

# A novel underdamped continuous unsaturation bistable stochastic resonance method and its application

Mengdi Li<sup>a</sup>, Peiming Shi<sup>a,\*</sup>, Wenyue Zhang<sup>a</sup>, Dongying Han<sup>b</sup>

<sup>a</sup> School of Electrical Engineering, Yanshan University, Qinhuangdao, Hebei 066004, P. R. China

<sup>b</sup> School of Vehicles and Energy, Yanshan University, Qinhuangdao, Hebei 066004, P. R. China

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## ABSTRACT

In view of the saturation problem of classical bistable stochastic resonance (CBSR) system, an underdamped continuous unsaturation bistable stochastic resonance (UCUBSR) system is investigated and the feasibility of the system for weak fault feature extraction is discussed. Firstly, based on the reason of saturation phenomenon, a new potential function is constructed, which can independently adjust the steepness of the potential walls. The signal to noise ratio (SNR) of the system is derived. Secondly, a modified unsaturation index, amplitude gain, is proposed, and the influence of the steepness on SR based on SNR and amplitude gain is analyzed. The simulation analysis shows that the amplitude gain can be considered as an appropriate index to quantify SR and has a certain compensation effect on the SNR applied to evaluate unsaturation performance. Finally, from the simulation and experiment, a larger amplitude gain indicates that the proposed system has better unsaturation and weak fault detection ability compared with unsaturation bistable stochastic resonance (UBSR), and a higher amplitude of the output signal at the characteristic frequency proves that the amplitude gain as an indicator can further guide the parameter adjustment of SR and facilitate faint fault signature identification.

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## 1. Introduction

Stochastic resonance (SR) was first proposed by Benzi to analyze the phenomenon of global climate change during glacial period [1]. Subsequently, due to the unique advantage that SR can enhance the characteristics of weak signals by noise, SR has been widely used in many fields, such as physics [2], neurology [3], medicine [4], ecology [5], especially signal processing [6–8].

Nowadays, the most widely used model is the classical bistable stochastic resonance (CBSR) system, but there is saturation in CBSR, which limits the ability of the model to enhance the characteristics of input signals [9]. Therefore, some scholars have studied the saturation problem of CBSR model. The structure of potential function affects the output of SR [10,11]. The saturation problem can be improved by linearizing the well walls on both sides of the potential function [12,13]. Qiao [14] established a piecewise bistable potential model to overcome output saturation. Experimental results showed that compared with CBSR system, the proposed system can obtain higher SNR and enhance the feature of weak signal better. Zhang [15] proposed a novel piecewise nonlinear bistable SR model. Based on the increased SNR, it is proved

that the proposed system was superior to CBSR system in fault feature extraction. Li [16] constructed an improved piecewise unsaturated bistable potential model, which can better alleviate the saturation problem and obtain a bigger output SNR. These models are based on the improved potential function of CBSR, by changing the structure of both sides of the potential well to alleviate the degree of saturation. However, they are all overdamped SR models, and it is well known that the first-order SR system is equivalent to a filter in signal processing and the output of the second-order system equation is equivalent to the secondary filtering. So, the second-order SR system has better filtering effect [17–19]. Zhang [20] studied a second-order underdamped tristable SR model can realize the weak fault feature extraction much better compared with traditional tristable SR model. Li [21] proposed a multi-parameter constrained potential underdamped SR method and affirmed the effectiveness of the proposed method. However, there is little research on the underdamped unsaturation bistable stochastic resonance system. In view of this, it is necessary to study the above system.

An interesting thing is that it is different from the traditional weak signal detection method to obtain the de-noising signal by suppressing noise. SR is to transfer the high-frequency noise energy to useful signal to improve the SNR by utilizing noise. Noise

\* Corresponding author.

E-mail address: [spm@ysu.edu.cn](mailto:spm@ysu.edu.cn) (P. Shi).

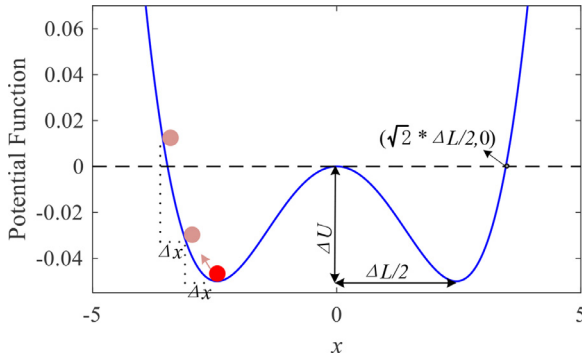


Fig. 1. Potential function in CBSR system.

is not only an important research object of weak signal processing, but also plays a vital role in other physical models [22–24].

When the system parameters, noise and input signal work together, the SR phenomenon occurs. In the actual situation, the input signal with noise has been determined, so the selection of system parameters to trigger SR is very important. There needs to be an index to quantify SR. In addition to the most commonly used SNR [25–28], there have also been other indicators for evaluating SR [29–31]. Huang [32] designed a new quantitative indicator piecewise mean value to qualify the performance of the nonlinear system response. He [33] employed the statistical complexity measure and the normalized Shannon entropy to evaluate SR of the time-delayed bistable system and verified the effectiveness of these two indexes. Xu [34] derived the spectrum amplification formula and used it to quantify the SR effect. Therefore, based on the mechanism of saturation phenomenon in CBSR system, an appropriate index can be proposed to evaluate the unsaturation ability of the system more accurately, and the system parameters need to be adjusted effectively based on the index. Due to the complexity of manual parameter adjustment, adopting intelligent optimization algorithm to search the optimal solution in rotating machine fault detection is more advantageous [35–38].

The rest of this paper is organized as follows: in Section 2, the saturation of CBSR is studied, the underdamped continuous unsaturation bistable stochastic resonance (UCBSR) method is proposed, and the SNR of the system is derived. In Section 3, a new unsaturation evaluation index is proposed, and the relationship between this index and SR phenomenon is studied. In Section 4, the unsaturation ability of the proposed system and the significance of the proposed index are proved from both simulation and experiment. The conclusion is given in Section 5.

## 2. Underdamped continuous unsaturation bistable SR system

### 2.1. Saturation phenomenon

Langevin equation was originally used to represent the transition of Brownian particle in nonlinear system under the action of random and periodic forces, which can describe CBSR system as follows

$$\begin{cases} \frac{dx}{dt} + \frac{dU_c(x)}{dx} = S(t) + \eta(t) \\ U_c(x) = -\frac{a}{2}x^2 + \frac{b}{4}x^4 \end{cases} \quad (1)$$

where  $U_c(x)$  is the potential function,  $a$  and  $b$  are the system parameters,  $S(t) = A\sin(2\pi ft + \varphi)$  is the periodic signal with amplitude  $A$ , frequency  $f$  and phase  $\varphi$ , and  $\eta(t) = \sqrt{2D}\xi(t)$  is the Gaussian white noise with  $\langle \eta(t) \rangle = 0$ ,  $\langle \eta(t)\eta(t+\tau) \rangle = 2D\delta(\tau)$ , where  $\tau$  is time delay and  $D$  is noise intensity. The structure of the potential function is shown in Fig. 1. The barrier height and the potential spacing are  $\Delta U = a^2/4b$ ,  $\Delta L = 2\sqrt{a/b}$ , and the ab-

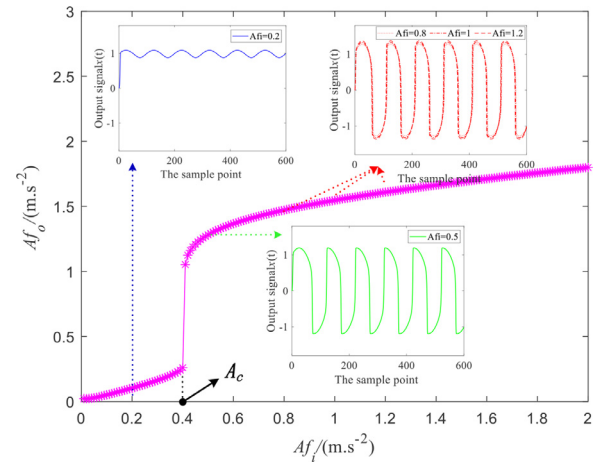


Fig. 2. Response of CBSR system with external periodic excitation only.

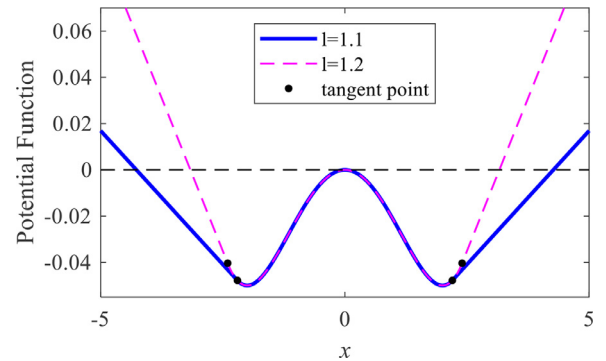


Fig. 3. Potential function in UCBSR system.

scissa of intersection of the right potential function and the x-axis is  $\sqrt{2} * \Delta L/2$ .

If there exists only external periodic excitation in the system,  $A_c \approx \sqrt{4a^3/(27b)}$  is a critical value for the occurrence of SR. When input signal amplitude  $A < A_c$ , the particle only makes local periodic oscillation motion near the potential well  $x_- = -\sqrt{a/b}$  or  $x_+ = \sqrt{a/b}$  on one side, and the one in the two wells is determined based on the initial value. When  $A > A_c$ , the particle can realize the transition between the two potential wells and make periodic motion in the two potential wells. When  $A$  continues to increase, the particle moves along the edge potential well wall. The slight motion of the particle needs to overcome the large potential energy due to the existence of potential function  $x^4$ . In terms of the potential function structure in Fig. 1, the solid sphere represents the particle. As the particle moves from the bottom of the well to the wall of the well, the higher the vertical distance is needed to move the same  $\Delta x$ , which limits the output amplitude of the CBSR model and results in saturation.

Fig. 2 shows the response amplitude ( $Af_o$ ) of CBSR system with external periodic excitation amplitude ( $Af_i$ ) only and briefly reflects the effect of potential function structure on system output. The system parameters are fixed as  $a = 1$ ,  $b = 1$ , and  $A_c \approx 0.385$  in this system. In this figure, with the increase of  $Af_i$ , the particle transits from the oscillation in the right well (when  $Af_i=0.2$ ) to the transition between the left and right wells (when  $Af_i=0.5$ ), and then the system response gradually falls into saturation state (when  $Af_i=0.8, 1.0, 1.2$ ). After saturation, the  $Af_o$  of the system no longer increases with the increase of the  $Af_i$ . This makes the CBSR system lose weak characteristic enhancement ability.

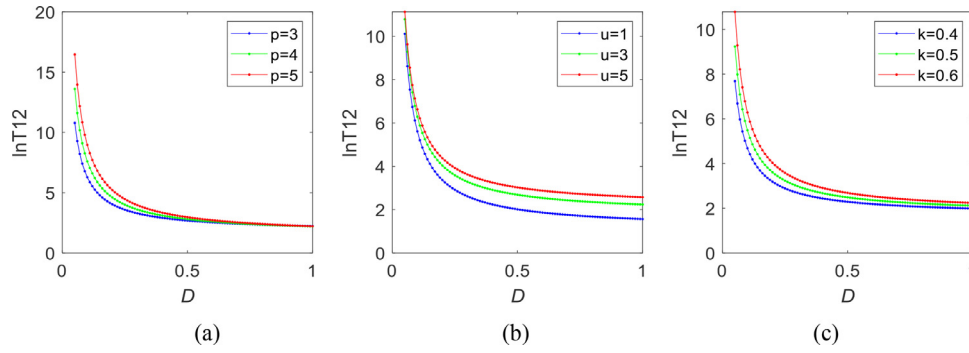


Fig. 4. MFPT versus noise intensity  $D$  for different system parameters with (a)  $u = 3$  and  $k = 0.6$  (b)  $p = 3$  and  $k = 0.6$  (c)  $p = 3$  and  $u = 3$ .

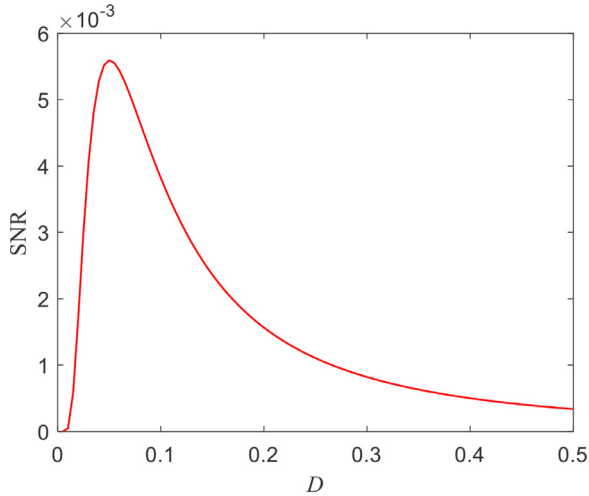


Fig. 5. SNR versus noise intensity  $D$  with  $A = 0.05$ ,  $f = 0.01$ ,  $p = 1$ ,  $u = 5$  and  $k = 0.4$ .

## 2.2. Potential function model and SNR derivation of UCUBSR system

To make up for the defect of CBSR saturation, an underdamped continuous unsaturation bistable stochastic resonance (UCUBSR) system is proposed, and it is controlled by the following differential equation.

$$\frac{d^2x}{dt^2} = -\frac{dU(x)}{dx} - k\frac{dx}{dt} + S(t) + \eta(t) \quad (2)$$

where  $k$  is the damping factor. The continuous potential function  $U(x)$  of UCUBSR system can be written as

$$U(x) = \begin{cases} -k_d(x + x_d) + y_d & x < -x_d \\ -\frac{px^2}{2u} + \frac{px^4}{4u^2} & -x_d \leq x \leq x_d \\ k_d(x - x_d) + y_d & x_d < x \end{cases} \quad (3)$$

where

$$\begin{cases} x_d = l\Delta L/2 & 1 < l < \sqrt{2} \\ k_d = -\frac{px_d}{u} + \frac{px_d^3}{u^2} \\ y_d = -\frac{px_d^2}{2u} + \frac{px_d^4}{4u^2} \end{cases} \quad (4)$$

In this model,  $p, u, l$  are the system parameters,  $k_d$  is the slope of the tangent point  $(x_d, y_d)$ .  $l$  is the steepness of the potential function, and the potential function structure of UCUBSR system for different  $l$  is shown in Fig. 3. The potential function model realizes the independent adjustment of barrier height  $\Delta U = p/4$ , potential distance  $\Delta L = 2\sqrt{u}$  and steepness  $l$ .

Then, for the convenience of deriving the SNR of the system, the Eq. (2) can be simplified as

$$\begin{cases} \frac{dx}{dt} = y \\ \frac{dy}{dt} = -\frac{dU}{dx} - ky + A\cos(\Omega t) + \sqrt{2D}\delta(t) \end{cases} \quad (5)$$

Let  $\frac{dx}{dt}, \frac{dy}{dt}, A, D = 0$ , three singularities of the system of equation  $(x_-, y_-) = (-\sqrt{u}, 0)$ ,  $(x_0, y_0) = (0, 0)$ ,  $(x_+, y_+) = (\sqrt{u}, 0)$  are acquired, and the corresponding linearization matrix is as follows [39]:

$$R_x = \begin{bmatrix} 0 & 1 \\ M_x & k \end{bmatrix} \quad (6)$$

where three singularities corresponding to  $M_x$  can be expressed as  $M_{x-} = -2p/u$ ,  $M_{x0} = p/u$ ,  $M_{x+} = -2p/u$ . The singular values are linearized respectively.

$$\begin{cases} \beta_{1,2} = \left( -k \pm \sqrt{k^2 - 8p/u} \right) / 2 & x = x_- \\ \lambda_{1,2} = \left( -k \pm \sqrt{k^2 + 4p/u} \right) / 2 & x = x_0 \\ \beta_{3,4} = \left( -k \pm \sqrt{k^2 - 8p/u} \right) / 2 & x = x_+ \end{cases} \quad (7)$$

According to Fokker-Planck equation, the probability density  $\rho(x, y, t)$  of particle motion can be expressed as

$$\begin{aligned} \frac{\partial \rho(x, y, t)}{\partial t} = & -\frac{\partial}{\partial x} [y\rho(x, y, t)] \\ & -\frac{\partial}{\partial y} \left[ \left( -ky + A\cos(\Omega t) - \frac{dU}{dx} \right) \rho(x, y, t) \right] \\ & + D \frac{\partial^2}{\partial y^2} \rho(x, y, t) \end{aligned} \quad (8)$$

Based on the adiabatic approximation theory [40], the distribution function of quasi steady state can be expressed as

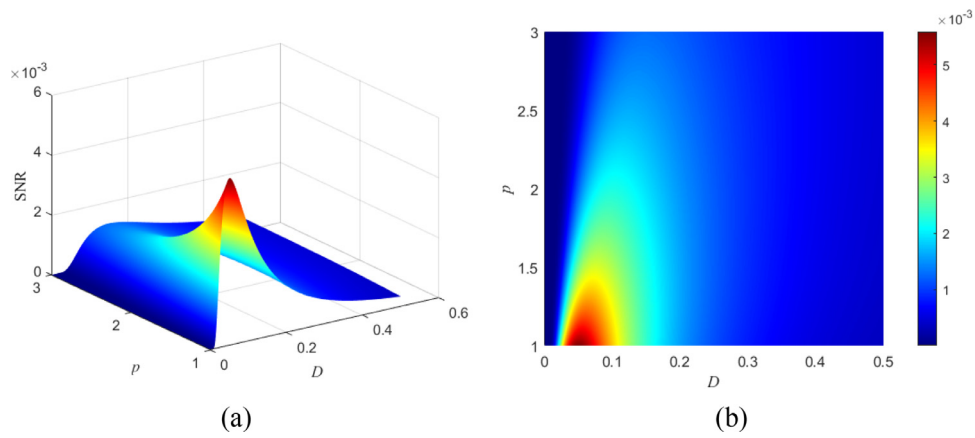
$$\rho_{st}(x, y, t) = \bar{N} \exp \left[ -\frac{\tilde{U}(x, y, t)}{D} \right] \quad (9)$$

where  $\bar{N}$  is the normalized constant and  $\tilde{U}(x, y, t)$  is the generalized potential well function obtained by small parameter expansion.

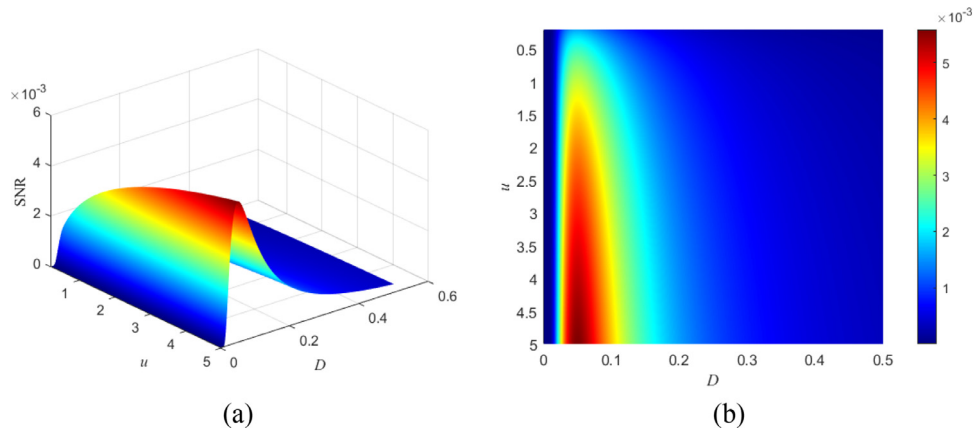
$$\begin{aligned} \tilde{U}(x, y, t) = & \frac{k}{2}y^2 + k \int [U'(x) - xA\cos(\Omega t)] dx = \frac{ky^2}{2} - kAx\cos(\Omega t) + \\ & -k_d(x + x_d) + y_d & x < -x_d \\ & k \left\{ -\frac{px^2}{2u} + \frac{px^4}{4u^2} \right. & -x_d \leq x \leq x_d \\ & \left. k_d(x - x_d) + y_d \right. & x_d < x \end{aligned} \quad (10)$$

Then, the probability transfer rate between the two potential wells can be written as follows:

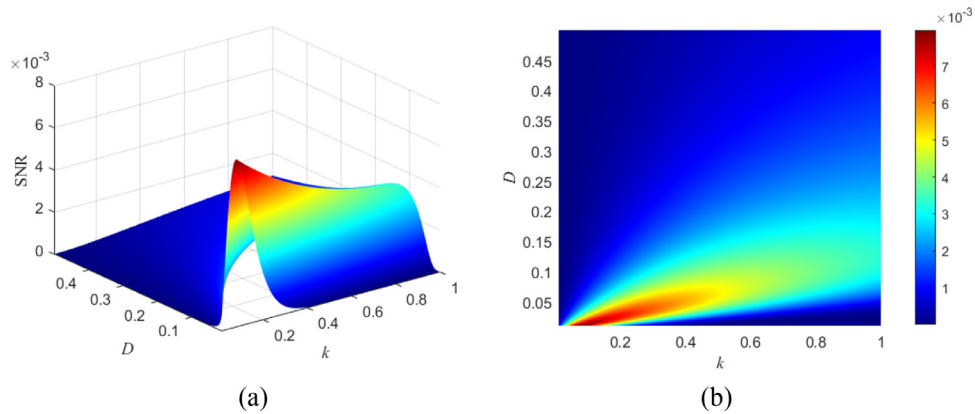
$$R_{\pm}(t) = \frac{\sqrt{\beta_1\beta_2}}{2\pi} \sqrt{-\frac{\lambda_1}{\lambda_2}} \exp \left( \frac{-\tilde{U}(x_0, y_0, t) + \tilde{U}(x_{\pm}, y_{\pm}, t)}{D} \right) \quad (11)$$



**Fig. 6.** SNR as a function of the noise intensity  $D$  and the system parameter  $p$  with  $A = 0.05$ ,  $f = 0.01$ ,  $u = 5$  and  $k = 0.4$ .



**Fig. 7.** SNR as a function of the noise intensity  $D$  and the system parameter  $u$  with  $A = 0.05$ ,  $f = 0.01$ ,  $p = 1$  and  $k = 0.4$ .



**Fig. 8.** SNR as a function of the noise intensity  $D$  and the damping factor  $k$  with  $A = 0.05$ ,  $f = 0.01$ ,  $p = 1$  and  $u = 5$ .

The mean first passage time (MFPT) of the UCUBSR system can be obtained as

$$T12(x_+ \rightarrow x_-) = 1/R_+ \quad (12)$$

$T21(x_- \rightarrow x_+) = T12(x_+ \rightarrow x_-)$  due to the symmetric generalized potential function when the value of  $\Omega t$  is  $\pi/2$ .

$R_{\pm}(t)$  after Taylor expansion, there is

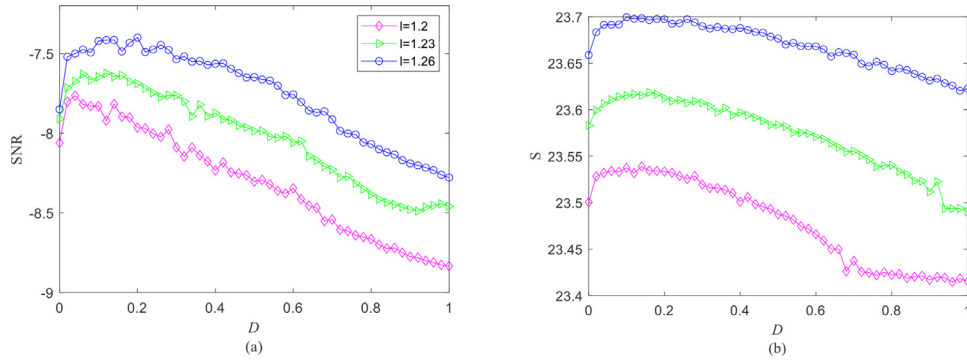
$$R_{\pm}(t) = \frac{\sqrt{\beta_1 \beta_2}}{2\pi} \sqrt{-\frac{\lambda_1}{\lambda_2}} \exp\left(-\frac{kp}{4D}\right) \left[1 \mp \sqrt{u} A \cos(\Omega t) + \frac{1}{2} (\sqrt{u} A \cos(\Omega t))^2 \mp \dots\right] \quad (13)$$

Let  $R_0 = \frac{\sqrt{\beta_1 \beta_2}}{2\pi} \sqrt{-\frac{\lambda_1}{\lambda_2}} \exp(-\frac{kp}{4D})$ , the system output power is

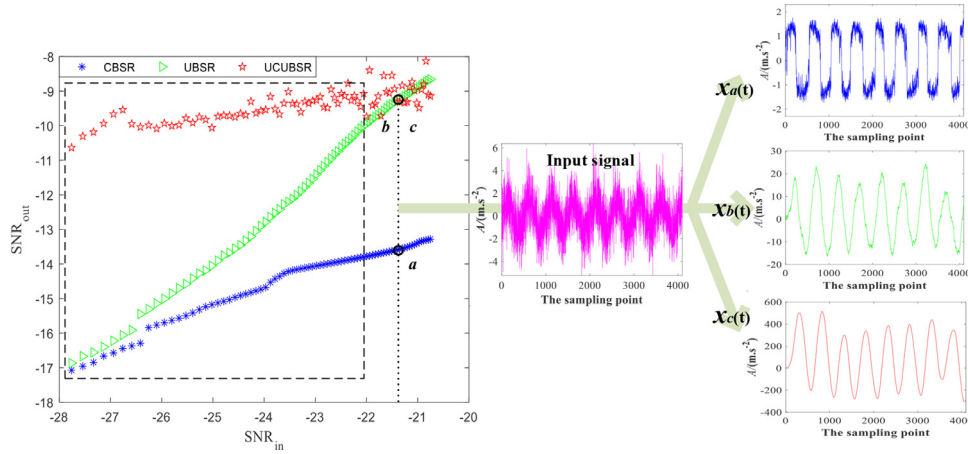
$$S(w) = S_1(w) + S_2(w) \quad (14)$$

where  $S_1(w)$ ,  $S_2(w)$  is the power spectrum of signal and noise respectively. Let  $R_1 \beta = k R_0 x_+ \frac{A}{D}$ ,  $S_1(w)$ ,  $S_2(w)$  can be expressed as follows:

$$\begin{cases} S_1(w) = \frac{\pi x_+^2 (R_1 \beta)^2}{2(R_0^2 + \Omega^2)} [\delta(w - \Omega) + \delta(w + \Omega)] \\ S_2(w) = \left[1 - \frac{(R_1 \beta)^2}{2(R_0^2 + \Omega^2)}\right] \frac{2x_+^2 R_0}{R_0^2 + \Omega^2} \end{cases} \quad (15)$$



**Fig. 9.** The relationship between the output SNR, amplitude gain  $S$  and noise intensity  $D$  for different parameter  $l$ .  $A = 0.5$ ,  $f = 0.01$ ,  $p = 0.1$ ,  $u = 1$  and  $k = 0.04$  (a) SNR (b)  $S$ .



**Fig. 10.** The unsaturation performance analysis based on SNR.

Finally, the SNR can be expressed as:

$$\text{SNR} = \frac{\int_0^\infty S_1(w)dw}{S_2(w = \Omega)} = \frac{\pi(R_1\beta)^2}{4R_0} \left[ 1 - \frac{(R_1\beta)^2}{2(R_0^2 + 4\Omega^2)} \right]^{-1} \quad (16)$$

Fig. 4 reveals the effect of noise intensity on MFPT for different parameters. The observation shows that MFPT decreases monotonously with the increase of noise intensity under different parameters. In addition, the larger the parameter value, the faster the decline. Therefore, a high barrier height, a wide potential spacing or a large damping factor will increase the difficulty of particles passing through the potential well and reduce the escape rate [41,42]. The relationship between SNR and noise intensity  $D$  is shown in Fig. 5. Similar to CBSR, the SNR of UCBSR first increases to the maximum and then decreases with the increase of noise intensity. Fig. 6 gives the three-dimensional graph of SNR, system parameter  $p$  and  $D$ . With increasing noise intensity  $D$ , each  $p$  exhibits a maximum SNR under different noise intensities, which is the identifying feature of SR phenomenon. From Fig. 6(b), with the increase of  $p$ , the peak value of the SNR decreases and the peak's position shifts slightly to the larger value of  $D$ , indicating that the higher the barrier height, the greater the noise intensity required to reach the maximum SNR and achieve optimal coordination. Fig. 7 reveals the three-dimensional graph of SNR, system parameter  $u \in [0.2, 5]$  and  $D$ . SR phenomena in the system occurs as the SNR curve is at the peak, and the maximum SNR gradually increases with the increase of  $u$ . Fig. 8 shows the three-dimensional diagram of SNR, damping factor  $k \in [0.01, 1]$  and  $D$ . As parameter  $k$  increases, the optimal SNR decreases and the value of  $D$  required to reach the optimal SNR increases, which implies

that increasing noise intensity  $D$  and the damping factor  $k$  can limit the appearance of the optimal SNR.

### 3. The characteristic analysis of SR based on SNR and amplitude gain

At present, most of the papers on CBSR saturation take the SNR of output signal as the evaluation of the system's unsaturation ability. The SNR of a signal is expressed as follows.

$$\text{SNR} = 10\log_{10}\left(\frac{Af_t}{\sum_j Af_j - Af_t}\right) \quad (17)$$

where  $Af_t$  is the amplitude of the characteristic frequency  $f_t$  in power spectrum of the signal and  $\sum_j Af_j$  is the sum of all frequency amplitudes.

#### 3.1. Unsaturation index based on amplitude gain

A new evaluation index of unsaturation, amplitude gain  $S$ , is proposed in this paper. The expression of  $S$  is as follows

$$S = 10\log_{10}\frac{Af_o}{Af_i} \quad (18)$$

where  $Af_i$ ,  $Af_o$  are respectively the amplitude of input signal and output signal at the characteristic frequency. The greater the  $S$ , the better the unsaturation performance.

To prove that the amplitude gain can be used as the evaluation index of the unsaturation ability of the SR system separately and effectively, Fig. 9 presents the relationships between the output



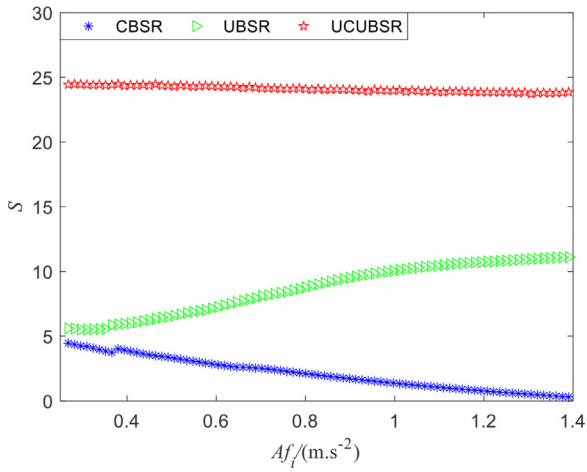


Fig. 11. Curves of the amplitude gain  $S$  and  $Af_i$  of input signal in different systems.

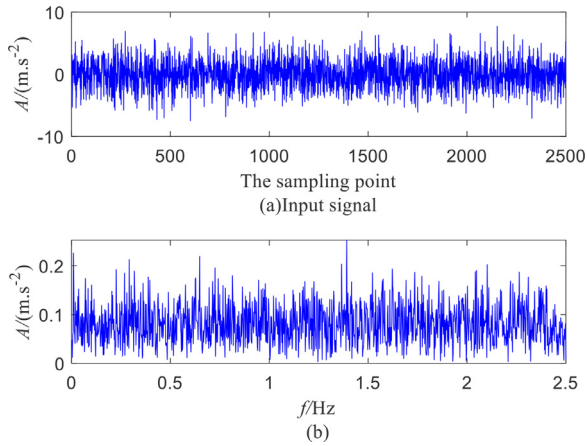


Fig. 12. (a) Time domain waveform and (b) spectra diagram of the input signal.

SNR, amplitude gain  $S$  and the noise intensity  $D$  for different system parameter  $l$ . Firstly, it is well known that the non-monotonic relationship of the SNR and noise intensity  $D$  is considered as the recognition characteristic of the existence of SR phenomenon as shown in Fig. 9(a). With the increase of  $l$ , the maximum SNR increases and the position of the maximum shifts towards the larger value of  $D$ . This implies that enlarge noise intensity  $D$  and system parameter  $l$  can promote the appearance of the maximum SNR. Then, SR phenomenon in terms of amplitude gain is analyzed in Fig. 9(b). There is always an obvious peak in the amplitude gain curve for  $l = 1, 1.23$  and  $1.26$ , reflecting the occurrence of SR. The amplitude gain can be considered as an appropriate index to quantify SR. Moreover, according to the definition of the amplitude gain, the feature amplitude enhancement capability of the system first increases and then decreases with the increase of noise intensity, and a bigger  $l$  can improve amplitude gain, leading to the promotion of the SR.

### 3.2. Comparison of unsaturation indexes

This chapter compares the proposed index with SNR in the evaluation of unsaturation ability of the different SR systems. Among them, there are CBSR system, UCUBSR system and unsaturation bistable stochastic resonance (UBSR) system mentioned in [14]. The amplitude of the sinusoidal signal  $S(t)$  is increased from 0.3 to 1.5 with a step length of 0.015, totally 81 inputs, and

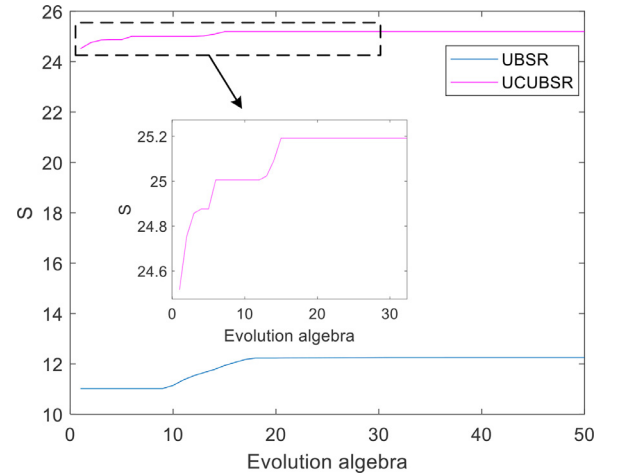


Fig. 13. Iterative process of PSO with  $S$  as objective function.

Table 1

Parameter settings in UBSR and UCUBSR.

| Input type    | Bound | $a$ | $b$ | $p$ | $u$ | $l$        |
|---------------|-------|-----|-----|-----|-----|------------|
| Analog signal | Upper | 5   | 5   | 5   | 5   | $\sqrt{2}$ |
|               | Lower | 0   | 0   | 0   | 0   | 1          |
| Fault signal  | Upper | 5   | 5   | 1   | 5   | $\sqrt{2}$ |
|               | Lower | 0   | 0   | 0   | 2   | 1          |

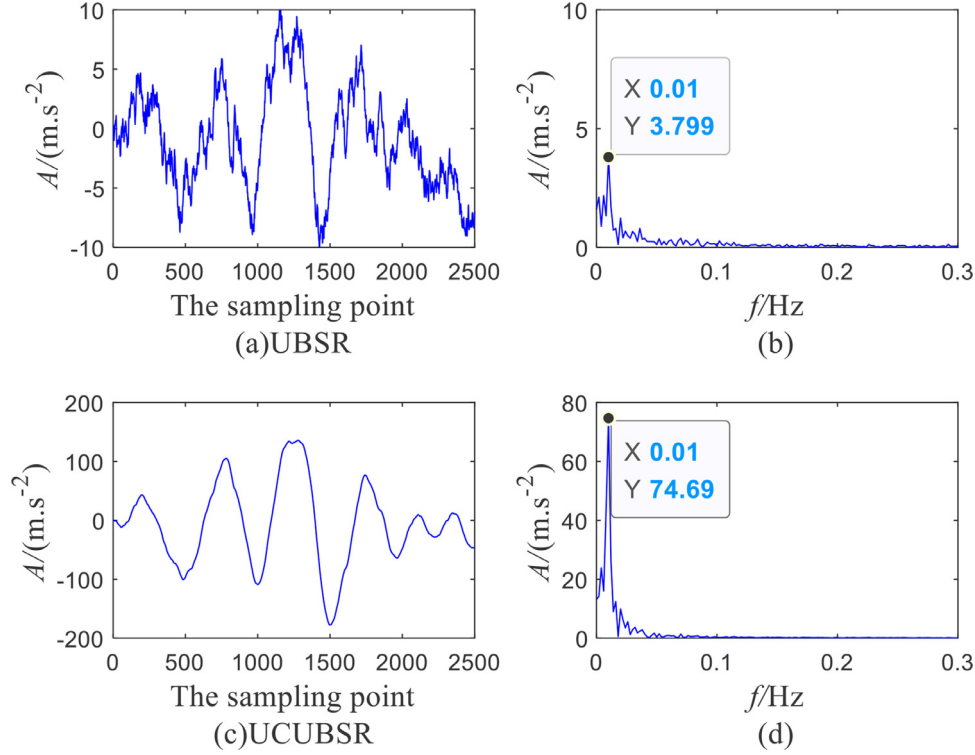
the Gaussian white noise  $\eta(t)$  with the noise intensity  $D = 0.5$  is added. We take the characteristic frequency  $f_t = 0.01$  Hz, sampling frequency  $f_s = 5$  Hz, sampling length  $N = 4096$ . The barrier height and the potential spacing of these three systems are the same, which are  $\Delta U = 0.25$  and  $\Delta L = 2$ , respectively. In addition,  $l = 1.1$ ,  $k = 0.04$  in UCUBSR system are set. Each input signal is processed by three models to obtain the corresponding output signal. The SNR of the input signal ( $SNR_{in}$ ) and the SNR of the output signal ( $SNR_{out}$ ) are calculated by Eq. (17), and the relationship between  $SNR_{in}$  and  $SNR_{out}$  in each model is shown in Fig. 10.

For the dotted rectangle in Fig. 10, the  $SNR_{out}$  of UCUBSR is the largest, followed by UBSR and CBSR in the same input signal. The unsaturation ability of UCUBSR is stronger than that of UBSR and CBSR. However, for the outside of the dotted rectangle in Fig. 10, the  $SNR_{out}$  of UCUBSR and UBSR is extremely close. It is not easy to judge the unsaturation performance of the two systems based on SNR. Specifically, when the  $S_1(t) = 1.275 \sin(2\pi f_t t)$ , the input signal and the output signals  $x_a(t)$ ,  $x_b(t)$  and  $x_c(t)$  obtained by CBSR, UBSR and UCUBSR are presented in Fig. 10. The  $SNR_{out}$  of CBSR, UBSR and UCUBSR are  $-13.5898$ ,  $-9.3065$ , and  $-9.3098$ , respectively. The latter two values are approximately the same, indicating that the unsaturation ability of UBSR and UCUBSR is equivalent based on SNR index. But the amplitude of output signal of UCUBSR is about 20 times higher than that of UBSR in the time domain diagrams. It can be seen that the SNR is obviously not convincing as an evaluation index of unsaturation ability.

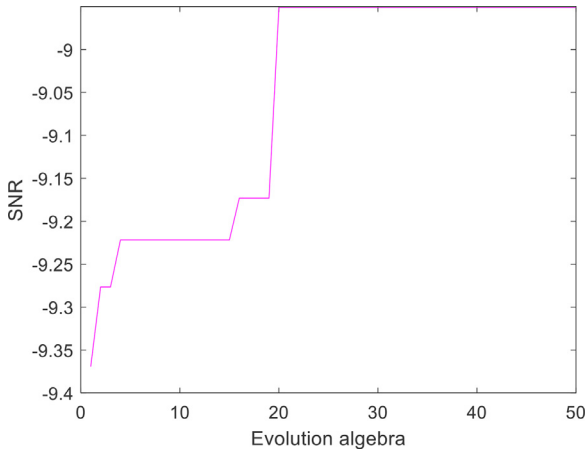
Then, the amplitude gain  $S$  of the above 81 groups of input signals processed by three systems is shown in Fig. 11. The  $S$  curve of the UCUBSR system is always higher than that of UBSR and CBSR, and there is no crossing between the curves like Fig. 10, which means the unsaturation ability of UCUBSR are the best, followed by UBSR, CBSR is the worst, and also proves the superiority of index  $S$ . The amplitude gain  $S$  as an evaluation indicator, it not only has a certain compensation effect on the SNR indicator, but also has a good degree of discrimination.

**Table 2**  
Particle swarm optimization results of the analog signal (damping factor  $k = 0.04$ ).

|        | $S_{max}$ | $SNR_{max}$ | system parameters                         | $Af_o$ |
|--------|-----------|-------------|---|--------|
| UBSR   | 12.2539   | /           | $a = 0.100, b = 4.9385$                   | 3.799  |
| UCUBSR | 25.1923   | /           | $p = 2.1514, u = 3.6117,$<br>$l = 1.0803$ | 74.69  |
| UCUBSR | /         | -8.9513     | $p = 1.2420, u = 2.3768,$<br>$l = 1.1162$ | 71.36  |



**Fig. 14.** Comparison of the output signal obtained by UBSR (a) and (b) and UCUBSR (c) and (d).



**Fig. 15.** Iterative process of PSO with SNR as objective function.

#### 4. Simulation analysis and experimental verification

The simulation signal and actual signal are used to verify the reliability of UCUBSR's unsaturation capability and amplitude gain index. For one thing, particle swarm optimization (PSO) is used to adjust system parameters, and the optimal output results of UBSR and UCUBSR are obtained to compare their unsaturation perfor-

mance. For another thing, the significance of the proposed index  $S$  is proved by the optimal output results of analog signal and fault signal in UCUBSR system.

##### 4.1. Parameter optimization by PSO

SR is extremely sensitive to system parameters. Matching system parameters is a vital way to trigger SR. PSO is a random search algorithm and adopted to search the best matching parameter pair of the UBSR system and UCUBSR system. To ensure the convergence of the algorithm, the parameter settings are listed in Table 1. Among them, the parameters of UBSR system are  $a$  and  $b$ , and  $p$ ,  $u$  and  $l$  are UCUBSR system parameters. Each model is optimized 10 times to get 10 best output results, and the maximum value of them is selected as the optimal output value of the model in the algorithm.

##### 4.2. simulation analysis

The signal generated by sine signal  $S(t) = 0.2\sin(0.02\pi t)$  and Gaussian white noise with noise intensity  $D = 5$  is used as the input signal of SR system. The basic settings are given as follows: sampling frequency  $f_s = 5$  Hz and sampling point  $N = 2500$ . The time-frequency diagram of input signal is shown in Fig. 12. In the spectrum of Fig. 12(b), the amplitude at  $f_t = 0.01$  is shielded by vast powerful noise and the frequency at the maximum amplitude

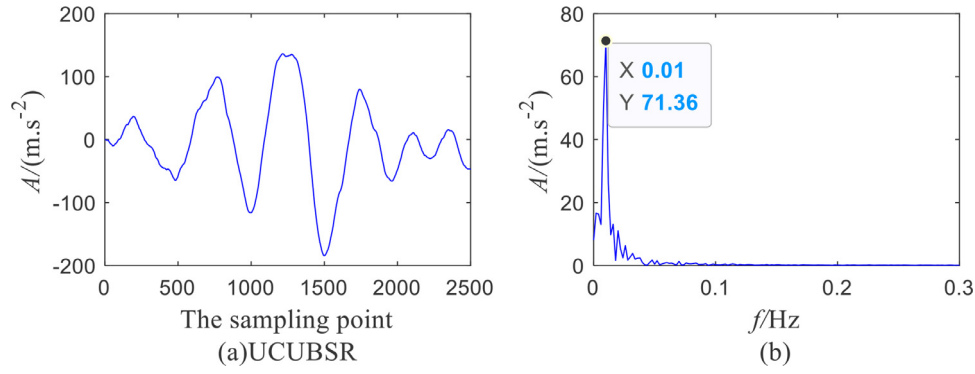


Fig. 16. (a) Time domain waveform and (b) spectra of the output signal.

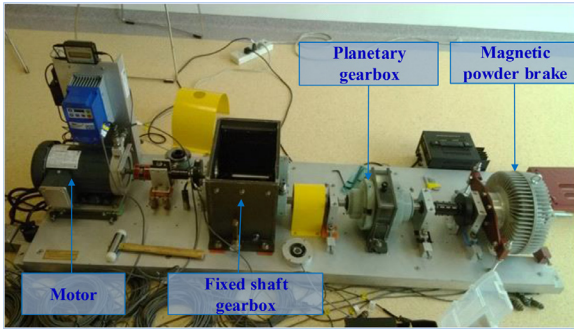


Fig. 17. Experimental platform.

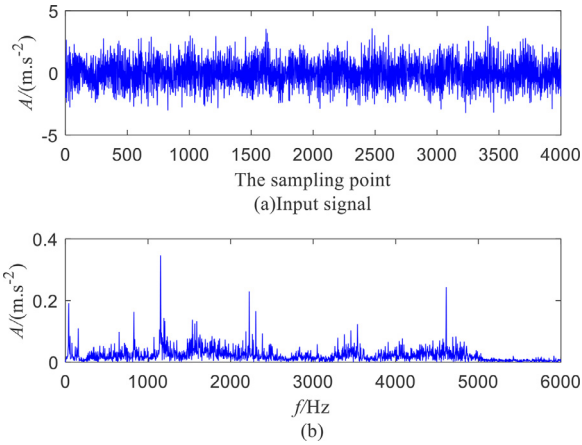


Fig. 18. (a) Time domain waveform and (b) spectra of the bearing outer ring fault signal.

is 1.362 Hz. It is quite difficult to extract the characteristic of the input signal.

To compare the unsaturation capability, PSO is used to optimize the parameters of UBSR and UCUBSR respectively with the amplitude gain  $S$  as the objective function. The optimization process of two systems is shown in Fig. 13. The algorithm converges to obtain the optimal amplitude gain ( $S_{max}$ ).  $S_{max} = 12.2539$  and the optimal parameters are  $a = 0.100$  and  $b = 4.9385$  in UBSR system.  $S_{max} = 25.1923$  and the optimal parameters are  $p = 2.1514$ ,  $u = 3.6117$  and  $l = 1.0803$  in UCUBSR system. Based on the  $S_{max}$ , the output signals are presented in Fig. 14. There exists a peak at the characteristic frequency in the spectrum diagrams in Fig. 14(b) and (d), illustrating that both systems can extract the feature of the weak signal. In addition, the  $S_{max}$  of UCUBSR system is 12.9384 higher than that of UBSR system, and the amplitude of output sig-

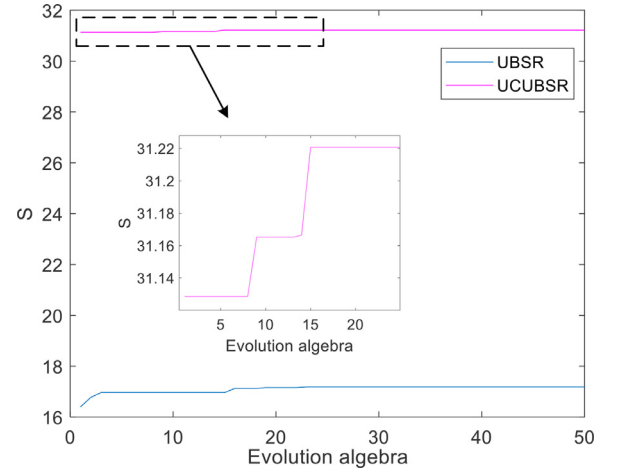


Fig. 19. Iterative process of PSO with  $S$  as objective function.

nal at characteristic frequency  $Af_o$  is 3.799 in UBSR system and 74.69 in UCUBSR system respectively. These indicate the proposed system improves the ability of weak signal feature enhancement and is better than the UBSR system in the unsaturation ability. The optimization results are compared in Table 2.

Then, to illustrate the significance of the proposed evaluation index, the output SNR is selected as the objective function of PSO algorithm to optimize the above analog signal in UCUBSR system. The search process is given in Fig. 15, and the optimal result  $SNR_{max}$  is  $-8.95$  and the corresponding parameters are  $p = 1.2420$ ,  $u = 2.3768$ ,  $l = 1.1162$ . After optimization, the time-frequency diagram of the output signal is obtained in Fig. 16. Obviously, the characteristic frequency  $f_t = 0.01$  Hz of the power spectrum is detected with maximum amplitude  $Af_o = 71.36$ . Furthermore, the  $Af_o$  in Fig. 14(d) is 3.3 bigger than that in Fig. 16(b). This shows that the amplitude gain further guides the parameter adjustment of SR, making the proposed system amplify in enhancement of feature extraction effect. The system processing results are summarized in Table 2.

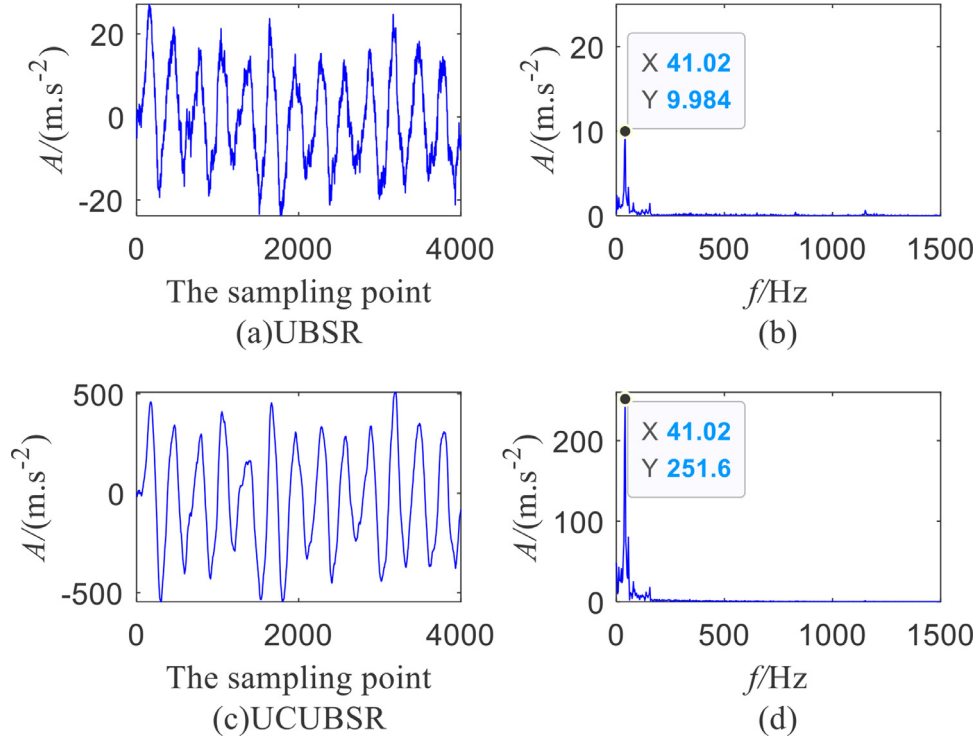
#### 4.3. Experimental verification

The bearing fault signal was collected on the experimental platform in Fig. 17, in which the outer ring of medium speed shaft bearing was in fault. The model of the bearing applied in the experiment was EK-16k. The test point was the middle speed end near the motor end. The speed ratio and load ratio are both 80%. The experimental setup is as below: the motor speed is 2400 r/min, the sampling frequency is set to 1.2 K Hz and the



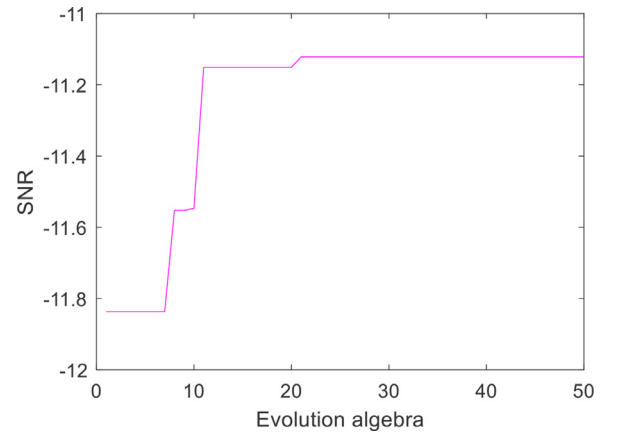
**Table 3**Particle swarm optimization results of the bearing outer ring fault signal (damping factor  $k = 0.04$ ).

|        | $S_{max}$ | $SNR_{max}$ | system parameters                         | $Af_o$ |
|--------|-----------|-------------|---|--------|
| UBSR   | 17.1958   | /           | $a = 0.100, b = 2.0907$                   | 9.984  |
| UCUBSR | 31.2207   | /           | $p = 0.1235, u = 3.2678,$<br>$l = 1.4142$ | 251.6  |
| UCUBSR | /         | -11.2257    | $p = 0.3933, u = 4.2480,$<br>$l = 1.0767$ | 227    |

**Fig. 20.** Comparison of the fault output signal obtained by UBSR (a) and (b) and UCUBSR (c) and (d).

sampling lasts 6 s. The first 4096 data of working condition 29 are selected as the fault signal to be tested. To satisfy the small parameter limit of SR, the secondary sampling frequency is fixed as 0.9 Hz [38]. The time-frequency diagram of the bearing outer ring fault signal is given in Fig. 18. In the spectrum diagram Fig. 18(b), the frequency with the peak is 1151 Hz, the frequency range gets wide, and the energy is mainly concentrated in the high frequency interference region. Apparently, the fault frequency  $f_{BFPO} = 41.435$  Hz cannot be distinguished due to the presence of strong background noise.

Firstly, taking the amplitude gain  $S$  as the objective function of PSO algorithm, the fault signal is processed by the UBSR system and UCUBSR system. Fig. 19 shows the process of searching the optimal result, and the optimization results of the bearing outer ring fault signal are compared in Table 3. The optimal result  $S_{max} = 17.1958$  and the corresponding parameters are  $a = 0.100$  and  $b = 2.0907$  in UBSR system.  $S_{max} = 31.2207$  and the optimal parameters are  $p = 0.1235$ ,  $u = 3.2678$  and  $l = 1.4142$  in UCUBSR system. The output time-frequency diagram of the two systems is given in Fig. 20. The output signal has a certain periodicity in Fig. 20(a) and (c). Then, by observing Fig. 20(b) and (d), the energy of high frequency interference signal is transmitted to the bearing outer ring fault signal through SR to highlight the fault characteristics, and a distinct peak appears at the frequency 41.02 approximately closed to the fault frequency, indicating that fault feature is clearly detected. Moreover, the  $S_{max}$  of UCUBSR system is 14.0249 higher than that of UBSR system and the  $Af_o$  of UCUBSR

**Fig. 21.** Iterative process of PSO with SNR as objective function.

system is nearly 25.2 times bigger than that of UBSR system. These demonstrate that the proposed method can alleviate the saturation problem more effectively and is better at detecting weak fault features in strong noisy background.

Then, to further prove the importance of the proposed index  $S$ , the output SNR is taken as the objective function in UCUBSR system. Fig. 21 reveals the search process of maximum output SNR  $SNR_{max} = -11.2257$  and the optimal parameters  $p = 0.3933$ ,  $u = 4.2480$ ,  $l = 1.0767$ . The optimized output signal is presented in

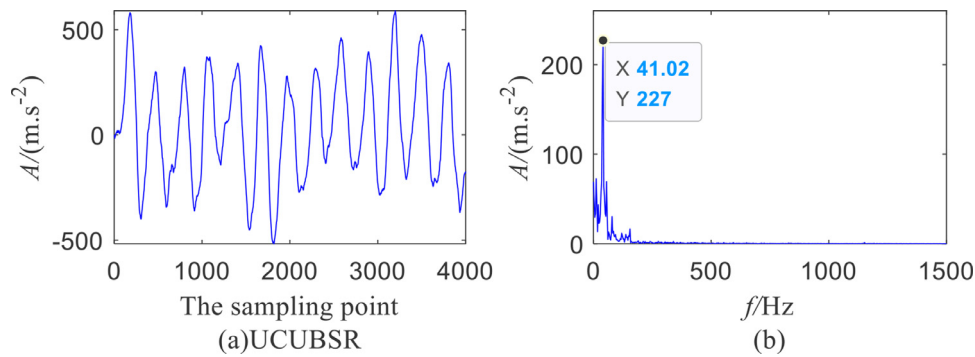


Fig. 22. (a) Time domain waveform and (b) spectra of the fault output signal.

Fig. 22, where the fault frequency 41.02 Hz with a pronounced peak  $Af_0 = 227$  in the power spectrum is notably highlighted. Compared with Fig. 22(b), the  $Af_0 = 251.6$  of the bearing outer ring fault signal in Fig. 20(d) is increased by 24.6. Thus, the frequency domain feature can be effectively enhanced when the amplitude gain  $S$  is taken as objective function. Briefly, the UCUBSR system with the amplitude gain  $S$  as objective function of the optimization algorithm can further improve amplification performance of system fault characteristic signal and facilitate bearing fault identification.

## 5. Conclusion

In conclusion, an underdamped continuous unsaturation bistable stochastic resonance system is put forward, and the effectiveness and superiority of the proposed system in weak fault feature extraction are studied by theoretical simulation and experimental analysis. The research shows that:

To overcome the saturation problem of CBSR system, a new potential function model is constructed, which can adjust the barrier height  $\Delta U$ , potential spacing  $\Delta L$  and steepness  $l$  independently. The SNR of the UCUBSR system is derived.

An improved evaluation index amplitude gain  $S$  is proposed. The effect of the system parameter  $l$  on SR based on SNR and amplitude gain demonstrates that the  $S$  is a suitable indicator for quantifying the SR. In addition, the simulation analysis proves that the  $S$  can make up for the deficiency of SNR as an evaluation index and has a good degree of discrimination.

In the simulation and bearing fault experiment, the amplitude gain is taken as the objective function of PSO. Compared with UBSR system, the UCUBSR system has larger amplitude gain. This proves that the proposed system has better ability of the unsaturation and weak fault characteristic enhancement.

In UCUBSR system, the higher output amplitude at characteristic frequency indicates the amplitude gain  $S$  can further guide the parameter adjustment of SR and enhance the amplitude enhancement ability of SR system, which is conducive to weak fault detection.

## CRediT author statement

**Mengdi Li:** Methodology, Software, Formal analysis, Writing-Original draft preparation.

**Peiming Shi:** Conceptualization, Data curation, Project administration, Writing - Review & Editing

**Wenyue Zhang:** Investigation, Visualization

**Dongying Han:** Resources, Writing- Reviewing and Editing

## Declaration of Competing Interest

The authors declare that they have no conflict of interest.

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