Discover Applied Sciences

Research

Bearing fault feature extraction based on MOMEDA and CS-Wood–Saxon stochastic resonance

ZhenYa Quan[1,2] · XueLiang Zhang[1]

Received: 18 September 2023 / Accepted: 20 December 2023
Published online: 29 January 2024

Abstract
Since rolling bearing is of great significance to ensure the safe and stable operation of rotating machinery, bearing fault feature extraction then demonstrates a hot topic of general interest in industry. In this work, we applied Multipoint Optimal Minimum Entroy Deconvolution Adjusted preprocessing algorithm to deal with the large amount of background noise containing in the collected bearing fault original signal. Then, the Wood–Saxon stochastic resonance nonlinear system model is adopted to solve the bearing fault feature extraction problem, which avoids the frequency interval and system parameters disadvantages in bistable stochastic resonance system. Furthermore, the parameter step and scale transform factor in the Wood–Saxon stochastic resonance nonlinear system is optimized adaptively by Cuckoo Search algorithm, in which way the output signal-to-noise of bearing fault signal is improved significantly. Therefore, the bearing fault feature can be extracted more effectively compared with the classical bistable stochastic resonance system model. Simulation and examples demonstrated that the proposed method can effectively reduce the noise in the signal and enhance the weak feature in bearing fault signal, so as to realize the accurate early bearing fault diagnosis.

Article Highlights

1 The output SNR of the weak fault signal can be improved significantly, thus we can detect the machinery fault as early as possible.
2 The fault feature characteristic frequency can be extracted efficiently and accurately, which carries out a technical reference for industrial applications.
3 This work gives out a solid foundation for the subsequent bearing fault type pattern recognition.

Keywords Bearing · MOMEDA · Wood–Saxon stochastic resonance · Weak fault · Signal-to-noise ratio

1 Introduction

Bearings and gear boxes are very critical parts for rotating machinery, and once failure occurs, it will cause various losses such as production line shutdown and casualties [1]. Therefore, monitoring and early fault diagnosis of rolling bearing and gear box operation process is of great significance to ensure the safe and stable operation of rotating machinery.

✉ ZhenYa Quan, fblwzyyx@163.com | [1]Shanxi Conservancy Technical Institute, Taiyuan 030032, China. [2]Taiyuan University of Science and Technology, Taiyuan 030024, China.

There are many methods for early fault diagnosis by monitoring weak signals, but most of them are extracted by eliminating background noise and highlighting characteristic signals. Random resonance uses noise to detect characteristic signals to achieve the purpose of searly bearing fault diagnosis [2]. Stochastic resonance was first proposed by Italian scholar Benzi [3], etc. Professor Hu Niaoqing [4] from National University of Defense Technology expanded the application range of stochastic resonance and introduced stochastic resonance into early fault enhancement detection of rotating machinery systems. At present, the most widely studied system of stochastic resonance is the classical bistable stochastic resonance model. However, the classical bistable stochastic resonance has some problems such as limitations in processing modulated signals and insufficient optimization of system parameters [5]. In 2015, Professor Leng Yonggang from Tianjin University constructed a tri-stable function based on the equilibrium point parameters, proposed a tri-stable system model driven by weak signal and noise, and studied the effects of damping ratio and equilibrium point parameters on the stochastic resonance of the system [6]. In 2015, Zhang et al. from Chongqing.[1]

University of Posts and Communications combined Levy noise with power function monostable stochastic resonance system to study the phenomenon of stochastic resonance under Levy noise excitation, and proposed a fault diagnosis method of multi-stable stochastic resonance bearing optimized by social simulation algorithm [7]. In 2017, Xie Yong et al. from Xi'an Jiaotong University studied the stochastic resonance of overdamped workboard potential system under the combined action of deterministic signal and Gaussian white noise.

Under the weak deterministic signal limit, a moment method for calculating the linear response of the system was proposed by combining linear response theory and perturbation expansion method [8]. In 2018, Chi Kuo [9] from Shijiazhuang Campus of Army Engineering University conducted a study on the application of Cuckoo algorithm to the optimization of stochastic resonance parameters. In 2019, Chi Kuo [10] et al., from Shijiazhuang Campus of Army Engineering University, proposed a fault diagnosis strategy based on Wood–Saxon in order to effectively detect bearing faults. In 2021, Xu Pengfei et al. [11] from Shanxi Agricultural University derived the system response amplitude and power spectrum amplification factor applicable to the general multistable model for the periodic potential system with multistable characteristics, and proposed the stochastic resonance of the periodic potential system with memory damping function under the joint excitation of external deterministic signal and internal noise. In addition, in 2016, Feng Yi et al. pointed out that the stochastic resonance system is effective for strengthening all frequency components near the optimal resonance frequency [12], but the processing effect is not very good for the optimal resonance frequency of small frequencies. For the envelope signal of small frequencies, the bistable stochastic resonance model is only effective for the frequency components with modulation characteristics. The author has made a comparative analysis in the previous literature, and MOMEDA is selected as the pre-processing filtering method in this paper. MOMEDA is a filtering method proposed by McDond [13] in 2017 to solve the problem of noise reduction effect by obtaining infinite pulse sequences as the target to solve the optimal filter.

On the basis of the above literatures, in addition to the bistable stochastic resonance (BSR) model, the Wood–Saxon system stochastic resonance model is used to extract the fault signal feature. A method combining CS adaptive Wood–Saxon stochastic resonance and MOMEDA was proposed to study bearing fault diagnosis, aiming at improving the output SNR(signal-to-noise ratio), and providing reference for effectively extracting the bearing fault signals detected in practice.

2 Wood–Saxon stochastic resonance system model and scaling transformation

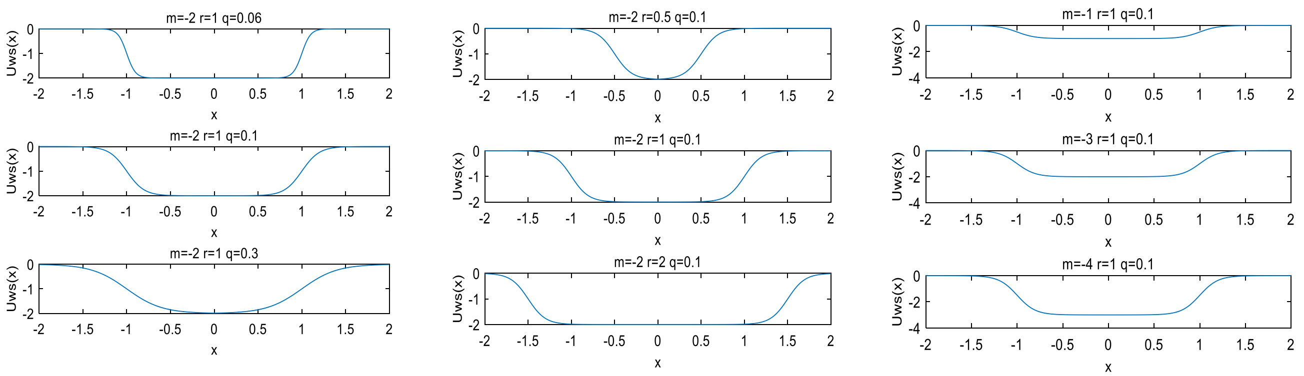
2.1 Wood–Saxon stochastic resonance model

The formula of the bistable stochastic resonance potential function is given in the literature [4]. This section mainly discusses the establishment of the Wood–Saxon stochastic resonance model, and the bistable stochastic resonance model is no longer listed.

The WS potential function is defined as [10]:

$$U_{ws}(x) = -\frac{m}{1 + \exp\left(\frac{|x|-r}{q}\right)} \tag{1}$$

[1] QUAN ZhenYa, Department of mechanical and electrical engineering, Shanxi Conservancy Technical Institute, Taiyuan, China. fblwzyyx@163.com.



(a)m is consistent with r, and q has a changing trend

(b)m is consistent with q, and r has a changing trend

(c)r is consistent with q, and m is changing trend

Fig. 1 Influence diagram of three parameters of WS single potential well

The shape and performance of WS single potential well are determined by three parameters: depth of potential well (m), radius of potential well (r) and steepness of potential well (q), and all three parameters are greater than 0.

Figure 1 shows the influence diagram of WS single potential well parameters. It can be seen from Figure (a) that the depth of potential well, the radius of potential well and the steepness of potential well interact and influence each other. When the radius and steepness of the potential well are certain, the width of the potential well does not change, but the depth gradually becomes shallow. The shape of the potential well can be determined by adjusting the parameters.

According to literature [10], $U_{ws}\prime(0)$ does not appear, so it is assumed that $U_{ws}\prime(0) = 0$. Substitute formula (1) into Langevin equation (LE) to get the following formula:

$$\frac{\mathrm{d}x}{\mathrm{d}t} = -\frac{m}{q}\mathrm{sgn}(x)\exp\left(\frac{|x|-r}{q}\right)\left(1+\exp\left(\frac{|x|-r}{q}\right)\right)^{-2} + S(t) + N(t) \tag{2}$$

where

$$\mathrm{sgn}(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases}$$

$S(t) + N(t)$ is a random signal entering the system.

2.2 Wood–Saxon stochastic resonance scaling

Wood–Saxon stochastic resonance scaling continues to use normalized scaling for signal conversion [4, 10].

The Wood–Saxon stochastic resonance normalization scaling is as follows:

Suppose $z = VKx\tau = Vt$, then Eq. (2) become

$$\begin{aligned}\frac{\mathrm{d}z}{\mathrm{d}\tau} = &-\frac{VK^2m}{VKq}\mathrm{sgn}(z)\exp\left(\frac{|z|-VKr}{VKq}\right)\times\left(1+\exp\left(\frac{|z|-VKr}{VKq}\right)\right)^{-2} \\ &+ K\left(S\left(\frac{\tau}{V}\right) + N\left(\frac{\tau}{V}\right)\right)\end{aligned} \tag{3}$$

where K and V are scale transform factors and amplitude transform factors respectively.

Equation (3) can be solved by the fifth-order Runge–Kutta algorithm (Eq. (4)) [10].The discrete signal $S(t)$ obtained in engineering practice is equal to the characteristic signal $F(t)$ plus noise $N(t)$, that is, $S(t) = F(t) + N(t)$.

$$\begin{cases} z' = f(n,z|m,r,q,H,K,s), z_1 = 0 \\ z_{n+1} = z_n + \frac{H}{6}(k_1 + k_2 + 2k_3 + k_4 + k_5) \\ k_1 = f(n,z_n|m,r,q,H,K,s_n) \\ k_2 = f\left(n, z_n + \frac{H}{2}k_1|m,r,q,H,K,s_n\right) \\ k_3 = f\left(n+1, z_n + \frac{H}{2}k_2|m,r,q,H,K,s_n\right) \\ k_4 = f\left(n+1, z_n + \frac{H}{2}k_3|m,r,q,H,K,s_n\right) \\ k_5 = f(n+1, z_n + Hk_4|m,r,q,H,K,s_n) \end{cases} \tag{4}$$

Here the step size is $H = a/f_s$, f_s is the sampling frequency, s_n is the *n*-th point of the input signal, and z_n is the *n*-th point of the stochastic resonance output.

2.3 CS optimization algorithm for parameter optimization of Wood–Saxon stochastic resonance model

Adaptive stochastic resonance problem is a multi-dimensional and multi-parameter continuous optimization of stochastic resonance effect due to automatic adjustment of system parameters under the same input signal. In 2021, An improved cuckoo search algorithm is proposed to solve the problem of task assignment and path planning for multiple robots. The path planning method can effectively realize the task assignment and path planning of multi-robot, and provide scientific basis for the endurance energy of multi-robot [14]. In 2020, Wang Haiyang of Shanghai University of Engineering Technology proposed a method for predicting the remaining life (RUL) of lithium batteries by using the improved Cuckoo algorithm (ICS) to optimize the correlation vector machine (RVM). Practical experiments and a series of error indicators verified that the ICS + RVM method proposed in this paper has higher accuracy in predicting the RUL of lithium batteries. It provides a reference for life prediction of rolling bearing [15]. In 2018, Chi Kuo [9] from Shijiazhuang Campus of Army Engineering University conducted a study on the application of cuckoo algorithm to the optimization of stochastic resonance parameters.

Cuckoo algorithm [16] has brought many applicable effects in the research of medical treatment, measurement, electronic information, aerospace and other fields. Aiming at the problems such as uncertainty of adaptive stochastic resonance parameters, poor calculation accuracy, multi-dimensional and multi-parameter continuous optimization, the characteristics of various algorithms were analyzed by reading relevant literature, and considering the influence of parameter optimization on stochastic resonance effect, the paper proposed the use of SNR as a fitness function of Cuckoo algorithm, is more conducive to fault feature extraction by optimizing the matching effect between adaptive stochastic resonance parameters. Stochastic resonance is to fix the values of parameters a and b or fix parameters a(b), adjust parameters b(a), and ignore the effect of interaction between parameters such as step size and scale change factor. Wood–Saxon stochastic resonance is no exception. In this section, the Wood–Saxon stochastic resonance parameters are adjusted to coordinate the parameters with the system and noise intensity, so as to achieve the best effect of stochastic resonance output. The parameter Settings of CS algorithm are shown in Table 1.

Considering the influence of the interaction between parameters on the output of stochastic resonance, CS algorithm was used to calculate the interaction matching of the step size H, scale transform factor K and amplitude transform factor V of the stochastic resonance parameters of the Wood–Saxon system, and the best matching values of the three parameters with the largest output SNR were found to facilitate the extraction of the output characteristic frequency of stochastic resonance.

According to the three rule assumptions of CS algorithm [17] and the steps of calculation, CS algorithm is used to search and optimize parameters H, K and V. According to the calculation of literature [10], when the amplitude transformation factor is constant and $V = 0.3209$, the influence chart of Wood–Saxon stochastic resonance parameters H, K and output SNR shows that the output SNR increases with the decrease of H and K values. The best matching diagram of parameters H, K and V is shown in Fig. 2.

In the Wood–Saxon system stochastic resonance model, when the amplitude transform factor $V = 0.3209$, CS algorithm continuously optimizes and adjusts the parameter step H and scale transform factor K until the three parameters reach the best matching value.

Table 1 Parameter values of Cuckoo Search Algorithm

Parameter class	Parameter value
Local search radius	0.05
The number of columns and columns in a self-learning structure	25
The number of self-learning times	1
Invariance probability	0.7
The probability of strategy 1	0.6
The crossover probability in strategy 2	0.5
Foreign discovery rate	0.25
Number of nests	36

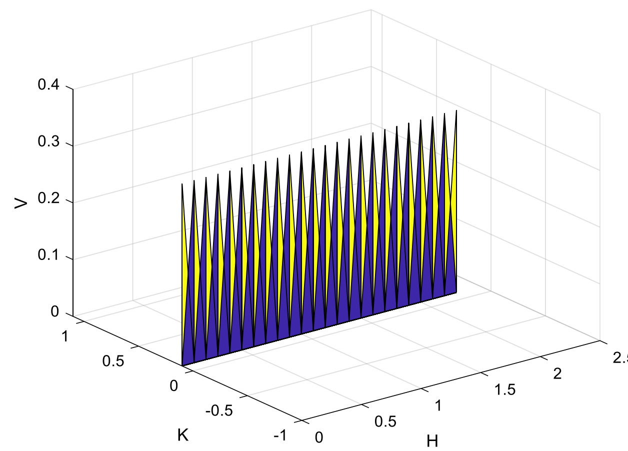


Fig. 2 Optimal matching diagram of H,K and V parameters

3 MOMEDA pre-processing filtering analysis in the sense of Wood–Saxon stochastic resonance

The stochastic resonance of classical bistable systems has some problems, such as the limitation of processing the original signal and insufficient optimization of system parameters [5]. According to the research in literature [12], it is effective for the stochastic resonance system to strengthen all frequency components near the optimal resonance frequency, but the processing effect is not very good for the optimal resonance frequency of small frequency. For the envelope signal of small frequency, only the frequency components with modulation characteristics are output effectively by using the bistable stochastic resonance model.In view of the above problems, the Wood–Saxon stochastic resonance model of the adaptive Wood–Saxon system is selected and compared with the bistable stochastic resonance model in filtering effect. According to the results of the author's previous filtering effect analysis, although the effect of extracting weak fault characteristic frequency by using MOMEDA as stochastic resonance pre-processing filter is not very obvious compared with the traditional time–frequency algorithm, and there are interference pulse components, the signal-to-noise ratio is increased by 58.76%, which is suitable for the analysis of low signal-to-noise ratio fault signals. Therefore, the filtering algorithm in this section continues to adopt MOMEDA algorithm.

3.1 Optimization and selection of MOMEDA parameters

The parameter selection of MOMEDA algorithm directly affects the filtering calculation. In order to obtain the best matching value of filtering length, test period and multi-point peak value to the filtering effect of MOMEDA, the parameters of MOMEDA are calculated, analyzed and selected in this section. The rolling bearing vibration fault data set collected by Dr. Eric Bechhoefer [18] on behalf of MFPT was used for the parameter selection of MOMEDA algorithm. The calculation data of bearing inner ring wear fault were intercepted with 5000 sampling points, the optimal filtering length

Table 2 Parameter calculation and analysis

Test cycle R	Multipoint peak-Murt	SNR_{in}	SNR_{out1}	SNR_{out2}
50	0.1685	-53.8765	-16.2215	-36.1570
60	0.2796	-54.9975	-15.2585	-21.1634
70	0.3461	-50.0498	-15.3177	-20.3746
80	0.2087	-43.6438	-17.0235	-34.5347
90	0.1863	-47.5598	-17.5544	-30.0384

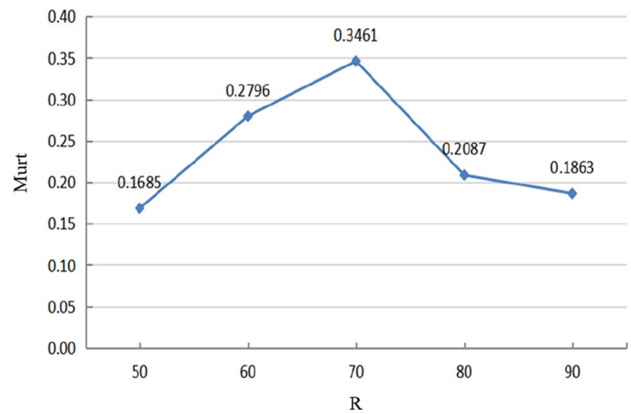


Fig. 3 Influence of R on Murt

was selected L = 1000, and 5 groups of test cycles were selected for MOMEDA parameter calculation and analysis. The calculation results are shown in Table 2:

The selection of filtering length, test period and other parameters directly affects the filtering effect of MOMEDA. In order to select appropriate parameters, achieve the best filtering effect and better extract the feature frequency. Given a certain filtering length, this section studies the influence of the test period on the filtering effect of MOMEDA and the influence on the SNR of the output of the objective function in an example. The multi-point peak value is normally distributed in the range of 50–90 test cycles (See Fig. 3).

SNR_{out1} and SNR_{out2} are the output curves of the Wood–Saxon system and the bistable system respectively.As shown in Fig. 4, when the input signal-to-noise ratio is certain, the test period R is equal to 50–90, and the variation range of SNR_{out1} is about 15%. The variation amplitude of SNR_{out2} is about 80%. It can be seen that the selection of parameter test period values has a great influence on the output of the Wood–Saxon system's stochastic resonance SNR. When R = 70, the output SNR is the largest and the output of the stochastic resonance is the best.

As can be seen from Fig. 5, when the input signal-to-noise ratio is certain, the multi-point peak Murt ranges from 0.1685–0.1863, and the variation range of SNR_{out1} is about 15%. The variation amplitude of SNR_{out2} is about 80%, indicating that the selection of parameter test period values has a great influence on the output of the Wood–Saxon system's stochastic resonance SNR. It can also be seen from Fig. 5 that when the multi-point peak Murt = 0.3461, the output SNR is the largest.

Through the calculation and analysis of the example, when the parameter test period of MOMEDA algorithm R = 70 and the multi-point peak Murt = 0.3461, the filtering effect of MOMEDA is the best, and the output SNR of the two different stochastic resonances is the largest.

3.2 Simulation and analysis of MOMEDA pre-processing filter in the sense of Wood–Saxon stochastic resonance

Suppose an input signal model is $S = S_1 + S_2$, where $S_1 = A\sin\left(2\pi f_d t\right)$, bearing weak fault signal S_1 is simulated by adding white noise. The signal parameters are as follows: amplitude $A = 1$, fault frequency $f_d = 50Hz$, noise intensity $D = 30V$, sampling frequency $f_s = 10000$ Hz.

A large amount of noise is added to the analog signal to simulate the bearing fault signal (Fig. 6), and the fault frequency of 50Hz cannot be extracted from the noise. The Wood–Saxon stochastic resonance method proposed in

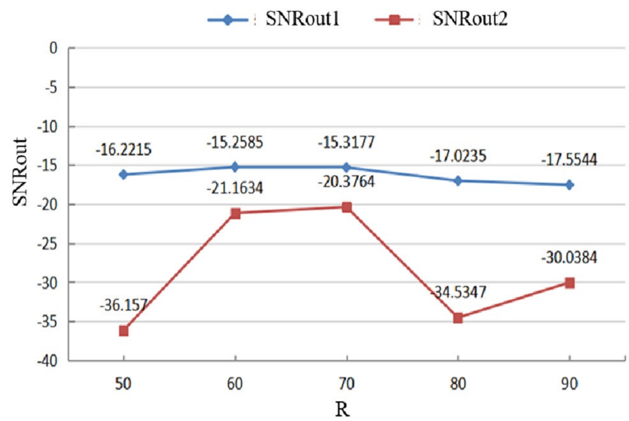


Fig. 4 Influence of R on output SNR

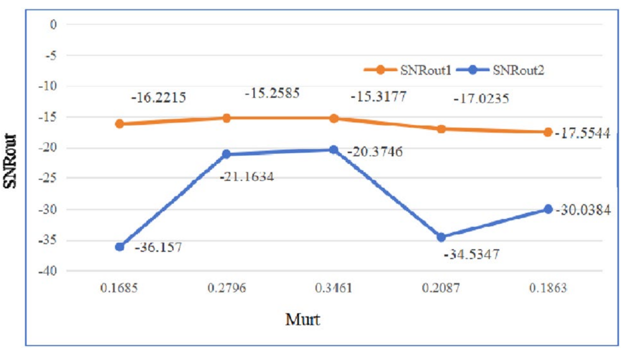


Fig. 5 Influence of Murt on output SNR

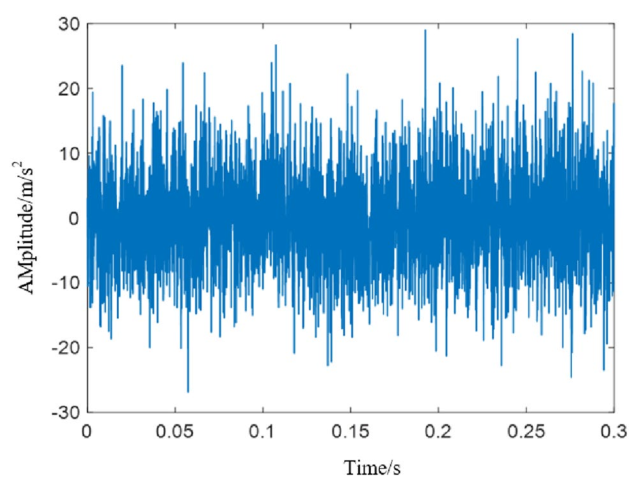


Fig. 6 Time-domain waveform of simulated signal

this paper is used to process the signal. After the simulated fault signal is processed by MOMEDA, high-frequency components with amplitudes exceeding 0.6 are effectively filtered out, and a series of obvious impact components conducive to feature extraction appear in the time-domain diagram in Fig. 7. After the signal is processed by MOMEDA filter, the signal is greatly improved and a series of periodic pulses appear, but the fault characteristic frequency is difficult to extract due to the influence of noise. Filtering not only removes high-frequency noise, but also provides matching noise intensity for stochastic resonance.

In order to verify the advantages and disadvantages of the bistable stochastic resonance and the Wood–Saxon stochastic resonance, the filtered signals were input into two kinds of stochastic resonance models respectively for characteristic frequency extraction. (Figs. 8, 9).

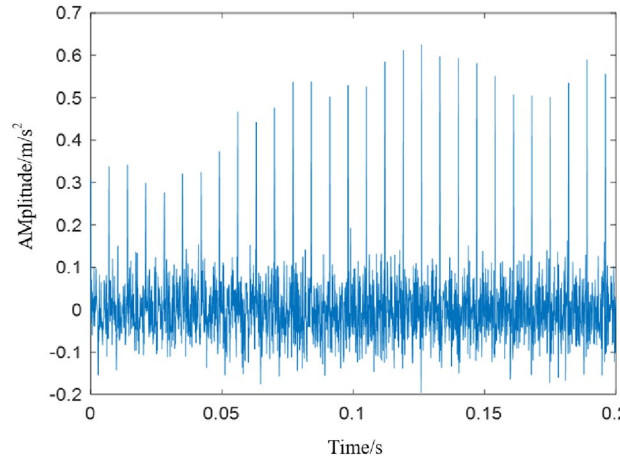


Fig. 7 Time domain waveform after MOMEDA filtering

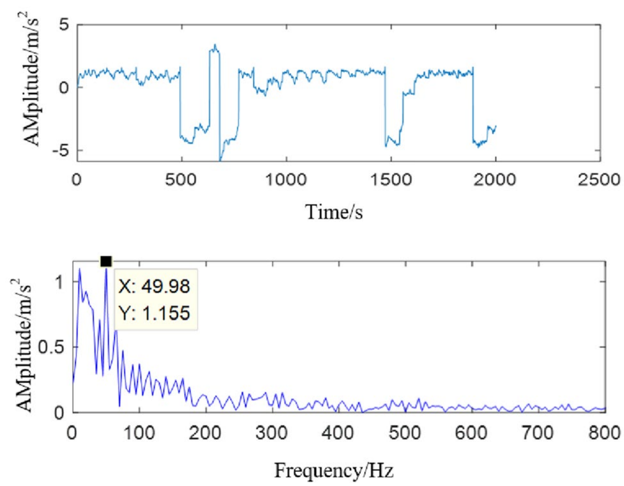


Fig. 8 Time-domain waveform and spectrum of CS-Wood–Saxon stochastic resonance output

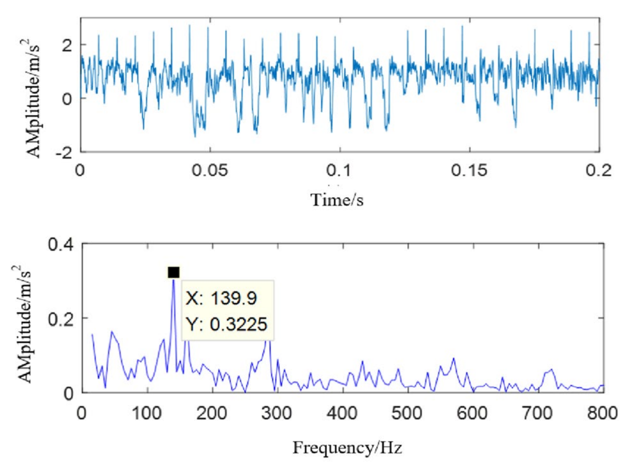


Fig. 9 Time-domain waveform and spectrum of CS-BSR output

With SNR as the objective function, the filtered signal is fed into the Wood–Saxon stochastic resonance model. As can be seen from Fig. 8, the system model, noise intensity and parameters achieve a synergistic effect, and the fault characteristic frequency is effectively extracted from the signal spectrum diagram after the Wood–Saxon stochastic resonance processing. It can be seen from Fig. 9 that the impact pulse signal with an obvious peak value of 139.9Hz appears in the spectrum diagram, and the fault frequency is not obvious. Compared with the impact pulse signal of 139.9Hz, the fault frequency is in the harmonics of the peak signal 139.9, which is difficult to extract. As can be seen from the comparison

Fig. 10 Bearing inner race failure

Table 3 Test bearing technical parameters

Parameters	Indicators	Parameters	Indicators
Rolling diameter	d = 5.969mm	Load	50lbs
Pitch diameter	D = 31.623mm	Gyration frequency	25Hz
Number of rolling elements	n = 8↑	Sampling frequency	$f_s = 16276$ Hz
Contact Angle	$\alpha = 0\,^{\circ}C$	Sampling number	6000
Bearing inner ring fault characteristic frequency	$f_d = 116$ Hz	Bearing outer ring fault characteristic frequency	$f_d = 81$Hz

of spectral graphs in Figs. 8 and 9, the Wood–Saxon stochastic resonance model is more effective than the bistable stochastic resonance model when extracting weak fault signals with low SNR in the calculation and analysis of simulation periodic signals.

4 Application of the proposed method for the fault diagnosis of rolling bearings

In the vibration signal of rotating machinery bearing fault, due to the different kinds and strengths of faults, the faults are coupled with each other, especially in the early signal of bearing fault, the impact component is weak in the signal, and it is easy to appear the problem of missing diagnosis or diagnosis error. This example uses the adaptive Wood–Saxon stochastic resonance model with weak dependence on noise characteristics to process the fault signal. By comparing the spectrum diagram of the classical bistable model and the Wood–Saxon model, it provides a new idea for the selection of stochastic resonance noise reduction model. This section proposes a bearing fault diagnosis method based on the combination of MOMEDA and CS adaptive Wood–Saxon stochastic resonance [4, 9, 18].

Now, the feature extraction and analysis of common bearing inner ring wear faults (as shown in Fig. 10 and Table 3) are carried out for further research. The experimental data of bearing inner ring wear failure were obtained from the bearing failure data set collected by Dr. Eric Bechhoefer, chief engineer of NRG system, on behalf of MFPT [19]. The working conditions of bearings are shown in Table 3. Bearing load conditions: load 50 pounds, input shaft speed of 25Hz.

The technical process of fault feature extraction for adaptive stochastic resonance bearing based on MOMEDA and Wood–Saxon is shown in Fig. 11.

As is shown in Fig. 11, the input fault signal is firstly transformed to envelop signals by Hilbert transformation. Then, MOMEDA method is applied to preprocess and filter the envelop signals in order to improve the SNR of the input signal. Next, with the attempt to extract the fault feature of rolling bearing effectively, CS algorithm is adopted by optimizing the key factors (H, K, V) in the Wood–Saxon stochastic resonance (Wood–Saxon SR). Meanwhile, by comparison with BSR, fifth-order Runge–Kutta algorithm is used to obtain a more precise result for the Wood–Saxon SR model, then a more higher output SNR of the fault signal. Finally, the bearing fault characteristic frequency can be extracted by the proposed CS-optimized Wood–Saxon SR method.

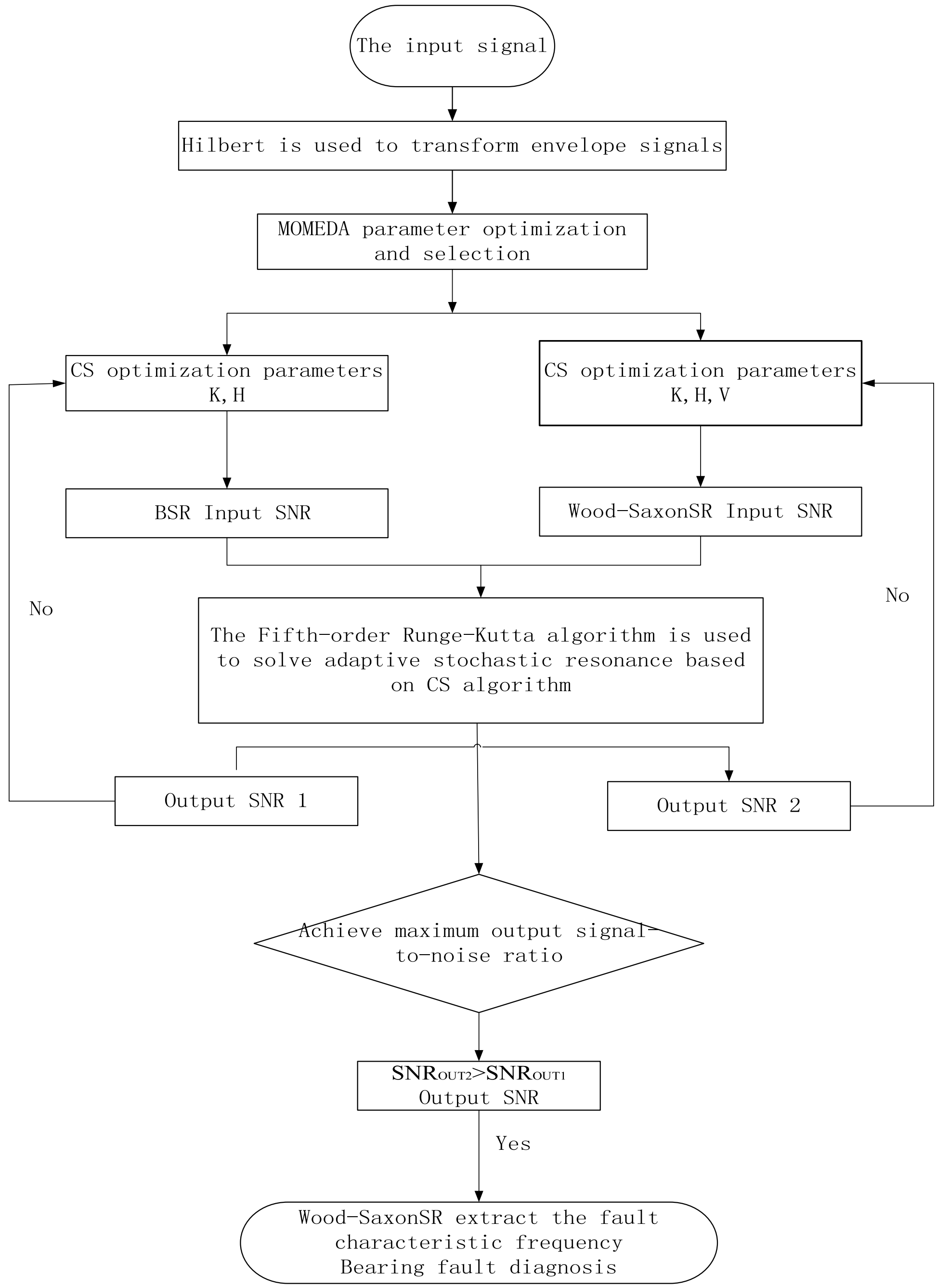
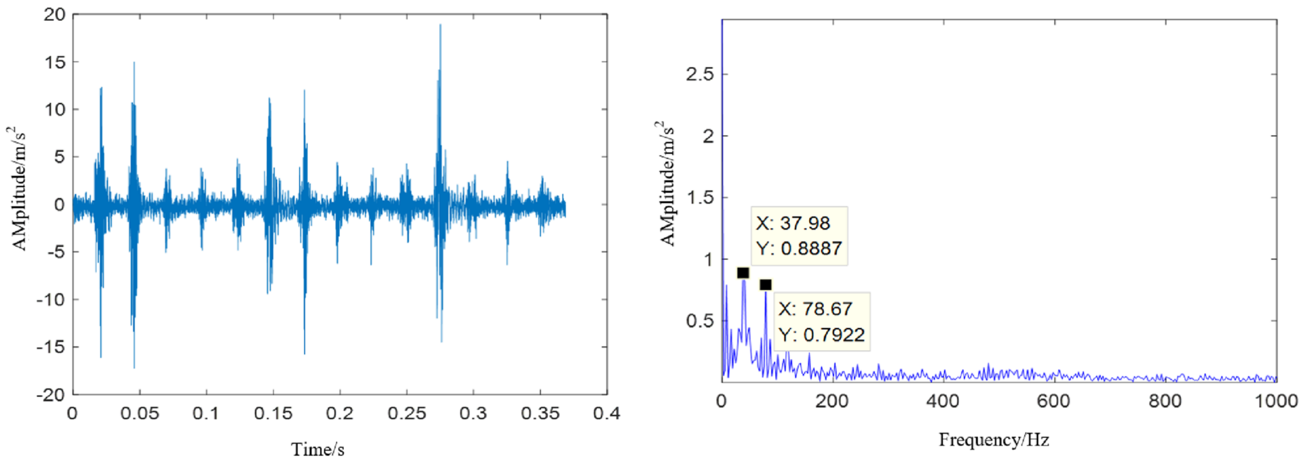


Fig. 11 Computational flow of CS-Wood–Saxon stochastic resonance

4.1 Filter analysis of bearing inner ring fault signal

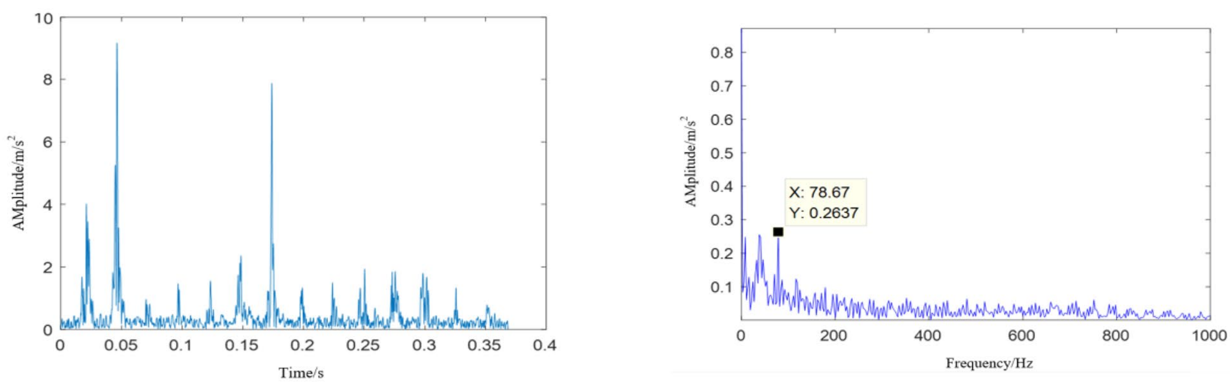
Figure 12 shows that obvious periodic impact components are distributed in 1000-2000Hz, 2000-4000Hz, and 4000-5000Hz frequency bands respectively. Due to the presence of a large amount of noise, the time-domain waveform is relatively complex and the amplitude is large.

In this section, measured signals in three frequency bands of 1000–2000 Hz, 2000–3000 Hz, and 4000–5000 HZ are respectively selected for Hlibert envelope spectrum analysis. Through calculation, analysis and comparison, it is found that there are few irrelevant spectrum lines in the time-domain diagram and spectral diagram of the 2000-3000Hz frequency band, and the fault characteristic frequency is not annihilated. Therefore, signals in the 2000–3000 Hz frequency band are selected for further research. As shown in Fig. 13.



(a) Time domain waveform (b) Spectrogram

Fig. 12 Time domain waveform and M-WS signal spectrum of collected signals



(a) Hilbert time domain waveform in 2000-3000Hz band (b) Hilbert spectrum diagram in 2000-3000Hz band

Fig. 13 Hlibert envelope spectrum of 2000–3000 frequency band

After Hlibert envelope spectrum analysis, frequencies in the range of 0–1000 Hz are intercepted. In the low frequency range of 200 Hz, there are two obvious impact signals, 37.98 Hz and 78.67 Hz respectively, and there are strong noise interference components distributed in the range. Further analysis is needed to extract the fault spectrum. In order to eliminate the influence of large pulses on stochastic resonance in the low frequency range, MOMEDA is used to filter the signal. Through the parameter optimization and numerical selection in Sect. 2.1, this paper analyzes the influence of the MOMEDA algorithm test period and multi-point peak value on the SRR output. According to the data analysis results, the optimal parameters of the calculation and analysis are input into the M-WS-SR (MOMEDA-Wood–Saxon-Stochastic Resonance) system.

As can be seen from Fig. 14, after MOMEDA filtering, the bearing fault signal is clearer and more obvious than the original figure. Within the range of 0–200 Hz, the 37.98 Hz and 78.67 Hz pulse signals shown in Fig. 12 are filtered out, and the spectral lines change periodically.

4.2 Comparative analysis of Wood–Saxon adaptive stochastic resonance

In this chapter, a bearing fault diagnosis method based on the combination of MOMEDA and Wood–Saxon adaptive stochastic resonance is proposed by comparing two kinds of stochastic resonance spectra of classical bistable model and Wood–Saxon model.

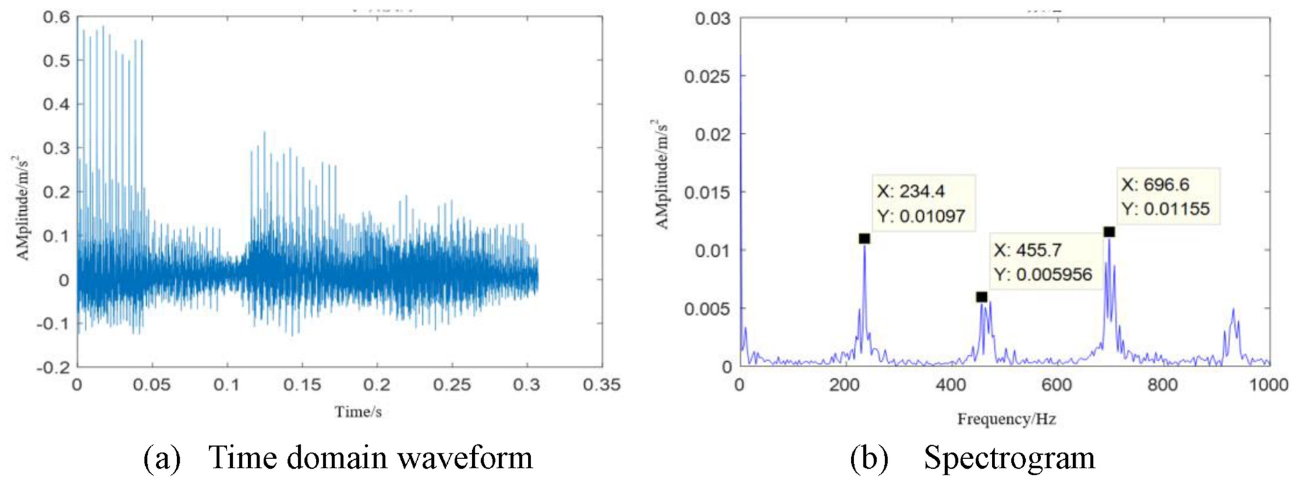


Fig. 14 M-WS time domain waveform and spectrum after MOMEDA filtering

As can be seen from the iterative convergence curve (a) in Fig. 15, at the initial stage of stochastic resonance optimization by Cuckoo algorithm (CS), the iterative curve in the Wood–Saxon system is approximately linear and converges when the number of iterations is equal to 4. In Fig. 15b for the bistable stochastic resonance system, the iteration curve is irregular and relatively steep. When the number of iterations is equal to 5 and the output signal-to-noise ratio is about -33, the local optimal solution appears, and when the number of iterations is equal to 10, the solution converges. It can be seen from the analysis that under the same conditions, the convergence speed of CS optimization parameters in the Wood–Saxon system is improved by nearly 20%.

The fault frequency of the bearing inner ring is $f_{BPFI} = 117$ Hz. After the collected signal is pre-processed and filtered by MOMEDA, it is input into two different stochastic resonance models. The calculated results are shown in Fig. 16. It can be seen from the two figures that both kinds of stochastic resonance systems can enhance the low-frequency pulse signal.

With further analyzed the result of SNR_{out2} for Wood–Saxon SR model, it is illustrated that the proposed method can increase the output signal SNR by 70% as for the case of R = 70. In this way, the fault characteristic frequency component is significantly improved and then the fault characteristic frequency of bearing inner ring is extracted effectively.

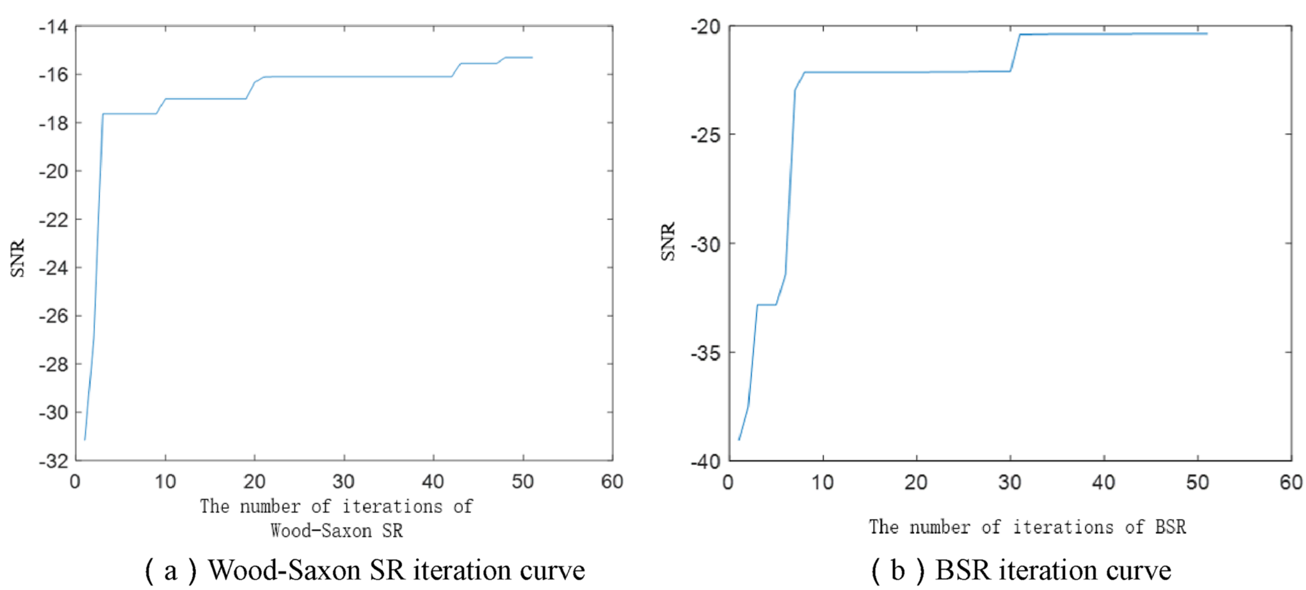


Fig. 15 Iterative convergence curve

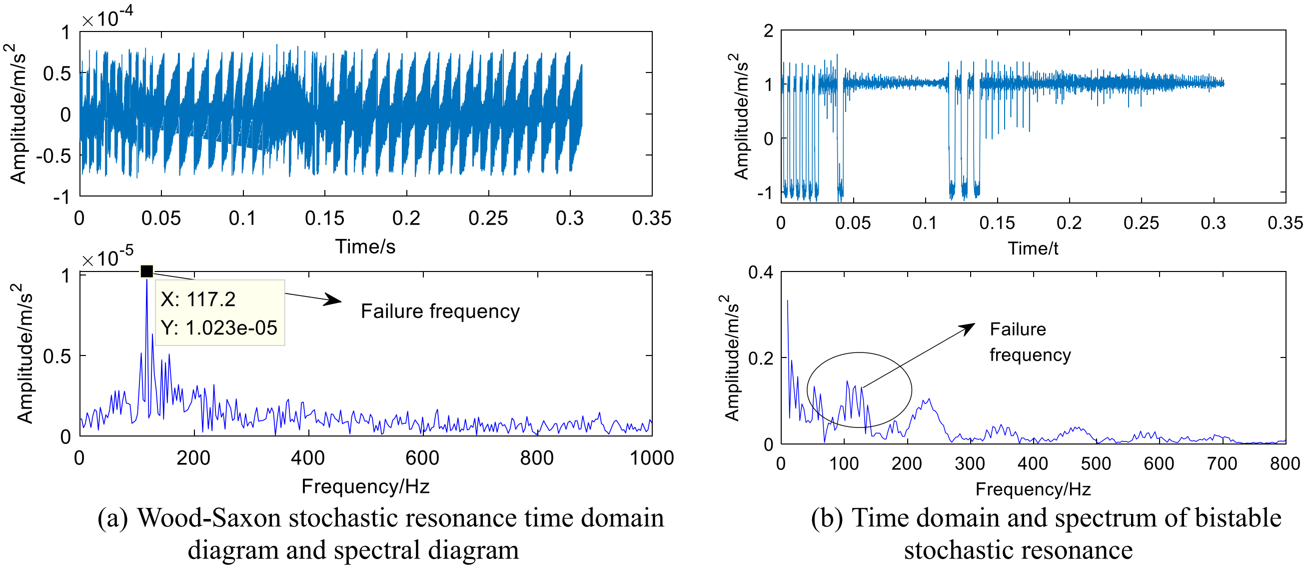


Fig. 16 BSR-WSSR models output time domain waveforms and spectrograms

Moreover, compared with BSR model, the output SNR of the bearing fault signal in Wood–Saxon SR model is increased significantly. And also, during R = 30–60, there is a linear increasing relationship between the test cycle R and the increased SNR (30–60%). The increasing percent is obtained by the SNR_{in} and SNR_{out}.

To be honesty, in order to obtain a higher output SNR and more precise fault feature frequency, CS algorithm and fifth-order Runge–Kutta algorithm are combined in the proposed method, which require a sufficient random-access memory of the computer and also more computing time is needed during the solving process of the Wood–Saxon SR model.

5 Conclusion

In this paper, Wood–Saxon stochastic resonance model is used for signal processing, and a method of bearing fault feature extraction combining Wood–Saxon adaptive stochastic resonance and MOMEDA is proposed. By comparing the spectrum diagram of stochastic resonance signals of classical bistable model and Wood–Saxon model, the signal-to-noise ratio can be effectively improved, and the characteristics and advantages of weak fault characteristic frequency can be easily extracted accurately compared with bistable stochastic resonance, and a new idea is provided for the selection of stochastic resonance noise reduction model.

1. The results show that when the parameter test period of the MOMEDA algorithm is R = 70 and the multi-point peak Murt = 0.3461, the filtering effect of MOMEDA is the best, and the output SNR of the two different stochastic resonances is the largest.
2. The Wood–Saxon stochastic resonance model is more effective than the bistable stochastic resonance model in extracting weak fault signals from the simulation period signal calculation and analysis.
3. Under the same conditions, the convergence rate of CS optimization parameters is improved by nearly 20% in the Wood–Saxon system stochastic resonance calculation.

Author contributions Quan Zhenya is mainly responsible for writing the entire paper, while Zhang Xueliang is the mentor who provides guidance during the process of Q completing the paper。

Funding The presented work was supported by the Postgraduate Education Innovation Project of Shanxi Province in 2018 (2018BY105).

Data availability The dataset of MFPT Bearing Fault is available at https://www.mfpt.org/wp-content/uploads/2020/02/MFPT-Fault-Data-Sets-20200227T131140Z-001.zip.

Declarations

Competing interests The authors declare that they have no conflict of interest.

References

1. Bilin P. Research on fault diagnosis method of EMU axle box bearing based on optimized RSSD and VMD. Beijing: China Academy of Railway Sciences, 2021;1–10
2. Zang G, Wu X. Stochastic resonance and bearing fault diagnosis basedon a Duffing-Van der Pol strongly coupled system. J Vib Shock. 2020;39(19):266–75.
3. Benzi R, Parisi G, Vulpiani A. Theory of stochastic resonance in climatic chaner. SIAM J Appl Math. 1983;43(3):565–78.
4. Hu N. Theory and method of stochastic resonance weak characteristic signal detection. National Defence Industry Press, 42–47.
5. Yu M, Jiang H, Zhang X. Research on Bearing Fault diagnosis of stochastic resonance optimized by social mimic algorithm. J Xinjiang Univ (Natural Science Edition in Chinese and English), 2021, 38(3): 355–60.
6. Lai Z, Leng Y. Dynamic response and stochastic resonance of tristable system. Acta Physica Sinica, 2015;64(20): 200503-1-200503-12.
7. Zhang G, Hu Tao, Zhang Tianqi. Analysis of power function monostable stochastic resonance under Levy Noise Excitation. Acta Physica Sinica, 2015;64(22): 220502-1-220502-9.
8. Xie Y, Liu R. Stochastic resonance of over-damped Washboard potential System. Acta Physica Sinica, 2017, 66(12): 120501-1-120501-10.
9. KuoChi JK, Xinghui Z, et al. Bearing fault diagnosis based on stochastic rosonance with Cuckoo search. Int J Perform Eng. 2018;14(3): 413–24.
10. Kuo C, Jianshe K, Xinghui Z. Experimental application of stochastic resonance based on Wood–Saxon potential on fault diagnosis of bearing and planetary gearbox. J Braz Soc Mech Sci Eng. 2019;41(11): 514-2–514-11.
11. Xu P, Gong X, Li Y., et al. Stochastic resonance of periodic potential systems with memory damping function. Acta Physica Sinica. 2022;71(08): 32–42.
12. Feng Yi Lu, Baochun ZD. Weak fault signal detection of bearing based on multi-stable stochastic resonance. J Vibr Meas Diagn. 2016;36(6):1169–74.
13. Mcdonald Gl, Zhao Q. Maximum correlated kurtosis deconvolution and application on gear tooth chip fault detection. Mech Syst Signal Process. 2017; 82: 461–477.
14. Yongsheng X, Xiaoxiao Z, Wenjian F. Application of improved cuckoo search algorithm in Multi-Robot task assignment and path planning. Comput Appl Softw. 2021;38(2):285–90.
15. Haiyang W, Wanqing S. Application of improved cuckoo search algorithm in lithium-ion batteries remaining useful life prediction. Intell Comput Appl. 2020;3(10):40–50.
16. Shuzhi G, Yue G, Yimin Z, et al. Adaptive cuckoo algorithm with multiple search strategies. Appl Soft Comput. 2021;106(10781):1–15. https://doi.org/10.1016/j.asoc.2021.107181.
17. Yang X. Nature-inspired metaheuristic algorithms. 2nd ed. London: Luniver Press; 2010. p. 105–8.
18. Xiong Z. Research on fault feature extraction and diagnosis of rolling bearing based on Kurtogram-based algorithms. Beijing: North China Electric Power University; 2019.
19. Bearing Fault Data Sets. Available online: http://www.mfpt.org/fault-data-sets/.