Research Article

Intelligent Diagnosis Model of Traction Seat of Urban Rail Vehicle Based on Harris Hawks Optimization

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Traction seat is an important connecting part of urban rail vehicle, which plays an important role in maintaining smooth running and power transmission of the vehicle body. Timely diagnosis of early failure of traction seat is the key to ensure the safe operation of urban rail vehicles. In order to realize the intelligent diagnosis of traction seat, a multialgorithm fusion scheme based on the Harris Hawk algorithm (HHO) is proposed to realize the fault diagnosis of traction seat. Firstly, the early mechanism of traction seat was studied, and the simulation experiment platform of urban rail vehicle traction seat was built to obtain the vibration data of the early crack traction seat model, so as to facilitate the simulation experiment research. Then, the vibration data of the traction seat were processed by HHO optimized variational mode decomposition (HVMD) to obtain several intrinsic mode functions (IMFs). Secondly, the multiscale permutation entropy (MPE) of each IMF is quantified and its average value is used to construct the energy characteristic vector. Finally, feature vectors are input into the HHO optimized support vector machine (HSVM) model to train a pattern recognizer. Through Python simulation verification, the results show that the model can accurately extract the characteristic information of traction seat and accurately identify the fault type, and the recognition rate reaches 100%.

1. Introduction

As an economical and practical urban public transport system, urban rail transit has the advantages of large capacity, energy saving, and environmental protection and has become the main force of urban transport development in the world. With the support of the state, urban rail transit is constantly improving and perfecting. At present, under the promotion of the state, the urban rail network is expanding, the number of urban rail vehicles is increasing, the maintenance services are also increasing, and the quality demand for operation and maintenance is also increasing. Under the current situation, the fault diagnosis of urban rail vehicles mainly relies on manual troubleshooting and processing but has not realized real-time status monitoring, and the troubleshooting process needs to spend a lot of manpower, material resources, and financial resources to do offline detection, diagnosis, and maintenance. In this environment, the importance of intelligent perception and operation and maintenance technology of urban rail vehicles is self-evident. For the rapid development of transportation, it is imperative to study the fault diagnosis of urban rail vehicles. The safe operation and condition monitoring of urban rail vehicles is an important research focus in the field of modern urban rail transit, which bears the responsibility of passengers’ safety and social stability.
In urban rail vehicles, traction seat is an important part connecting the car body and bogie. The traction seat not only plays the role of power transmission but also plays the role of traction and braking. At the same time, it can also ensure the smooth running of urban rail vehicle by avoiding the interference of bogie and car body when driving in complex sections. Traction seat load is a complicated and intense vibration environment for a long time, this makes the traction seat easy to produce slight early cracks in a weld, The early crack detection is very difficult to the operation and maintenance of the vehicle. If the crack of the traction seat is not found in time, once the crack expands, it will bring safety hazards to the safe operation of the vehicle. Crack fault is a common defect in mechanical structure and is also one of the common factors causing the failure of mechanical equipment. In recent years, mechanical equipment is often accompanied by cracks in the operation of the occurrence of disasters and accidents, prompting many experts and scholars to begin to study mechanical cracks. In the field of urban rail transit, the state of traction seat affects the effectiveness and reliability of urban rail vehicles, and the traditional traction seat fault detection method has disadvantages of poor real-time performance and low efficiency. Therefore, the establishment of an intelligent traction seat fault detection system can prevent the further expansion of early cracks in time to solve the occurrence of accidents.

At present, the crack detection of mechanical equipment is mainly divided into two aspects [1–10]: one is the nondamage detection method: the integration of modern technology with physical or chemical technology to create equipment that can detect the thermal, acoustic, optical, electrical, magnetic, and other reaction changes within the material, to detect the crack defects of mechanical equipment; the second is the intelligent diagnosis method: analyze the vibration signals of the mechanical equipment collected, extract the sensitive characteristics of the equipment, and then, use the pattern recognition method to identify the crack state. Traditional nondamage detection technologies (such as ultrasonic detection, X-ray detection, eddy current detection, and magnetic particle detection) can detect cracks in mechanical equipment without damaging or affecting the performance of the test object, which has been widely used in engineering [1–6]. When the traditional nondamage detection technology cannot meet the requirements, many scholars adopt intelligent diagnosis methods to diagnose crack faults and adapt to more engineering applications, among which the vibration diagnosis method is the most widely studied [7–10]. Literature [7] analyzes gear cracks based on vibration signals and proposes a re-weighted singular value decomposition (RSVD) method for periodic pulse extraction, which has achieved good results in fault detection and severity assessment. Literature [8] proposed a numerical fault detection model based on dynamic transmission error (DTE). The experimental results show that with the increase of crack level, the meshing stiffness of gear decreases, which provides a scheme to solve the crack fault in gear operation. In Reference [9], the Jensen-Shannon Divergence (JSD) algorithm was proposed, which had high sensitivity in measuring small changes between probability distributions and could detect small cracks (0.01 mm~0.04 mm) that could not be detected in baseline impedance signal measurement. In literature [10], the gear meshing stiffness under different crack sizes was calculated by using the analytical tooth crack model. Then, considering the nonlinearity of backlash and bearing clearance, a 3-dof spur gear pair model was established. Based on the multiple statistical indicators obtained from the nonlinear frequency response of the gear system, to assess the vibration characteristics of the gear system and fault condition, the experiment results show that the built model can predict the meshing stiffness of the gear system and vibration behavior of crack, and the corresponding vibration analysis, for researchers and engineers to provide the reference for tooth crack detection. It can be seen from the above research that the crack method based on vibration diagnosis has a solid theoretical foundation and has been fully studied, on the basis of the previous research results, according to the data source, data processing method, and fault identification model of traction seat fault diagnosis. Therefore, based on the data and the characteristics of the traction seat data collected, an intelligent fault diagnosis model based on HHO_VMD and HHO_MPE_SVM is proposed based on the vibration diagnosis method (i.e., the framework of “signal acquisition + feature extraction + pattern recognition”). The model puts forward novel improvement measures in feature extraction and pattern recognition.

Fault diagnosis is affected by mechanical equipment signals, signal analysis methods, and signal features. In the aspect of signal feature extraction, the commonly used signal analysis methods are classical statistical analysis, time-domain, frequency-domain, and time-frequency domain combined methods. The signal analysis method is developed from classical Fourier transform, short-time Fourier transform, wavelet transform, empirical mode decomposition, empirical mode decomposition, empirical wavelet transform, and variational mode decomposition. Because of the complexity of the mechanical system, these methods are not always feasible, many experts and scholars try to on the basis of the signal analysis methods was improved, and the existing research mostly stays in the experimental validation phase. The feature extraction method has some limitations in practical application, and domestic and foreign researchers put forward various solutions for feature extraction algorithm. Jardine et al. studied statistical indicators in time domain and frequency domain to diagnose the advantages and disadvantages of bearing faults [11]. Ahrabian et al. extended the synchronous compression transformation method from one-dimensional to parallel multidimensional in time-frequency analysis, which improved the antinoise performance of the algorithm [12]. Wu et al., considering the superior performance of variational modal decomposition (VMD) in signal processing, proposed an algorithm based on EMD-VMD asymptotic reconstruction and quadratic decomposition to solve the difficulty in accuracy of bearing fault diagnosis [13]. Zhang et al. analyzed wind force sequence based on VMD and built a prediction model, proving that VMD has a better prediction effect compared with other decomposition methods [14]. Sun et al. used VMD to decompose the signal into multiple IMFs to improve the
signal-to-noise ratio, laying a foundation for the visual detection of laser ultrasonic track surface defects [15]. Xu et al. developed a variable mode decomposition method to optimize management parameters, a particle swarm optimization algorithm, and a method based on maximum entropy, which can accurately detect the existence of leakage in the pipeline [16]. Jiang et al. proposed an improved VMD strategy in view of the fact that VMD can be used to reveal weak transient pulses in complex vibration signals, but its reasonable modal number is difficult to be set in advance. This method combines the advantages of traditional VMD and empirical mode decomposition (EMD) and adaptively selects sensitive intrinsic mode function (IMF) components for fault component analysis using the proposed index values to solve this difficulty [17]. Glowacz and other scholars based on the current gear fault diagnosis mainly based on vibration signals; acoustic signal analysis research is less. A gear fault diagnosis method based on deep learning based on acoustic signal analysis was proposed. Time-domain and frequency-domain signals are input to the model as original signals, without feature engineering [18]. Zhang et al. proposed a VMD optimization method based on the grasshopper optimization algorithm (GOA) to analyze vibration signals of rotating machinery, which can estimate the optimal modal number and modal frequency bandwidth control parameters matching the analyzed vibration signals [19]. Many studies have demonstrated the obvious advantages of VMD in signal decompositon. In order to further quantify the characteristics of fault signals extracted from vibration signals, some scholars use nonlinear parameter estimation (entropy theory). According to literature [20], multiscale permutation entropy can describe the complexity and randomness of signals. Reference [19] mentioned that MPE has stronger robustness compared with sample entropy, approximate entropy, and permutation entropy and can study information changes of time series at multiple scales, so as to extract fault features more comprehensively. The different crack types of the traction seat of the bogie will lead to the characteristics of nonlinear and nonstationary vibration signals collected. Since the complexity is difficult to analyze, this experiment uses VMD, an adaptive signal processing tool, to reveal the complex vibration signals of the traction seat. In addition, in order to study traction on the output time series of complex systems, which contains abundant characteristic information, this paper decides to adopt MPE calculation of the traction characteristic information and can dig the hidden more abundant characteristic information in time series, which accurately reflects the change of system, scale for more than the original single state.

An important link in fault diagnosis is the selection of pattern recognition methods. At present, an artificial neural network (ANN) is a commonly used pattern recognition method, which has the advantages of strong adaptability, strong robustness, and good fault tolerance. Through sufficient data training, the mapping relationship of nonlinear input and output can be obtained [21]. However, ANN has the disadvantages of overfitting, slow convergence speed, and easy to fall into local extremum, which makes the diagnostic accuracy of ANN not high enough. Support vector machine (SVM) is a new computational learning method developed by Vapnik on the basis of statistical learning theory, which can successfully solve the problems of overfitting, local optimal solutions, and slow convergence in ANN [22]. SVM has been successfully applied in many fields [23–27]. For example, in the intelligent intrusion detection system, the SVM intrusion detection algorithm has been widely used to quickly and accurately identify intrusions [23]; in the field of healthcare, the application of SVM to accurately diagnose Alzheimer’s disease (AD) and its early mild cognitive impairment (MCI) is crucial to provide early treatment for patients [24]; in text detection, SVM has high-dimensional spatial learning ability and adopts SVM as a texture classifier. Compared with the text detection method of the neural network, the SVM classifier proves the superiority of this method [25]; in the field of image recognition, SVM technology is currently a research hotspot in the field of pattern recognition. Their combination not only effectively solves the problem but also improves the accuracy of classification and prediction [26, 27]. In this paper, SVM is selected to classify the state of traction seat according to the typical characteristics of traction seat samples.

Based on the above analysis of fault diagnosis results of vibration diagnosis methods, VMD, MPE, and SVM were selected as the theoretical basis for the study of crack fault identification of traction seat of urban rail vehicles in this experiment. Considering that selecting appropriate parameter values is crucial to the accuracy of fault identification, parameter selection combined with an intelligent optimization algorithm can directly affect the effectiveness of feature extraction and the accuracy of state classification and then directly affect the fault diagnosis results [28–30]. In recent years, a large number of optimization algorithms have been applied to solve complex optimization problems in various fields, among which HHO is a new optimization algorithm whose potential in practical problems has not been extensively studied [31]. Compared with the existing metaheuristic algorithms and traditional methods, HHO’s global search capability can better select the parameters of VMD, MPE, and SVM.

The main contributions of this paper are as follows:

(i) According to the difficulty of the lack of traction seat data, the operating force of the traction seat under the actual working condition was simulated, the appropriate experimental instruments were selected, reasonable parameters were set, and vibration data were collected

(ii) According to the characteristics of traction seat vibration signal, a reasonable signal processing method is selected to extract the feature set which can better represent the traction seat operation state. The pattern recognition algorithm suitable for the state characteristics of the traction seat is selected to identify the uneven crack state of the traction seat

(iii) According to the importance of determining reasonable parameters, the key parameters of VMD and SVM were optimized adaptively by the intelligent optimization algorithm HHO
(iv) The hybrid model based on VMD, MPE, and SVM algorithms has accurate diagnostic performance. The model can be used to accurately diagnose different crack conditions of traction seat.

In this paper, based on the data acquisition of traction seat, VMD, MPE, and SVM algorithms are used to diagnose the fault state of traction seat of urban rail vehicles, in which HHO is used for parameter optimization of multiple algorithms. The validity of HVMD and HMSVM fault diagnosis models is verified by experiments. This method provides a new guarantee for the safe operation of urban rail vehicles and has practical engineering application value.

2. Theory and Method

In the operation of urban rail vehicles, bogies bear high frequency and random variation of load, and there is a large probability of structural failure, leading to the decline of vehicle running quality, and even leading to derailment and overturn. In order to ensure the safe operation of urban rail vehicles, we must pay attention to the frequent cracks of traction seat. A fault diagnosis model of HVMD_HMSVM is proposed to detect the early crack fault of traction seat and to prevent irreparable loss caused by further crack propagation. At present, there are several difficulties in the fault diagnosis research of urban rail vehicle bogie traction seat as follows:

(1) Acquisition of traction seat data set: at the present stage, the fault diagnosis of traction seat crack is mainly through data analysis and mining, while urban rail vehicle data is extremely scarce. Therefore, the acquisition of traction seat data is a difficulty in current research. In order to solve the difficulty that there is no test data at present, the simulation experiment platform of bogie traction seat is built in this experiment.

(2) Feature extraction of traction seat signals: at present, there are two problems of “redundancy” and “sparsity” in signal feature analysis, which cannot be comprehensively analyzed. In order to solve the problem of feature extraction, an information processing method of HHO_VMD_MPE was proposed to extract the feature information contained in the traction seat signal comprehensively.

(3) Pattern recognition of traction seat fault: in the process of crack fault identification of traction seat, the selection of a classifier will affect the diagnosis accuracy. In order to solve the errors existing in the current pattern recognition, the HHO_MPE_SVM algorithm is proposed, and the feature set is input into the classifier of HHO_SVM to accurately identify the fault types.

In view of the technical difficulties existing in the traction seat at the present stage, the bogie traction seat was taken as the research object, the simulation experiment platform was completed, and the traction seat diagnostic model based on HVMD_HMSVM was constructed. The general framework of the research method is shown in Figure 1, which can be described as six steps, as follows:

(1) Data samples of traction seat vibration signals were obtained on the simulation experimental platform.

(2) Use HHO to optimize VMD parameters, using the optimized HHO_VMD signal decomposition, to obtain IMFs.

(3) Calculate the MPE values of each modal component and construct feature vectors to describe the state characteristics of traction seat.

(4) The traction seat sample data obtained in Step 3 were divided into two groups according to a certain proportion for training samples and test samples, respectively.

(5) HHO was used to optimize SVM to obtain the HHO_SVM diagnostic model.

(6) Input the training samples into HHO_SVM for training to obtain the HHO_SVM classifier, and then input the test samples into the trained HHO_SVM classifier to identify the traction seat fault type through the classifier.

2.1. Experimental Platform Construction and Traction Seat Data Acquisition. The traction seat of urban rail vehicles is affected by complex factors in vehicle operation. On the one hand, it is affected by the environment, such as temperature difference, strong and weak light, and bad weather, and on the other hand, it is affected by complex forces, such as the vertical and transverse force of the route, bend impact force, and heavy load. Under the influence of many factors, traction seat is prone to wear, corrosion, deformation, etc., which eventually leads to early slight cracks in traction seat, and cracks usually appear at the weld. It is difficult to obtain the operating state data of traction seat of urban rail vehicle under actual working conditions, and it is impossible to fully analyze the data for fault diagnosis, resulting in low diagnostic accuracy. In order to prevent the irretrievable loss caused by the bad evolution of the early crack, the detection method of the traction seat early crack was studied. Therefore, the vibration data of the traction seat model of the early crack was firstly provided in the experiment, so as to facilitate the study of the detection of the early crack failure state of the traction seat.

According to the maintenance standard of the bogie of the urban rail train in China, it can be known that when there are scratches and cracks on the surface of the parts and parts, their depth is less than or equal to 10% of the steel plate thickness, and they need to be polished to eliminate them. Welding is required when the defect depth is greater than 10% of the plate thickness and cracks can be visually detected. According to the above criteria, the different widths and depths of the traction seat cracks of urban rail vehicles were used as the quantitative representation indexes for different crack failure states. Namely, the traction seat...
crack fault state is divided into no crack state (normal state), small crack state, and large crack state. That is, when there is a crack on the traction seat surface whose width is less than or equal to 10% of the thickness of the vertical plate, it is a small crack state and needs to be polished to eliminate it. When the crack width is greater than 10% of the thickness of the vertical plate, it is a big crack state and must be repaired by welding. In the normal state, no operation is required. Experimental design traction seat model size: roof and bottom plate is 30 cm long, 20 cm wide, the height between the roof and bottom plate is 20 cm, the middle support plate is a trapezoidal plate, the upper bottom is 21 cm long, the lower bottom is 26 cm long, and the distance between the two support plates is 15 cm. The vertical plate thickness is 1.3 cm. Due to the crack fault that happens in traction seat welding place, therefore making fault model, not the side of the base plate and support plate works welded completely, set aside as a weld as the crack fault, the simulation of traction seat produced two different degree of crack model and a normal traction model, respectively, set the model for the degree of crack corresponding cracks (normal status is not set). The traction seat without crack was quantified as the normal model. The early crack width and depth of 1 mm × 3 mm was the small crack model, and 2 mm × 8 mm was the large crack model (Table 1, Figure 2).

According to the common failure states of the traction seat (Table 1), the simulation experiment platform of urban rail vehicle bogie was built, including the real model and simulation model of the traction seat (Figure 2). In the dynamic response experiment, the measured signal is generally the structural excitation vibration response signal. In this experiment, the method of acceleration is selected for the detection of vibration signal. Since the early crack signal is difficult to detect, the dynamic performance, frequency response bandwidth, and sensitivity of the sensor need to be considered. A piezoelectric accelerometer is widely used in vibration signal detection due to its advantages of convenient use, good reliability, fast dynamic response speed, wide frequency band, and so on. The CAYD051V piezoelectric acceleration sensor is selected to be installed on the experimental object. The sensitivity of the sensor is up to 100 mV/g, and weak traction seat signal can be detected. The host computer and wireless transmission technology were used to obtain the original, true, and reliable data source of the traction seat (Figure 3). Experimental environment: Inter(R) Core (TM) I7-7700HQ CPU @ 2.80 GHz, 16 GB RAM, Python3.7.

In the process of train running, the vibration of traction seat will change with the change of speed, even if the train is in a uniform speed state, the vibration of traction seat will change with the change of road conditions, so the experimental signal must be dynamic change, here choose to provide vibration signal source with frequency sweep instrument; the output end of the sweep is connected to the input port of the power amplifier through the signal line; the signal output end of the power amplifier is connected to the excitation source input port of the shaker; the shaker is connected to the side plane of the crack traction seat through the magnetic excitation top rod. The top rod must be perpendicular to the side plane; otherwise, the shaker will be damaged during the excitation. In order to reduce the interference of data acquisition, the traction seat must be suspended by elastic rope; in order to weaken the interference of the impact of the excitation top rod and avoid the sensor falling off due to too intense vibration, the acceleration sensor is installed on the traction seat bottom plate and installed through the magnetic head adsorption; the signal line of the acceleration sensor is connected with the acceleration sensor to the YE6213 data acquisition card; the YE6213 data acquisition card is connected to the PC through USB, and the data acquisition system matching the data acquisition card is installed on the PC to collect and store vibration data. After the control and sensing devices are installed, the entire system needs to be checked (Figure 3 shows the device connection diagram). According to the actual operating conditions and relevant theoretical basis, determine the experimental excitation frequency range of 100 Hz to 2500 Hz; the excitation output mode of frequency sweep is set as fixed.
frequency output, and the output signal is a steady sinusoidal signal. Frequency sweep output frequency from 100 Hz to 2500 Hz fixed output excitation signal; sampling frequency was set as $F_s = 12$ KHz; sampling time $t = 5$ s; the sampling interval is $T = 1$ h, and 6,000 samples and 30 sets of data are collected in each state. After the completion of experimental data collection, the data of the three states were selected. Finally, according to the specific experimental situation, 600 groups of data were selected for the experiment, including 200 groups of samples in the normal state, large crack state, and small crack state. According to the experimental situation, 75% were randomly selected as the training set. Take 25% as the test set. The details are shown in Table 2.

### Table 1: Classification of traction seat status.

<table>
<thead>
<tr>
<th>State</th>
<th>Normal</th>
<th>Small crack</th>
<th>Big crack</th>
</tr>
</thead>
<tbody>
<tr>
<td>Judging basis: crack width and depth</td>
<td>No set fault</td>
<td>1 mm × 3 mm</td>
<td>2 mm × 8 mm</td>
</tr>
</tbody>
</table>

2.2. Traction Seat Feature Extraction Based on HMVMD

2.2.1. Harris Hawks Optimization. Harris Hawks Optimization (HHO) is a novel crowd-based algorithm proposed by Heidari et al. in 2019, inspired by the smartest birds around: Harris eagle (chestnut-winged eagle) developed a corresponding stochastic mathematical model by simulating its behavior when hunting rabbits. The HHO algorithm has been used to solve several optimization problems, including manufacturing, feature selection, classification, and engineering design. Because the structure is good, it can flexibly improve the optimization performance, and the selection of parameters determined by HHO is the most appropriate choice at present. The HHO algorithm mainly includes three stages: exploration stage, transition stage from exploration to development, and development stage, which are briefly introduced as follows:

Stage 1 (exploration stage): escape energy $|E| \geq 1$, or the location of the Harris Hawks according to the location of the rabbit and with the center position of the entire group vector difference, such as type (1) shown in the following:

$$X(t+1) = \begin{cases} X_{\text{rand}}(t) - r_1 |X_{\text{rand}}(t) - 2r_2 X(t)|, & q \geq 0.5, \\ (X_{\text{rabbit}}(t) - X_m(t)) - r_3 (LB + r_4 (UB - LB)), & q < 0.5, \end{cases}$$

(1)

where $X(t+1)$ and $X(t)$ represent the position of the eagle in the $t+1$ and $t$ iterations, respectively. $X_{\text{rand}}(t)$ represents the position of the random eagle in the $t$ iteration, and $r$ and $q$ are uniformly distributed random numbers in the interval [0,1]. $X_{\text{rabbit}}(t)$ and $X_m(t)$ represent the rabbit position (the optimal value of the current iteration) and the center position of the eagle flock. LB and UB represent the upper and lower bounds of the value range, as shown in the following:

$$X_m(t) = \frac{1}{N} \sum_{i=1}^{N} X_i(t),$$

(2)
where $X_i(t)$ represents the position of each eagle at iteration $t$ and $N$ represents the total number of eagles.

Stage 2 (transition stage): when the $|E| > 1$, one is exploratory behavior. After the exploration phase, there is a transition phase before entering the mining phase. In this transient stage, the rabbit energy needs to be modeled according to

$$E = 2E_0 \left(1 - \frac{t}{T}\right),$$

(3)
where $E$ is the escape energy of the rabbit, $T$ is the maximum number of iterations, and $E_0$ is the initial energy value of the rabbit. According to the physical condition of the victim, the random number $[-1, 1]$ is uniformly distributed. As $E_0$ moves towards $-1$, it means the victim is losing energy, and vice versa.

According to rabbit behavior, rabbit energy is inversely proportional to time. That means as long as $t$ goes up, $E$ goes down. According to Harris, when $|E| \geq 1$, the eagle decided either to search different areas, to detect the location of rabbit, or move forward into the development phase.

Stage 3 (development stage): when the $|E| < 1$, indicating that the eagle has discovered the direction of the rabbit and needs to model two behaviors. According to the energy of the rabbit absolute value $|E|$ compared with 0.5 percentage and escape $r$ judgment, it can be divided into two kinds of behavior, four kinds of strategy:

1. Soft siege. If $|E| \geq 0.5$, $r \geq 0.5$, then the rabbit escape has high energy; at the same time, the probability of successful escape is higher than 50%. This means that the eagle will carry out a soft siege and update its position according to

$$X(t + 1) = \Delta X(t) - E|JX_{\text{rabbit}}(t) - X(t)|,$$

where $\Delta X(t)$ is the position difference between rabbit and eagle, and the calculation method is as follows:

$$\Delta X(t) = X_{\text{rabbit}}(t) - X(t).$$

$J$ is a random number, representing the jump intensity that can be obtained, as shown in the following:

$$J = 2(1 - r_5),$$

where $r_5$ is a random number that varies between 0 and 1.

2. Fast dive soft siege. If $|E| \geq 0.5$, $r < 0.5$, it indicates that rabbits have higher energy. However, the chances of a successful escape are not great. In this case, the eagle will engage in a soft siege but will gradually dive quickly. The eagle’s next move will be based on the following:

$$Y = X_{\text{rabbit}}(t) - E|JX_{\text{rabbit}}(t) - X(t)|.$$

The eagle will compare the current position to the previous dive to evaluate which is better. If the previous dive was better, the eagle would take advantage of it. If not, the eagle will make a new dive using the LF formula, as shown in LF formula (8). Harris eagle will then evaluate the $Y$ and $Z$ positions and reupdate the positions according to formulas (9), (10), and (11).

$$\text{LF}(x) = 0.01 \left( \frac{|u|^{1+\beta}}{|v|^{1+\beta}} \right),$$

where $D$ is the problem dimension and $S$ is a random vector with a size of $1 \times D$. The LF function can be calculated from equation (8), where $u$ and $\sigma$ are random numbers that vary between 0 and 1. $\beta$ is a constant value of 1.5. The formula for calculating $\sigma$ is shown in (10).

$$\sigma = \left( \frac{(1 + \beta) \sin (\pi \beta/2)}{(((1 + \beta)/2) \times \beta \times 2^{[\beta/2]})} \right)^{1/\beta},$$

$$X(t + 1) = \begin{cases} \text{Y, } & F(Y) < F(X(t)), \\ \text{Z, } & F(Z) < F(X(t)) \end{cases}$$

(3) A siege. If the $|E| < 0.5$, $r \geq 0.5$, which means the rabbit has a relatively low energy, but it has a medium chance of making a successful escape. In this case, the eagle will carry out a difficult siege and update its equations according to

$$X(t + 1) = X_{\text{rabbit}}(t) - E|\Delta X(t)|$$

(4) Fast dive hard siege. If the $|E| < 0.5$, $r < 0.5$, it means the victim has low energy and a low chance of escape. In this case, the eagle will also perform a difficult encirclement, but with a gradual rapid dive, the eagle’s next position will be updated using equation (11). $Z$ is calculated by equation (9) and $\tilde{Y}$ by equation (13), as shown in the following:

$$Y = X_{\text{rabbit}}(t) - E|JX_{\text{rabbit}}(t) - X_m(t)|$$

### 2.2.2. Variational Modal Decomposition.

The VMD algorithm is an adaptive, quasiorthogonal, and completely non-recursive decomposition method, which can be divided into two processes of constructing variational problem and solving variational problem: (1) constructing variational problem (equation (14)): the original input signal $x(t)$ was decomposed into $K$ IMF components $u(t)$, each component $u(t)$ was demodulated by Hilbert transform to obtain its envelope signal and then mixed with the estimated center frequency $\omega_k$. Under the constraint that the sum of all $u(t)$ components was equal to the original signal $x(t)$, the construction of the variational problem is shown in equation (14). (2) To solve the variational problem (equation (15)): the constrained variational problem is transformed into an unconstrained variational problem by adding Lagrange multiplication to calculate $\lambda(t)$ and quadratic penalty factor $\alpha$, as shown in equation (15). Alternate Direction Method of
Multiplier (ADMM) is used to obtain the saddle point in equation (15), that is, the optimal solution of

\[
\min_{\{u_k\}, \lambda} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}
\]

\[\text{s.t.} \sum_{k=1}^{K} u_k = x(t),\]

(14)

where \( \partial_t \) is the partial derivative of \( t \); \( \delta(t) \) is the shock function.

\[
L(\{u_k\}, \omega_k, \lambda) = \alpha \sum_k \left\| \partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2
\]

\[+ \left\| x(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 + \left\langle \lambda(t), x(t) - \sum_{k=1}^{K} u_k(t) \right\rangle.\]

(15)
The data of traction seat has the characteristics of non-linearity, nonstationarity, randomness, and noise. In order to better describe these characteristics, the vibration signal of traction seat needs to be decomposed into multiple components. There are some defects in wavelet transform, empirical mode decomposition, and ensemble empirical mode decomposition, which are not suitable for the analysis of traction seat vibration signal. VMD not only ensures the integrity of the characteristics but also improves the computational efficiency of the algorithm. Compared with other common time-frequency domain processing methods, VMD can better solve the problems

![Figure 6: Time-domain diagram of traction seat in three states.](image-url)

The data of traction seat has the characteristics of non-linearity, nonstationarity, randomness, and noise. In order to better describe these characteristics, the vibration signal of traction seat needs to be decomposed into multiple components. There are some defects in wavelet transform, empirical mode decomposition, and ensemble empirical mode decomposition, which are not suitable for the analysis of traction seat vibration signal. VMD not only ensures the integrity of the characteristics but also improves the computational efficiency of the algorithm. Compared with other common time-frequency domain processing methods, VMD can better solve the problems...
of modal aliasing and boundary effect of signal decomposition and has good robustness to noise; this paper introduces the VMD algorithm. VMD was used to decompose the original vibration signal of the traction seat into $K$ intrinsic mode functions (IMF) under limited bandwidth, and the corresponding IMF central frequency was extracted, so that the mode $u_k$ fluctuated around the central frequency $K$.  

2.2.3. Multiscale Permutation Entropy. Mechanical equipment usually contains rich feature information at multiple scales. In order to study the complexity change of time series at multiple scales, MPE can mine more rich feature information hidden in time series, so as to accurately reflect the change of the system and obtain more state quantity than the original single scale. MPE can be summarized as follows:

![Frequency-domain diagram of traction seat in three states.](image)

Figure 7: Frequency-domain diagram of traction seat in three states.
calculate a group of permutation entropy values in time series of different scales, combine coarse-grained process with permutation entropy, and calculate results in different time scales by calculating the entropy of coarse-grained time series. The MPE algorithm includes two steps: (1) using coarse-grained process to obtain multiscale time series from original time series; (2) calculate the PE value of each coarse-grained time series.

The detailed process is as follows:

1. For a given time series \( x(k), k = 1, 2, \cdots, N \), the coarse-grained sequence is obtained after coarse-grained processing, as shown in

\[
y_j^\tau = \frac{1}{\tau} \sum_{i=\lfloor(j-1)\tau+1\rfloor}^{\lfloor j\tau \rfloor} x_i, 1 \leq j \leq \left\lceil \frac{N}{\tau} \right\rceil,
\]

where \( \tau \) is the scale factor and is a positive integer. \( \lfloor a \rfloor \) is an integer less than or equal to \( a \).

2. Multiscale permutation entropy MPE can be obtained by calculating the permutation entropy PE value of coarse-grained time series, as shown in

\[
\text{MPE}(x, \tau, m, \delta) = \text{PE}\left(y_j^\tau, m, \delta\right),
\]

where \( m \) is the embedding dimension; \( \delta \) is the delay parameter.

PE is a method to analyze mechanical equipment under one-dimensional time series, but it cannot analyze all the characteristic information of mechanical equipment comprehensively. In order to analyze the characteristics of traction seat vibration signal in detail and study the characteristics of equipment under multiscale time series, more states hidden in the time series can be excavated, so as to reflect the traction seat fault state more accurately.

### 2.2.4. HMVMD

At present, there are “redundancy” and “sparsity” in signal characteristic analysis, which can not achieve effective and comprehensive signal analysis. An information processing method based on HHO_VMD_ MPE is proposed to extract feature information comprehensively. Due to its good structure and high optimization performance, HHO is used to solve several optimization problems (such as manufacturing, feature selection, classification, and engineering design). In view of the advantages of HHO in optimization, selecting HHO to determine parameter values is a more appropriate scheme at present.

In this section, when feature extraction of traction seat vibration signal is carried out, VMD is used to process vibration signal of traction seat, and HHO is used to adaptively select the optimal parameter combination of VMD \([k, a]\).

In the process of HVMD, the fitness function is designed to achieve the best searching effect. Kurtosis index (KI) and Spearman correlation coefficient are two common indexes in mechanical equipment damage. If KI is used as the optimization target to optimize VMD parameters for fault feature extraction, some influences with large vibration amplitude but dispersed distribution can be omitted. The correlation coefficient can represent the similarity of two signals but is easily affected by noise, in view of their own shortcomings and complementary elimination. Therefore, this paper constructed the kurtosis index (SKI) integrating the Spearman correlation coefficient as the objective function of VMD parameter optimization. SKI is defined as follows:

\[
\text{KI} = \frac{(1/N)\sum_{i=1}^{N} (x_i - \bar{x})^4}{(1/N)\sum_{i=1}^{N} (x_i - \bar{x})^2},
\]

\[
S_{X,Y} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E^2(X)} \sqrt{E(Y^2) - E^2(Y)}},
\]

\[
\text{SKI} = |S| \times |K|, \quad |S| \leq 1.
\]
(a) The traction seat is decomposed by HVMD in normal state

Figure 9: Continued.
(b) HVMD decomposition spectrum of traction seat under small crack state

**Figure 9:** Continued.
\( N \) is the signal length; \( S \) is the correlation coefficient between signals \( X \) and \( Y \).

The extraction process of traction seat features is shown in Figure 4. Firstly, the position vector of the eagle group was initialized. SKI was used as a fitness function, and the fitness of each eagle was calculated. Then, the iterative formula was selected to update iteratively by judging the size of the convergence factor until the termination condition was satisfied, and the optimal VMD parameter combination was output.

In order to more accurately reflect the characteristic information of the traction seat fault state, as the common permutation entropy (PE) is far from enough to only study the one-dimensional time series, MPE is used to conduct multiscale analysis of the vibration signals of the traction seat under the time series to study the complexity changes of the time series under the multiscale. You can get more states hidden in time series.

2.3. Traction Seat Pattern Recognition Based on HSVM

2.3.1. Support Vector Machine. SVM is proposed based on statistical learning theory and based on the VC dimension theory and the minimum structural risk theory of statistical learning theory. It obtains the best-expected value from limited sample information through learning. It is widely used in mechanical equipment fault diagnosis and pattern recognition. SVM is a machine learning method based on small sample data processing. By mapping low-dimensional sample space to high-dimensional space, the nonlinear problems in sample space are transformed into linear problems in.
Figure 10: Continued.
high-dimensional space to solve nonlinear classification problems. Through this method, the optimal solution of the problem can be obtained well, so as to avoid the problem of trapping local optimal.

The essence of SVM: for a nonlinear problem that is difficult to deal with in the original low-dimensional space, it can be transformed into a linearly separable problem in higher dimensional feature space under the action of kernel function. A hyperplane is found to divide samples in a high-dimensional space, so that the distance between the nearest sample objects of the two kinds of samples distributed on both sides of the hyperplane is the largest. For the training sample \( M = \{ (x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m) \} \), the classification function constructed based on the principle of structural risk minimization is shown in formula (18):

\[
F(x) = \text{sign} \left( \sum_{i=1}^{m} a_i y_i k(x_i, y_i) + d \right) 0 < a_i < C, \quad (21)
\]

where \( x_i \) and \( y_j \) are input feature vectors; \( y_j \) is the output vector; \( m \) is the total number of training samples; \( a_i \) is the Lagrange multiplier; \( k(x_i, y_j) \) is the kernel function; \( C \) is the penalty factor; \( d \) is the threshold.

State identification is the last and most important step in fault diagnosis. The final result of fault diagnosis depends on the selection of an appropriate pattern recognition classifier. In practice, the sample size of crack fault characteristic of traction seat of locomotive bogie is small, so it is required that pattern recognition classifier can be trained by small

![Figure 10: MPE diagram of the delay time \( t \) of small crack in traction seat under different embedding dimensions.](image-url)

(c) Embedding dimension \( m = 6 \)

(d) Embedding dimension \( m = 7 \)
sample, and then identify the crack state of traction seat with high accuracy.

2.3.2. HSVM. The HHO_MPE_SVM (HSVM) algorithm is proposed to reduce the diagnosis error and identify the fault type accurately. In the process of traction seat diagnosis, the selection of parameters is worth considering. The scale factor $s$, embedding dimension $m$, sequence length $N$, delay time $t$, penalty coefficient $C$, and kernel function parameter $g$ of MPE and SVM will affect the accuracy of fault diagnosis. With the classification accuracy as the evaluation index, HHO is used to optimize the parameters of MPE and SVM simultaneously, which is a beneficial attempt for traction seat fault diagnosis. Fault diagnosis process based on HMSVM is shown in Figure 5. The specific construction process is described as follows:

1. The training set and test set are constructed and normalized

2. HHO parameter initialization. Set the sum of random values, set the sum of upper and lower bounds, the maximum number of iterations, set the value range of parameter combination $[m, t, S, C, g]$, select the Gaussian kernel function, and randomly initialize the initial position of the Harris eagle group

3. Using the classification accuracy of SVM as fitness function, the fitness of each individual eagle group was calculated to find and preserve the best habitat position of the individual eagle group in the current population

4. The HHO algorithm is used to optimize the habitat position of individual eagles

5. The fitness function was used to recalculate the fitness of each optimized eagle group and update and save the current optimal eagle group individual position

Figure 11: MPE diagram of small cracks in traction seat under different embedding dimensions.

Figure 12: Under different scales, the three health states of traction seat are MPE diagram.
(6) Determine whether the iteration termination conditions are met. If so, end the optimization; otherwise, continue the cycle.

(7) Output the spatial position corresponding to the fitness value of the best eagle group, that is, the optimal parameter combination $[m, t, s, C, g]$.

3. Experimental Verification

3.1. Signal Analysis Based on HHO_VMD. The vibration signals of the traction seat in three states were collected through the experimental platform, and the vibration signals of each state were $6000 \times 20$, $6000 \times 60$ in total. In order to ensure the accuracy of data and the prediction speed of the experiment, the number of sampling points $N$ was set to 1024 as the experimental data set. Figures 6 and 7, respectively, show the time-domain and frequency-domain analysis of a group of original vibration signals in three states of the traction seat when $N = 1024$.

Figures 6 and 7 show that the time-domain and frequency-domain waveforms of the three states of the traction seat show different changes, indicating that the method based on vibration signals can realize the identification of the traction seat state, but there is uncertainty. In order to identify the fault state of traction seat more accurately, VMD is used to decompose the vibration signal of traction seat.

Taking the large crack fault of traction seat as an example, in the experiment, the number of modes of the VMD algorithm $K \in [2, 10]$ is an integer, and the penalty parameter $a \in [200, 4000]$ is taken as an integer. The change of the SKI value of the VMD parameter with the number of Harris update iterations after HHO optimization is shown in Figure 8. Figure 8 shows that SKI is -241.75, corresponding to the optimal position, namely, the optimal parameter combination $[4, 2383]$. After the optimization parameters are
obtained, VMD decomposition is performed on the vibration signal of the traction seat, and the IMF component is obtained by the decomposition, as shown in Figure 9. It can be seen from Figure 9 that each IMF central frequency is independent from each other, which can effectively avoid the mode aliasing problem. Using this method, relatively pure modal components can be obtained quickly.

3.2. Experimental Verification Based on HHO_MPE. From the above analysis, it can be seen that there are obvious differences between the signals of the traction seat in the normal state and the two fault states. Next, according to the characteristics of traction seat vibration signal under the actual working condition, the MPE was used to analyze the experiment. Set the time series to $N = 1024$. The delay time is generally set as 1-6, and the scale factor $s = 12$ is set in the experiment. Figure 10 shows the change of MPE value of small crack state under different embedding dimensions (due to the limited space, a failure state of traction seat is taken as an example). It can be concluded that the delay time $t = 1$ is more appropriate. The embedding dimension is generally 3-8. Figure 11 shows the MPE values of small crack states under different embedding dimensions ($t = 1$, scale factor $s = 12$). By comparison, it can be concluded that embedding dimension $m = 4$ is more appropriate. Figure 12 shows (delay time $t = 1$, embedding dimension $m = 4$) the MPE values of the traction seat in three states under different scale factors $S$. The comparison shows that

Table 3: Multiscale permutation entropy values of the three health states of the traction seat (only part is shown due to limited space).

<table>
<thead>
<tr>
<th>State</th>
<th>Sample</th>
<th>MPE1</th>
<th>MPE2</th>
<th>MPE3</th>
<th>MPE4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal (0)</td>
<td>0</td>
<td>0.816852</td>
<td>0.868982</td>
<td>0.892605</td>
<td>0.918061</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.708248</td>
<td>0.844968</td>
<td>0.781680</td>
<td>0.897962</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.847388</td>
<td>0.886976</td>
<td>0.910367</td>
<td>0.911917</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.860285</td>
<td>0.883452</td>
<td>0.914914</td>
<td>0.941772</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.844852</td>
<td>0.896652</td>
<td>0.931031</td>
<td>0.929070</td>
</tr>
<tr>
<td>Small crack (1)</td>
<td>0</td>
<td>0.727376</td>
<td>0.729275</td>
<td>0.551191</td>
<td>0.707729</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.792196</td>
<td>0.650526</td>
<td>0.565574</td>
<td>0.645749</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.746012</td>
<td>0.640071</td>
<td>0.619615</td>
<td>0.567530</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.756012</td>
<td>0.645144</td>
<td>0.623558</td>
<td>0.603248</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.748917</td>
<td>0.647531</td>
<td>0.597829</td>
<td>0.618770</td>
</tr>
<tr>
<td>Big crack (2)</td>
<td>0</td>
<td>0.724450</td>
<td>0.825055</td>
<td>0.758960</td>
<td>0.770725</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0.703779</td>
<td>0.844347</td>
<td>0.742504</td>
<td>0.782242</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.725932</td>
<td>0.841112</td>
<td>0.767185</td>
<td>0.767448</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.706949</td>
<td>0.823326</td>
<td>0.750810</td>
<td>0.831523</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.709567</td>
<td>0.840849</td>
<td>0.749813</td>
<td>0.794277</td>
</tr>
</tbody>
</table>

Figure 14: Three state diagrams of traction seat based on HHO_MPE.
the scale factor $s = 6$ is more appropriate. To sum up, it can be concluded from observation and comparison that it is appropriate to select $m = 4$, $t = 1$, and $s = 6$ as MPE parameters, respectively. Figure 12 shows that the normal state and fault state of the traction seat can be distinguished by manually selected parameters, but the fault type cannot be further distinguished.

In order to further illustrate the MPE values the importance of reasonable selection, Figure 13 shows the different parameter selection, pulling the MPE values under different conditions, it is not hard to find: the MPE parameters selection, traction is mixed overlapping between different states, and distinguishing between each other is not obvious, which is not conducive to further accurate judgment of the traction state type. According to the manually selected MPE parameters, it is impossible to distinguish the three states of the traction seat accurately. In order to avoid the inaccuracy of selected parameters, HHO was used in this experiment to optimize MPE parameters, and the optimization results were as follows: $m = 4$, $t = 4$, and $s = 14$. Figure 14 shows the three-state diagrams of traction seat of HHO_MPE. It is not difficult to find that the three states of the traction seat can be accurately separated at different scales. At the high scale, the MPE of the different states of the traction seat has no overlap and is clearly distinguished from each other, which is conducive to further accurate judgment of the state type of the traction seat.

When the traction seat fails, different modal components will contain different impact components. In order to check the fault information contained in each modal component, the MPE of each IMF component was calculated and the feature vector was formed, which was used as the input data for fault diagnosis. 90 sets of vibration signals of the traction seat in three states were processed in the experiment, with a total of $3 \times 90$ sets of data for feature analysis. That is, for the 4 IMF of each group of data, the MPE of each IMFs is calculated for quantitative processing, respectively, and the average value of the MPE of each IMF is taken to construct the energy feature $Y = \frac{1}{C} \text{MPE}_1, \text{MPE}_2, \text{MPE}_3, \ldots, \text{MPE}_4$, as shown in Table 3 (due to space limitation, 5 groups of each state of the traction seat are displayed; MPE only selects the first 4 dimensions for display).

As can be seen from Table 3, the normal state and fault state of traction seat can be clearly identified. There are also obvious differences between MPE values of large crack and small crack in fault state. From the analysis, it can be concluded that the IMF of each IMF component is calculated, and the average value of MPE of each IMF is taken to construct feature vectors, which are used as input data for fault diagnosis to further identify the type of traction seat state.

### 3.3 Pattern Recognition Based on HHO_SVM

After the above experiments, after the feature vector containing the traction seat feature information is extracted, an effective pattern recognition algorithm is needed for fault diagnosis. In this experiment, H SVM was selected for traction seat fault diagnosis. In order to verify that the diagnosis model of H SVM has better fault diagnosis ability, the same traction

<table>
<thead>
<tr>
<th>SVM model</th>
<th>Parameter C</th>
<th>Kernel function $g$</th>
<th>Accuracy (%)</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>48.92</td>
<td>135.00</td>
<td>95.56</td>
<td>8.78</td>
</tr>
<tr>
<td>PSO_SVM</td>
<td>78.23</td>
<td>175.04</td>
<td>97.78</td>
<td>107.92</td>
</tr>
<tr>
<td>WOA_SVM</td>
<td>91.11</td>
<td>111.82</td>
<td>98.89</td>
<td>102.18</td>
</tr>
<tr>
<td>HHO_SVM</td>
<td>57.13</td>
<td>73.03</td>
<td>100.00</td>
<td>188.42</td>
</tr>
</tbody>
</table>
seat feature vectors were used as input data to HHO_SVM, WOA_SVM, PSO_SVM, and SVM models, respectively, for fault identification. The population parameters of the first 3 models are all 30, and the maximum iteration times are 200. Among them, the optimization range of SVM penalty parameter C is [0.01,200], the optimization range of kernel function parameter G is [0.01,200], the training data is 270 groups, and the test data is 90 groups. Finally, the classification results of the four models are compared and analyzed as shown in Table 4. The accuracy of different models is shown in Figure 15.

It can be seen from Table 4 that the accuracy of all the four classification models can reach more than 95%, indicating that the feature extraction method of HVMD_MPE adopted in this experiment is feasible and contains relatively complete feature information of traction seat. Figure 15 illustrates the following: HHO effect compared with other algorithms at the beginning of the number of iterations is poorer, attributed to HHO, WOA, and the population initialization in a different way of PSO, HHO to avoid falling into local optimum, as much as possible for a wide range of global search; finally, on the whole, achieve HSVM least number of iterations and identify fault has the highest accuracy.

4. Conclusion

In this paper, a bogie traction seat fault diagnosis model based on HVMD and HMSVM is constructed. HHO was used to optimize the parameters to determine the best parameter combination of VMD, MPE, and SVM. The VMD with optimized parameters was used to decompose the traction seat vibration signal. The calculated MPE values of each IMF were quantified, and the average MPE values of each IMF were taken to form feature vectors, which were used as input data for fault diagnosis. Finally, the effective feature vectors are extracted and input into the classifier HSVM to automatically identify the fault types. Finally, the accuracy of fault identification reaches 100% by using the vibration data set of traction seat, which proves the effectiveness and generalization of the proposed method.

Data Availability

The data and the Python programs used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Authors’ Contributions

The author’s contributions are as follows: Qi Chang helped in the conceptualization, methodology, data curation, software, validation, investigation, and original draft. Minglei Zheng performed the investigation, review, and editing. Jiaxin Luo and Junfeng Man reviewed and edited the manuscript. Lin Li provided test guidance and reviewed the manuscript. Yiping Shen performed criticism and correction. Yi Liu helped in guiding conceptualization and methodology and providing test guidance, criticism, and correction.

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