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Study on Denoising Method of Acoustic Emission Signal of Natural Gas Pipeline Ball Valve Internal Leakage

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Abstract

In order to solve the problem of acoustic emission signal denoising of ball valve internal leakage in natural gas pipeline, based on the wavelet packet threshold denoising, a multi-objective evolutionary algorithm to optimize the wavelet packet threshold denoising method is proposed. Firstly, the improved threshold function is adopted, the signal-to-noise ratio (SNR) and the mean square error (MSE) are used as the evaluation indicators, and the MOEA/D optimization algorithm is used to optimize the parameters k and a of the threshold function and the threshold λ, and establish the multi-target fitness model of the acoustic emission signal. Finally, the simulation signal and experimental signal are used for research and analysis. The experimental results show that wavelet packet threshold denoising and MOEA/D optimized wavelet packet threshold denoising significantly improve the SNR of the acoustic emission signal of ball valve internal leakage. Compared with the wavelet packet threshold denoising, the proposed method improves the SNR by a maximum of 45.65% and reduces the MSE by a maximum of 85.99%.

Keywords

Acoustic emission; Ball valve internal leakage; Signal denoising.

1. Introduction

As the main transportation method of oil and natural gas, oil and gas pipelines play an irreplaceable role in energy transportation. As an important part of pipelines, valves have been widely used in the fields of petroleum, chemical industry, power stations, metallurgy, and nuclear energy. They are essential fluid control equipment in industrial installation system and play an extremely important role in the entire industrial system [1, 2]. With the increase of service time, improper operation during use, and defects in the valve production process, internal leakage of the valve may occur, which may cause fires, explosion and other accidents, causing huge economic losses, and even endangering personnel safety. Therefore, valve internal leakage detection is the most important technical link in valve production and application.

AE technology is a dynamic online nondestructive testing method that can quickly detect and monitor the leakage of pipeline valves online without stopping production [3, 4]. However, there is a large amount of mechanical, electromagnetic and other noises in the process of AE signal acquisition that has serious interference with the AE signal. Therefore, denoising is the prerequisite for valve internal leakage detection, and it is of great significance to study the practical and efficient denoising method of AE signal of ball valve internal leakage.

The AE signal of ball valve internal leakage is a non-stationary time-varying signal. Wavelet analysis has good time-frequency localization, which is especially suitable for the analysis of non-stationary signals, and has been widely used in the field of signal denoising [5-9]. Compared with wavelet analysis, the wavelet packet denoising is a more precise multi-resolution time-frequency analysis method, which further decomposes the high-frequency part

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that is not subdivided in wavelet analysis. The frequency band of sound pressure signal during the internal leakage of ball valve is wide, and wavelet packet denoising has certain advantages compared with wavelet threshold denoising which only decomposes the low-frequency signal part. In this paper, a method of MOEA/D optimized wavelet packet threshold denoising is proposed to denoise the AE signal of the ball valve internal leakage of the natural gas pipeline at oil and gas gathering and transportation station. Based on the wavelet packet threshold denoising, the improved threshold function is adopted, and the MOEA/D optimization algorithm is adopted to optimize the parameters k, a and threshold λ. Taking the SNR and the MSE as the fitness function, a multi-objective fitness model of AE signals is established to realize the automatic optimization of the parameters and achieve the best denoising effect on the signal.

2. Method

2.1. Wavelet Packet Threshold Denoising

Wavelet packet decomposition is a further optimization of wavelet transform. The main idea of the algorithm is that, on the basis of wavelet transform, at each level of signal decomposition, not only the low-frequency sub-band will be further decomposed, but also the high-frequency sub-band will be further decomposed. And it is able to select the corresponding frequency band adaptively according to the characteristics of the analyzed signal to match the signal spectrum, and then the wavelet coefficients in the frequency band can be reconstructed, which can improve the time-frequency resolution. The three-layer decomposition process of the wavelet packet is shown in figure 1, where S is the original signal, A is the low-frequency, D is the high-frequency, and the sequence number at the end indicates the number of layers of the wavelet packet decomposition.

The decomposition and reconstruction formulas of wavelet packet coefficients are as follows:

$$\begin{cases} d_k^{j+1,2n} = \sum_l h_{2l-k}\, \mathrm{d}_l^{j,n} \\ d_k^{j+1,2n+1} = \sum_l \mathrm{g}_{2l-k}\mathrm{d}_l^{j,n} \end{cases} \tag{1}$$

$$d_l^{j,n} = \sum_k h_{l-2k}\, \mathrm{d}_l^{j+1,2n} + g_{\ l-2k}\, \mathrm{d}_l^{j+1,2n+1} \tag{2}$$

In Eqs. (1) and (2), d refers to the wavelet coefficient, h and g are low and high pass filter coefficients, l and k are the number of decomposition layers, j and n are the wavelet packet nodes numbers.

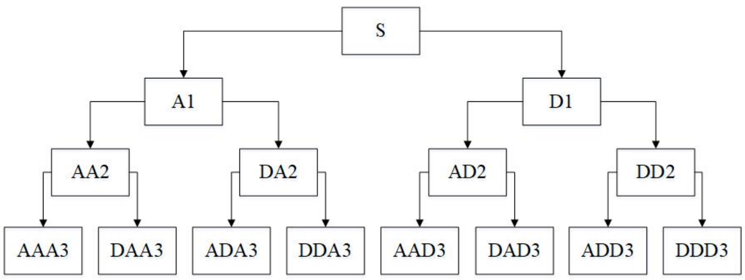


Figure 1. The decomposition process of the wavelet packet

2.2. Improved Threshold Function

The commonly used soft and hard threshold functions have the shortcomings of fixed deviation and sudden signal changes when performing signal denoising. Therefore, this paper adopts an improved threshold function [10], which can be expressed as:

$$w=\begin{cases} w-\operatorname{sgn}(w)(\frac{2k}{2k+1})(\sin(\frac{\pi\lambda}{2w}))^{a}\lambda, |w|\geq\lambda \\ \frac{w^{2k+1}}{(2k+1)\lambda^{2k}}, |w|<\lambda \end{cases} \tag{3}$$

Where k and a are positive numbers, which are the adjustment factors of the improved threshold function. The threshold function can be made to have different degrees of approximation and smoothness by adjusting the values of k and a. When k approaches infinity and the value of a gradually increases from zero, the threshold function gradually changes from a soft threshold function to a hard threshold function.

2.3. MOEA/D optimization Algorithm

MOEA/D [11] converts a multi-objective optimization problem into multiple scalar quantum problems composed of uniformly distributed weight vectors. For each new solution generated, the solution near the sub-problem is replaced based on the aggregation function. The advantages of MOEA/D are as follows:

(1) Faster convergence and low computational complexity.

(2) For relatively simple problems, the solution distribution of MOEA/D is relatively uniform.

MOEA/D mainly applies the Chebyshev method to determine the fitness function, which decomposes the multi-objective optimization problem into N sub-problems, and the k-th sub-problem has the following form:

$$\begin{cases} \left\{\min g^{te}(x|w^{k},z^{*})=\max_{1\leq j\leq m}\left\{w_{j}^{k}\left|f_{j}(x)-z_{j}^{*}\right.\right\}\right. \\ \text{s.t.}\quad x\in\Omega \end{cases} \tag{4}$$

Where w^k（k=1,...,N）is the k-th weight vector, and $\sum_{j=1}^{n}W_{j}^{k}=1$, Q is the feasible region, $\sum_{j=1}^{n}W_{j}^{k}=1$ is the reference point of the k-th sub-problem.

In each iteration, the algorithm selects a set of current optimal solutions and compare with each set of solutions after the mutation, and then a better solution is selected to replace it by the continuous evolution, which can select the solution that is closest to the Pareto optimal solution [12].

Since the final result obtained from the fitness function is a scalar, when the value of an objective function is too large compared with other objective functions, it may lead the algorithm with the Chebyshev's method as the fitness function to fall into a local optimum. The Chebyshev's method is improved by combining the weight summation method [13], and the improved Chebyshev's method is shown as follows:

$$\begin{cases} \left\{ \min g^{te}(x \middle| w^k, z^*) = \max_{1\le j\le m} \left\{ w_j^k \left| f_j(x) - z_j^* \right| \right\} + s\sum_{i=1}^{m} \left| f_j(x) - z_j^* \right| \right. \\ \text{s.t.} \quad x \in \Omega \end{cases} \tag{5}$$

Where *s* is a constant. This method has the characteristics of fast convergence of the weight summation method and good distribution of the Chebyshev's method. The influence of the two methods on the objective function can be balanced by adjusting the size of *s*.

2.4. MOEA/D optimized Wavelet Packet Threshold Denoising

In the process of wavelet packet threshold denoising, the denoising requirements of different noisy signals are different, and the parameters *k* and *a* of the threshold function can be adjusted to meet different signals. The parameters *k*, *a* and threshold λ are optimized by the optimization algorithm to achieve the best denoising effect.

Taking the SNR and the MSE as the evaluation indicators, the calculation formulas are shown in Eqs. (6) and (7), respectively.

$$R_{SNR} = 10\lg \left[\frac{\sum_{i=1}^{n} x^2(i)}{\sum_{i=1}^{n} [(x(i) - y(i))^2]} \right] \tag{6}$$

$$R_{MSE} = \frac{\sum_{i=1}^{n} [x(i) - y(i)]^2}{n} \tag{7}$$

In Eq. (6) and Eq. (7), x(i) is the original signal, y(i) is the denoised signal, and *n* is the number of sampling points. The larger the R_{SNR} is and the smaller the R_{MSE} is, indicating that the denoising effect is better, which can effectively remove noise and retain more details of the signal.

The MOEA/D algorithm is used to optimize the parameters *k*, *a* and the threshold λ, and the multi-objective fitness model of AE signal is established as shown in Eq. (8).

$$\begin{cases} \max & R_{SNR}(k, a, \lambda) \\ \min & R_{MSE}(k, a, \lambda) \\ s.t. & k \ge 1 \\ & a > 0 \\ & 0 < \lambda < \max(x_i) \end{cases} \tag{8}$$

The result of denoising is related to the parameters *k*, *a* and threshold λ of the threshold function. Therefore, the parameters *k*, *a*, and λ can be used as independent variables, and the MOEA/D algorithm can be used to solve the the problem of optimization model. The process is shown in figure 2.

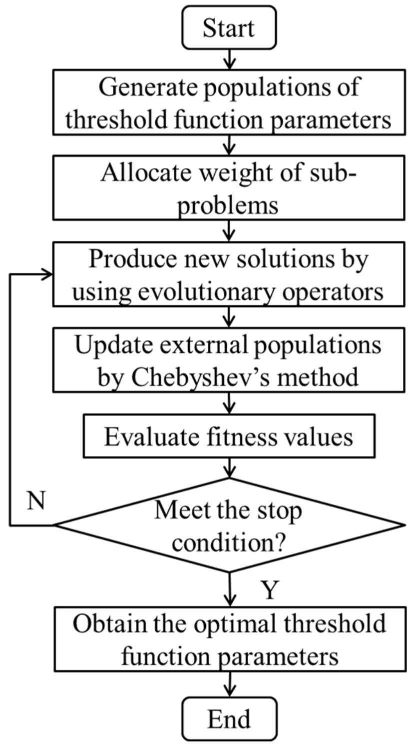
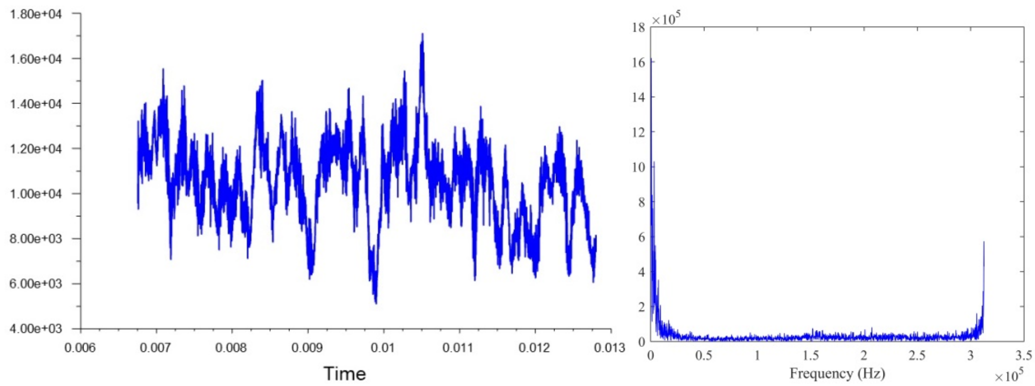


Figure 2. Flow chart of MOEA/D optimized wavelet packet threshold denoising.

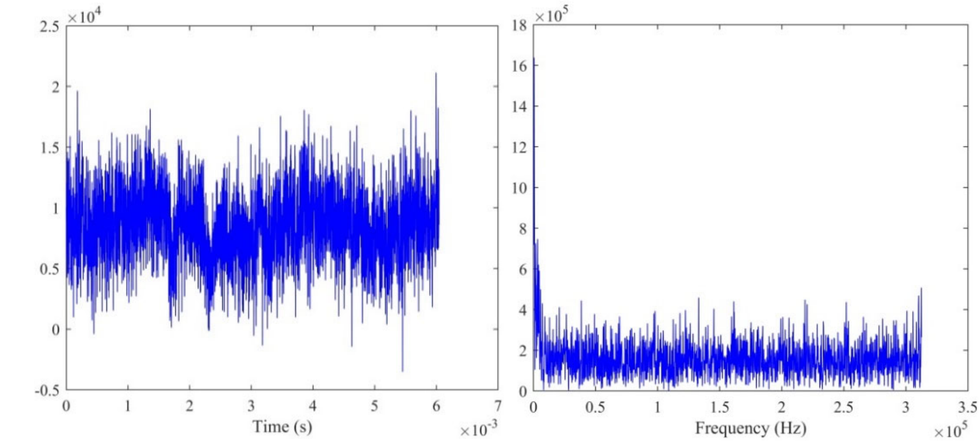
3. Simulation Analysis

Taking the fluid medium as methane, the inlet pressure is 0.3Mpa and the outlet pressure is 1 standard atmosphere, the acoustic pressure signal of the ball valve internal leakage when the valve opening is 5° is obtained by finite element simulation as a pure signal, as shown in figure 3(a), and the frequency spectrum is shown in figure 3(b). From figure 3(b), it can be seen that the signal exhibits a wide frequency range between 0-320 kHz. Gaussian white noise is added to the pure signal to obtain a noise signal with a SNR of 10, as shown in figure 4.



(a) (b)

Figure 3. Sound pressure signal diagram. (a) time domain, (b) frequency domain.



(a) (b)

Figure 4. Noisy signal. (a) time domain, (b) frequency domain.

After the signal is decomposed by the wavelet packet, the value of the decomposed wavelet packet coefficient is less than the threshold is removed by setting a threshold. In order to select the optimal wavelet basis function and the optimal number of decomposition layer, the commonly used symN wavelet and dbN wavelet are selected for soft threshold denoising of noisy signals, and the SNR and the MSE are used as the evaluation indicators.

The SNR of different decomposition layers of symN series wavelet and dbN series wavelet are shown in figure 5 (a) and (b), respectively. And the MSE are shown in figure 5 (c) and (d), respectively.

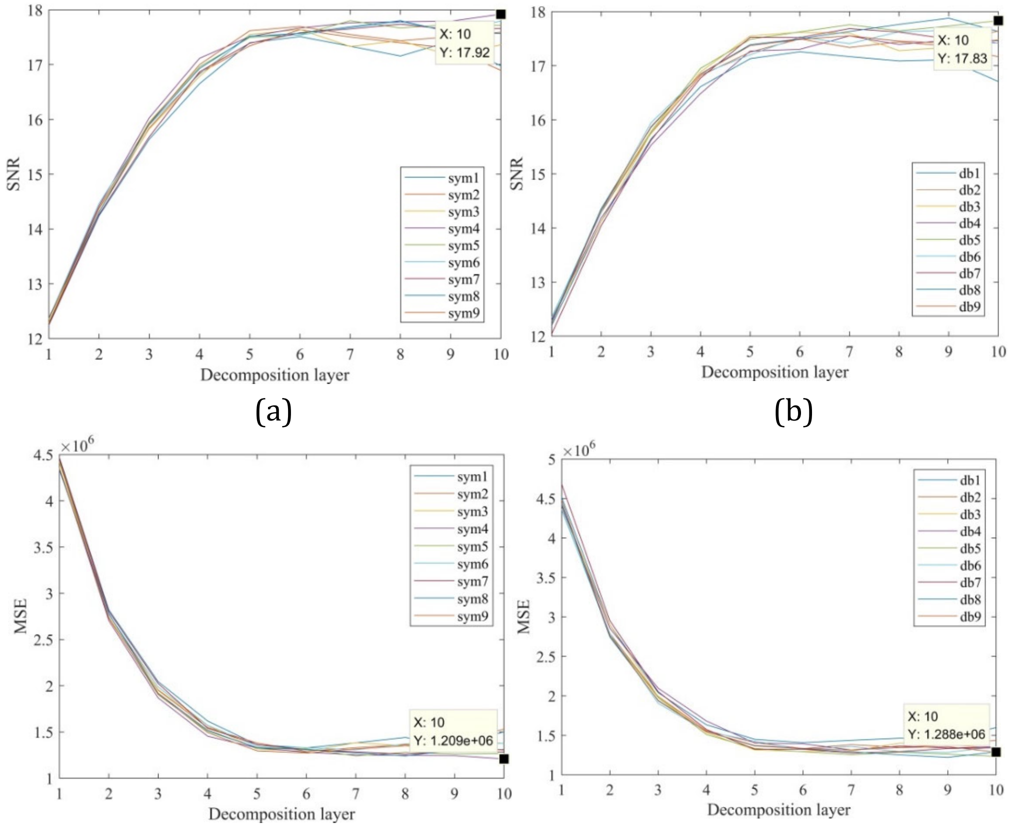


Figure 5. The SNR and MSE of different decomposition layers of symN series wavelet and dbN series wavelet

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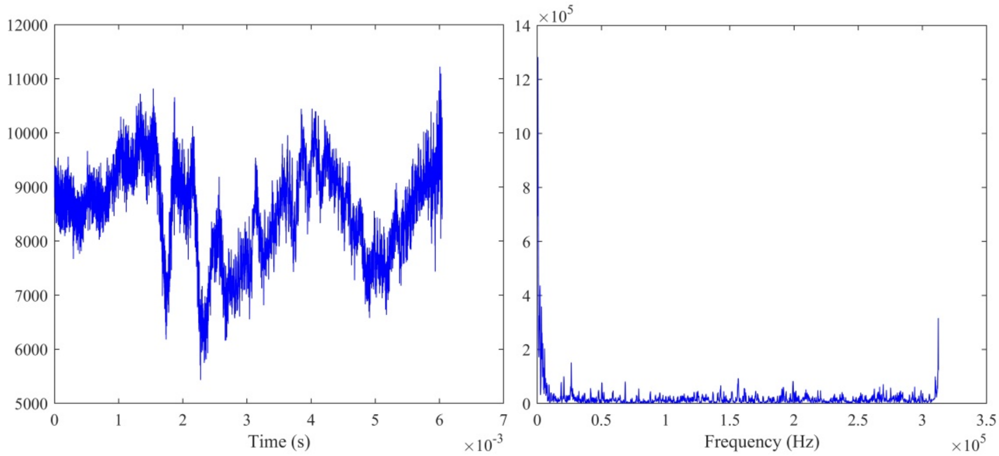
It can be seen from figure 5 that the best effect is achieved when the number of decomposition layer of the sym4 wavelet basis function is 10. However, when the number of decomposition layer of different wavelet basis functions reaches 5, there is little difference in signal-to-noise ratio and mean square error with the increase of decomposition layer. Therefore, the sym4 wavelet basis function is selected, and the number of decomposition layer is 5.

The MOEA/D optimized wavelet packet threshold denoising method is used to denoise the noisy signal. The result is shown in figure 6. It can be seen from figure 6 that the internal leakage sound pressure signal is a broadband signal with a frequency between 0-320kHz. The SNR and MSE of the original signal, wavelet packet threshold denoising and MOEA/D optimized wavelet packet threshold denoising are compared as shown in Table 1.



(a) (b)

Figure 6. MOEA/D optimized wavelet packet threshold denoising to denoise noisy signals. (a) time domain, (b) frequency domain

Table 1. The SNR and MSE of the original signal, wavelet packet threshold denoising, and MOEA/D optimized wavelet packet threshold denoising

	SNR(dB)	MSE
The original signal	10	7.46×10^{6}
Wavelet packet threshold denoising	17.92	1.21×10^{6}
The proposed method	20.41	6.40×10^{5}

It can be seen from Table 1 that the SNR of the sound pressure signal of leakage is significantly increased and the MSE is significantly reduced after the wavelet packet threshold denoising and MOEA/D optimized wavelet packet threshold denoising. And MOEA/D optimized wavelet packet threshold denoising has 12.2% higher SNR and 47.05% lower MSE than wavelet packet threshold denoising. Therefore, MOEA/D optimized wavelet packet threshold denoising is better than wavelet packet threshold denoising.

4. Experimental Analysis

4.1. Experimental Setup

According to the detection principle of the AE signal of the ball valve internal leakage, combined with the requirement and purpose of the experimental research, the natural gas pipeline ball valve internal leakage simulation experimental platform is built as shown in figure 7.

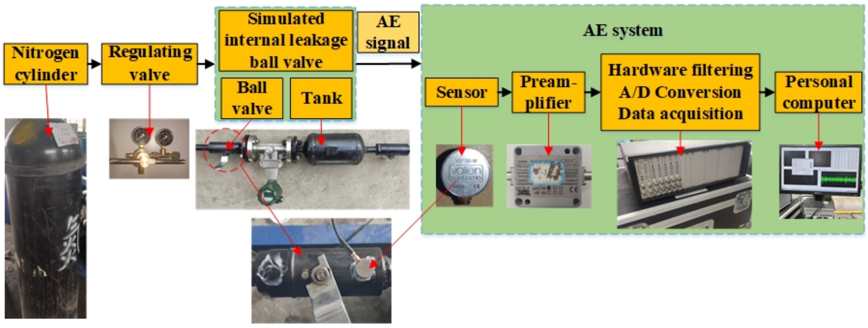


Figure 7. Schematic diagram of the ball valve internal leakage experimental platform.

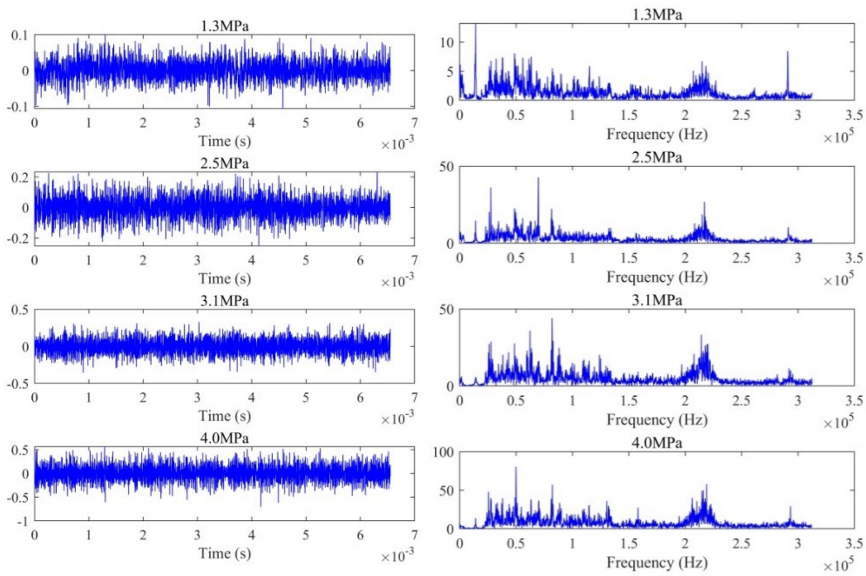
The pipeline diameter is 1 inch, and the maximum pressure resistance is 10MPa. The tested ball valve is an integrated manual switch ball valve. Due to the larger ball valve on the oil and gas station pipeline, it is valve cavity volume is larger, thus the tank is used to simulate the valve cavity, while playing a buffer role, as shown in figure 7. The tank and the ball valve together as a simulation of the ball valve internal leakage. The internal leakage is simulated by adjusting the opening of the ball valve, the leakage medium is nitrogen, and the output pressure can be adjusted within the range of 0-10MPa through the installed pressure regulating valve.

The Vallen Amsy-6 AE acquisition system is used to detect the AE signal of ball valve internal leakage. The sampling frequency is 0.625MHz; the amplification of preamplifier is 36dB; the threshold value is set to 30dB, the sensor model is VS150-M, and Vaseline is used as the coupling agent.

4.2. Experiment and Result

4.2.1. The AE signal of the ball valve internal leakage with different inlet pressures at the same opening

The opening of the ball valve is adjusted to 10°, and the output pressure is adjusted to 1.3MPa, 2.5MPa, 3.1MPa and 4.0MPa respectively, and the AE signal of the ball valve internal leakage is collected as shown in figure 8. The MOEA/D optimized wavelet packet threshold denoising is used to denoise the AE signal of the ball valve internal leakage with different inlet pressures at the same opening, and the results are shown in figure 9.



(a) (b)

Figure 8. The AE signal of the ball valve internal leakage with different inlet pressures at the same opening. (a) time domain, (b) frequency domain.

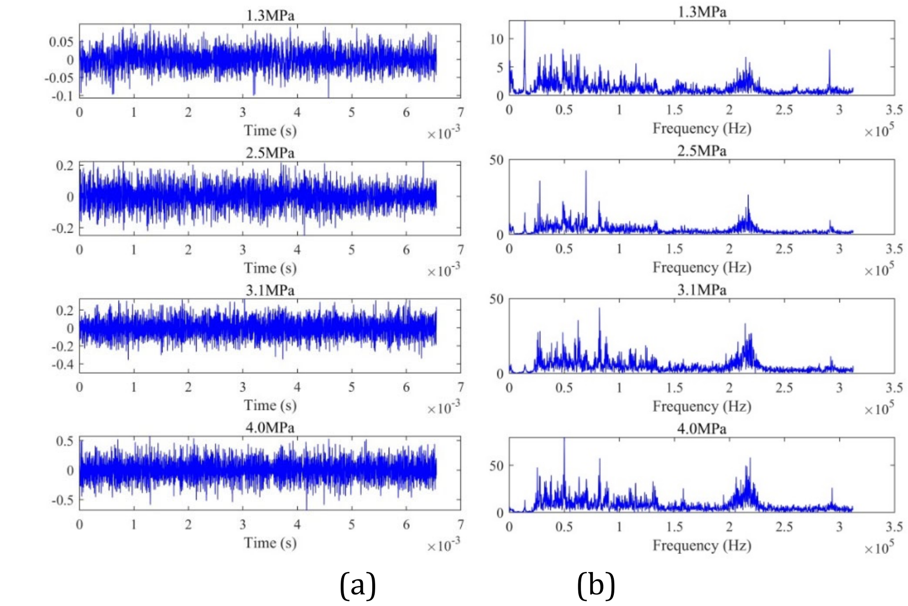


Figure 9. The MOEA/D optimized wavelet packet threshold denoising to denoise the AE signal of the ball valve internal leakage with different inlet pressures at the same opening. (a) time domain, (b) frequency domain.

4.2.2. The AE signal of the ball valve internal leakage with different openings at the same inlet pressure

The output pressure of the nitrogen cylinder is kept at 2MPa, and the opening of the ball valve is adjusted to 10°, 20°, 30° and 40° respectively, and the AE signal of the ball valve internal leakage is collected as shown in figure 10. The MOEA/D optimized wavelet packet threshold denoising is used to denoise the AE signal of the ball valve internal leakage with different openings at the same inlet pressure, and the results are shown in figure 11.

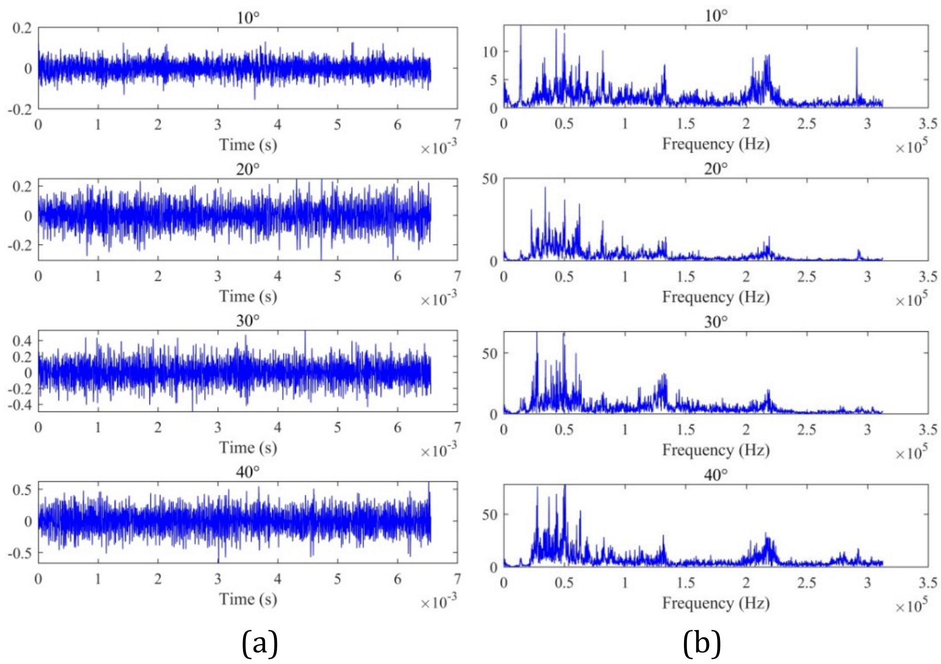
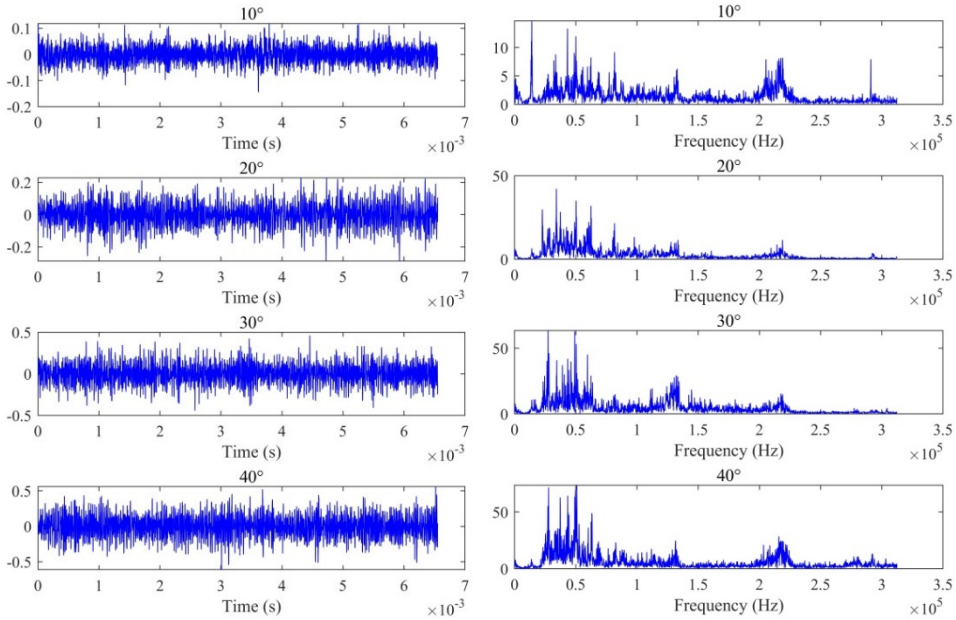


Figure 10. The AE signal of the ball valve internal leakage with different openings at the same inlet pressure. (a) time domain, (b) frequency domain.



(a) (b)

Figure 11. The MOEA/D optimized wavelet packet threshold denoising to denoise the AE signal of the ball valve internal leakage with different openings at the same inlet pressure. (a) time domain, (b) frequency domain.

4.3. Discussion and Analysis

It can be seen from figure 8 and figure 9 that the amplitude of the AE signal of ball valve internal leakage at different pressures increases with the increase of pressure, and its frequency spectrum ranges from 0-320kHz, among which is relatively high at 20-50kHz, 140kHz, and 220kHz. The denoising results of wavelet packet threshold denoising and MOEA/D optimized wavelet packet threshold denoising on AE signal of the ball valve internal leakage with different inlet pressures at the same opening, as shown in Table 2. It can be seen from figures 8, 9 and Table 2 that the proposed method can effectively suppress the burrs in the signal and the signal spectrum information is well preserved, the SNR is improved, and the MSE is reduced. And it can be seen from Table 2 the proposed method improves the SNR by a maximum of 45.65% and reduces the MSE by a maximum of 85.99% compared to wavelet packet threshold denoising.

Table 2. Comparison of SNR and MSE of wavelet packet threshold denoising and MOEA/D optimized wavelet packet threshold denoising of denoising AE signal of the ball valve internal leakage with different inlet pressures at the same opening

	SNR(dB)				MSE			
	1.3 MPa	2.5 MPa	3.1 MPa	4.0 MPa	1.3 MPa	2.5 MPa	3.1 MPa	4.0 MPa
Wavelet packet threshold denoising	10.23	10.28	10.56	9.12	7.22×10^{-5}	44.30×10^{-5}	90.70×10^{-5}	339.4×10^{-5}
The proposed method	17.97	18.02	19.09	16.78	1.22×10^{-5}	7.47×10^{-5}	12.71×10^{-5}	58.50×10^{-5}

It can be seen from figure 10 and figure 11 that when the pressure remains constant, the amplitude of AE signal increases with the increase of the opening of the ball valve, and the frequency domain of AE signal with different openings is roughly the same. The frequency spectrum is between 0-320kHz, and the amplitude is higher at 50kHz, 140kHz, and 220kHz. It can be seen from figures 10(a) and 11(a) that the proposed method can effectively suppress the burr in the signal, and as shown in figures 10(b) and 11(b) that the signal spectrum information is well preserved. The results of SNR and MSE comparison are shown in Table 3. It can be seen from Table 3 that the SNR of the proposed method is 43.23% higher than that of the wavelet packet threshold denoising, and the MSE is 80.04% lower.

Table 3. Comparison of SNR and MSE of wavelet packet threshold denoising and MOEA/D optimized wavelet packet threshold denoising of denoising AE signal of ball valve internal leakage with different openings at the same inlet pressure

	SNR(dB)				MSE			
	10°	20°	30°	40°	10°	20°	30°	40°
Wavelet packet threshold denoising	9.18	10.43	9.71	9.79	14.83×10^{-5}	56.48×10^{-5}	180.2×10^{-5}	298.0×10^{-5}
The proposed method	16.18	17.18	16.57	16.75	2.96×10^{-5}	11.92×10^{-5}	37.16×10^{-5}	60.07×10^{-5}

5. Conclusion

A MOEA/D optimized wavelet packet threshold denoising method is proposed in this paper. On the basis of the wavelet packet threshold denoising, an improved threshold function is adopted, SNR and MSE are taken as evaluation indicators, and the parameters k, a and threshold λ are optimized by MOEA/D optimization algorithm, so as to establish a multi-objective fitness model of the AE signal of the ball valve internal leakage. The simulation signal and experimental signal are compared and analyzed, and the results show that the proposed method can effectively suppress the burr in the signal and retain the signal frequency information well. Compared with the wavelet packet threshold denoising, the proposed method can improve the SNR by a maximum of 45.65% and reduce the MSE by a maximum of 85.99%.

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