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Study on the improvement of welding process parameters of steel pipe in Dianzhong water diversion project using particle swarm optimization algorithm

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Abstract The water diversion project in central Yunnan is a large-scale engineering project related to Yunnan people's livelihood, in which the welding quality of steel pipe directly affects the overall safety of the project. The traditional welding process parameters optimization method is inefficient and complex, and it is difficult to achieve multi-objective optimization. In order to optimize the welding process parameters of steel pipe in Yunnan-China water diversion project and improve the project quality, this study proposes a multi-objective optimization method based on the improved particle swarm optimization algorithm. The multi-objective optimization of steel pipe welding process parameters was realized by establishing the correlation model between welding power, welding speed, defocusing amount, swing amplitude, swing frequency and performance indexes such as melting depth, depth-to-width ratio, porosity, etc., combined with the genetic optimization neural network prediction model. The results show that the optimal combination of process parameters obtained by the improved particle swarm algorithm is 4.75 kW of welding power, 2.63 m/min of welding speed, 1.05 mm of out-of-focus, 1.78 mm of swing, and 90 Hz of swing frequency. The welding melt depth obtained by using this parameter combination reaches 8.915 mm, with a depth-to-width ratio of 0.729 and a porosity of only 1.137%, which is better than the traditional optimization algorithm in all performance indicators. In engineering practice, the welding process after applying the improved particle swarm algorithm realizes the qualification rate of 99.88% for steel pipe weld seam at one time, the qualification rate of 99.91% for longitudinal seam, 99.85% for circumferential seam, and the qualification rate of 100% for delivery inspection. The study proves that the improved particle swarm algorithm has the characteristics of high efficiency and high precision in the optimization of steel pipe welding process parameters, which can provide reference for similar projects.

Index Terms Particle swarm optimization algorithm, Dianzhong water diversion project, steel pipe welding, process parameter optimization, multi-objective optimization, genetic optimization neural network

I. Introduction

Central Yunnan is the political, economic and cultural center of Yunnan Province, located in the watershed of the four major water systems of Jinsha River, Lancang River, Honghe River and Nanpanjiang River, with shortage of water resources and frequent early disasters, and it is one of the famous dry and early water-scarcity zones in Yangtze River Basin [1], [2]. The Dianzhong Diversion Project is a mega water transfer project proposed by China to solve the serious water shortage problem in central Yunnan, which is a strategic infrastructure project for the sustainable development of Yunnan Province, and is also the first of the 10 major landmark projects among the 172 major water conservancy projects to be started before 2020 in China [3]. The project task to urban life and industrial water supply, taking into account the agricultural and ecological water, the implementation of the project can effectively alleviate the contradiction of water shortage in central Yunnan in a longer period of time, to improve the vegetation cover, the water receiving area of the river, the ecology of the plateau lakes and the water environment, to promote the coordinated economic and social development of Yunnan Province, sustainable development has an important role [4]-[6]. Dianzhong water diversion project has a total length of 664 kilometers, and the water transmission steel pipe accounts for more than 1/3, which is carried out with X80 grade high-strength steel pipe. Compared with the traditional construction steel properties, due to the water transmission project all for the underground cave canal project, complex geological characteristics, the project requires on-site ring welding a one-time to achieve 99.2% and above the qualification rate, and regular corrosion demand indicates that the depth of fusion control accuracy needs to be up to ± 0.3 mm, but the X80-grade high-strength steel pipe in the welding link may produce cold cracks, welding rework rate rises [7]-[11]. Therefore, there is an urgent need to optimize the welding parameters.

The particle swarm optimization algorithm is to transform the problem to be optimized into a search problem in a multi-dimensional space, considering each solution as a particle in the space, and each particle will update its speed and position according to its own historical optimal solution and the group's optimal solution in the expectation of finding a better solution. The advantages of the particle swarm optimization algorithm are its simplicity, ease of implementation and faster convergence speed, and it also has better global search ability, robustness, dynamic response characteristics, and is able to cope with complex multi-objective optimization problems [12]-[14].

Large-scale water diversion project is an important infrastructure to solve the regional water shortage, in which the steel pipe water transmission system as the core component of the project, its quality is directly related to the safe operation and service life of the project. As a key process of steel pipe manufacturing, the welding quality of steel pipe welding has a decisive impact on the safety and reliability of the entire water diversion project. In the process of steel pipe welding, welding process parameters such as welding power, welding speed, defocusing amount, swing amplitude and swing frequency have a complex and important impact on welding quality. Reasonable welding process parameters can improve the melt depth and depth-to-width ratio of the weld and reduce the porosity, thus improving the welding quality and reducing the risk of leakage of the pipeline in the process of use. Traditional welding process parameter optimization mainly relies on rules of thumb and repeated tests, which is not only inefficient, but also difficult to achieve comprehensive multi-objective optimization. In recent years, the application of artificial intelligence and optimization algorithms in the field of engineering has become more and more widespread, providing new methods and ideas for the optimization of welding process parameters. Particle swarm optimization algorithm, as a kind of group intelligence optimization algorithm, has the advantages of fast convergence speed, simple implementation and few parameters, which is suitable for solving multi-objective optimization problems. However, the standard particle swarm algorithm is easy to fall into the local optimal solution, so it needs to be improved to improve its global search ability and convergence performance. Meanwhile, the evaluation of welding quality involves multiple indicators, which are often in conflict with each other, and how to find a balance point between multiple indicators is a key issue in the optimization of welding process parameters. In addition, the relationship between welding quality and process parameters is complex and difficult to be described by a simple mathematical model, which requires the establishment of an effective prediction model to assist the optimization process. As a major water conservancy project in Yunnan Province, the welding quality of steel pipes in the central Dianzhong water diversion project is crucial to the safe operation of the whole project, so the optimization of its welding process parameters is of great significance in engineering practice.

In this study, for the optimization of steel pipe welding process parameters of Dianzhong Water Diversion Project, the basic principle and process of particle swarm algorithm are analyzed firstly, and then a multi-objective optimization model with welding power, welding speed, defocusing amount, swing amplitude and swing frequency as the variables, and depth of fusion, depth-to-width ratio and porosity as the objectives is established. In order to improve the performance of the particle swarm algorithm, improvement strategies including linear decreasing of inertia weights, adaptive change of acceleration factor and limiting the search position of particles are proposed to form an improved particle swarm optimization algorithm. At the same time, a welding quality prediction model was established by using the genetic optimization neural network algorithm, which was combined with the improved particle swarm algorithm to realize the multi-objective optimization of the welding process parameters of steel pipe. Through the comparative analysis with the traditional optimization algorithm, the advantages of the improved particle swarm algorithm in optimization efficiency and welding quality are verified. Finally, the optimized welding process parameters are applied to the actual steel pipe welding in the Dianzhong water diversion project, and the effect is evaluated through experimental verification and engineering application to provide reference for similar projects.

II. Key technologies and methodologies

II. A. Particle Swarm Algorithm

II. A. 1) Particle Swarm Algorithm Strategy Analysis

Particle Swarm Algorithm (PSO) [15], [16] is an intelligent algorithm proposed to optimize the process parameters by observing the flock feeding behavior of bird animals in nature.

The basic strategy concept of Particle Swarm Algorithm: it is assumed that there are many different supply points in one space, which serve as the food source for the bird flock feeding. The purpose of bird feeding is to find the food source with the most sufficient food among all the supply points, and all the supplied food can be understood as the global solution set, and the sufficient food source is the optimal solution in the solution set. In addition to searching for food, the birds will also transmit information about their feeding location to other companions, so that all companions can find the location of the food in the end. The final location where the flock gathers is the optimal solution.

The basic strategy of particle swarm algorithm to optimize the process parameters: the ultimate goal of particle swarm algorithm is to make all the particles find the optimal solution in the global space, the first step of the algorithm is to give all the particles an initial random position and set a random initial speed. Then the particle movement speed and the optimal solution position has been obtained by the optimal position of the search for the optimal position of the advancement. Accompanied by the solution and the passage of time, the particles will be known in the global space of the optimal solution location has been basically explored, and finally through the observation of the particle swarm gathered one or more aggregation point that is the optimal solution in the global location information.

II. A. 2) Algorithm flow

Particle swarm algorithm of the algorithm step structure is simple, its algorithm to optimize the nature of the process parameters is a group of optimal particles in space to do the optimal movement, but the particles in the process of searching for the optimal is subject to the particles themselves to move before the previous best position (PBest, PB), but also by the adjacent particles to move before the previous best position (NBest, PB) influence. So the particle's velocity innovation as a function of each generation dimension during the solution iteration is as follows:

$$v_{id}^{k+1} = v_{id}^{k} + c1r1(PB_{id}^{k} - x_{id}^{k}) + c2r2(NB^{k} - x_{id}^{k}) \tag{1}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{2}$$

where, v_{id}^{k} is the velocity of the i th particle in the k th iteration, x_{id}^{k} is the real-time position of the i th particle in the k th iteration, d is the number of dimensions, r is the random variable, c is the acceleration coefficient, PB_{id}^{k} is the position of the optimal solution of the i th particle in the k th iteration, NB_{id}^{k} is the location of the optimal solution during the swarm solving iteration.

The block diagram of the solution procedure of the particle swarm algorithm is shown in Fig. 1.

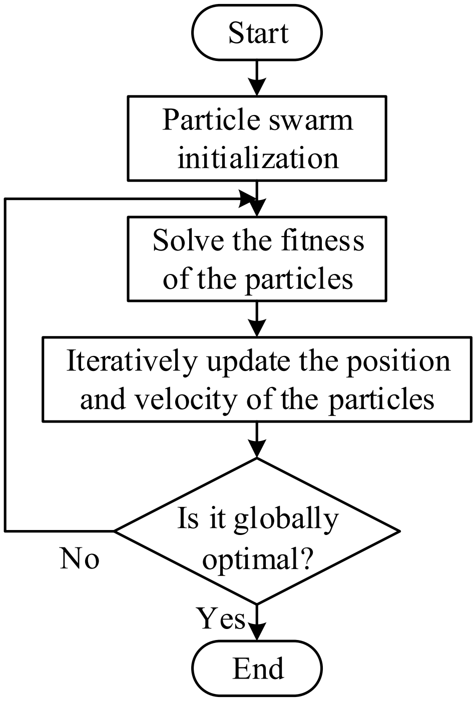

Figure 1: Block diagram of the solution program

II. B. Multi-objective optimization modeling of welding process parameters

The welding process parameters of steel pipe for water diversion project (welding power, welding speed, defocusing amount, swing amplitude and swing frequency) have an effect on the performance parameters of the weld (melt depth, depth-to-width ratio and porosity, etc.), and the performance parameters of the weld reflect the quality of the weld. Therefore, it is extremely important to improve the performance of steel pipe welds by multi-objective optimization of process parameters.

II. B. 1) Multi-objective optimization modeling

In this section, the regression model between weld performance indicators and process parameters is selected, and the performance parameters of the weld are expressed as a function of the process parameters, i.e., $y_i = f_i(LP, WS, FP, OA, OF)$, and y_i denotes the i th performance indicator, $i = 1,2,3$.

The optimization model consists of variables, constraints and objective functions. Based on the actual situation of weld quality demand and process parameters, the following multi-objective optimization model is established.

(1) Variables and constraints

In this section, welding power, welding speed, defocusing amount, swing amplitude and swing frequency are taken as variables, and the value range of the variables is taken as the inequality constraints:

$$s.t.\begin{cases} 4.5kW \le LP \le 5kW \\ 2.2m/\min \le WS \le 3m/\min \\ -2mm \le FP \le 2mm \\ 1mm \le OA \le 4mm \\ 60Hz \le OF \le 300Hz \end{cases} \tag{3}$$

(2) Objective function

The greater the depth of fusion of the weld, the better the weld performance. The larger the depth to width ratio of the weld, the better the performance of the weld. The smaller the porosity of the weld, the better the performance of the weld. Therefore, four objective functions are set in this section as follows:

$$goal\begin{cases} \min\{-DP\} \\ DP \ge 3mm \\ \min\{-DW\} \\ \min\{PW\} \end{cases} \tag{4}$$

where, melt depth $DP = f_1(LP, WS, FP, OA, OF)$, Depth-to-width ratio $DW = f_2(LP, WS, FP, OA, OF)$,Porosity $PW = f_3(LP, WS, FP, OA, OF)$.

II. B. 2) Pareto Solution Sets

Multi-objective optimization problems differ significantly from single-objective optimization problems. For single-objective optimization problems, there is only one objective function to find the best solution, i.e., the global optimal solution, which outperforms any of the other solutions. In contrast, for multi-objective optimization problems, there are usually more than one objective function. Since there is usually a conflict between the objective functions, the optimization of one objective function will lead to the deterioration of one or more other objective functions, so there is almost no solution that can make all the objective functions optimal at the same time. Therefore, a multi-objective optimization problem can hardly get an optimal solution, and generally only a non-dominated solution, i.e., a Pareto optimal solution, can be obtained [17]. Assuming that there are m objective functions $f_i(x), i = 1,2,\ldots,m$, the solution x_1 dominating the solution x_2 is defined as:

$$\begin{cases} f_i(x_1) \ge f_i(x_2), i = 1,2,\cdots m \\ f_i(x_1) > f_i(x_2), \exists j \in \{1,2,\cdots m\} \end{cases} \tag{5}$$

An undominated solution is defined as the absence of an arbitrary solution dominating that solution, and the set consisting of undominated solutions is the Pareto solution set. Each solution in the solution set cannot be proved to be optimal. Typically, a multi-objective optimization problem in engineering selects one or more suitable solutions in the Pareto solution set as the final optimal solution.

II. C. Process parameter optimization solution based on improved particle swarm algorithm

II. C. 1) Particle Swarm Algorithm Improvement Strategy

Aiming at the problem that PSO algorithm is easy to fall into the local optimum during the search process, the particle search process is dynamically adjusted through the linear decreasing of inertia weight, adaptive change of acceleration factor and restriction of the particle search position, which results in the formation of the Improved

Particle Swarm Optimization (IPSO) algorithm. The improvement strategies to make the improved particle swarm algorithm globally search specific at the early stage of search are as follows:

(1) Strategy 1: Inertia weights ω linearly decreasing

The larger the ω the stronger the global search ability, the smaller the ω the stronger the local search ability, using inertia weights linearly decreasing way, so that the ω with the increase in the number of iterations and reduce:

$$\omega^{(t)} = \omega_{\max} - \frac{t(\omega_{\max} - \omega_{\min})}{T} \tag{6}$$

where, $\omega^{(t)}$ is the inertia weight at the t th iteration, $\omega_{\max}$ is the maximum inertia weight, $\omega_{\min}$ is the minimum inertia weight, t is the number of the current iteration, and T is the number of the total number of selected generations.

(2) Strategy II: Acceleration factor adaptive change

The larger the acceleration factor c_1 the stronger the local search ability, the larger the c_2 the stronger the global search ability, using the strategy of adaptive change of acceleration factor with the number of iterations t, so that in the early stage of the search c_1 is smaller and c_2 is bigger, in the late stage of the search c_1 is bigger and c_2 is smaller:

$$c_1^{(t)} = c_{1\min} + \frac{t(c_{1\max} - c_{1\min})}{T} \tag{7}$$

$$c_2^{(t)} = c_{2\max} - \frac{t(c_{2\max} - c_{2\min})}{T} \tag{8}$$

where, $c_1^{(t)}, c_2^{(t)}$ is the acceleration factor when the algorithm performs the t th iteration, $c_{1\max}, c_{2\max}$ is the maximal acceleration factor, $c_{1\min}, c_{2\min}$ is the minimal acceleration factor, and T is the maximal number of iteration.

(3) Strategy III: Limit particle search position

In the optimization process, the particle is easy to jump out of the search space when its speed is too large, in order to ensure that the particle is always within the search range, the position of the particle is restricted:

$$x_{\min} \le x_i \le x_{\max} \tag{9}$$

where, x_i represents the particle position, $x_{\min}$ is the lower limit of particle search, and $x_{\max}$ is the upper limit of particle search.

II. C. 2) Welding quality prediction model of GABP algorithm

Genetic Optimization Neural Network (GABP) [18], [19] effectively overcomes the problems faced by traditional BP networks and significantly enhances the accuracy of prediction results through a specific encoding method and iterative computation process.

The GABP algorithm is utilized for prediction and trained on steel pipe welding process dataset for optimization. The H and P are taken as the processing and input sets, while the processing effect set O_p and the constraint set S are taken as the output sets. In order to ensure the balance between the amount of data and computational efficiency, a network structure containing a single hidden layer is designed, with the number of neurons in the hidden and output layers, and the number of neurons in the input and hidden layers being N and M, respectively, and the number of nodes in the hidden layer, C_M, being determined by the following equation:

$$\sum_{i=0}^{N} C_M > K \tag{10}$$

where K is the number of samples.

Considering that each input term has a different magnitude, the normalization of the sample parameters needs to be completed first:

$$d' = \frac{2(d - d_{\min})}{d_{\max} - d_{\min}} - 1 \tag{11}$$

where d, d' corresponds to the initial data and the processed data, respectively.

The GABP optimization parameters are configured by means of binary coding for LF threshold, OF and LF connection weights, LF and IF connection weights, and IF threshold. In order for the BP network to achieve lower prediction error, the fitness function is set, which is calculated based on the error paradigm between the predicted output and the desired target. The specific calculation equation is as follows:

$$\| X \|_2 = \sqrt{x_1^2 + x_2^2} \tag{12}$$

where, x_i denotes the difference between the predicted results of energy consumption and the expected and actual values of tool life. X is a one-dimensional matrix built using x_i .

II. C. 3) Optimization model of steel pipe welding process parameters

The specific steps for optimizing the steel pipe process parameters of water diversion project using IPSO algorithm are as follows:

(1) Randomly initialize the particle swarm. According to the range of wire baking process parameters randomly generated particle swarm, each particle corresponds to a set of steel pipe process parameter combinations.

(2) Calculate the adaptation degree of particles. Take the difference between the predicted value and the standard value of the baked wire quality index as the adaptation degree, and the adaptation degree is calculated as:

$$fitness = f(x) - Obj \tag{13}$$

where x represents the steel pipe welding process parameters, $f(x)$ represents the prediction results of the GABP quality index prediction model, and Obj represents the standard values of steel pipe welding quality index.

(3) Update pbest and gbest. pbest represents the position with the lowest individual fitness, and gbest represents the position with the lowest fitness in the population, and update the individual optimal position (pbest) and global optimal position (gbest) according to the values of particle fitness.

(4) Update ω according to strategy 1 and c_1 and c_2 according to strategy 2.

(5) Update the velocity v and position x of the particle. Update Eq:

$$v_{i+1} = \omega \times v_i + c_1 \times r_1 \times (pbest_i - x_i) + c_2 \times r_2 \times (gbest_i - x_i) \tag{14}$$

$$x_{i+1} = x_i + v_i \tag{15}$$

where ω denotes the inertia weights, c_l and c_2 denote the learning factors, and r_l and r_2 denote the constants between 01.

(6) Limit particle position. Judge whether there are particles whose positions are out of range, and put the out-of-range particles back to the search range.

(7) Judge whether the set maximum number of iterations is reached, if the maximum number of iterations is reached then output the optimal combination of steel pipe welding process parameters, if the maximum number of iterations is not reached then repeat steps (2) ~ (7).

III. Results and analysis

III. A. Optimal Pareto solution set for welding process parameters

Optimization of steel pipe welding process parameters for water diversion projects is a typical multi-objective task. Here the IPSO algorithm is used to realize the multi-objective optimization of steel pipe welding process parameters, which can get the compromise solutions between the three optimization objectives, which are also called non-inferior solutions, that is, there are no other solutions that are better than these solutions on all three objectives. The surface composed of non-inferior solutions is called Pareto-optimal surface.

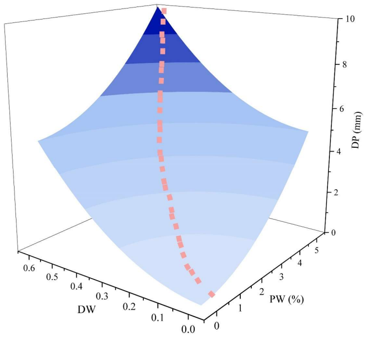

Figure 2: Pareto optimal surface

Figure 2 shows the Pareto optimal surface formed by 300 non-inferior solutions. As can be seen from the figure, the Pareto-optimal surface is skewed because there is no non-inferior solution that optimizes all three objectives simultaneously. Therefore, the optimization of melt depth (DP) comes at the cost of deterioration of depth-to-width ratio (DW) and porosity (PW), while the optimization of depth-to-width ratio also comes at the cost of reduction of the other two parameters. In the non-inferiority solution can be selected to meet the needs of different engineering applications, the pink point set in the figure is the optimal welding process parameters obtained by the IPSO algorithm, and the optimal combination of parameters is further analyzed in the following.

III. B. Optimization results of steel pipe welding parameters

In this section, based on the above, the optimization results of welding process parameters of steel pipe for water diversion project based on improved particle swarm algorithm are analyzed. The welding process parameters optimization results are shown in Figure 3. As can be seen from the figure, the optimal position of IPSO: [4.75kW, 2.63m/min, 1.05mm, 1.78mm, 90Hz], corresponds to the welding power (LP), welding speed (WS), the amount of out-of-focus (FP), the oscillation amplitude (OA) and the oscillation frequency (OF) respectively, the optimized five process parameters The numerical solution, at this time the optimal solution of IPSO is 322. As the number of iterations of the particle swarm algorithm increases, the convergence of the objective function value is reached at about 17 times, and after that there is a very small range of fluctuation.

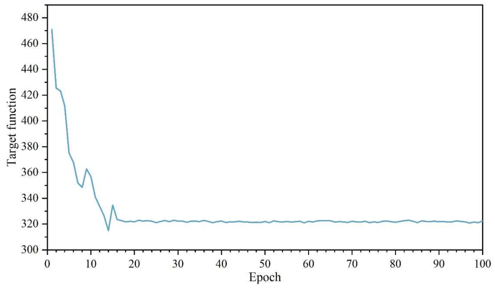

Figure 3: Optimization results of welding process parameters

In addition, this section compares the welding process parameter data and simulation time for different conventional multi-objective optimization algorithms with the algorithm in this paper. The comparison of welding process parameter data of different optimization algorithms is shown in Table 1. Through software simulation, the simulation time of the traditional multi-objective optimization algorithm is 9.4-19.3 h. The simulation time of the IPSO algorithm, which is optimized by the PSO algorithm, is only 4.7 h, which reduces the simulation time of the traditional algorithm by 50%-75.65%, and the computational efficiency is greatly improved. The corresponding comparison optimization algorithm also obtained the optimization parameters of steel pipe welding in water diversion projects, such as NSGA-II algorithm to get the welding power (LP), welding speed (WS), the amount of out-of-focus (FP), the swing amplitude (OA) and the swing frequency (OF) parameter values of 4.60Kw, 2.52m/min, respectively, 1.50 mm, 2.30 mm, and 150 Hz.In the following, the effects of the optimized process parameters provided by several optimization algorithms on the welding quality of steel pipes in water diversion projects are compared and analyzed.

Table 1: Different optimization algorithm welding process parameters data

Algorithm	NSGA-II	GA	GWA	PSO	IPSO
LP (kW)	4.60	4.70	4.65	4.55	4.75
WS (m/min)	2.52	2.44	2.10	2.85	2.63
FP (mm)	1.50	1.30	1.60	1.48	1.05
OA (mm)	2.30	3.00	2.80	1.70	1.78
OF (Hz)	150	90	100	85	90
Time (h)	9.4	16.8	13.5	19.3	4.7

III. C. Comparative analysis of welding quality

In this section, the welding process optimization parameters provided by NSGA-II, GA, GWA, PSO and IPSO algorithms are sequentially noted as Scheme 1 to 5. In order to verify the feasibility of the optimization scheme of the welding process parameters of the steel pipe of the diversion project proposed in this paper, the welding effect validation test is carried out in combination with the GABP welding quality prediction model established above. Welding effect verification test results are obtained as shown in Table 2.

In five groups of validation tests, the maximum relative errors of the predicted depth of melt (DP), depth-to-width ratio (DW) and porosity (PW) are 2.478%, 2.820% and 3.379%, respectively, which are less than the set relative error threshold value of 5%, indicating that the prediction model adopted in this paper has high accuracy. In addition, the welding parameters of steel pipe welding optimization obtained by the depth of melt, depth to width ratio, porosity directly responds to the quality of the weld, and the greater the value of the depth of melt and depth to width ratio of the weld quality, the better the quality of the weld, the smaller the porosity the better the quality of the weld. As a result, comparing the five schemes, it can be seen that the IPSO optimization model in this paper achieves the best weld quality, and the experimental measured values of depth of fusion, depth-to-width ratio, and porosity are 8.915 mm, 0.729, and 1.137%, respectively. From the experimental maximum prediction error and welding quality test measured values, this paper's IPSO optimization model combined with the GABP prediction model can better achieve the task of optimizing the welding process parameters of steel pipe for water diversion projects.

Table 2: Test results of welding effect

Scheme	Type	DP (mm)	DW	PW (%)
1	Predictive value	5.517	0.619	1.279
	Experimental value	5.605	0.630	1.268
	Relative error	1.570	1.746	0.868
2	Predictive value	6.462	0.547	1.364
	Experimental value	6.375	0.532	1.351
	Relative error	1.365	2.820	0.962
3	Predictive value	3.267	0.379	1.744
	Experimental value	3.188	0.384	1.687
	Relative error	2.478	1.302	3.379
4	Predictive value	4.916	0.537	1.427
	Experimental value	4.873	0.545	1.389
	Relative error	0.882	1.468	2.736
5	Predictive value	8.734	0.738	1.129
	Experimental value	8.915	0.729	1.137
	Relative error	2.030	1.235	0.704

III. D. Example of optimization of steel pipe welding in Dianzhong water diversion project

This section applies the model proposed in this paper in a water diversion project in Dianzhong to optimize the parameters of steel pipe welding process in this project. In this project, the total amount of pressure steel pipe fabrication works is 95317.60t, and the total length is 43190 m. According to the design requirements, the length of steel pipe unit fabrication is 3m, and there are 11653 units in total. The length of longitudinal seam reaches 43,190m, and the length of ring seam reaches 177,910m, of which the length of welded seam requiring preheating reaches 11,795m.

The pressure steel pipe fabrication of this project is carried out in a standard plant with assembly line operation and equipped with submerged arc welding center. The steel fork pipe is welded in pieces in the factory, preassembled in general, and welded in the whole group on site. Temporary coverings are used and temperature and humidity meters are equipped to monitor the welding environment temperature and air relative humidity at regular intervals, so that the welding work is carried out under better environmental conditions.

After the steel pipe welding project, 10 steel pipe unit bids were randomly selected to carry out the steel pipe welding defect degree and one flaw detection pass rate test to evaluate the application effect of particle swarm optimization algorithm in the water diversion project. The welding defect degree of steel pipe in the project refers to the severity of defects in the welded joints, such as porosity, cracks and other defects, the higher the degree of defects, the worse the strength, sealing and durability of the welded joints, which may result in pipeline fracture in the water diversion process. The passing rate of one flaw detection refers to the percentage of the number of qualified welded joints to the total number of tests in the first NDT, reflecting the stability of the welding process.

Figure 4 shows the statistical results of steel pipe defect degree and one-time flaw detection pass rate. From the figure, it can be seen that the one-time qualified rate of steel pipe welding flaw detection has been at a high level, and the qualified rate of each sampled section is above 99.4%, with the average qualified rate reaching 99.88%. The defect degree of the sampled sections are all less than 3mm, and there is no crack phenomenon in the steel pipe, which reaches the qualified standard. According to the survey, the length of longitudinal seam in the whole project is 4162.49m, the defective length is 3.27m, and the qualified rate of weld once probing reaches 99.91%.

The length of circumferential seam is 14710.35m, the defect length is 5.43m, and the qualified rate of weld flaw detection reaches 99.85%. The overall passing rate of delivery inspection is 100%. The successful implementation of this project for the use of intelligent algorithms to optimize similar projects to play a certain reference role.

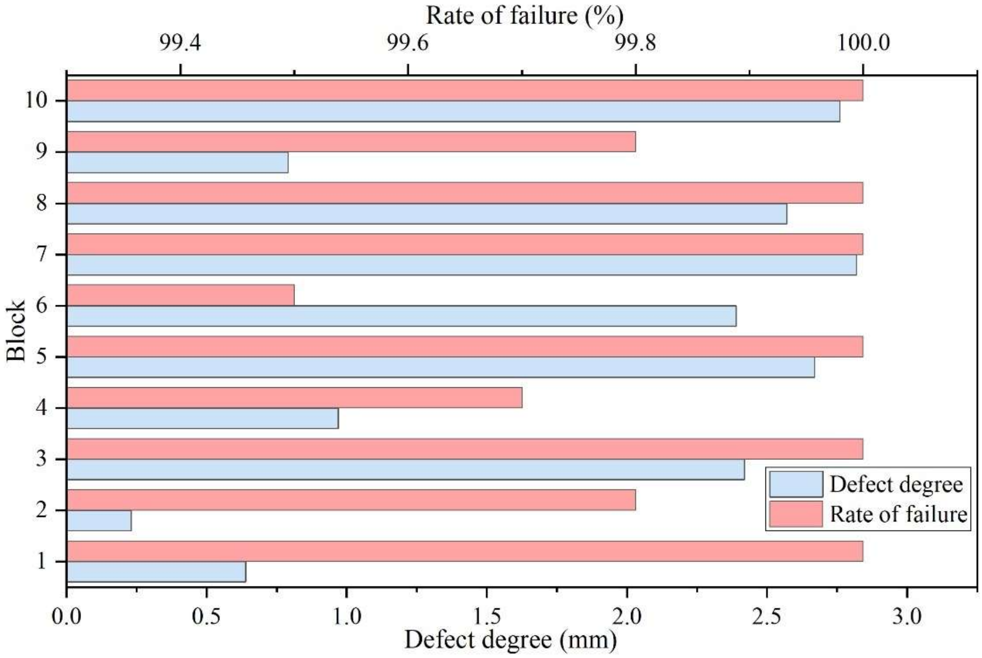

Figure 4: The defect degree of the steel pipe and the rate of inspection

IV. Conclusion

By improving the particle swarm optimization algorithm to optimize the welding process parameters of steel pipe in Dianzhong water diversion project, the following main conclusions are drawn:

The improved strategy of linearly decreasing inertia weights, adaptive change of acceleration factor and limiting the search position of particles effectively solves the problem that traditional particle swarm algorithms are prone to fall into local optimization. The simulation time of the improved IPSO algorithm is only 4.7 hours, which is 50%, 72.02%, 65.19% and 75.65% shorter than the traditional NSGA-II, GA, GWA and PSO algorithms, respectively.

The results of multi-objective optimization based on Pareto optimal surface show that the optimal combination of welding process parameters are welding power 4.75 kW, welding speed 2.63 m/min, defocusing amount 1.05 mm, swing amplitude 1.78 mm, and swing frequency 90 Hz, through which excellent welding quality indexes can be obtained with the melting depth of 8.915 mm, depth-to-width ratio of 0.729, and porosity of 1.137%. The maximum relative error of GABP prediction model is only 3.379%, which proves the high accuracy prediction ability of the model.

In the practical application of Dianzhong Water Diversion Project, the optimized welding process parameters make the average passing rate of steel pipe welding with one flaw detection reach 99.88%, among which the passing rate of longitudinal seam flaw detection is 99.91%, the passing rate of annular seam flaw detection is 99.85%, and the overall passing rate of handover inspection is 100%. Defect degree of the sampled sections are less than 3mm, and there is no crack phenomenon, to meet the project quality requirements.

Improved particle swarm algorithm combined with GABP prediction model optimization method of steel pipe welding process parameters, taking into account the computational efficiency and optimization effect, can effectively solve the welding multi-objective optimization problem, for large-scale water diversion project steel pipe welding process parameters optimization provides a new idea and method reference.

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