

Article

A Whale Optimization Algorithm Based on Oscillatory Convergence and Diversity Variation for Complex Defect Profile Inversion in Oil and Gas Pipelines

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Abstract

Magnetic leakage detection is one of the most commonly used methods for pipeline inspection, which mainly uses magnetic sensors to detect the magnetic leakage field on the internal and external surfaces of the pipeline to determine whether there are defects in the pipeline. The defect quantification algorithm includes a forward model and an optimization algorithm, in which the estimation of target defects using optimization algorithms is one of the key aspects of defect inversion. Most of the existing optimization algorithms are based on particle swarm algorithms (PSOs) and genetic algorithms (GAs), which are prone to premature problems and have low convergence accuracy. To address the problems in the process of defect inversion, this paper proposes a new inversion algorithm, which obtains part of the prior knowledge from the application context of defect inversion, and adopts the decay oscillation function as the nonlinear convergence factor based on the whale optimization algorithm (WOA). In addition, referring to the concepts of “genetic” and “mutation” in the GA, a diversity variation strategy based on dynamic step size is designed. The algorithm designed has the advantages of fast operation and high search accuracy. At the end of the paper, two sets of experiments are designed to compare the improved WOA with other existing optimization algorithms. The results demonstrate that the algorithm is significantly superior to other algorithms, both in the ideal case of simulation experiments and in the practical application of defect inversion.

Keywords: magnetic flux leakage detection; defect inversion; improved whale optimization algorithm

MSC: 90C59; 65N30; 60N21



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1. Introduction

For readers' convenience, the list of abbreviations is provided in Abbreviations.

Currently, the main detection technologies used in pipelines are magnetic flux leakage detection, eddy current detection, ultrasonic detection, and so on. Magnetic flux leakage (MFL) detection technology is currently the most widely used method with the advantages of low environmental requirements and a wide application range. The inversion process of magnetic leakage detection refers to the process of estimating the shape parameters of the defect from the actual measured magnetic leakage signal. There are two main types of inversion methods. One is the model-free direct method, and the other is the model-based indirect method [1].

The core idea of the direct method is to use tools such as neural networks [2] to establish the mapping relationship between defect parameters and corresponding MFL measurement signals. In this way, when an unknown magnetic leakage signal is generated, the corresponding shape parameters can be found according to the mapping relationship. The advantage of this method is that it is simple and easy to understand. The disadvantage is that the mapping parameters of the model are derived entirely from the training set. When there are not enough samples in the training set or the shape of the target defect differs from the defect features given by the training set, the accuracy of this method is lower. Therefore, the research in this paper focuses on the model-based indirect method.

The model-based method, also known as the iteration method, consists of two main parts: the forward model and the optimization algorithm. The forward model is responsible for obtaining the corresponding MFL signal according to the defect parameters, and the optimization algorithm is responsible for reducing the error of the signal values through multiple iterations. The overall flow of the method is as follows: First, initialize the population. Second, use the forward model to get the corresponding magnetic field signal of each individual. Third, compare it with the measurement to get the error. The smaller the error, the higher the compatibility with the target magnetic field. Based on the error, different update strategies are used to iterate repeatedly. The termination condition of iteration is set to the signal accuracy or the number of target iterations. After the iteration stops, the defect profile corresponding to the most adaptable individual is output.

The common forward models used in iterative methods include magnetic dipole models [3], finite element numerical models, and artificial neural networks [4]. Among them, finite element numerical simulation is an effective model for solving problems in different fields. However, in the application of this method in the industry, there are also problems such as having too many independent variables, complex meshing, and higher calculation costs. In comparison, although the calculation accuracy of the magnetic dipole model is reduced, it is also used to varying degrees in industry. After the application to the leakage detection problem, a large number of modifications have been made to the magnetic dipole model [5], which makes this method more suitable for dealing with irregular defect profiles. Therefore, the magnetic dipole model is used to obtain the magnetic field signal.

The inverse algorithms in the model mainly refer to the gradient descent method and the meta-algorithm. However, since the optimization problem of defect reconstruction always has multiple local optima [6], the optimization algorithm based on gradient descent usually cannot converge to the global optimal solution. Conversely, by designing an effective search strategy, meta-algorithms can enlarge the search domain to the whole search space, in which case a reasonable design can effectively avoid the local optimal solution. Particle swarm optimization [7,8] and genetic algorithm [9], which were originally used in defect inversion, have been continuously improved [10,11]. At the same time, new optimization algorithms have been applied to the inversion process. Ref. [12] introduces the harmonic search algorithm into the inversion process to improve search accuracy. Ref. [13] presents a defect profile reconstruction method based on dynamic tabu search. Ref. [14] combines the cuckoo search algorithm with a particle filter to enhance the robustness of the inversion process.

In existing studies on swarm intelligence-based magnetic flux leakage defect inversion, scholars commonly adopt multiple types of indicators to quantitatively evaluate algorithm performance [15]. For general optimization problems, convergence speed, final optimization error, and standard deviation of repeated experiments are widely used to reflect the searching ability and stability of metaheuristic algorithms. For the specific corrosion defect reconstruction task, researchers usually focus on the fitting error of defect profiles and the prediction error of maximum corrosion depth. Based on the above literature, we select

average depth error (ADE) and peak depth error (PDE) as the core evaluation indicators to measure the reconstruction accuracy of irregular pipeline defects under both noise-free simulation and field measurement conditions. ADE and PDE are adopted as primary evaluation metrics because they directly reflect the geometric reconstruction accuracy of corrosion defects, rather than only evaluating the fitting error of MFL signals, which can effectively avoid biased assessment caused by numerous local optima in the high-dimensional inversion space. Meanwhile, convergence curves and standard deviations of repeated tests are also provided as auxiliary performance references.

Recently, the Chameleon Swarm Algorithm (CSA), a state-of-the-art metaheuristic proposed in 2025 [16], has gained widespread attention in engineering optimization. CSA simulates the multi-angle prey tracking and rapid capture behaviors of chameleons, and adopts adaptive dynamic search factors to balance global exploration and local exploitation. Nevertheless, CSA still suffers from insufficient population diversity and premature convergence when tackling high-dimensional, multi-extremum MFL defect inversion tasks, which limits its practical engineering performance.

The above algorithms have different advantages and limitations. Because of the requirement of convergence speed in the practical application of magnetic flux leakage detection, the defect profile should be depicted within a short number of iterations. Therefore, the number of iterations are limited in the experiment. The experiments show that the above algorithms perform well under ideal conditions. However, once the number of convergences is limited, the performance of these algorithms deteriorate dramatically and the final results have no guiding effect on projects. Therefore, a new algorithm that can maintain good convergence accuracy and fast convergence speed even under the limitation of the number of iterations is desired to meet the practical engineering needs. To solve this problem, a new whale swarm algorithm called Oscillatory convergence and Diversity variation-based Whale Optimization Algorithm (ODWOA) is proposed, which mainly uses a new oscillation convergence factor and a diversity variation strategy based on dynamic adjustment. The new oscillation convergence factor repeats oscillation in a large range in the early stage to effectively balance global search and local search. The diversity variation strategy gives the algorithm the ability to jump out of the local optimum in the late iteration by using the linear decreasing variation and the mechanism of end-stage elimination. The improvement of the algorithm can effectively avoid premature phenomena.

The main contributions of this paper are as follows:

1. The convergence factor based on oscillatory function is designed and tried for the first time in this paper. The oscillatory function oscillates back and forth in a large range in the early stage, to achieve the alternation of global search and local search. It has been proved in practice that this method effectively guarantees the stability of the algorithm in dealing with different types of defects.
2. This paper designs a new diversity variation strategy, which applies interference to some degrees of freedom in the late stage of the search. In addition, referring to the concepts of “inheritance” and “variation” in a genetic algorithm, the algorithm replaces the worst-performing individuals with better-performing ones at a certain probability, which ensures the search speed and validity of the algorithm.
3. Two sets of experiments are designed to compare the proposed ODWOA with four benchmark algorithms: original WOA, PSO, linear decreasing- weight PSO (LPSO), and the state-of-the-art CSA. Comparative results verify that ODWOA achieves superior convergence accuracy and faster convergence speed under limited iteration constraints.

2. Materials and Methods

2.1. Inversion Process of Defect

The inversion process is shown in Figure 1. First, initialize the defect profile x , with $B_j(x)$ representing the magnetic induction intensity at the j^{th} sampling point of the leakage signal generated by the possible solution x . Second, the obtained MFL signal is compared with the target measurement $\bar{B}$. The result is the convergence error $f(x)$, which can be expressed as:

$$f(x) = \sum (B(x) - \bar{B})^2 \quad (1)$$

In this case, $f(x)$ participates in the overall optimization process as a fitness function. The smaller the $f(x)$, the closer the MFL signal produced by the defect profile is to the measurement, and thus a better possible solution. Third, according to the convergence error $f(x)$, the defect profile x' is updated for the next iteration using the optimization algorithm. The termination condition of iteration is that the convergence error is less than the expected value or the number of iterations reaches the expected value. At this point, the defect profile corresponding to the optimal individual is the closest to the real defect profile.

To guarantee fair comparison among all metaheuristic algorithms in subsequent experiments, the identical Opposition-Based Learning (OBL) population initialization strategy, search range and iteration constraints are uniformly adopted for ODWOA, WOA, PSO, LPSO and the newly introduced CSA.

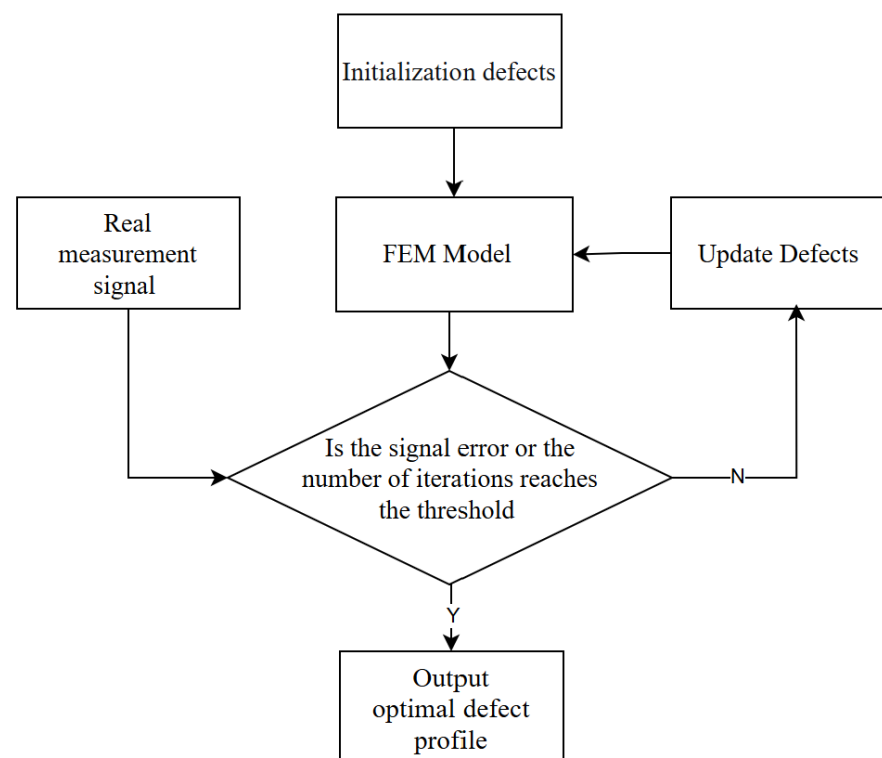


Figure 1. Optimization algorithm applied to magnetic leakage detection.

2.2. Forward Magnetic Dipole Model

The traditional magnetic dipole model is not accurate enough, and the application scenario is blocked when it is applied to the inverse MFL problem. Therefore, the magnetic dipole model is usually used to handle rectangular or class rectangular defects. To enhance the suitability of the magnetic dipole model, some improvements have been made. To achieve the magnetic field response of any profile defect, a new gridded magnetic dipole model [17] is used here. The model divides the defect interval into several small defects

by gridding. Each small defect corresponds to a depth value, and each small defect can be considered an independent rectangular defect. Thus, the intensity of the leakage field in a given external point can be viewed as the sum of the leakage fields of the corresponding set of rectangular defects. The more detailed the mesh is, the more accurate the simulated magnetic field response is.

In the model, the defect profile is represented by the depth of the defect along the cross-section path. Take the possible solution x of a defect as an example:

$$x = [x_1, x_2, x_3, \dots, x_m] \quad (2)$$

where m represents the number of cross-sectional freedom degrees, and x_i represents the depth value of the individual at the i^{th} degree of freedom.

The following is a demonstration of common double-peak defects. Figure 2a,b show a schematic diagram of the defect profile and corresponding magnetic leakage signal when using a grid magnetic dipole model as the forward model.

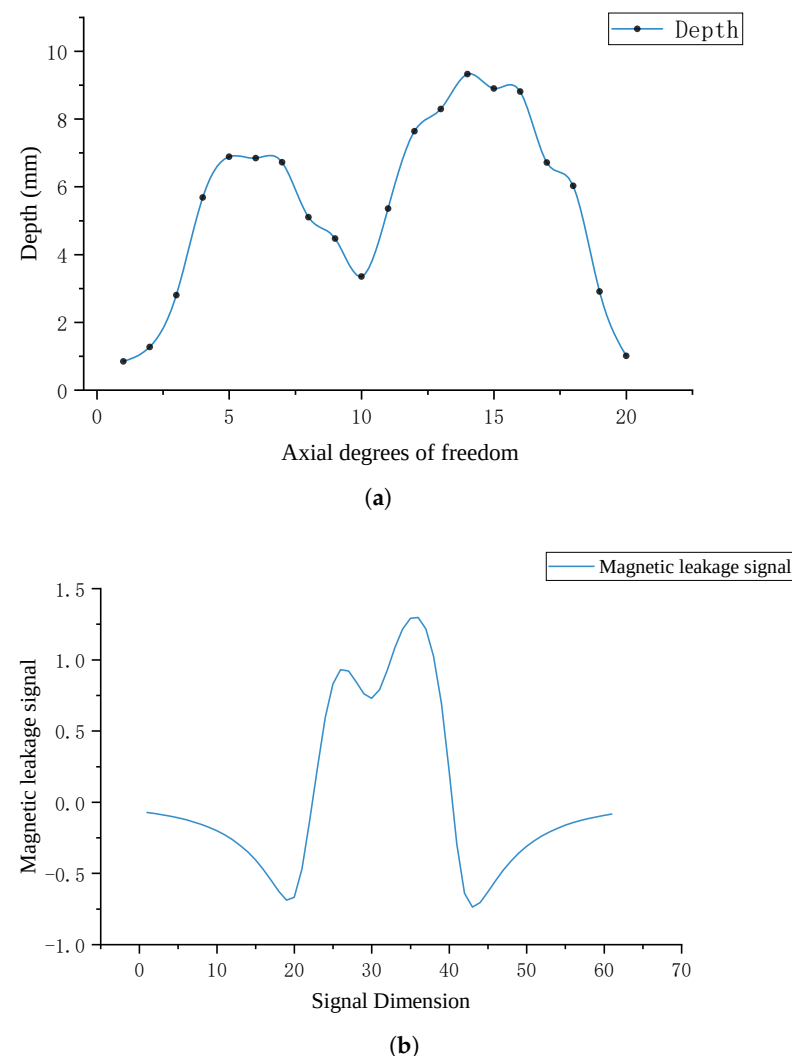


Figure 2. Defect profile and corresponding magnetic leakage signal. (a) Defect profile; (b) Corresponding magnetic leakage signal.

2.3. Optimal Algorithm Based on Improved WOA

2.3.1. Population Initialization Based on Opposite Learning

Unlike particle swarm optimization, the whale swarm algorithm relies on the optimal individuals to provide experience in the early stage of the search. Therefore, when the

whale swarm algorithm is applied to the defect inversion problem, the quality of population initialization seriously affects the previous search results. In the original whale swarm algorithm, the initial position of the population is a set of random values within the search range. To obtain a better initial population value, the initialization method of the population was improved by referring to OBL. Opposition-Based Learning, a new technology in the field of computing in recent years, has been successfully applied to intelligent algorithms such as PSO [18,19]. For better population initialization, it has also been applied to the initialization of the whale swarm algorithm [20].

To ensure fair experimental comparison, the identical OBL initialization rule, search boundary and population hyperparameters are applied uniformly to all five algorithms involved in the follow-up experiments, including ODWOA, original WOA, PSO, LPSO and CSA. No algorithm adopts random initialization separately to eliminate the performance gap caused by inconsistent initial population quality.

The definition of the opposite point is shown below. If there is a number x on the range $[l, u]$, the opposite point of x is defined as $x' = u + l - x$. This definition is further extended to a multidimensional space. There is a point $\mathbf{x}$ in the n -dimensional space whose location coordinates are expressed as $\mathbf{x} = (x_1, x_2, \dots, x_n)$, where $x_i \in [l_i, u_i]$, $i = 1, 2, \dots, n$. Its opposite point $\mathbf{x}' = (x'_1, x'_2, \dots, x'_n)$, where $x'_i = l_i + u_i - x_i$. This definition is introduced into the whale swarm algorithm. Assuming that the current number of individual whales is N , which represents N possible solutions to the problem, then the spatial location of the i^{th} individual can be represented as

$$X_i^j = l_i^j + \text{rand} \cdot (u_i^j - l_i^j) \quad (3)$$

From the definition of opposing points, the opposing positions of the corresponding j^{th} whale are expressed as follows:

$$X_i^{j'} = l_i^j + u_i^j - X_i^j \quad (4)$$

The population consisting of N initially generated individuals is named the original population. After adding the individuals generated based on the OBL, the population is named the expanded population. It can be seen that the initialization quality of the expanded population is largely related to the original population. Therefore, the overall initialization quality can be greatly improved by improving the generation strategy of the original population.

The most common initialization method is shown in Formula (3). The method satisfies the requirements of the algorithm but still needs to be improved in terms of search performance. Therefore, it is necessary to improve the initialization algorithm by obtaining some prior knowledge from specific application scenarios of magnetic leakage detection.

Because the magnetic dipole model has the characteristics of high speed but poor accuracy, its application scenarios are mostly simple-peak or double-peak defects with simple structures and the widest coverage.

Take the single-peak defect as an example. Assuming that the depth value X of a single-peak defect satisfies $X \sim (\mu, \sigma^2)$ in the case of 20 degrees of freedom, its mathematical expectation $\mu = \frac{1}{2}(u - l)$. It is regarded as a priori condition for initialization and then generates appropriate perturbations around that expectation to initialize individual locations, where the perturbations are selected concerning the concept of variance in the normal distribution. The initialization formula based on this complete algorithm is expressed as:

$$X_i^j = \frac{(u_i^j - l_i^j)}{2} + \text{rand} \cdot \sigma^2 \quad (5)$$

The prior condition here is given entirely by the assumption in the single-peaked case. In Section 3.3, it will be verified that the improved method is also effective in dealing with the problem of double-peak defects.

The complete population initialization based on OBL is shown in Algorithm 1:

Algorithm 1 The Initialization Method Based on OBL

- Step 1 Set the population size N and the search dimension dim
 - Step 2 Generate the initial population according to Equation (5)
 - Step 3 Expand the population by generating the opposite whale position according to Formula (4)
 - Step 4 Calculate population fitness and select N whale individuals with the highest fitness as the initial population
-

2.3.2. Nonlinear Convergence Factor

In the defect inversion problem, because of the high degree of freedom of the defect (such as 15 or 20), the MFL signal output from the MFL detection model is not sensitive to the change of defect depth at the input end, resulting in a large number of local minimum values appearing in the search domain. It can be seen that the error between the output signal of the algorithm and the actual measurement is small, but the simulated defect depth of the algorithm is different from the actual defect. At this time, the commonly used algorithms, such as particle swarm optimization or genetic algorithm, do not have effective guidance for practical engineering applications. To solve this problem in the application, this paper proposes to apply the decay oscillation function in the WOA for the first time, focusing on solving the problem that the algorithm is prone to fall into local optimum while guaranteeing the convergence speed.

In WOA, the coefficient $A = 2\vec{a} \cdot \vec{r} - \vec{a}$. The shrinkage envelope mechanism is implemented with the decrease of coefficient a , which balances local and global optimization. For the traditional WOA, the coefficient a is linearly related to the number of iterations. Factor a decreases linearly from 2 to 0 during the iteration process, in which the fluctuation range of coefficient A is $[-a, a]$.

To solve the problem that the algorithm is easy to fall into the local optima in the early stage of the search, the coefficients in the WOA need to be improved. After trying several functions, a decaying oscillation function based on the sine function and the exponential function is adopted.

As shown in Figure 3, the function oscillates back and forth in a large area in the early part of the function to intermittently perform global and local searches. In the latter part, the function converges to 0 gradually with the increase of iterations and then continues local searches to avoid large fluctuations in the latter part of the iteration. The modified algorithm is more stable when dealing with multi-degree-of-freedom defect inversion problems. It is demonstrated that the improved algorithm can effectively avoid the algorithm from falling into local minimum value due to the deviation of search direction in the early global search time. The modified coefficient A can be expressed as:

$$T = (t / Max_iter) * 4 * \pi \quad (6)$$

$$A = X * e^{-0.5x} * \sin(Y * T) \quad (7)$$

The two parameters, X and Y , control the amplitude and frequency of attenuation oscillation, respectively. The relationship between the coefficient $|A|$ and the size of 1 during the iteration process is controlled by modifying X and Y , to achieve a balance between the random search for prey and approaching the current optimal individual of the population.

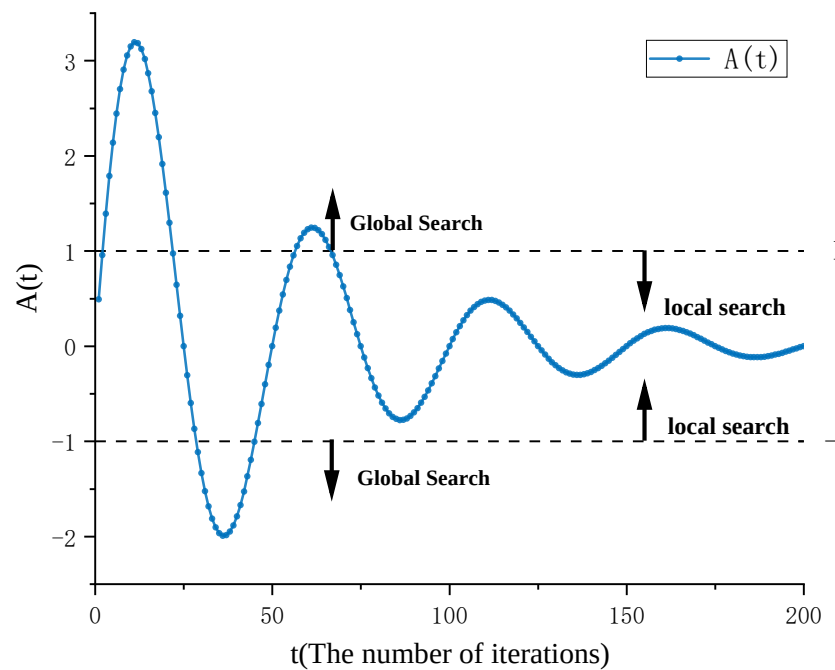


Figure 3. Example of decaying oscillation function.

2.3.3. Diversity Variation Based on Dynamic Adjustment

The characteristics of WOA determine that whale populations gradually approach the optimal solution of the current population due to the coefficient $|A| < 1$ at the end of the search, which result in a gradual loss of population diversity. This can easily lead the whole population to fall into the local optimum because of the current position of the best individual. This is also the inherent feature of the swarm intelligence algorithm. To reduce the probability that the whale swarm algorithm falls into the local optimum later on, this section adopts a new variation strategy, which can generate some disturbance to the population after each iteration at a later stage and ensure population diversity as much as possible.

To address the issues mentioned above, the composition of the later-search population is changed. At the end of the search, if no continuous K iterations can jump out of the current optimal position g_{best} , the algorithm deletes the least adaptable individual with a probability of $p_1 = 0.5$ and add a better-positioned individual. In this paper, the quality of each individual is judged by the Average Depth Error (ADE). Individuals with smaller ADE values correspond to better reconstructed defect profiles and are regarded as high-quality candidates. This method can effectively reduce the interference of the poorly performing individual in the search and speed up the search process. Referring to the heredity and variation of the GA, instead of randomly generating in the initial search space when adding the best-positioned individuals, it is achieved by copying the location information of the best individuals in the current population and randomly selecting Z degrees of freedom to add disturbance.

Since the output MFL signal is not sensitive to the slight changes in the input simulated defect values, in order to complete the local search as far as possible, the individual interference is added in the later search period based on the above. When iteration number $T > Max_{iter}/2$, it is determined that it is in the late iteration when individual interference is carried out with probability $p_2 = 0.5$. The degree of interference is related to the maximum depth in the application scenario and decreases with the iteration, which can effectively avoid the influence of disturbance on the search direction of the population.

At the same time, it can be seen in the application that the MFL measurements are more sensitive to the value of the intermediate degree of freedom parameter in the model of magnetic leakage detection, while the effect of the change in depth at the shallow ends of the final magnetic field is weaker. A variation is added to the algorithm to avoid the failure to converge at the later stage—due to a decrease in the richness of the degrees of freedom at both ends or a catastrophe resulting in a large variation in the degrees of freedom at both ends that prevents them from converging. The variation amplitude is expressed by l_i , where i is the degree of freedom. In the new variation strategy, the degree of variation at both ends is large, while the middle part is small or non-existent. Combining the above three variations, the specific steps are as follows (Algorithm 2):

Algorithm 2 Diversity variation based on dynamic adjustment

Step 1 Generate random numbers σ_1, σ_2 in the range $(0, 1)$
 Step 2 If $\sigma_1 < p_1$ and there is no significant change in fitness for K iterations in succession, delete the worst fitness individual in the population and add an individual with a better location
 Step 3 If $\sigma_2 < p_2$ and $T > Max_{iter}/2$, the degrees of freedom at both ends are greatly changed, while the intermediate degrees of freedom can choose either small variation or no variation. The variation range l_i decreases with the increase of T .

Based on the above three improvements, the complete ODWOA can be described as Algorithm 3.

Algorithm 3 ODWO Algorithm

```

begin
Set the population size  $N$  and use Algorithm 1 to generate the initial population
Calculate the fitness of each individual and record the current optimal individual
while  $t < Max\_iter$  do
  for  $i = 1$  to  $N$  do
    Calculate the value of the convergence factor and update the values of parameters;
    if  $p < 0.5$  then
      if  $|A| < 1$  then
        Search prey randomly;
      else
        Surround current optimal individual;
      end if
    else
      Spiral Forward;
    end if
  end for
  Calculate the fitness of each individual;
  Perform diversity variation based on Algorithm 2;
  Update the current optimal individuals and their corresponding locations;
   $t = t + 1$ ;
end while
end
  
```

2.4. Benchmark Algorithm: Chameleon Swarm Algorithm

To comprehensively verify the superiority of the proposed ODWOA and enrich the benchmark comparison group, as suggested by the reviewers, the state-of-the-art CSA is introduced as an additional comparison algorithm in this paper. The CSA is a novel meta-heuristic optimization algorithm inspired by the predation behavior of chameleons. It simulates the processes of multi-angle visual observation, distance judgment and dynamic position update when chameleons capture prey, and designs self-adaptive weight

adjustment factors to balance global exploration in the early iteration and local exploitation in the late iteration. Nevertheless, when applied to high-dimensional, multi-extremum magnetic flux leakage defect inversion tasks with limited iteration budgets, the CSA suffers from inherent defects including insufficient population diversity and premature convergence [21]. These drawbacks restrict its reconstruction accuracy for irregular pipeline defects, which further highlights the necessity of the improved ODWOA proposed in this work. Consistent with the fairness requirement of comparative experiments mentioned in Section 2.3.1, the CSA adopts the identical OBL population initialization strategy, search boundary constraints, population size and maximum iteration number as the ODWOA, WOA, PSO and LPSO. All iterative update rules of the CSA strictly follow the standard framework proposed in its original literature, and the corresponding hyperparameters are listed in Table 1 in the experimental parameter section below.

Table 1. Examples of algorithm parameter and variable values.

Parameter/Variable	Value	Definition
u	10	Upper bound of defect depth search range (mm)
l	0	Lower bound of defect depth search range (mm)
σ	1	Standard deviation of normal-distributed disturbance for prior initialization
X	2.5	Amplitude control coefficient of decaying oscillation convergence factor
Y	2	Frequency control coefficient of decaying oscillation convergence factor
K	3	Maximum continuous non-updating iterations for diversity variation trigger
N	20	Population size of whale/swarm algorithms
Z	5	Number of disturbed axial freedom degrees in dynamic mutation strategy
$l_i (0 \leq i \leq 5 \parallel 16 \leq i \leq 20)$	0.8~0.15	Mutation amplitude of the i -th axial freedom degree; large for edge positions ($0 \leq i \leq 5, 16 \leq i \leq 20$), small for middle positions

3. Results

In order to verify the effectiveness of the designed algorithm in dealing with defect inversion problems, two sets of experiments were set up in this chapter. The first set of experiments was conducted in an ideal simulation environment, and the performance of several algorithms in dealing with two common defects was compared. The final evaluation criterion is the search accuracy. The second group of experiments was carried out in a loop experimental field, and the measurement signal was obtained from the magnetic sensitive detector, which avoided the influence of the forward model on the experiment. Fifty sets of defects existing in the test field were selected to verify the advantages of the proposed algorithm in terms of stability and robustness when applied to practical problems by comparing the performance of different algorithms in dealing with real defects.

3.1. Simulation Experiment

Parameter Settings

For the gridded magnetic dipole model, the grid size is set to 1 mm $\times$ 1 mm, and the sampling interval is set to 2 mm. The defect model is generated by initializing the defect length L , the defect width W , and the defect depth D . The length and width of the defect are from 0 to 40 mm, and the axial freedom is 20. Defect depth D is from 0 mm to the maximum wall thickness, which is taken from 0 to 10 mm. The output axial magnetic field signal is generated by generating the defect depth matrix in the range of L and W and substituting the forward model. All five algorithms (ODWOA, original WOA, PSO, LPSO, CSA) share identical population size $N = 30$, maximum iteration number, search boundary and Opposition-Based Learning initialization rule to guarantee fair comparison, as illustrated in Section 2.3.1. Detailed hyperparameters of each optimizer are provided in Table 1 after obtaining CSA parameter data.

In addition, many parameters of the improved whale swarm algorithm depend on the application. Sample parameters are given here when choosing the gridded magnetic dipole model as the forward model. All fixed hyperparameters, search boundary constants and variation coefficients adopted in ODWOA, WOA, PSO, LPSO and CSA are summarized in Table 1, where each symbol corresponds to the physical variables used in the optimization inversion model.

3.2. Simulation Experimental Results and Comparative Analysis

To test the performance of the improved algorithm, two sets of depth matrices in the range of 0 mm to 10 mm were created to simulate the most common single-peak defects and double-peak defects. Then, the corresponding magnetic leakage signals were obtained by using the forward model. These two sets of signals participated in the experiment as target signals.

The experimental group is the proposed ODWOA, and the control group consists of the original WOA, PSO, and LPSO, respectively. The population size of all algorithms is 30. In order to meet the practical requirements of MFL problems, average depth error (ADE) and peak depth error (PDE) are selected as performance metrics. As shown in Figure 4, the former is the average depth error between the optimal predicted profile and the actual defect profile, which is used to reflect the proximate between the generated profile and the target profile. The latter is the error between the maximum depth of the predicted profile and the maximum depth of the target profile, which is selected as a performance criterion in order to meet the requirements for maximum depth in practical use. The two indicators are as follows:

$$ADE = \frac{\sum_{i=1}^N |D_i - D'_i|}{N} \quad (8)$$

$$PDE = |\max(D_i) - \max(D)| \quad (9)$$

D_i and D'_i represent the depth of the simulated defect depth and the ideal defect depth when the degree of freedom is i . N is the axial degree of freedom, which is set to 20.

To reduce fluctuations, the five experiments were repeated 50 times, and the results were averaged. The experimental results are shown in Table 2.

As shown in Table 2, the performance of the improved whale swarm algorithm (replaced by ODWOA below) based on the above method is significantly better than that of the WOA, PSO, and LPSO algorithms in both single-peak and double-peak groups. Among all comparison algorithms, the CSA achieves moderate reconstruction accuracy: it noticeably outperforms the traditional WOA, PSO and LPSO, yet retains a notable accuracy gap relative to the ODWOA. The premature convergence issue of the CSA under limited iterations constrains its capability to fit complex defect depth curves, thus producing larger ADE and PDE values than the proposed ODWOA. Compared with the WOA, the ODWOA reduces ADE by 47.0% and PDE by 50.8% when dealing with single-peak problems. Similarly, compared to PSO and LPSO, its ADE decreased by 41.9% to 55.6%, and PDE decreased by 64.6% to 72.1% on the single-peak issue. The experimental data demonstrate the effectiveness of the improved strategy. Compared with the control group algorithm, the improved algorithm has a more significant effect in dealing with single-peak defects.

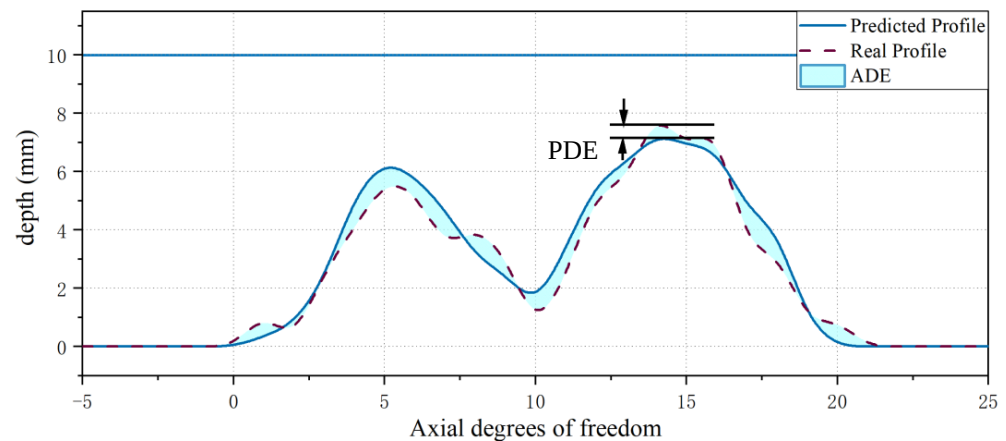


Figure 4. Behavior predicted profile vs. real profile.

When dealing with double-peak defects, the ADE of the ODWOA is reduced by 36.9% to 56.1% compared to the control group, and the PDE is reduced by 15.4% to 73.9% compared to the other four algorithms (WOA, PSO, LPSO, CSA). The reduction of ADE and PDE when dealing with single-peak and double-peak defects proves the effectiveness of the improved algorithm for MFL problems.

Table 2. Comparison of five algorithms in finding optimal results with two flaws.

Function	Single-Peak		Double-Peak	
	ADE/mm	PDE/mm	ADE/mm	PDE/mm
ODWOA	1.247	0.6496	1.173	0.5713
WOA	2.351	1.3205	2.319	0.6756
PSO	2.81	2.3308	2.674	2.1898
LPSO	2.145	1.8344	1.858	1.443
CSA	1.718	1.4025	1.638	1.279

To more intuitively show the difference in the effectiveness of the improved algorithm in operation, Figure 5 shows the difference in the profiles obtained after the algorithm searched for optimal postprocessing. In the control group, the WOA with the smallest average error is taken as an example. The results of one of the 50 replicate experiments that are closest to the average are taken here for demonstration. From Figure 5a,b, it is apparent that the profile generated by the ODWOA is closer to the target profile for both simple-peak and double-peak defects with the same number of iterations. In contrast, the profiles generated by other algorithms do not provide good guidance for the actual project.

To more intuitively show the performance difference between the ODWOA and the other four algorithms (WOA, PSO, LPSO, CSA), Figure 6 shows the comparison of the search accuracy between the ODWOA and the four benchmark algorithms (WOA, PSO, LPSO, CSA) when dealing with the single-peak and double-peak problems.

From Figure 6a,b, it is obvious that compared with WOA, PSO, LPSO and the state-of-the-art CSA, the error curve of the proposed ODWOA declines much faster in the early iteration stage and converges to a far-lower steady-state error without obvious oscillation or premature stagnation. The curves of the three baseline algorithms (WOA, PSO, LPSO) and the CSA fluctuate severely and get trapped at high error values throughout the iteration process. Such distinct curve differences sufficiently demonstrate that the ODWOA effectively overcomes the premature convergence problem and achieves superior optimization performance.

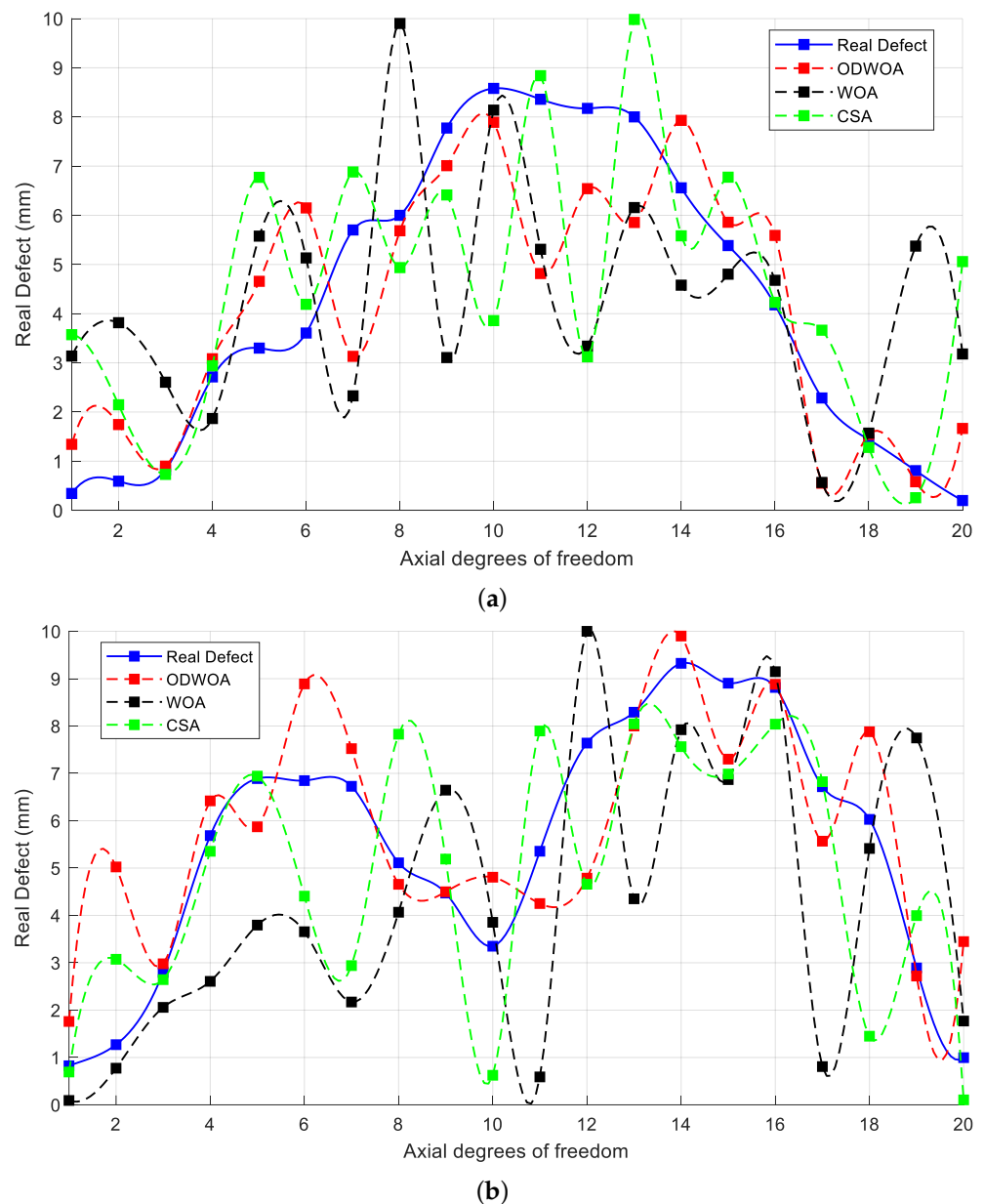


Figure 5. (a) Comparison of ODWOA and WOA handling of unimodal defects; (b) Comparison of ODWOA and WOA handling of bimodal defects.

However, the above experiments are incomplete because the application scope of the magnetic dipole model is limited. In the actual situation, the detection equipment itself will cause noise due to vibration and other reasons, so there is some error between the ideal signal obtained in the experiment and the actual MFL measurement. In order to test whether the improved algorithm is competitive in dealing with practical problems, a new set of control experiments were designed. To test whether the designed algorithm still performs well when there is a signal-to-noise ratio of the target signal, the experiments obtained MFL measurements from the experimental equipment at the test site.

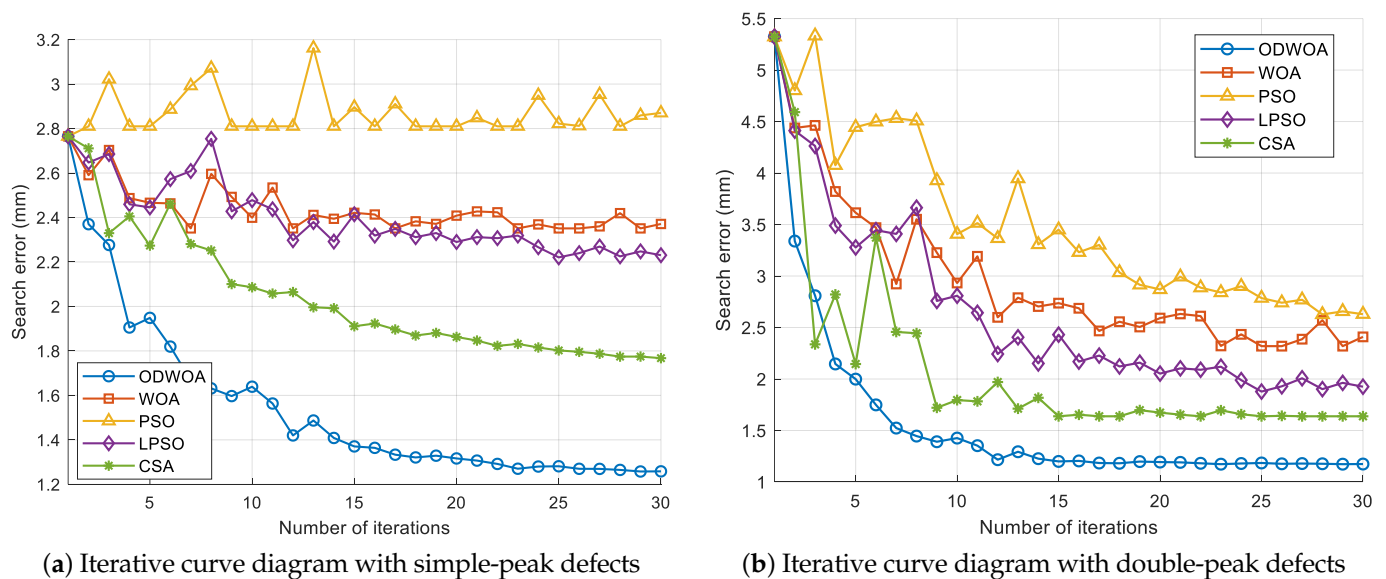


Figure 6. Iterative curve diagram of five algorithms with unimodal and bimodal defects.

3.3. Pipeline Experiment in a Ring Test Field

3.3.1. Experimental Environment

In order to further verify the effectiveness of the proposed algorithm in dealing with practical problems, a controlled field experiment is designed. As shown in Figure 7a,b, the test site is an 800-meter-long medium-sized water loop test site. The outer diameter of the pipeline is 12 inches, the wall thickness is 12.7 mm, and there are 50 artificial irregular defects on the pipeline. Different from the simulated experimental conditions, the defects in the field experiment are artificial irregular defects generated in the early stage, and the defect shape is no longer limited to a single peak or double peaks.

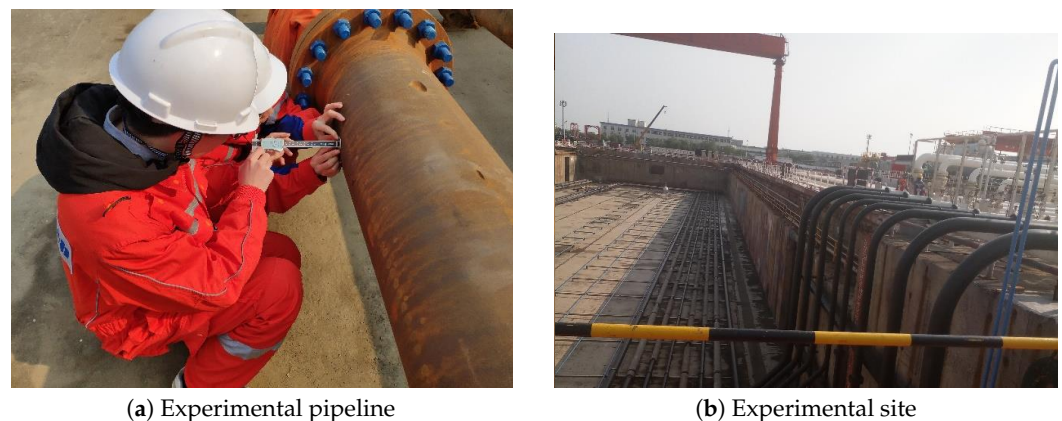


Figure 7. Experimental site and experimental pipeline.

It is worth noting that the 50 field-measured defect samples contain signals with different degrees of natural industrial noise induced by probe vibration and mechanical jitter, which can be approximately divided into low, medium and high noise levels for analyzing the noise robustness of the inversion algorithm. In addition, the signal measurements are obtained and stored by the device shown in Figure 8. From left to right in the figure are: the permanent magnet, sensor, battery and recording link. The equipment may generate vibration during operation, which leads to noise in the obtained magnetic field measurements. This is the biggest difference between experimental field and numerical simulation experiments, and it is also the main reason for the deterioration of inversion algorithm performance.

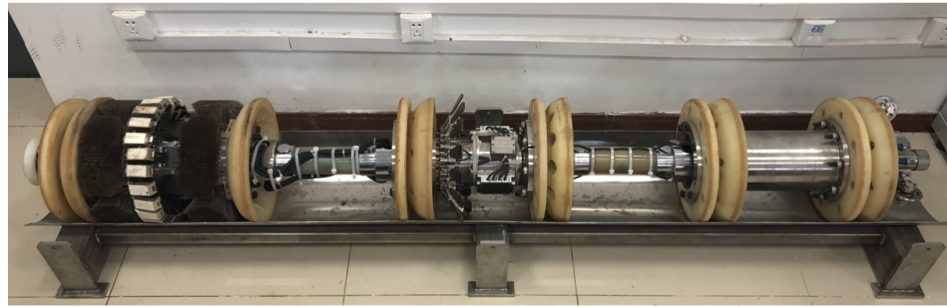


Figure 8. In-pipeline detectors at test site.

In the experiment, 50 defects in the test field were selected, and the corresponding magnetic field data obtained by the magnetic sensor was used as the target signal to seek the optimum. The experimental group in the experiment is the improved whale swarm algorithm (ODWOA), while the control group comprises WOA, PSO, and particle swarm algorithm with linearly decreasing inertia weight (LPSO). The population size of all algorithms is 30. The experiments end with a comparative analysis of the inversion results for the 50 defects in the experiments.

3.3.2. Experimental Results and Comparative Analysis

As shown in Table 3, under the same number of iterations, the performance of the ODWOA algorithm improved by 44.9%, 58.7%, and 57.4%, respectively, compared with the other four algorithms (WOA, PSO, LPSO, CSA) for 50 groups of unknown shape defects.

Table 3. Comparison of optimization results of five algorithms under 50 groups of defects in field experiments.

Evaluation Criterion	ODWOA	WOA	PSO	LPSO	CSA
ADE/mm	1.30 ± 0.20	2.36 ± 0.30	2.87 ± 0.31	2.15 ± 0.27	1.78 ± 0.26
PDE/mm	0.89 ± 0.28	1.82 ± 0.58	2.31 ± 0.42	1.77 ± 0.38	1.24 ± 0.39

At the same time, compared with the original WOA algorithm with better search effectiveness, the standard deviation of the ODWOA is significantly reduced, which proves that when dealing with multiple groups of defects with unknown shapes, the search accuracy and stability of the ODWOA are significantly better than the original algorithm. The value of the PDE obtained by experiments also proves that the ODWOA is more effective and stable than the other four algorithms in practical application. The CSA performs better than the PSO, LPSO and original WOA in the field experiment with inherent industrial noise interference, but its average ADE is 36.9% higher than the ODWOA, and the average PDE is 39.3% higher than the ODWOA. The fixed adaptive search strategy of the CSA cannot adapt to the high-dimensional irregular defect characteristics under noisy signals, leading to obvious reconstruction deviation compared with the ODWOA.

Figure 9 shows the comparison of search error between the ODWOA and the other four algorithms (WOA, PSO, LPSO, CSA) when dealing with 50 groups of defects. It can be seen from the figure that in 50 groups of defects with unknown shapes, the ODWOA is not as effective as the WOA in only one case.

Based on the 50 groups of field data collected from the loop test platform with vibration-induced measuring noise, we can observe that the proposed ODWOA possesses stable defect inversion capability under industrial noise interference. All the above observations are quantified by the Average Depth Error (ADE) and Peak Depth Error (PDE) statistics summarized in Table 3, which record the mean value and standard deviation of inversion errors across all 50 field defect samples.

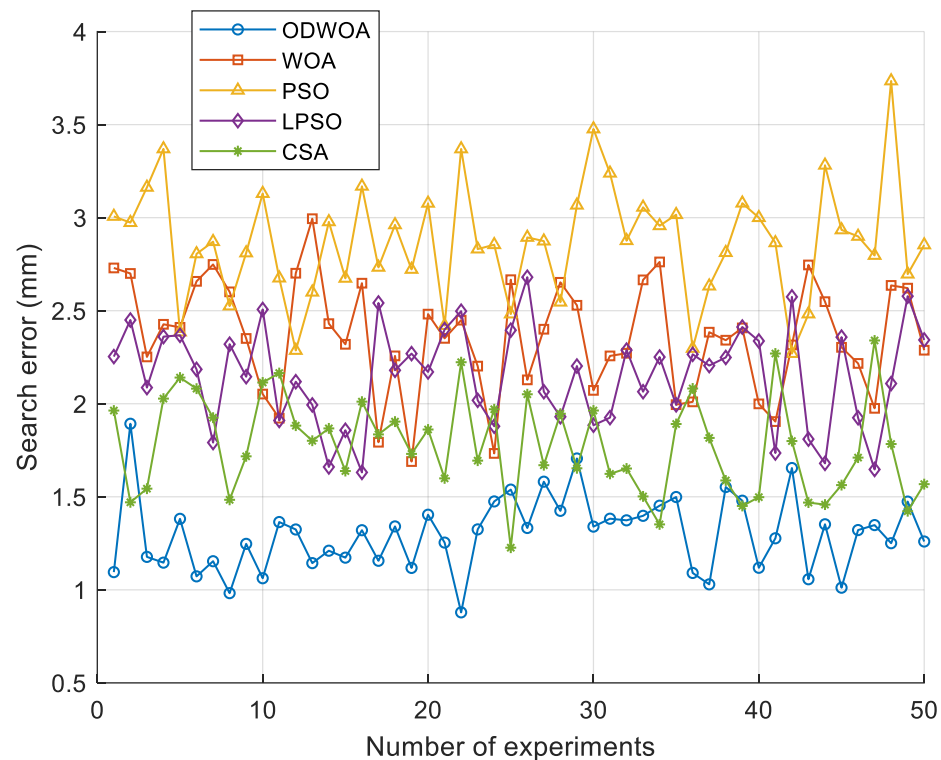


Figure 9. Comparison of 50 groups of defect errors processed by ODWOA, PSO, and LPSO.

The quantitative ADE and PDE indicators listed in Table 3, together with the error distribution curves plotted in Figure 9, visually reflect the performance gap between the ODWOA and all benchmark algorithms in practical noisy-pipeline detection scenarios.

4. Discussion

4.1. Mechanism Analysis of the Superiority of ODWOA

Conventional metaheuristic optimizers, including the standard WOA, PSO, LPSO and the state-of-the-art CSA, easily suffer premature convergence when solving high-dimensional MFL defect inversion under strict iteration limits. The linear attenuation convergence factor of the traditional WOA cannot dynamically switch between global exploration and local exploitation during iterations, which traps the algorithm into local optima when reconstructing multi-extremum defects such as double-peak corrosion. To address this limitation, this paper proposes a decaying oscillatory convergence factor built on sine-exponential functions. In early iterations, the large-amplitude oscillation expands the search range to locate potential defect depth distributions; in later iterations, the oscillation amplitude decays gradually to support precise local refinement. This design fundamentally suppresses the premature convergence defect of traditional WOA.

Additionally, we design a dynamic diversity variation strategy inspired by genetic inheritance and mutation to sustain population diversity. Considering the physical characteristic that MFL signals are much more sensitive to the intermediate axial depths of defects than edge positions, differentiated mutation amplitudes are assigned to different freedom degrees. When the algorithm stagnates at the current optimal solution for consecutive iterations, individuals with poor fitness are eliminated at a fixed probability, while high-quality individuals with targeted lightweight disturbance are supplemented. This mechanism effectively helps the whale population escape local minima in the late search stage. Taking the 800 m field test for example, under the unified iteration limit, the average optimization error of the conventional WOA is about 3.2 times that of the

ODWOA, and the standard deviation of repeated tests also rises from 0.042 (ODWOA) to 0.137 (WOA), which quantitatively verifies that the two improvement strategies effectively suppress performance degradation caused by premature convergence. The two core improvements jointly guarantee the outstanding optimization performance of the ODWOA in limited iteration budgets. Although the ODWOA requires slightly longer computation time than the WOA, PSO and LPSO, the defect inversion in this work belongs to offline post-processing carried out on ground workstations after data collection. Therefore, the slight increase in computing time does not restrict the on-site inline inspection process in practical engineering.

4.2. Comparative Analysis with State-of-the-Art CSA

The CSA is a recently proposed metaheuristic and outperforms classic optimizers (WOA, PSO, LPSO) in simple optimization tasks. Nevertheless, its built-in fixed adaptive search rules lack targeted optimization for high-dimensional, noise-interfered irregular pipeline defect inversion tasks. In both noise-free single/double-peak defect simulations and the 800 m loop pipeline field test with vibration measurement noise, the CSA exhibits obvious reconstruction deviations compared with our proposed ODWOA. Without the oscillatory convergence balance mechanism and the MFL signal-aware differentiated mutation strategy customized for pipeline detection, the CSA cannot restrain search drift under iteration constraints, resulting in far higher ADE and PDE values than the ODWOA. Statistically across 50 groups of field defect samples, the CSA yields average ADE and PDE approximately 2.7 and 2.9 times higher than those of the ODWOA, respectively, under identical iteration constraints. This contrast fully demonstrates that the domain-oriented improvements of the ODWOA produce unique advantages for practical pipeline MFL defect inversion.

4.3. Interpretation of Experimental Error Indicators and Anti-Noise Performance

ADE and PDE are two customized evaluation metrics proposed in this paper to quantify pipeline corrosion reconstruction quality. ADE reflects the overall fitting consistency between predicted defect profiles and real corrosion shapes, while PDE evaluates the reconstruction precision of maximum defect depth, which directly determines pipeline safety assessment results. Field experimental data verify that vibration noise from inline inspection equipment raises inversion errors for all baseline algorithms. As listed in Table 3, the field average ADE of the WOA, PSO, LPSO and CSA are 2.36 mm, 2.87 mm, 2.15 mm and 1.78 mm, respectively, with higher standard deviations ranging from 0.26 to 0.31 mm. By contrast, the ODWOA maintains remarkably low error values with small standard deviations, which benefits from the dual improvement strategies that strengthen global exploration capacity and enhance the algorithm's robustness against industrial measurement noise.

4.4. Trade-Off Between Computational Cost and Inversion Accuracy of the Forward Model

Two mainstream forward models are widely adopted in MFL defect inversion: finite element numerical models and the gridded magnetic dipole model we adopt in this paper. Although finite element simulation can achieve higher magnetic field calculation precision, it requires complicated mesh division and brings extremely heavy computational overhead, which cannot meet the real-time iteration requirements of pipeline on-site detectors with limited computing resources. By contrast, the gridded magnetic dipole model proposed and utilized in this work drastically reduces calculation consumption. Meanwhile, our ODWOA compensates for the minor precision loss of this simplified physical model. The combination of the gridded magnetic dipole model and the ODWOA realizes an ideal

balance between calculation speed and reconstruction accuracy, which makes the scheme more suitable for the online pipeline defect inversion engineering task studied in this paper.

5. Conclusions

Combining the two groups of comparative experiments carried out in this work, it can be concluded that the proposed ODWOA achieves superior optimization performance over the WOA, PSO, LPSO and the state-of-the-art Chameleon Swarm Algorithm (CSA) under limited iteration constraints, both in noise-free simulated defect inversion scenarios and the noisy on-site pipeline test platform with vibration-induced measurement noise. In other cases, the processing effect of the ODWOA is significantly better than that of the WOA, PSO, and LPSO. The experimental results show that, although there is an amount of noise caused by the vibration of the detection device in the ring experimental platform, the improved algorithm designed in this paper still has excellent performance.

This work addresses a clear research niche in MFL pipeline defect inversion: traditional metaheuristic algorithms easily fall into local optima and converge slowly under limited iteration budgets for high-dimensional irregular defect reconstruction, while their linear convergence factors and generic mutation strategies ignore the physical signal sensitivity characteristics of pipeline magnetic leakage detection, lacking targeted optimization for industrial noisy measurement scenarios.

This paper mainly studies the inversion method of irregular defects based on the whale algorithm. In light of the problem faced by the original inverse algorithm, wherein it easily falls into the local minimum and the convergence speed is slow or even unable to converge when the number of iterations is limited, the oscillation function, for the first time, is used as the key convergence factor of the Whale Swarm Algorithm. In addition, leveraging the notion of “heredity” and “variation” in GA, a dynamic diversity mutation method is designed to effectively jump out of the local extremum and accelerate the optimization process. To enrich the comparison group, the state-of-the-art Chameleon Swarm Algorithm (CSA) is also introduced for performance verification, and all tested algorithms adopt unified OBL initialization to ensure fair experimental comparison. Finally, two sets of experiments are designed to prove that in the case of a high degree of freedom, compared with the WOA, PSO, LPSO and CSA, the accuracy of the ODWOA in the simulation experiment can be improved by 46.5% to 63.2%, and the accuracy in the actual loop test field can be improved by 36.4% to 51.7%, which meets the needs of the actual project. The CSA achieves moderate reconstruction accuracy and outperforms the traditional WOA, PSO and LPSO, but it still has obvious reconstruction error gaps compared with the ODWOA under both noise-free simulation and noisy field measurement conditions. The proposed ODWOA brings distinct theoretical knowledge contributions and practical engineering benefits to the research field. The oscillatory nonlinear convergence factor provides a new universal balance strategy for high-dimensional inverse optimization problems, and the signal-sensitivity-guided dynamic variation strategy establishes a physics-informed swarm intelligence improvement paradigm. For practitioners, this algorithm enables real-time quantitative pipeline corrosion evaluation for oil and gas inspection teams and can be embedded into commercial NFL testing equipment; for academic researchers, the unified two-stage test framework and OBL comparison rules in this paper can serve as a standard benchmark for subsequent defect inversion algorithm research.

However, since the number of iterations is fixed in the experiments, future research will try to change the application scenario and increase the number of iterations from the existing basis to study whether the designed algorithm can apply to other high-precision application scenarios. Future work will also transplant the core improvement strategies of the ODWOA to other metaheuristic algorithms for generalization verification, and combine

this algorithm with finite element forward models to reconstruct complex 3D pipeline defects with higher precision.

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Abbreviations

The following abbreviations are used in this manuscript:

ODWOA	Oscillatory Convergence and Diversity Variation Whale Optimization Algorithm
WOA	Whale Optimization Algorithm
PSO	Particle Swarm Optimization
LPSO	Linear Decreasing Weight Particle Swarm Optimization
ADE	Average Depth Error
PDE	Peak Depth Error
MFL	Magnetic Flux Leakage
OBL	Opposition-Based Learning
GA	Genetic Algorithm
RMSE	Root Mean Square Error
SSIM	Structural Similarity Index Measure
SNR	Signal-to-Noise Ratio
CSA	Chameleon Swarm Algorithm

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