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Research Article

Application of Improved WOA in Hammerstein Parameter Resolution Problems under Advanced Mathematical Theory

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With the development of industrial demand, precise identification of system models is currently required in the field of industrial control, which limits the whale search algorithm. In response to the fact that whale optimization algorithms are prone to falling into local optima and the identification of important Hammerstein models ignores the issue of noise outliers in actual industrial environments, this study improves the whale algorithm and constructs a Hammerstein model identification strategy for nonlinear systems under heavy-tailed noise using the improved whale algorithm. Results showed that it had a lower rank average and an average success rate of 95.65%. It found the global optimum when the number of iterations reached around 150 and had faster convergence speed and accuracy. In identifying Hammerstein model under heavy-tailed noise, the average prediction recognition accuracy of the improved whale algorithm was 92.38%, the determination coefficient was 0.89, the percentage fitting error was 0.03, and the system error was 0.02. This research achievement has certain value in the field of industrial control and can serve as a technical reference.

1. Introduction

As science and technology develop, China's industrial sector has also flourished, among which the petrochemical industry has become a hot topic in the current new era. Industrial transformation and low-carbon development have become urgent tasks to be completed [1]. To accelerate the low-carbon upgrading and transformation of the petrochemical industry, optimizing its industrial process control plan and refining the control process are the most important steps [2]. At present, the mainstream model for parameter identification of nonlinear systems is the single-input single-output (SISO) Hammerstein model with single-input and single-output mode. Research on identifying important multiple-input multiple-output (MIMO) Hammerstein models is relatively scarce, and noise is often ignored in parameter identification of nonlinear models. However, the impact of noise on the model in the actual industrial environment is an inevitable issue [3]. As machine learning algorithms develop, intelligent optimization has gradually been applied to control the process. As a computational model based on the behavior patterns of biological populations, it does not need to analyze the structural information of control problems and has strong computational capabilities [4]. Among them, the most commonly used intelligent optimization algorithm is whale optimization algorithm (WOA), which has a simple structure and can adjust control parameters with flexibility. However, due to its simple structure, it is also impossible to achieve division of labor and cooperation after initializing the first-generation population. In addition, the position update mechanism of the whale optimization algorithm is also relatively single, which makes it easy for the algorithm to fall into a local optimization dilemma prematurely during the iteration process. The reason for choosing the WOA for research is that it has shown good performance in solving complex optimization problems. The WOA is an optimization algorithm based on the social behavior of bird flocks, which seeks the optimal solution by simulating the flight and foraging behavior of bird flocks. This algorithm has the advantages of simplicity, flexibility, and ease of implementation and has been widely applied in many fields. In the Hammerstein parameter resolution problem, the WOA can be used to find the optimal parameter configuration, achieving optimal predictive performance of the model. Compared with existing work, using the improved WOA to solve the Hammerstein parameter resolution problem can further improve the predictive performance and stability of the model. By improving the search mechanism of the WOA, introducing new mutation operators, and improving local search strategies, nonlinear features and parameter constraints in the Hammerstein model can be better handled, resulting in more accurate and reliable parameter configurations. In addition, the improved WOA can further expand its application scope in solving complex optimization problems by combining with other optimization algorithms. So this study attempts to improve the whale algorithm by proposing an improved whale optimization algorithm (IWOA) that optimizes its structure and position update mechanism to improve its stability and reliability. Based on introducing the optimized whale algorithm to heavy-tailed noise interference, two new identification schemes are attempted for the SISO Hammerstein model and MIMO Hammerstein model.

This study includes five parts. The second part reviews the current research results. The third part introduces the methods of this study. The fourth part conducts experiments and analyzes the results based on the methods in the second part. The fifth part summarizes the conclusions of this study.

2. Related Works

Among the emerging intelligent optimization algorithms in recent years, the whale optimization algorithm is often used for controlling and adjusting parameters. In ship deformation measurement, the dynamic deformation parameters of inertia matching methods are severely affected by the environment. On this issue, Wang et al. derived a mapping mechanism and an objective function based on the data in the sliding window [5]. On this basis, an improved whale optimization algorithm based on logical mapping was designed for parameter identification. Results showed that it can effectively identify parameters.

In the field of information technology, the IT outsourcing process is vulnerable to schedule risks, which have the potential to result in significant losses [5]. Using distributed decision-making theory, Lu et al. established a dual-layered model. The analysis results indicated that this method can control schedule risk. Different customer preferences that impact decision results were analyzed. The effectiveness of the two-layer whale optimization algorithm was demonstrated through the solution and analysis of numerical examples. The results indicated that the double-layer whale optimization algorithm had higher accuracy, making it more competitive [6].

In terms of battery management systems, Pan et al. proposed a method that used a unique global search whale optimization algorithm to identify electrochemical model parameters. Firstly, four operating conditions of 1C, 0.5C, and 2C were performed, and the parameters based on 1C charging and discharging were identified. Results indicated that electrode-related parameters' influence on lithium ion migration affected calculation performance accuracy, with electrode porosity having the greatest impact [7]. Liu et al. proposed a point cloud data processing method using whale optimization algorithm to enhance the assessment of internal blockage and deterioration in sewage pipelines. The applicability of this method was verified in actual sewage systems, and the results showed that it can accurately and effectively reconstruct the three-dimensional model of the sewer [8].

In terms of modeling, Jiang et al. proposed a model using grey modeling technology to improve the predictive performance of existing models and expand their applicability. To avoid inherent errors, an improved nonlinear grey Bernoulli model was obtained. Results indicated that the prediction accuracy of this model was higher, and it was more suitable for these practical situations [9]. Tian et al. proposed a new data-driven model to improve process data modeling accuracy. Regularization and kernel parameters were optimized using an improved whale optimization algorithm. Finally, a regularization based on sum kernel was proposed. To verify the modeling performance, a study was conducted using the industrial process of purified terephthalic acid as an example. The simulation results showed that the proposed model can achieve high accuracy, verifying the feasibility and effectiveness of the proposed method [10].

Zong et al. used the Wiener-Hammerstein system to solve the integrity problem of input and output data in the system. The study added auxiliary models after analyzing nonlinear elements and optimized the model using particle swarm optimization algorithm. The results indicate that the system can significantly improve the accuracy and convergence speed of data [11]. Jui and Ahmad designed an algorithm for identifying continuous time Hammerstein systems based on the average multivariate optimization algorithm and the sine cosine algorithm. The study made two modifications using algorithms, namely, modifying the average design parameter update mechanism and the hybrid of multiverse optimizer and sine cosine algorithm. The results indicate that this method has also achieved better performance in modeling dual rotor systems and flexible robotic arm systems and provides better solutions [12]. In order to improve the performance of the Hammerstein-Wiener system, Zong et al. integrated particle swarm optimization algorithm with gravity search algorithm and designed a system for identifying the system in question. The system adds an oscillation index attenuation inertia factor and introduces chaotic membership degree. The results indicate that the model can significantly improve the convergence speed and recognition accuracy of the algorithm [13]. Zong et al. used an auxiliary model combined with a hybrid particle swarm gradient algorithm to solve the problem of incomplete recognition data caused by dual rate sampling. By using auxiliary models and hybrid particle swarm gradient algorithms, nonlinear identification problems can be transformed into optimization problems in parameter space, optimizing performance through algorithms. The results show that the performance of the hybrid particle swarm gradient algorithm is significantly improved due to the particle swarm algorithm and gradient iteration algorithm, which not only improves the linear optimization speed and recognition accuracy but also avoids the problem of premature convergence [14]. Janjanam et al. used evolutionary optimization algorithms coupled with Kalman filtering to solve the parameter estimation problem of Hammerstein nonlinear systems. Research on using Kalman filtering to adjust parameters while also using optimization algorithms to globally optimize the output results will effectively improve the optimization performance of nonsystem parameters. The results indicate that the algorithm can significantly improve the accuracy and convergence speed of parameter estimation [15]. Mehmood and Raja used weighted differential evolution to estimate the parameters of the Hammerstein-Wiener model (HWM). Conduct a detailed, comprehensive, and robust analysis of multiple autonomous experiments by heuristic estimation of HWM adjustable parameters under different degrees of freedom and noise levels using WDE and genetic algorithms (GAs). The results indicate that the method used in the study outperforms the existing methods in terms of accuracy, convergence, and complexity [16].

In summary, experts have conducted many studies on the application of whale algorithm in improving control accuracy and parameter identification, but their efforts to improve the reliability and stability of whale algorithm applications are limited. So how to ensure that the whale algorithm has high control accuracy and parameter recognition accuracy while still having high stability and reliability is a topic worth studying.

3. Parameter Resolution Research of Nonlinear Systems Based on Improved WOA

At present, in the field of industrial control, precise identification of system models is required. Traditional identification methods such as least squares and maximum likelihood are limited, and whale search algorithms are gradually being applied to nonlinear system parameter identification problems. However, the algorithm structure of the Whale algorithm is monotonous, which can make the first-generation population unable to cooperate and waste search resources. Moreover, the mechanism for updating the population's position is single, which can easily lead to falling into local optima during the iteration process [17]. In response to these issues, this study integrates bidirectional collaborative operations in the first section to improve the WOA. In the second section, two new identification schemes are constructed for the SISO Hammerstein model and MIMO Hammerstein model based on the introduction of optimized whale algorithm to heavy-tailed noise interference.

3.1. Improvement of WOA Based on Bidirectional Collaborative Operations. The WOA has attracted much attention due to its unique algorithm structure. This algorithm can achieve a smooth transition between whale contraction and outward search through the numerical variation of parameter vector A, which means that it finds a balance point between global surveying and local development. This balancing ability is an important reason why WOA outperforms other optimization algorithms. However, the WOA has an obvious structural problem: it lacks the ability to balance survey and development control. This means that in some cases, the WOA may fall into a single search pattern, leading to inaccurate or inefficient search results [18–20]. More seriously, if the WOA uses an entire population to survey candidate optimal solutions or develop the current optimal solution, it will result in a significant waste of search resources. This not only leads to a decrease in the convergence accuracy of the algorithm but also slows down its convergence speed and may even result in search failure, as shown in the flowchart of the WOA in Figure 1. Therefore, for the improvement of the WOA, it is necessary to focus on solving the problem of how to improve search efficiency and accuracy while maintaining a balance between global and local search.

Firstly, a certain random probability is used to cause differential mutations in some whale individuals, and Gaussian interference is randomly added during the process. Then, greedy selection strategy and adaptive crossover are integrated into the whale algorithm structure to accelerate convergence speed while ensuring that the population evolution is moving in the correct direction. At the same time, in order to improve its global search ability, it is necessary to optimize the population distribution. This study set the mutation probability to 0.2 according to the Renchenberg criterion and selected some individuals for differential mutation operations [21]. Equation (1) describes the specific mathematical model.

$$\overrightarrow{D_r} = \left[\overrightarrow{X_{r1}}(t) - \overrightarrow{X_{r2}}(t)\right] + \overrightarrow{X_{r3}}(t) - \overrightarrow{X_{r4}}(t). \tag{1}$$

In equation (1), $\overrightarrow{D_r}$ represents the information exchange channel between randomly selected whales and X_{r1}, X_{r2}, X_{r3}, and X_{r4} represent randomly selected whale individuals other than the current whale, respectively. Equation (2) describes the probability density.

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\left[(x-\mu)^2/2\sigma^2\right]}. \tag{2}$$

In equation (2), μ represents the mean and σ^2 represents the variance. The smaller the variance, the greater the probability, which is a concentrated distribution of probability. The larger the variance, the wider the probability distribution. Adding Gaussian high interference through the information channel can improve the distribution characteristics of whale individuals. This study uses Gaussian interference with a mean of 0 and a variance of 1 to improve the distribution characteristics of whales. To increase whale population potential diversity, adaptive crossover probability is set to determine whether the system performs position update operations. Equation (3) describes the adaptive crossover mathematical model [22].

$$X_i^j(t+1) = \begin{cases} X_i^j(t), & \text{if } r < \text{cr}, \\ X_i^j(t+1), & \text{if } r \geq \text{cr}. \end{cases} \tag{3}$$

In equation (3), $X_i^j(t)$ is the solution of the i-th meridian in the population to the j-th individual dimension and cr is the crossover probability. The smaller the value of cr, the longer the algorithm's running time and convergence speed

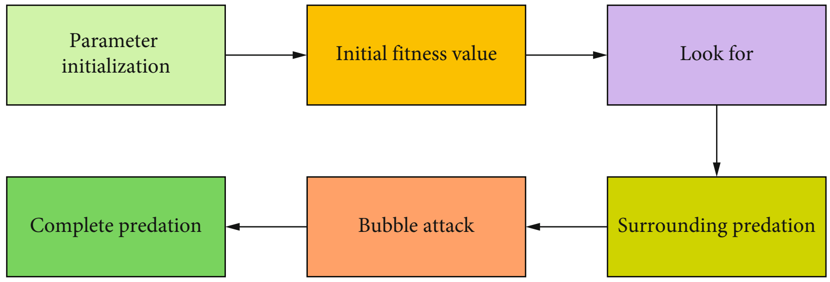


Figure 1: Flowchart of WOA.

and the smaller the population diversity. The larger the cr, the shorter the running time and slower the convergence speed and the greater the population diversity. This study also takes into account the negative effects cr brings, and in order to eliminate its impact, an adaptive crossover probability is set, as described in the following equation.

$$\mathrm{cr} = m + (0.5 - m) \bullet \sin\left(t \bullet \pi / 2 \bullet t_{\max}\right). \quad (4)$$

In equation (4), m is a constant within [0, 0.5] of the adaptive crossover probability to ensure a balance between the population diversity and convergence speed. Figure 2 shows the distribution curve of the adaptive crossover probability, and in the early iteration stage, the smaller the cr, the faster the growth speed and the faster the algorithm convergence speed and running time. As iterations increase, cr increases, and the growth tends to stabilize, resulting in a large population. The diversity increases through adaptive crossover probability, and the algorithm's global search ability improves.

Next, greedy selection is performed on the new whale individuals and the original whale individuals obtained through differential mutation and adaptive crossover. The offspring with higher fitness values participate in the iteration, which is described in the following equation.

$$\vec{X}(t+1) = \begin{cases} \vec{X}(t), & \text{if } f\left(\vec{X}(t+1) \le f\left(\vec{X}(t)\right)\right), \\ \vec{X}(t+1), & \text{otherwise.} \end{cases} \quad (5)$$

In equation (5), both $f(\vec{X}(t+1))$ and $f(\vec{X}(t))$ represent fitness values. In the later stage of algorithm operation, the last elimination mechanism can eliminate the individual with the worst fitness value in the whale population, and a new individual is randomly generated to replace it. This process is represented in the following equation.

$$\overrightarrow{X_w}(t+1) = \vec{X} * (t) + \mathrm{rand} \bullet \left(\vec{X} * (t) - \overrightarrow{X_w}(t)\right). \quad (6)$$

In equation (6), rand is a random function. Figure 3 shows the structural process for optimizing the bidirectional collaborative operation of structure and position update mechanism. It can be seen that after the whale population is randomly initialized, its control parameters are updated, and differential mutation operation, adaptive crossover operation, or position update operation is determined through the judgment of rand. Then, whether the updated individual exceeds the boundary is determined, and finally, the optimal solution is obtained through greedy selection and last bit elimination.

3.2. Hammerstein Model Identification for Nonlinear Systems under Heavy-Tailed Noise. This study constructs two new identification schemes for the SISO Hammerstein model and MIMO Hammerstein model based on the introduction of optimized whale algorithm to heavy-tailed noise interference. As a probability distribution model, the heavy-tailed distribution follows the characteristic distribution of F, which satisfies the mathematical expression described in the following equation [23].

$$\bar{F}(x) = 1 - F(x) \approx c x^{-\alpha}, \infty > c > 0, \alpha > 0. \quad (7)$$

In equation (7), α represents the tail index, and the smaller the α, the thicker the heavy-tailed distribution curve tail, and $F(x)$ represents the probability density eigenvalue. This study mainly focuses on the Student t-distribution noise and binomial mixed Gaussian distribution noise in the heavy-tailed distribution. Equation (8) describes the system noise interference signals involved in system identification [24].

$$e(k) = \left[e_1(k), e_2(k), e_3(k) \cdots \cdots e_n(k)\right]^T. \quad (8)$$

In equation (8), $e(k)$ is the set of interference signals. Equation (9) describes the distribution of Student's t.

$$e_i(k): \ t\left(\mu_i, \delta_i^2, \nu_i\right). \quad (9)$$

In equation (10), $t(\mu_i, \delta_i^2, \nu_i)$ is the univariate Student t -distribution, where μ_i, δ_i^2, and ν_i are positional parameters, proportional parameters, and degrees of freedom, respectively. Equation (10) describes the binomial mixed Gaussian distribution noise.

$$e_i(k): \ (1 - \alpha_i) N_1\left(\mu_i, \delta_i^2\right) + \alpha_i N_2\left(\mu_i, k_i \delta_i^2\right). \quad (10)$$

In equation (10), the Gaussian distribution with a mean μ_i of 0 and a variance of δ_i^2 is $N_1(\mu_i, \delta_i^2)$, $N_2(\mu_i, k_i\delta_i^2)$ represents the part of the pulse interference with a μ_i and a $k_i\delta_i^2$, α_i represents its probability, and k_i is the variance factor of the

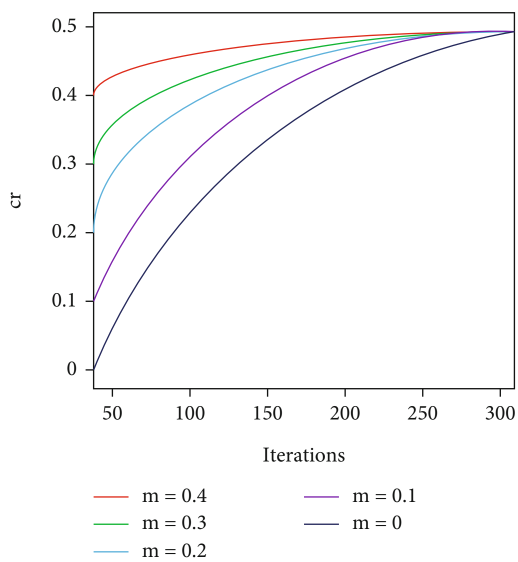


Figure 2: Adaptive cross probability distribution curve.

pulse interference, with a value greater than or equal to 1. In the identification process of the SISO Hammerstein model under heavy-tailed noise, equation (11) describes the SISO Hammerstein model.

$$A\left(z^{-1}\right) = 1 + \alpha_1 z^{-1} + \quad \cdots \cdots + \alpha_n z^{-n}. \tag{11}$$

In equation (11), z^{-1} represents one unit delay. Figure 4 shows the Hammerstein structure. It can be seen that its identification task includes two parts: estimating linear dynamic link parameters and simulating model nonlinear output. The $e(k)$, $y(k)$, $u(k)$, and $x(k)$ in the figure represent the noise interference signal, sampled output, sampled input, and output of nonlinear system static part, respectively. $F(u(k))$ is the static Hammerstein nonlinearity, and $A(z^{-1})$, $B(z^{-1})$, and $C(z^{-1})$ all represent known polynomial orders.

When estimating the parameters of the linear dynamic link, equation (12) describes the weight vector of the feedback channel.

$$\alpha = [\alpha_1, \alpha_2, \cdots, \alpha_n]^T. \tag{12}$$

Equation (13) describes the adaptive parameter vector of the feedforward part.

$$b = [b_1, b_2, \cdots, b_r]. \tag{13}$$

During the identification process, the position of whale individuals in IWOA corresponds to the parameter vectors to be identified in the system. This study uses the mean square error function as the fitness function, and its mathematical model is described in the following equation [25].

$$\mathrm{MSE} = \frac{1}{J}\sum_{k=1}^{J} [y(k) - \hat{y}(k)]^2. \tag{14}$$

In equation (14), J is the sampling data length, $y(k)$ is the actual system output at k, and $\hat{y}(k)$ is the estimated system output at k. Figure 5 shows the process of using IWOA to identify the SISO Hammerstein model and minimize the mean square error index, and the optimal solution obtained after optimization calculation is the parameters required to be identified by the SISO Hammerstein model. Specifically, the first step is to obtain the real system input and output sampling data, construct the nonlinear part of the model using FLANN, and calculate the model output. Next, the algorithm position and parameters are initialized, and the parameter identification results are obtained by minimizing algorithm mean square error (MSE). Finally, the satisfaction of the current identification results is evaluated, and if not satisfied, return to the previous step to continue iteration.

In identifying MIMO Hammerstein model under heavy-tailed noise, equation (15) describes its mathematical model.

$$y(k) = \sum_{i=1}^{n_0} A_i y(k-1) + \sum_{j-1}^{n_b} B_i x(k-j) + e(k). \tag{15}$$

In equation (15), $y(k)$ is system output sampled data at k, A_i and B_i are dynamic linear parameter vectors, and $e(k)$ is noise interference that follows a heavy-tailed distribution function. In the identification process, this study used MSE function as the fitness function, and its mathematical model was described in the following equation [26].

$$\mathrm{MSE} = \frac{1}{J}\sum_{i=1}^{i}\sum_{k=1}^{J} [y_i(k) - \hat{y}_i(k)]^2. \tag{16}$$

In equation (16), J is the sampling data length, i is the number of input and output, $y_i(k)$ is the actual output of the i-th channel in the model, and $\hat{y}_i(k)$ is the estimated output of the i-th channel. To identify the model parameters, it is necessary to first sample the real input and output data under heavy-tailed noise interference to obtain the estimated output of the model. Then, after initializing, IWOA minimizes the mean square error and obtains the most effective solution currently available. Finally, evaluate the satisfaction of the current identification results, and if the department is satisfied, return to the previous step to continue the iteration.

4. Experimental Results and Analysis

This experiment included two parts. The first part tested the performance of IWOA. The second part conducted experiments on the identification effect of Hammerstein model under heavy-tailed noise. In the detection experiment, the maximum iteration was set to 300 and the population size N was set to 50. In order to avoid accidental results as much as possible, the number of independent runs for each benchmark function of the operation was set to 20. The processor used Intel i5 9300H and was tested in a 64-bit Windows 10 PC environment with a RAM size of 16 GB. The main steps of applying the WOA to solve the problem of the Hammerstein model are population initialization, fitness evaluation, selection operation, mutation operation, crossover operation,

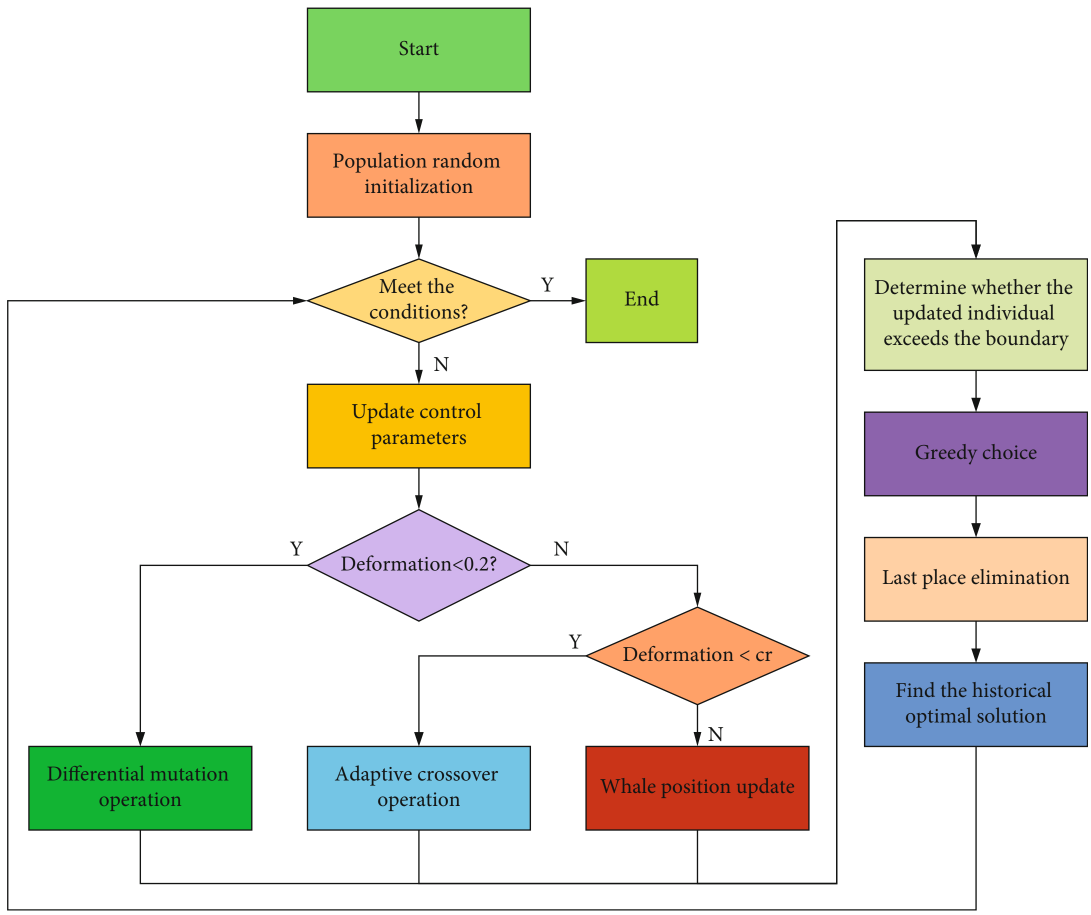


Figure 3: Structure process of improved whale algorithm.

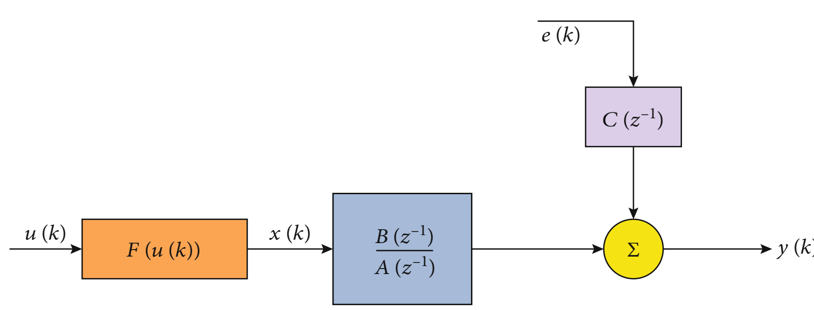


Figure 4: Hammerstein model structure.

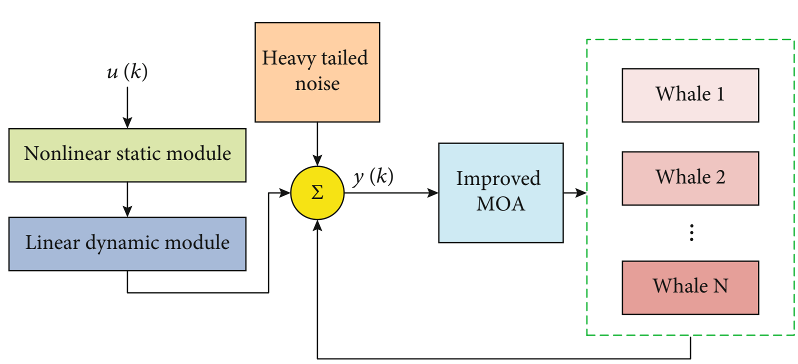


Figure 5: SISO Hammerstein model identification process.

Table 1: Experimental result data of the original WOA and IWOA.

Algorithm index	Optimal value	Worst value	Average value	Standard deviation	Rank mean
Improved WOA	2.04E-03	2.47E+01	8.79E-01	4.68E+00	1.58
WOA	2.83E+01	2.89E+01	2.80E+01	4.89E-01	4.39
Result of multimodal function operation					
Improved WOA	2.87E-10	1.12E-01	3.25E-03	5.02E-03	1.43
WOA	1.07E-01	1.03E+00	4.83E-01	2.67E-01	5.16

Table 2: Rank sum comparison.

Index algorithm	WOA	Improved WOA	GA	PSO
20 unimodal function operations				
Rank sum	104	37	128	121
20 multimodal function operations				
Rank sum	116	32	157	136

local search, global search, and termination condition. The WOA searches for the optimal solution by balancing population search and parameter adjustment, while combining local search and global search to improve search efficiency and accuracy. In specific applications, adjustments and optimizations need to be made based on the specific situation of the problem to achieve better recognition results.

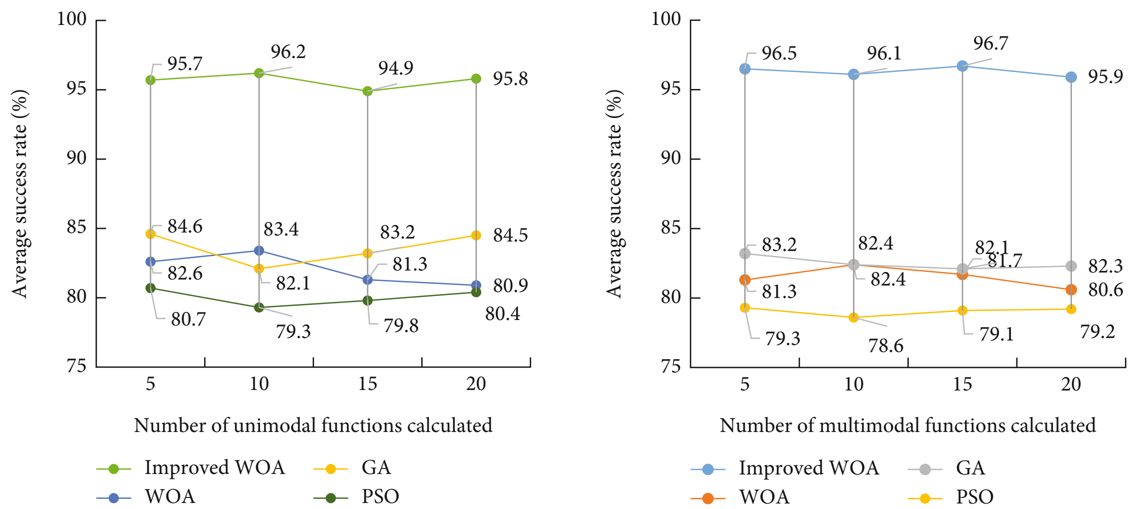
4.1. Experimental Results and Analysis of Improved WOA Performance Detection. To comprehensively reflect the operational algorithm performance, the experimental indicators were selected as optimal value, worst case, average value, standard deviation, success rate, and rank. In the experiment to verify the impact of the random evolution strategy based on structural optimization and the optimized position update strategy on the whale algorithm, the original and improved whale algorithms were selected as the experimental objects, and five unimodal functions and five multimodal functions were subjected to operational experiments. The unimodal function can evaluate the development ability of algorithms, while the multimodal function can evaluate the survey ability of algorithms. Table 1 presents the algorithm experimental results. Compared with the original whale algorithm (OWOA), IWOA performed better in unimodal function operations and had a lower rank average of 1.58, demonstrating stronger local development ability and better stability. The rank average of OWOA was 4.39, which was 2.81 higher than IWOA, reflecting the effectiveness of position update mechanism and random evolution strategy improvement. In addition, in the operation of multimodal functions, IWOA showed greater competitiveness, with a rank average of 1.43. It exhibited strong survey ability in many local optimal solutions of multimodal functions, and its rank average was 3.73 lower than OWOA.

Table 2 provides a comparison of the rank sum in the operation of 20 unimodal and 20 multimodal functions. The rank sum of IWOA in the operation of unimodal functions was 37, which was 67 lower than that of the original one. In multimodal function operation process, the rank sum of IWOA was 32, which was 84 lower than OWOA and about a quarter of the rank sum of OWOA.

To compare IWOA performance with other algorithms used for problem identification, its success rate was compared under 20 unimodal functions and 20 multimodal functions. Figure 6 shows the success rate comparison of the four algorithms. The average success rate of IWOA was overall higher than the other three comparative algorithms. In 20 unimodal function operations, its average success rate was 95.65%, and the variation range between the maximum and minimum average success rates was between 1.3%. In contrast, the overall success rate of genetic algorithm and original whale algorithm was between 80% and 85%, and the fluctuation range between the maximum and minimum success rates was greater than that of IWOA. The average success rate of both algorithms was about 13 percentage points lower than that of IWOA. In the operation of 20 multimodal functions, the average success rate of IWOA was 96.3%, and the variation range between the maximum and minimum average success rates was between 0.8%. Compared to other comparative algorithms, improved WOA performance was better.

Figure 7 shows a comparison of the convergence curves of IWOA, OWOA, the genetic algorithm, and the particle swarm optimization algorithm. In the early stage of convergence, where the number of iterations was between 50 and 100, the other three algorithms cannot avoid falling into local optima. However, IWOA already found the global optimum when the number of iterations reached around 150 with a faster convergence speed and accuracy.

4.2. Experimental Results and Analysis of Hammerstein Model Identification under Heavy-Tailed Noise. To test the identification performance of IWOA for the SISO and MIMO Hammerstein model under heavy-tailed noise, the identification prediction results were compared. The number



(a) Comparison of success rates in unimodal function operations (b) Comparison of success rates in multimodal function operations

FIGURE 6: Comparison of success rates of the four algorithms.

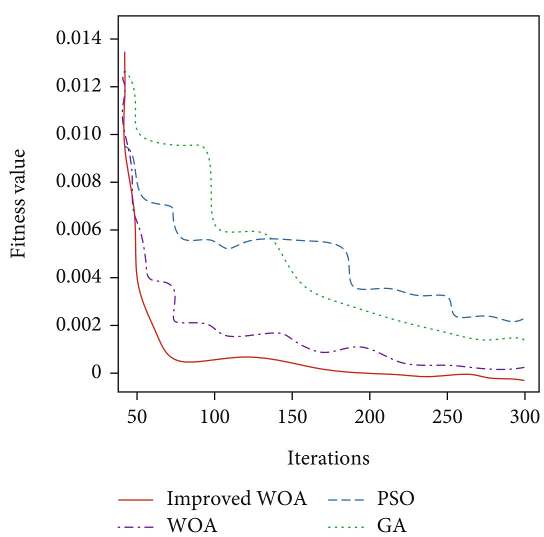


FIGURE 7: Convergence curves of the four algorithms.

of collected samples was 50, and the experimental sampling data length was 100. For the Hammerstein model, the coefficient of determination R^2, percentage fit error (PFE), and systematic error (SE) of evaluation indicators have been added.

Figure 8 shows the parameter identification performance of the SISO Hammerstein model tested five times by the four algorithms under the same excitation signal. IWOA had an overall higher parameter identification accuracy than the other three comparative algorithms. The average prediction recognition accuracy of IWOA was 95.36%, and the predicted output had a high fit with the actual output of the model. The average accuracy of WOA is 81.9%, that of GA algorithm is 83.46%, and that of PSO algorithm is 79.96%. The accuracy of the improved whale algorithm is about 11 to 13 percentage points lower compared to others.

Figure 9 shows the parameter identification performance of the four models gradually adding heavy-tailed noise signals during the five tests of the SISO Hammerstein model. With heavy-tailed noise signal addition, the overall parameter identification accuracy of the four algorithms showed a downward trend. After improvement, the accuracy of the whale algorithm decreased by about 5 percentage points overall, but still maintained at over 90%. The average accuracy of the improved whale algorithm is 92.38%, the average accuracy of the WOA is 79.28%, the average accuracy of the GA algorithm is 79.7%, and the average accuracy of the PSO algorithm is 76.28%. Compared to the other three comparative algorithms, the identification accuracy of the other algorithms has decreased significantly, ranging from 13 to 16 percentage points lower than the average accuracy of the improved whale algorithm.

In the parameter identification performance testing experiment of MIMO, Table 3 presents the statistical results of the linear parameters identified by MIMO in the experiment. Under the influence of heavy-tailed noise, the identification scheme using IWOA can accurately identify the linear parameters of the model. Compared to the other three algorithms, the parameter identification accuracy was higher. The determination coefficient was 0.89, the percentage fitting error was 0.03, and the system error was 0.02.

Figure 10 shows the convergence of the four algorithms in the MIMO Hammerstein model parameter identification process. The improved WOA achieves high convergence accuracy when iterated to 98 times. The WOA completed convergence at 168 iterations. The PSO algorithm completed convergence at 205 iterations. The GA algorithm completed convergence at 283 iterations. This indicates that the improved whale algorithm has a faster convergence speed compared to the other three comparative algorithms, strong escape ability, and the highest convergence accuracy. Compared to genetic algorithms and particle swarm optimization algorithms, the convergence speed of

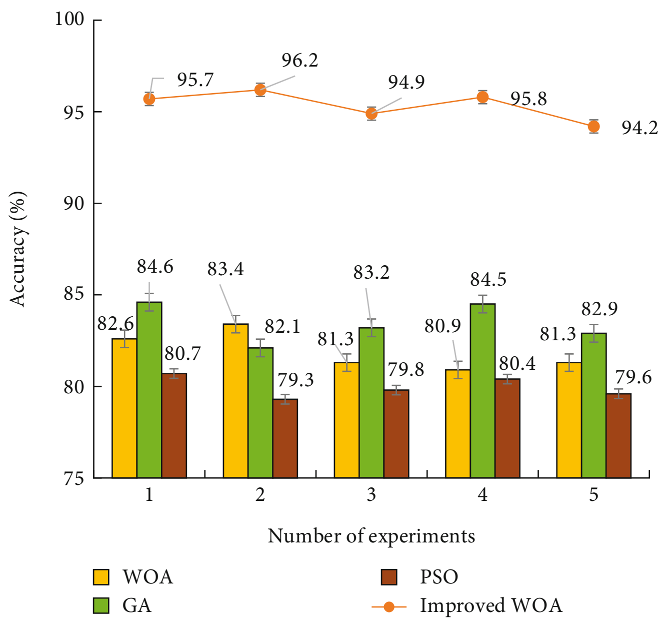


Figure 8: Comparison of parameter identification accuracy of the four algorithms.

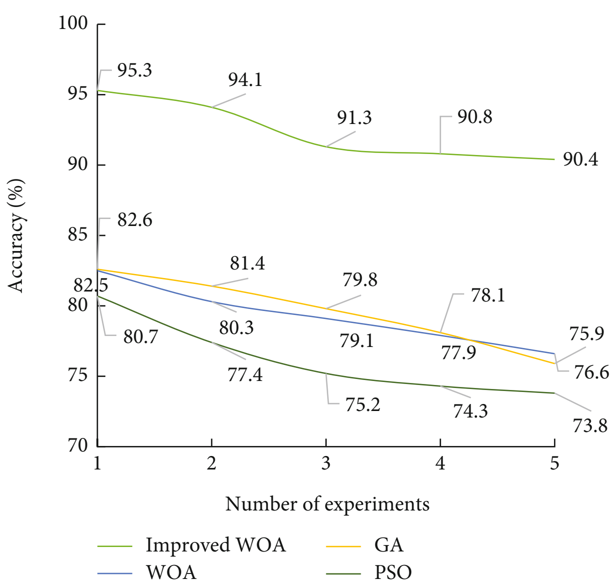


Figure 9: Comparison of parameter identification accuracy of the four algorithms under heavy-tailed noise.

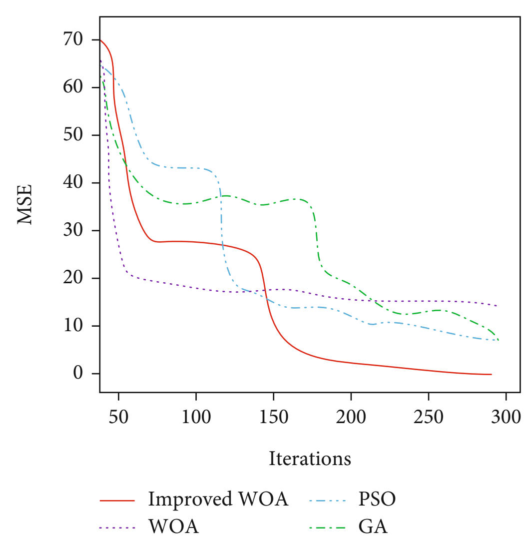


Figure 10: Convergence curves of the four algorithms in the parameter identification process of MIMO Hammerstein model.

Table 3: Linear parameters for MIMO Hammerstein model identification.

Algorithm	Linear parameter values				R^2	PFE	SE	MSE
Real parameters	0.37	0.2	1.14	2.26	/	/	/	/
Improved WOA	0.38	0.19	1.16	2.23	0.89	0.03	0.02	0.12
WOA	0.42	0.27	1.35	2.17	0.71	0.24	0.17	0.19
GA	0.26	0.14	1.52	1.98	0.59	0.47	0.36	0.27
PSO	0.31	0.29	1.37	2.51	0.63	0.25	0.22	0.26

the original whale algorithm is faster, but the convergence accuracy is poorer.

5. Conclusion

OWOA makes it difficult for the first-generation population to work together, wastes search resources, and easily falls into local optima. Moreover, research on the identification of important MIMO Hammerstein models is relatively scarce, neglecting the problem of noise outliers in actual industrial environments. This study proposes an improved whale optimization algorithm for optimizing its structure and position update mechanism and constructs two new identification schemes for the SISO Hammerstein model and MIMO Hammerstein model based on introducing the optimized whale algorithm to heavy-tailed noise interference. Results showed that IWOA had a lower rank average of 1.58 during the operation of unimodal functions, demonstrating stronger local development ability and better stability. In the operation of multimodal functions, its rank average was 1.43, which was 3.73 lower than OWOA. The average success rate of IWOA was generally higher than comparative algorithms. In the operation of 20 unimodal functions, the average success rate of IWOA was 95.65%, and the global optimal was found when the number of iterations reached about 150. In identifying SISO, the average prediction recognition accuracy of IWOA was 95.36%, and the average accuracy of IWOA after introducing heavy-tailed noise was 92.38%. In the parameter identification of MIMO, the error rate of IWOA was a determination coefficient of 0.89, a percentage fitting error of 0.03, and a system error of 0.02. This study is effective for whale optimization algorithms, with faster convergence speed and accuracy. The construction of a new identification strategy for the Hammerstein model under heavy-tailed noise interference shows better data fitting ability and model interpretation ability, but the number of selected nonlinear system sample models is relatively small, which is also an area for improvement in the future.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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