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RESEARCH ARTICLE

Research on a Novel Denoising Method for Negative Pressure Wave Signal Based on VMD

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ABSTRACT The key to accurately locate pipeline leakage is to effectively reduce the noise in the leakage signal. However, the leakage signal has the characteristics of nonlinear and dynamic change, and the denoising effect of the traditional method is limited. In order to reduce the positioning error caused by noise, a novel denoising method based on variational mode decomposition (VMD) is proposed. First, the correlation coefficient is used to screen effective intrinsic mode function components. Then, an optimization method of VMD decomposition layers k by using minimum information entropy is utilized. Thus, the optimal number of layers and noise reduction signal can be obtained. Finally, the leakage point can be obtained by the principle of negative pressure wave (NPW). Simulation results show that the SNR can effectively improve by using the method in this paper. In laboratory experiments, this method can be used to effectively denoise the pressure signal while preserving the original signal characteristics as much as possible. Furthermore, From the perspective of positioning accuracy, compared other methods, the proposed method can achieve better positioning effect, and the average relative positioning error is 2.03%.

INDEX TERMS Negative pressure wave, denoising, variational mode decomposition, correlation coefficient, information entropy, leak location.

I. INTRODUCTION

The water pipes are the lifeblood of a city, it provides the most convenient and economical way of transporting water resources. However, during pipeline operation, corrosion, aging and external interference factors may cause pipeline leakage [1], [2], [3]. This may not only pollute urban water sources and threaten people's lives and health, but also cause the waste of water resources. Therefore, in order to reduce the negative impact caused by leakage, it is very necessary to study pipeline leakage alarm and leakage point location.

For water supply pipeline leak detection, the signal processing technology based on acoustic signal [4], optical fiber signal [5]and NPW signal [6]have been widely studied and applied. Among them, the method based on NPW signal is favored by researchers because of its low price, easy operation, long transmission distance, and high stability accuracy [7].

In the urban pipe network, the pressure signal is inevitably mixed with a lot of noise due to the interference of external environment noise, measurement devices, turbulence and pump adjustment. Among them, turbulence is a major reason of strong noise. In addition, due to the change of environments and pipeline conditions, the noise characteristics are not the same [8], [9]. The noise makes it difficult to identify the abrupt point of NPW, which will lead to a large error in locating the leakage point, and sometimes even lead to the location failure. Therefore, the signal noise reduction processing is particularly important. The denoised signal can clearly represent the change of NPW pressure drop caused by leakage.

In the traditional denoising methods, wavelet denoising can be achieved by setting a reasonable threshold [10]. But if the pressure signal and the noise are both uncertain, it is

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difficult to choose an accurate threshold. Empirical mode decomposition (EMD) can be used for adaptive signal decomposition. However, this algorithm lacks sufficient mathematical theory derivation, and there are some problems of mode aliasing and end effect [11]. Although ensemble EMD (EEMD) improves some of the shortcomings of EMD, it still lacks the definition of extreme points, and the robustness of signal decomposition is not good enough [12]. To solve the above problems, Dragomiretskiy [13] proposed VMD, and it is based on Wiener filtering theory. VMD is different from the cyclic screening and stripping signal processing method used by EMD and EEMD algorithms when acquiring IMF components. Instead, the signal decomposition process is transferred to the variational framework, and the frequency center and bandwidth of each component are determined by iteratively searching the optimal solution of the variational model. Thus, the signal can be self-adaptive to achieve frequency domain segmentation and effective separation of each component, and the local features of the data can be highlighted. This method has better noise robustness and good sampling effect [14]. This algorithm has sufficient mathematical theory foundation. It overcomes the problems of EMD and EEMD algorithms [15].

The signal decomposition degree is determined by the number of VMD decomposition layers k. Therefore, researchers have proposed many VMD parameter optimization methods. Li et al. [16] proposed a novel feature extraction method of ship-radiated noise signal based on VMD and slope entropy. Zhang et al. [17] utilized the maximum weighted kurtosis index. Diao et al. [18] proposed a parameter optimization method based on particle swarm optimization (PSO). In order to determining the number of modes, Li et al [19]proposed a frequency-aided method. In order to solve the problem of rolling element bearing fault diagnosis under complicated operating conditions, Ni et al [20] proposed a fault information-guided VMD (FIVMD) method for extracting the weak bearing repetitive transient. Compared with the traditional methods, these methods have achieved good results. However, they also have the disadvantages of large amount of computation and long computation time [21]. In order to solve these problems effectively, a new method based on minimum information entropy is proposed to optimize the k value, and the optimal noise reduction signal is obtained.

VMD is used to breaks down the leak signal into multiple IMF components. The noise is mainly located in the invalid IMF component, while the very important pressure signal is contained in the effective IMF component. Obviously, we need to select the IMF component containing the effective pressure signal to reconstruct the signal, so that denoising can be achieved. Therefore, the setting and selection of IMF is particularly important.

Based on the VMD, this paper proposed an adaptive noise reduction method for leakage signals of urban water supply pipelines. The correlation coefficient is firstly used to screen the effective IMF components, and the optimal decomposition layers number k is determined and the optimal denoising signal is obtained by using the minimum information entropy. Finally, the time difference is obtained through the optimal denoising signal to achieve the accurate leakage location.

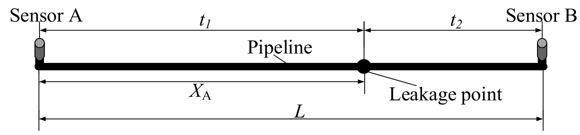

FIGURE 1. Schematic diagram of leak location based on NPW.

II. METHODOLOGY

A. THE PRINCIPLE OF PIPELINE LEAKAGE LOCATION BASED ON NPW

The schematic diagram of leak location based on NPW is shown in Figure 1. When a water supply line leaks, there is a sharp drop in pressure at the leak point. This pressure drop will propagate as a NPW to the upstream and downstream ends of the pipe. This abrupt pressure point is often referred to as the NPW inflection point. Through the upstream and downstream NPW inflection point respectively, the time difference Δt between them to the two sensors can be calculated. As shown in Figure 1, when the pipe length L, the NPW velocity v and time difference $\Delta t = t_1 - t_2$ are known, we can calculate the position of leakage point through Eq. (1).

$$X_A = \frac{1}{2}(L + v\Delta t) \tag{1}$$

where the NPW velocity v can be calculate by Eq. (2) [22]:

$$v = \sqrt{\frac{K/\rho}{1 + \frac{K}{E}\frac{D}{e}C_1}} \tag{2}$$

where,

K-Bulk modulus of water, Pa;

ρ-Density of water, kg/m^3;

E - Young's modulus of pipe material, Pa;

D - Pipe inner diameter, m;

e - Tube thickness, m;

C_1 - Correction factor. C_1 is related to the constraint conditions of the pipeline [23], which is set as 1 in this paper.

In Eq. (1), the pipe length L can be measured. Under the same pipe condition, v is a constant. Therefore, the accurate calculation of Δt is the key problem of leak location. As mentioned above, Δt is obtained from the inflection point of the two NPW. Because of noise, the accuracy of determining inflection point will be reduced, thus affecting the accuracy of leakage point positioning. In order to solve this problem, this paper extraction method of inflection point, and finally realizes the purpose of reducing the positioning error of leakage point.

B. ADAPTIVE NOISE REDUCTION METHOD BASED ON VMD

1) SIGNAL DECOMPOSITION BASED ON VMD

VMD decomposes the signal into k IMF components, and the bandwidth of each component in the frequency domain has a specific sparsity. The bandwidth of each IMF component is obtained by H^1 Gaussian smoothing of the demodulated signal, and the constrained variational problem of VMD is defined as [24]:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] \mathrm{e}^{-j\omega_k t} \right\|_2^2 \right\}$$
$$\text{s.t.} \sum_k u_k = f \tag{3}$$

where, $\{u_k\} = \{u_1, \ldots, u_k\}$ is k IMF components by decomposing the signal f, and $\{\omega_k\} = \{\omega_1, \ldots, \omega_k\}$ represents the center frequency corresponding to each component. In order to solve the constrained variational problem of Eq. (3), the Lagrange multiplier λ and the quadratic penalty factor α are introduced at the same time. The augmented Lagrange function is shown in Eq. (4):

$$\begin{aligned} &L\left(\{u_k\}, \{\omega_k\}, \lambda\right) \\ &= \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \\ &\quad + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle \end{aligned} \tag{4}$$

Alternate direction method of multipliers (ADMM) is used to obtain the saddle point of Eq. (4), and iteratively update u_k, ω_k and λ to obtain the optimal solution in the frequency domain, thereby obtaining each intrinsic mode function $\{u_k\}$ and its corresponding center frequency $\{\omega_k\}$.

2) PARAMETER OPTIMIZATION BASED ON INFORMATION ENTROPY

Assuming a one-dimensional random sequence $x(n) = (x_1, x_2, \ldots, x_i, \ldots, x_n)$. If the probability of obtaining x_i obeys the probability distribution $p(x_i)$. Then, the information entropy $H(x)$ of the sequence can be expressed as:

$$H(x) = -\sum_{i=1}^{n} p(x_i) \log p(x_i) \tag{5}$$

The larger the $H(x)$, the higher the uncertainty of the probability distribution $p(x_i)$.

After using VMD to decompose signals, the effective IMF components are used to reconstruct the noise reduction signal. However, the algorithm needs to predetermine the decomposition number k of IMF, which will directly affect the degree of signal decomposition and the center frequency $\{\omega_k\}$. Therefore, the noise reduction effect of each k value corresponding to the reconstructed signal is different. The optimization of k value is particularly important for signal noise reduction. Considering that information entropy is a dimensionless index that can be used to describe the uncertainty of the system, this index has a simple principle and can be used as a basis for the selection of system parameters. When using VMD to denoise signals, noise signals appear more disordered than pressure signals, and its uncertainty is greater. Therefore, the information entropy can be used as a characterization of the noise content in the signal. The less noise the reconstructed signal contains, the smaller its information entropy. When the information entropy reaches the minimum, the noise in the reconstructed signal is considered to be the minimum. The k value is optimal and the denoising effect is optimal.

Before the optimal k can be calculated, the reconstructed signals corresponding to different k values should be obtained first. Therefore, in order to achieve signal reconstruction, it is necessary to screen the effective IMF components.

3) IMF COMPONENTS SELECTION AND SIGNAL RECONSTRUCTION

In the process of leak detection and location of urban water supply pipeline, the signal collected by the sensor are all random signals. When using VMD for signal decomposition and noise reduction, an important problem is to retain the effective component and eliminate the noise component. The conventional method is to select the effective component through the empirical parameters. The disadvantage of this method is that the prior information of signal and noise needs to be mastered in advance. To overcome the above deficiencies, the effective IMFs is screened by using correlation coefficient in this paper. According to [25], in the absence of fixed interference, we can assume that the two noise signals collected by the sensors are not correlated, while the negative pressure wave signals are correlated. One of the two signals is used as a detection signal, and the other is used as a reference signal. Firstly, VMD is used to decompose the detection signal into multiple IMF components. Secondly, the correlation coefficient between each IMF component and the reference signal is calculated. Finally, the effective components containing the pressure signal are selected for signal reconstruction.

The signals collected by the two sensors are $x_1(t)$ and $x_2(t)$ respectively:

$$\begin{cases} x_1(t) = s(t) + n_1(t) \\ x_2(t) = \beta s(t - \Delta t) + n_2(t) \end{cases} \tag{6}$$

where $s(t)$ is the pressure signal, β respects the attenuation factor, $n(t)$ is noise.

In the process of applying the correlation analysis signals, the IMF component containing the pressure signal is strongly correlated with the reference signal, and vice versa. Therefore, the components with strong correlations will be retained. Let $x_1(t)$ be decomposed by VMD into k components: $u_1(t), u_2(t), \ldots, u_k(t)$, then the correlation coefficient between the k-th component $u_k(t)$ and $x_2(t)$ can be expressed as:

$$R_{ux} = \frac{\sum_{i=1}^{n} (u_{k,i} - \bar{u}_2)(x_{2,i} - \bar{x}_2)}{\left\{ \sum_{i=1}^{n} (u_{k,i} - \bar{u}_2)^2 \sum_{i=1}^{n} (x_{2,i} - \bar{x}_2)^2 \right\}^{1/2}} \tag{7}$$

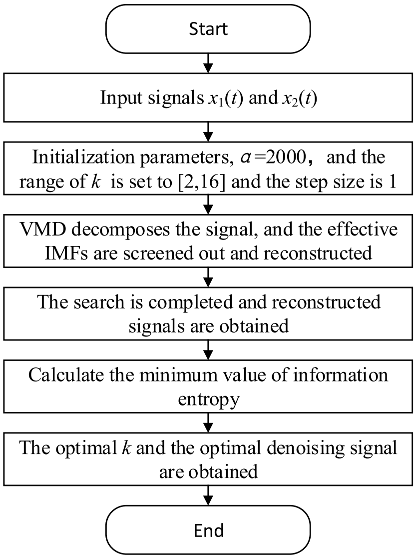

FIGURE 2. Adaptive noise reduction process based on VMD.

where $\bar{u} = \sum_{i=1}^{n}(u_{k,i})/n$, $x = \sum_{i=1}^{n}(x_{2,i})/n$, and n is the length of the signal. To simplify the calculation, the absolute value of Eq. (7) is taken and normalized. According to the definition of correlation coefficient [26], we consider those IMF components with relatively higher correlation coefficients ($R_{ux} \geq 0.3$) to be effective components and labeled as $u_i'(t)$. The $u_i'(t)$ will be used for signal to reconstruction. The reconstructed signal is called x'':

$$x'(t) = \sum_{i} u_i'(t) \tag{8}$$

According to the above method, the reconstructed signal under different k values can be obtained. Then, the reconstructed signal with minimum information entropy is found. The optimal k and the optimal denoising signal can be obtained. And obviously there is a problem here, which is that the larger the value of k, the greater the amount of computation. Li et al. [27] searched the range for optimizing k. According to their research results, the range of k is set to [2], [16], and the step size is 1, and the penalty factor [28] α is 2000 in this paper.

To sum up, the proposed VMD-based leakage signal adaptive noise reduction process is shown in Figure 2. The algorithm is executed are as follows:

1) Two leakage signals $x_1(t)$ and $x_2(t)$ are respectively collected by sensors at both ends of the pipeline. Initialize the parameters k, step size and α.

2) VMD is used to decompose the signal into k IMF components. The method in section *II-B3*) is used to select effective IMF components and reconstruct them.

3) Calculate the information entropy of the reconstructed signals. According to the minimum information entropy, the optimal decomposition layers k and the optimal denoising signal are searched out.

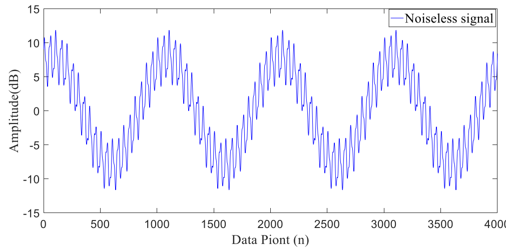

FIGURE 3. The simulated noiseless signal.

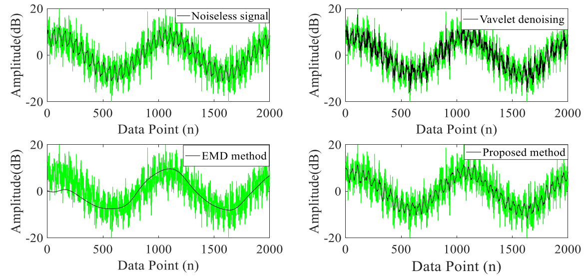

FIGURE 4. Simulation signal and the other three methods denoising results.

According to the above analysis, experience parameters do not need to be set in advance by using the method proposed in the paper, and the principle is simple and the calculation amount is small.

III. SIMULATION EXPERIMENT

In order to verify the denoising ability of the proposed method, the simulation signal composed of three frequency components, 100 Hz, 40 Hz and 2 Hz, is constructed in this section.

The constructed simulation signal is shown in Figure 3 and is called noiseless signal. As mentioned above, there is a time difference when the NPW caused by leakage propagates to both ends of the pipe. In order to objectively apply the proposed method, X_1 is delayed by 20 points to obtain the reference signal X_2. The signal curve of X_2 is similar to X_1 and is therefore not shown.

Gaussian white noise is added to the noiseless signal, and the noisy signal with SNR of 4 dB is obtained. The low-pass filter method [29], wavelet denoising [30], EMD method [6] and the proposed method are used to denoise the noisy signal. Figure 4 shows the noisy signal (green part), the noiseless signal and the denoising results of the three methods. The result obtained by low-pass filter is similar to the wavelet method, and it is therefore not shown. In order to clearly observe the processing effect of each method, 2000 data points of the denoised signals are shown in the Figure3.

In Figure 4, the green part represents the noisy signal, and the black curve represents the noiseless signal and the denoising results of each method. The image on the right of the first row is the effect of wavelet denoising. The left figure in the second row is the effect diagram of EMD denoising. The right figure in the second row is the denoising effect

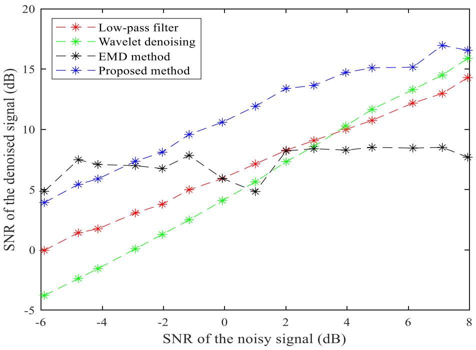

FIGURE 5. The SNR of the signal after denoising by each method.

of the method proposed in the paper. As can be seen from the figures, the signal after wavelet denoising still has a lot of noise, and it is difficult to observe the real curve of the noiseless signal. The low-pass filter method has a similar result and is not shown here. The result of the EMD method is extremely smooth. The result is inconsistent with the curve of the noiseless signal, and the signal has been distorted. The signal curve of the proposed method is well consistent with the noiseless signal, and the useful characteristic information is well conserved. Therefore, the proposed method achieves effective noise reduction for the noisy signal.

In order to verify the denoising effect of the proposed method under different SNR, noisy signals with different SNRs were obtained by adding Gaussian white noise of different intensities to the noiseless signals. The low-pass filter method, wavelet denoising, the EMD method and the proposed method are used, and the denoising results are shown in Figure 5. In this figure, the abscissa is the SNR of the noisy signal, and the ordinate is the SNR of the signal after denoising.

In Figure 5, the SNR of the proposed method is significantly higher than that of the low-pass filter method and wavelet denoising. As the SNR of the noisy signals increases, the SNR of these three methods gradually approaches. This may be because the empirical parameters set by the low-pass filter and wavelet denoising are more suitable for the condition of relatively high SNR. The EMD method has three results with higher SNR than the proposed method. However, these results are similar to the EMD result in Figure 4, where the signal has been distorted. The average SNR improvement of the proposed method is 11.22 dB, which is about 3.91-5.4 dB higher than the other three methods.

It can be concluded that compared with the other three methods, our method can effectively improve the SNR of the signal and conserve the useful characteristic information of the original signal. This method is more suitable for the denoising of the NPW signal.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL ENVIRONMENT

To verify the NPW denoising effect of various methods, a leakage simulation experimental system was built, as shown in Figure 6.

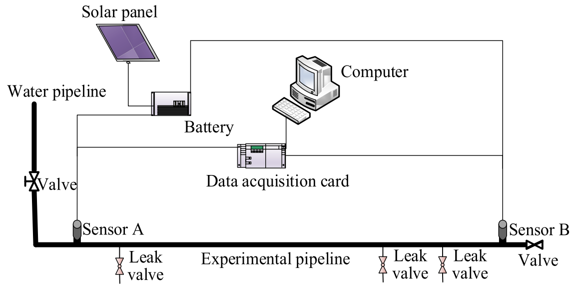

FIGURE 6. Schematic diagram of the experimental system.

TABLE 1. The simulated leak point layout.

Experiment number	L (m)	Leak point	L_A (m)
		1	14.47
1	17.34	2	11.34
		3	2.47
		4	17.34
2	23.34	5	14.47
		6	2.47

The experimental pipeline is directly connected to the urban water supply network. The pipe material is carbon steel, and the inner diameter of the pipe is 0.08 m. We simulated the burst leakage by rapidly opening a valve, and the leakage area is about 25 mm^2. A high frequency dynamic pressure sensor with a range of 0∼0.6 MPa is used to collect pressure signals. The sensors are powered by the battery. The data collected by the pressure sensor is transmitted to the computer by acquisition card. The sampling frequency of the signal is 2000Hz, and the pressure in the pipeline fluctuates slowly between 0.16 MPa and 0.21 MPa.

In order to verify the effectiveness of the proposed method, the results of two groups of experiments are provided in this paper. The design of experimental parameters is shown in Table 1. Where, L is the length of the pipeline between the two sensors, and L_A is the distance between the leak point and sensor A. In the first set of the experiment, L is 17.34 m, and three simulated leaks 1, 2 and 3 are set. L_A corresponding to these leakage points is 14.47 m, 11.34 m, and 2.47 m, respectively. In the second set of the experiment, L is 23.34 m, and three simulated leaks 4, 5 and 6 are set. L_A corresponding to these leakage points is 17.34 m, 14.47 m, and 2.47 m, respectively.

According to the parameters in Table 2, the NPW velocity is calculated. Ref. [14] studied leakage location of water supply pipeline in two experimental environments. The fluid in the pipe and the material and dimensions of the metal pipe are similar to this paper. Therefore, we adopt the same bulk modulus of water and Young's modulus of pipe material as in Ref. [14].

TABLE 2. Experimental parameters.

Pipeline inner diameter (D)	0.08 m
Density of the water (ρ)	998.203 kg/m^3
Tube thickness (e)	0.003 m
Bulk modulus of water (K)	2.1×10^8 Pa
Young's modulus of pipe material (E)	2.1×10^{11} Pa
Sampling rate (f)	2000Hz
Pressure of the pipeline	0.16~0.21 MPa

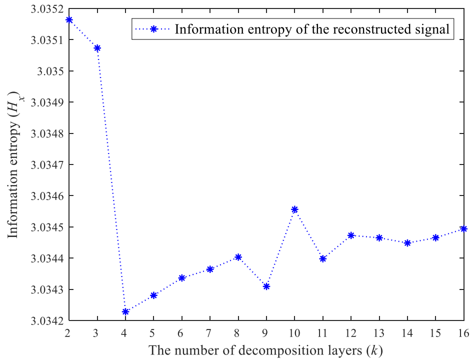

FIGURE 7. Information entropy of the reconstructed signal corresponding to different *k* values.

According Eq. (2), the wave velocity v of the NPW is 452.67 m/s.

The environmental conditions of the real urban water supply pipeline system are very complicated, and the external temperature may change greatly along the pipeline. The temperature will affect the Young's modulus of pipe material and the bulk modulus of water, which will affect the velocity of the NPW. Therefore, in the complex urban pipeline environment, it is necessary to calibrate the wave velocity according to the actual situation.

B. LEAK SIGNAL DENOISING

According to the noise reduction process in section *II-B*, the leak signal is denoised. The information entropy of the reconstructed signal corresponding to different k values is shown in Figure 7.

In Figure 7, when k is 4, the information entropy is minimum. At this time, the k value is the optimal, and the noise in the reconstructed signal is relatively the least, and the denoising effect is the optimal. Similarly, the optimal denoising signal under the condition of no leakage can be obtained.

The denoising results of the proposed method are compared with the low-pass filter method [29], wavelet denoising [30], and the EMD method [6]. The cut-off frequency of the low-pass filter is 20 Hz. A 'Sym4' wavelet with 4-layer decomposition is used when applying wavelet denoising [30]. EMD uses the IMF components selection method as described in section *II-B3*). Figure 8 is the denoising results of the leak signal.

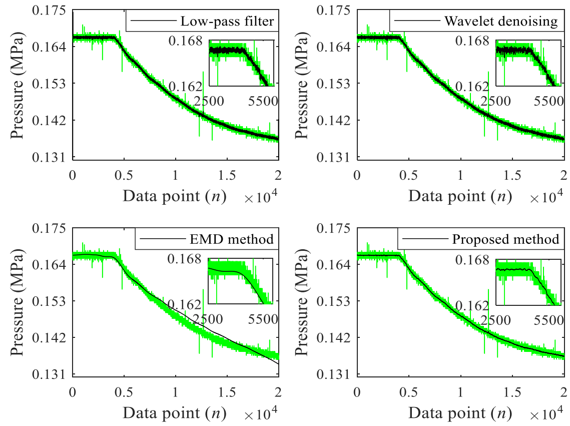

FIGURE 8. Comparison of leak signal denoised by four methods(2000Hz).

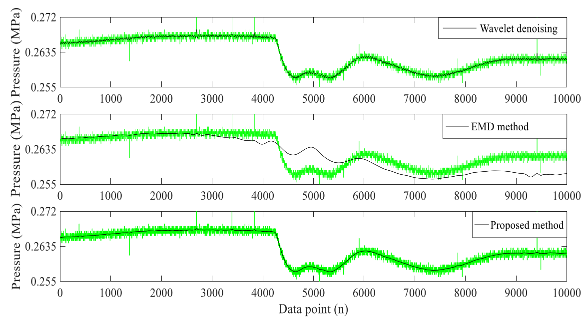

FIGURE 9. Comparison of leak signal denoised by four methods(500Hz).

In Figure 8, the green part represents the leakage signal, and the black curve is the denoising results corresponding to each method. The inflection point area of the NPW is partially enlarged, as shown in the rectangular box. When a leak occurs, the inflection point is completely covered by noise, despite the obvious pressure drop, and the leakage localization cannot be carried out. After the signal is denoised by low-pass filter or wavelet denoising, although the abrupt noise is effectively suppressed, it can be seen from the denoising results that there are still small noises in the processed signal, which also makes it difficult to obtain the inflection point of pressure drop. For EMD, its denoising effect is similar to that of simulation signal. Although the small noise is eliminated and a smooth signal is obtained, the signal is distorted due to excessive smoothing of the original signal. Similarly, the inflection point of NPW is also difficult to extract. After the signal is denoised by the proposed method, not only a smooth signal is obtained, but also the inflection point of the NPW is also obvious, which obviously provides a strong support for the precise location of the leakage point.

In order to verify the effectiveness of the proposed algorithm, under the condition that the sampling frequency is 500Hz, the leakage condition in Table 2, where L is 17.34m and L_A is 2.47m, is tested. Wavelet method, EMD method and the method proposed in this paper are adopted for noise reduction, and the results are shown in Figure 9.

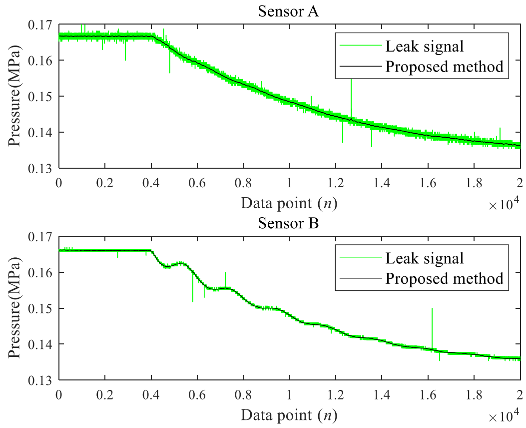

FIGURE 10. Leak signal and its denoised signal.

An analysis of the denoising results in Figure9 shows that the wavelet denoising results still contain a large number of small noises and burst disturbances, which are likely to cover up the real inflection point when extracting the negative pressure wave inflection point. The results obtained by EMD method are very smooth, but the noise reduction signal has been seriously deviated from the real negative pressure wave curve. The method proposed by this paper obtains a relatively smooth signal curve, and the small fluctuation and burst interference are well suppressed. The noise reduction results are basically consistent with the fluctuation trend when the sampling frequency is 2000Hz, and the pressure drop curve caused by leakage is also very clear, which lays a foundation for accurately extracting the inflection point of negative pressure wave.

C. LEAKAGE LOCATION

Take leakage point 4 in Table 1 as an example for analysis, due to the external environment and the pressure fluctuation in the water supply pipeline, the leakage signal collected by the sensor has a lot of abrupt noise and small noise. These noises obviously affect the accurate extraction of the inflection point of the NPW, thus increasing the positioning error. Therefore, the method proposed in this paper will be used to denoise the two leakage signals. The denoising results are shown in Figure 10. The denoised signal is very smooth and retains the waveform characteristics of the original signal, and has an obvious inflection point of the NPW.

In order to calculate the time difference Δt between the two NPW signals. Let the inflection point of the NPW signal collected by sensor A be n_1 and that of NPW signal collected by sensor B be n_2. The sampling frequency is f ($f = 2000$ Hz).

$$\Delta t = \frac{n_1 - n_2}{f} \tag{9}$$

In order to verify the advantages of our method in leak location, four methods are used to locate the leak point 4. In the rectangular box in Figs. 10-13, the red and green curves represent the denoised signal and the original leakage signal

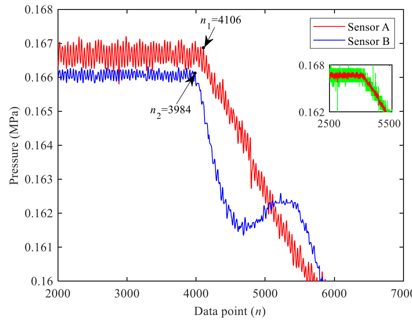

FIGURE 11. The result of the low-pass filter method.

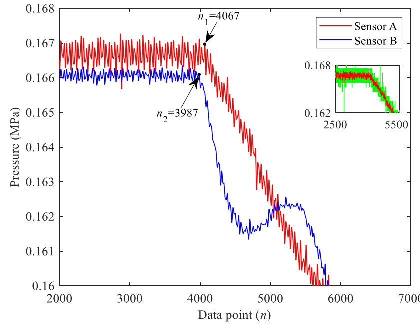

FIGURE 12. The result of wavelet denoising.

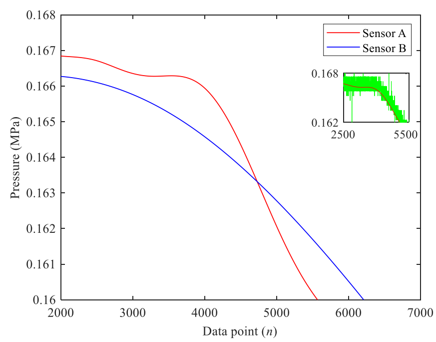

FIGURE 13. The result of the EMD method.

of sensor A, respectively. The result of sensor B is similar. Therefore, it is not shown in the figure. The result of the low-pass filter method is shown in Figure 11, where n_1 =4106 and n_2 =3984. Substituting n_1 and n_2 into Eq. (9), we get $\Delta t = 0.061s$. According to Eq. (1), if $L = 23.34$ m, then $X_A = 25.48$ m. The real distance between the leak point and sensor A is 17.34 m. Therefore, the absolute error is 8.14 m, and the relative positioning error is 34.88%. In Figure 12, the result of wavelet denoising is similar to that of the low-pass filter method. According to the above calculation method, X_A is obtained as 20.72 m. The absolute positioning error is 3.38 m, and the relative error is 14.48%. The result of the EMD-based method is shown in Figure 13. There is no obvious inflection point in the figure, and it is difficult to locate the leakage. The result of the proposed method is shown in Figure 14. X_A is

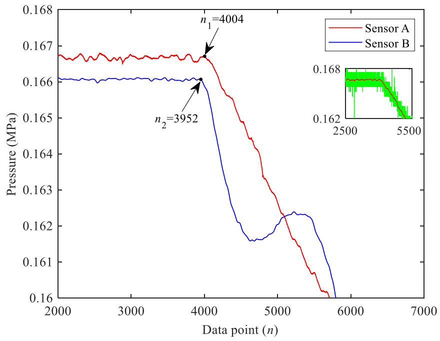

FIGURE 14. The result of the proposed method.

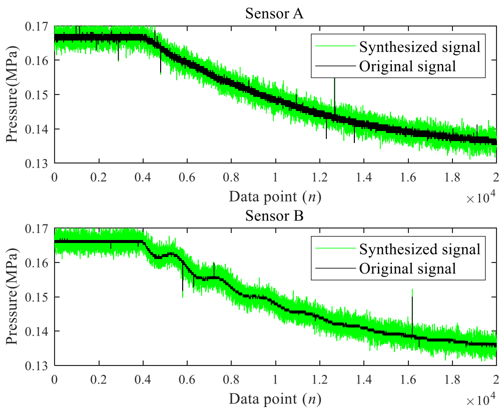

FIGURE 15. Original signal and its synthesized signal.

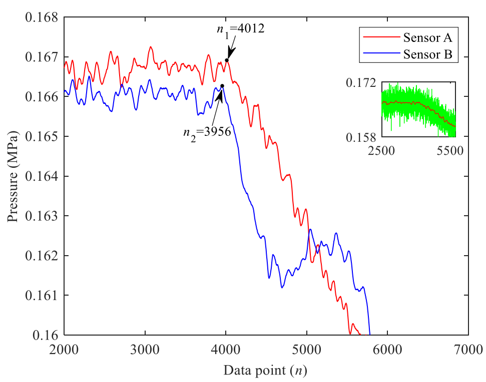

FIGURE 16. The synthesized signal is denoised by the proposed method.

obtained as 17.55 m. The absolute positioning error is 0.21 m, and the relative error is 0.9%.

In order to study the application effect of the proposed method under the condition of relatively low SNR. Two synthesized signals with relatively low SNR are obtained by adding Gaussian white noise with a frequency range of 0-1 kHz to the original leakage signal. As shown in Figure 15, the black part is the original leakage signal, and the green part is the synthesized signal. Compared with the original leakage signal, the noise in the synthesized signal is greatly increased, and the inflection point of the NPW is more difficult to identify.

TABLE 3. Leak location results.

#	※	L_A (m)	X_1 (m)	E_1 (%)	X_2 (m)	E_2 (%)	X_3 (m)	E_3 (%)
	1	14.47	9.35	29.53	12.86	9.28	14.22	1.44
1	2	11.34	8.44	16.72	8.67	15.4	11.61	1.56
	3	2.47	4.03	9	No	No	2.9	2.48
	4	17.34	25.48	34.88	20.72	14.48	17.55	0.9
2	5	14.47	×	×	15.29	3.51	15.18	3.04
	6	2.47	×	×	7.94	23.44	1.82	2.78

The effect of the method proposed in this paper on the noise reduction of the synthesized signal is shown in Figure 16. The red and green curves represent the denoised signal and the synthesized signal of sensor A, respectively. Compared with Figure 14, the denoising result of the synthesized signal has more small fluctuations. Nevertheless, the inflection point is still clear. To study the influence of the added noise on the leakage location, the leak point 4 is located according to the inflection point of the two denoised signals. The positioning result is 18 m, the absolute error is 0.66 m, and the relative error is 2.83%. This error can meet the requirements of actual leakage location. When using the low-pass filter method, wavelet, and the EMD to process the synthesized signal, the leakage location is not realized. Therefore, our method still has certain applicability under strong noise conditions.

To further verify the leakage location effect of the proposed method, four methods were used to locate the remaining five leak points in Table 1, and the results are shown in Table 3. Where, X_1 is the positioning result of the low-pass filter method, and E_1 is the relative positioning error; X_2 is the result of the wavelet method, and the relative positioning error is E_2; X_3 is the result of the proposed method, and the relative positioning error is E_3. "×" indicates that the location fails. The EMD method does not achieve localization. The results are not listed in Table 3.

The pressure signal in the pipeline has non-stationary and non-linear characteristics. However, the low-pass filter method and wavelet denoising rely on experience to select parameters, and their denoising effects on such signals are limited. The method based on EMD distorts the reconstructed signal due to modal aliasing and end effects. After screening out the effective IMF components and optimizing the number of decomposition layers, the proposed method realizes adaptive noise reduction of the leakage signal. In addition, this method is based on VMD, which can effectively eliminate modal aliasing. Therefore, compared with the other three methods, the proposed method has better adaptability and robustness to noise interference.

In Table 3, the minimum relative positioning errors of the low-pass filter method and wavelet denoising are 9% and 3.51% respectively, and the positioning cannot be performed when the error is largest. In this paper, the denoising method based on EMD always fails to locate the leakage point. The minimum relative positioning error of the proposed method is 0.9%, and the maximum is 3.04%. Therefore, compared with the other three methods, the proposed method has a smaller leakage location error, and the location result is more stable.

Based on the above experimental results, we compare the positioning effect of the method proposed in this paper with that of wavelet only when the sampling frequency is 500Hz. The leakage location is conducted according to the experimental conditions in Table 2, where L is 17.34m and L_A is 2.47m. The leak location value of wavelet method is 8.67m, and the relative error is 35.76%. The leak location value of the method proposed by us is 2.03m, and the relative error is 3%. Compared with the wavelet method, the proposed method has higher positioning accuracy and more stable results. This conclusion is consistent with the experimental results at 2000Hz sampling frequency. Therefore, it can be considered that the method proposed in this paper can achieve good results in denoising the leakage pressure signal of water supply pipeline and locating the leakage point.

V. CONCLUSION

Due to the influence of noise contained in the pressure signal, it is difficult to locate the leakage point when the leakage occurs. In order to solve the problem of noise interference, this paper proposed an adaptive denoising method for the leakage signal based on VMD, which effectively improves the accuracy of pipeline leakage location. The main conclusions are as follows:

1) When VMD decomposes signals, it is difficult to select effective IMF components after decomposition due to the need to set the number of decomposition layers in advance, coupled with its disadvantages of modal aliasing and end effect. The proposed method uses correlation coefficient to screen the effective IMF components. According to the minimum value of information entropy, the number of decomposition layers is determined and the optimal noise reduction is achieved. Based on this, this method has good adaptability and improves the dependence of traditional denoising methods on empirical parameters.

2) Simulation experiments show that the proposed method can effectively improve the SNR. The denoising results of the leakage signal show that, compared with the other three methods, the proposed method retains the signal waveform characteristics, and can identify an obvious inflection point of NPW.

3) The leakage location results show that, compared with the traditional methods, the minimum relative error of the proposed method is reduced by 2.61%. This further demonstrates the effectiveness of the proposed method in pipeline leak location.

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