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Research on Weak Vortex Signal Detection Based on Stochastic Resonance

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Abstract. Vortex flowmeters are easily affected by vibration interference of pipelines and various equipment when used in industrial field. Especially in the measurement of small flow, the noise signal will be superimposed on the output signal of the sensor, the vortex signal is easily submerged, and the measurement of small flow is limited. Aiming at the problem that the small flow vortex signal is very weak and difficult to detect under actual working conditions, an adaptive stochastic resonance(ASR) detection method based on ensemble empirical mode decomposition(EEMD) is proposed. Firstly, the vortex signal is denoised and preprocessed by EEMD, and the appropriate component is selected to reconstruct the signal by using the correlation coefficient as the screening criterion. Then, the system parameters are optimized in parallel by particle swarm optimization to achieve the best stochastic resonance result. The numerical simulation and experimental research results show that this method can improve the output power spectrum amplitude of the vortex signal with small flow, effectively obtain the vortex frequency, realize the measurement of small flow, and enhance the detection ability of weak signal.

Keywords. vortex flowmeter; signal processing; stochastic resonance; ensemble empirical mode decomposition

1. Introduction

Vortex flowmeter is a vibrating flowmeter, and its frequency is proportional to the flow rate. However, various vibrations in the industrial site make the vortex signal mixed with noise, especially in the measurement of small flow, the vortex signal is weak and easily overwhelmed by noise, resulting in limited measurement [1-2]. Scholars at home and abroad have done a lot of research on vortex signal processing methods, such as classical spectrum analysis method, wavelet transform method, adaptive filtering method, etc. [3-5]. These methods mostly weaken the noise extraction signal through the characteristic difference between the signal and the noise, which will inevitably damage the useful signal in the processing process, and have certain limitations.

Stochastic resonance(SR) is a nonlinear processing method. Under the combined action of nonlinear bistable system, signal and noise, noise energy is used to enhance weak signals,reflecting the influence of random motion of microscopic particles on macroscopic variables[6]. For the situation that the vortex signal is easily disturbed by

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the noise in the field, the stochastic resonance method can improve the measurement accuracy and expand the lower limit of the measurement. The concept of SR was proposed by Benzi's team [7] to explain the periodic occurrence of ancient meteorological glaciers; in 1989, McNamara et al.[8] gave a bistable two-state stochastic resonance based on the assumption of adiabatic approximate small parameters mathematical representation of the model.According to the ability of SR noise to enhance the output signal and the characteristics of vortex signal, this paper proposes a classic bistable stochastic resonance (CBSR) method based on EEMD to extract weak vortex signal. This method makes full use of the signal decomposition performance of EEMD and the signal enhancement ability of stochastic resonance to achieve the purpose of enhancing the fault characteristics of the low frequency band of the FFT spectrum.First, The signal is decomposed by EEMD, and the normalized correlation coefficient is used as the evaluation standard, and the main IMF components are selected for signal reconstruction. Then, the system parameters are optimized and selected by particle swarm algorithm (PSO), and input the reconstructed signal after preliminary noise reduction into CBSR for signal feature enhancement. Finally, the output signal-to-noise ratio(SNR) is used to evaluate the system enhancement effect. To achieve the optimal output of nonlinear systems, enhance weak periodic signals, and improve the system's ability to extract vortex signals.

2. Adaptive Stochastic Resonance System Based on EEMD

2.1. Ensemble Empirical Mode Decomposition(EEMD)

Ensemble empirical mode decomposition (EEMD) is a multiple-time empirical mode decomposition of superimposed white Gaussian noise, and is a noise-assisted analysis method. The EEMD method is essentially an improvement to the EMD algorithm. It is mainly based on the characteristic that the mean value of white noise is zero. White noise is added to the signal, and EMD is still used to decompose it. The decomposed results are averaged. The higher the number of times, the smaller the influence of noise on the decomposition result. Using EEMD to decompose the signal, the steps to achieve preliminary filtering and noise reduction are as follows:

(1) Add normally distributed white noise to the vortex signal to form a series of new signals

(2) The signal added with white noise is taken as a whole, and then EMD is decomposed to obtain IMFs

(3) Average the IMFs of the corresponding modes to obtain the EEMD decomposition result

(4) Use the normalized correlation coefficient to filter the effective IMF corresponding summation, and obtain the signal after preliminary noise reduction

2.2. Classical Bistable Stochastic Resonance Model

SR can enhance weak signal features with appropriate noise through nonlinear dynamical systems. The classical bistable model is the most widely used nonlinear model. Its potential function expression is:

$$U(x) = -ax^2/2 + bx^4/4 \quad a>0, b>0 \tag{1}$$

where a and b are system parameters. Fig.1 shows the bistable potential well diagram with a=1, b=1. It can be seen from Fig.1 that the potential function has two steady-state points $x_{1,2} = \pm\sqrt{a/b}$ and one non-steady-state point $x=0$, and the potential barrier height is $\Delta U = a^2/4b$.By changing the values of a and b, bistable potential well diagrams with different shapes are obtained as shown in Fig.2 The width of the potential well and the height of the potential barrier vary with the value of the system parameters.

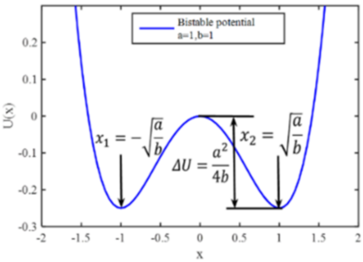

Figure 1. Bistable potential in SR

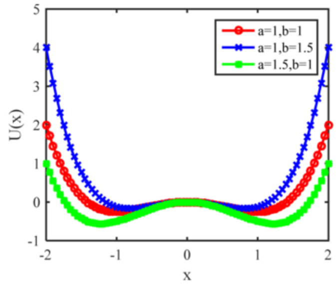

Figure 2. Bistable potential with different parameters

The occurrence process of stochastic resonance is usually expressed by the Langevin equation:

$$\frac{dx}{dt} = -U'(x) + A\cos(2\pi f_0 t + \varphi) + N(\mathrm{t}) \tag{2}$$

where N(t) is additive white Gaussian noise.

SNR reflects the enhancement effect of the nonlinear system on the signal. The calculation formula of the output SNR based on the adiabatic approximation theory is:

$$SNR = \frac{\sqrt{2}a^2A^2}{4bD}\exp\left(-\frac{a^2}{4bD}\right) = \sqrt{2}\Delta U\left(\frac{A}{D}\right)^2 e^{-\Delta U/D} \tag{3}$$

With the increase of noise intensity, the output SNR firstly increases sharply, then peaks and then decreases continuously. When the output SNR reaches a peak value, the system is considered to have the best stochastic resonance.

2.3. Numerical Calculation Method

The output of the SR system needs to be solved by a numerical solution algorithm, because the approximate analysis or analysis is no longer applicable to the output of the nonlinear system, or the solution is extremely complicated, so the differential equation is usually converted into a difference equation to solve. In this paper, the Runge-Kutta algorithm is a numerical method for solving differential equations. The main idea of this method is to interpolate in the selected integral interval, optimize the slope continuously, and obtain updated results. The overall expression of the Runge-Kutta algorithm is shownin equation 4.

$$\begin{cases} x_{n+1} = x_n + \frac{1}{6}(k_1 + k_2 + k_3 + k_4) \\ k_1 = h(ax_n - bx_n^3 + u_n) \\ k_2 = h[a(x_n + \frac{k_1}{2}) - b(x_n + \frac{k_1}{2})^3 + u_n] \\ k_3 = h[a(x_n + \frac{k_2}{2}) - b(x_n + \frac{k_2}{2})^3 + u_{n+1}] \\ k_4 = h[a(x_n + \frac{k_3}{2}) - b(x_n + \frac{k_3}{2})^3 + u_{n+1}] \end{cases} \tag{4}$$

$x(n)$ represents the nth output, $u(n)$ represents the nth input item $s(t)$, and h is the iteration step size.

2.4. Selection of Control Parameters

Existing SR methods mainly focus on choosing appropriate optimization parameters and fitting functions. Since the noise level of a machine fault signal is difficult to estimate because the source signal is unknown and only the received signal can be measured. The vibration has to go through a complex path before reaching the sensor, and noise from different sources will be introduced into the collected signal. Therefore, noise is indeed contained in the acquired signal, but the details of the noise such as noise type, noise distribution and noise level are difficult to determine. Therefore, in adaptive SR methods designed for practical signals, system parameters are widely used as tuning objects.SR is a parameterized system, and the selection of optimal system parameters has a significant impact on the detection accuracy. The output SNR is used as the system evaluation index, The system parameters are optimized and selected by PSO. PSO is an iterative-based optimization algorithm. The system is initialized as a set of random solutions, and the optimal value is searched through iteration. The advantage of PSO is that it is simple and easy to implement, and there are not many parameters to adjust.

3. Simulation Results of Bistable Stochastic Resonance System

In order to verify the effectiveness and practicability of the method, MATLAB is used for signal simulation and analysis to verify the effectiveness of the method. When the input signal is a low-frequency signal, set the input signal amplitude A = 0.1, frequency f_0 = 0.01Hz, noise intensity D = 2, sampling frequency f_s =5 Hz, the number of sampling points N=10240, the time domain and frequency domain diagrams of the output signal are shown in the figure.

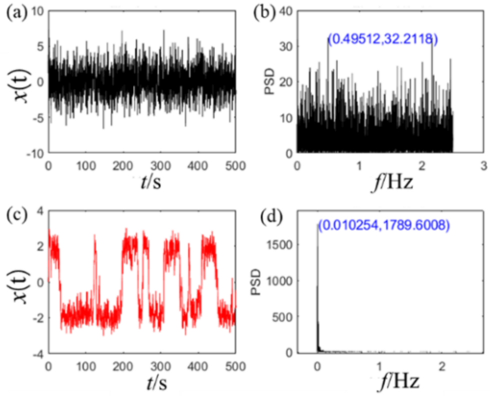

Figure 3. Time-domain waveform and power spectrum of the Simulation signal

Fig.3(a) shows the graph of noisy signal after adding Gaussian white noise to the low-frequency characteristic signal. Because the background noise is too large, the overall time-domain signal is cluttered, irregular, and loses periodicity; after FFT transformation, the graph The frequency of the target signal cannot be directly identified on the power spectrum shown in Fig.3(b); the time domain diagram of the signal output after being processed by the bistable system is shown in Fig.3(c). The power spectrum of the output signal is shown in Fig.3(d), the noise energy is significantly weakened in the frequency domain, and the useful input signal is enhanced. The target frequency f_0 = 0.01Hz has the highest amplitude, which is 1789.6. Simulation results confirm that the method can identify the vortex signal frequency submerged by noise, and is suitable for weak signal detection under strong noise background.

4. Vortex Signal Experiment Results

The vortex flow acquisition device adopts a vortex flowmeter with an accuracy of 0.5 and a diameter of 50mm, and collects a vortex signal with a flow rate of 6.48m^3/s for analysis. The corresponding frequency theoretical value under this flow rate is 16.66Hz. The smaller the flow, the smaller the lift generated by the vortex, and the weaker the periodic signal of the vortex street, so it is easy to be submerged in the site noise. Figures Fig.4(a) and Fig.4(b) are the time domain diagram and power spectrum of the vortex signal. The vortex signal is submerged in noise, and the characteristic frequency of the vortex signal cannot be directly extracted from the power spectrum of the signal. After the vortex signal is processed by the stochastic resonance system, there is a significantly larger power spectrum peak in Fig.4(d), and the corresponding frequency f=16.668Hz, which is the characteristic frequency, indicating that the bistable stochastic resonance control method based on EEMD can be effective to detect the characteristic frequencies of weak vortex signals.

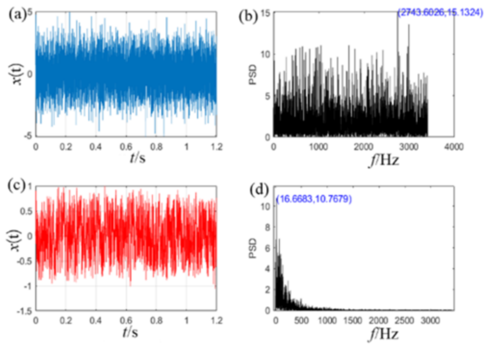

Figure 4. Time domain diagram and power spectrum diagram of vortex signal

5. Conclusion

Aiming at the characteristics that the small flow vortex signal is easily submerged by noise, CBSR system based on EEMD is proposed in this paper to improves the power spectrum at the characteristic frequency of the small flow vortex signal. The theoretical and experimental results show that this method can effectively extract the vortex features. This method is of great significance for expanding the application range of stochastic resonance to solve practical engineering problems.

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