD and GWO-VMD highlights the importance of appropriately selecting both K value and quadratic penalty coefficient α. Inappropriate parameter choices lead to issues such as overdecomposition and mode copying, which distort the signal's features and reduce the accuracy of the decomposition. In contrast, the AOA-VMD method exhibited improved performance in mitigating these issues. By optimizing both K and α, AOA-VMD ensures a more accurate feature extraction and avoids the problems associated with over-fragmentation and mode duplication. This leads to a more precise separation of the signal components and enhanced denoising effectiveness, particularly in complex acoustic signal scenarios.

The central frequency of the IMF1 component was approximately 500 Hz, which was closely aligned with the frequency of the original signal, as shown in Fig. 4. According to Peng et al. (2021), IMFs with a correlation coefficient below 0.5 are considered noise and should be removed. The remaining IMFs effectively capture the characteristics of the simulated signal with minimal information loss. Table 1 presents the correlation coefficients between each IMF component and original signal. The results indicate that the correlation coefficients R for IMF3 through IMF6 are all below 0.5, whereas the coefficients for IMF1 and IMF2 exceed 0.5. Therefore, IMF1 and IMF2 were identified as the primary modal components. IMFs with correlation coefficients below the threshold were classified as noise components and discarded.

Table 1. Correlation coefficients for IMF.

Component	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6
R	0.6520	0.7323	0.4571	0.4127	0.1619	0.1057

3.4 Signal noise reduction

The retained IMFs containing the main components of the lea signal were reconstructed to recover the overall characteristics of the signal. By integrating core modal components, such as IMF1 and IMF2, a complete waveform reflecting the essence of the leakage signal was reconstructed. Based on the improved wavelet threshold method, the reconstructed signal is denoised, the db4 wavelet is used as the basis function, and multi-scale information is obtained by five-layer decomposition, which reduces the noise interference and preserves the signal characteristics well. Fig. 10 shows the signal after noise reduction. Compared to the original signal, its main features are more prominent, waveform details are clearer, and noise and clutter are significantly reduced, which provides reliable data support for subsequent feature extraction and leak point tracing.

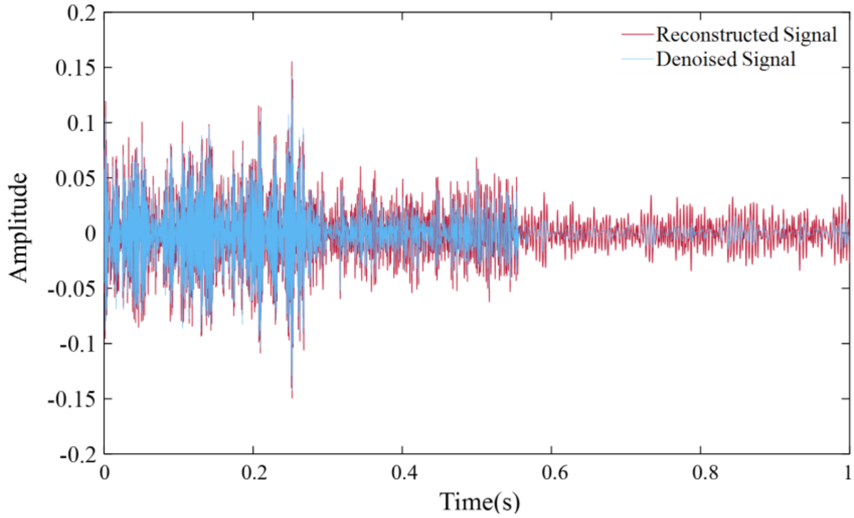


Fig. 10 Comparison of denoised and reconstructed signals

To evaluate the denoising performance of the proposed algorithm and several comparative algorithms, this study incorporated commonly used denoising performance metrics (Qiao et al. 2021): SNR, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics assess the correlation between the original signal and the signals processed by various denoising methods, allowing for a comparative analysis of the denoising efficacy of each algorithm. Table 2 presents the results. A higher SNR value and lower MSE and RMSE indicate superior denoising performance. Table 2 demonstrates that the developed algorithm consistently outperformed the other algorithms across the introduced denoising performance metrics, thereby validating its effectiveness and superiority in denoising leak signals from subsea natural gas pipelines.

Table 1. Superiority search of three optimization algorithms and experimental results.

Algorithm	SNR	MSE	RMSE
VMD	30.88	0.0628	0.3713
WT	31.93	0.0533	0.3249
AOA-VMD-WT	37.92	0.0236	0.1542

4 Conclusions

This study proposes a denoising approach for subsea natural gas pipeline leak signals by combining the AOA-optimized VMD and WT techniques. AOA optimizes the key parameters of the VMD, including the number of decomposition modes and penalty factor. By constructing an optimization model that minimizes the energy entropy, the AOA enhances the global search capability and adaptability of the VMD parameter optimization process. This results in a more precise parameter selection, improving both the accuracy of signal decomposition and computational efficiency. Compared with traditional manual parameter-setting methods, the proposed AOA-optimized VMD method better meets the denoising requirements of leak signals in complex subsea environments.

Compared with existing optimization methods, such as GA and GWO, AOA-VMD shows promising results in signal decomposition and denoising, particularly when processing complex leak signals. This effectively separates useful signals from noise, demonstrating strong robustness and high accuracy. The simulation results indicate that AOA-VMD improves the feature extraction of leak signals and optimizes the denoising process, demonstrating its potential in subsea pipeline leak detection. This method not only improves the signal processing accuracy but also provides a feasible technical solution for pipeline maintenance in a complex submarine environment.

Furthermore, this study applies the WT to the IMFs obtained from VMD decomposition. By calculating the correlation coefficients between each IMF and the original signal, the modes containing the primary leak features were selected, and the noise components were removed. The retained IMFs were then reconstructed and further denoised using an improved wavelet threshold function, which significantly enhanced the quality and stability of the signal. The simulation results suggest that AOA-VMD-WT performs well in denoising across various noise backgrounds. Future studies will combine the integration of advanced optimization algorithms and machine learning techniques. Further validation in more complex subsea environments could confirm the detection and localization accuracy of the leakage signals, which will offer a more intelligent and efficient solution for subsea pipeline safety monitoring.

CRediT authorship contribution statement

Conceptualization: C Wang. and X. Li, Methodology, C Wang. and X Li; formal analysis, C Wang; investigation, C Wang. and Y Zhang; resources, X. Li, C Wang, and Y Zhang; writing—original draft preparation, C Wang. and X Li; writing—review and editing; C Wang. and X Li.; visualization, C Wang.; supervision, X Li.; All authors have read and agreed to the published version of the manuscript.

Use of AI

During the preparation of this work, the author(s) did not use any AI tools or services for tasks, including writing, data analysis, or content generation. The entire manuscript was created by the authors through original research, thinking, and writing. All contents were reviewed, edited, and validated by the authors, who take full responsibility for the accuracy and integrity of the publication.

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Declaration of competing interests

There is no conflict of interest. The funders had no role in the study design; collection, analyses, or interpretation of data; writing of the manuscript; or decision to publish the results.

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