ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Optimization of welding process parameters and quality control of automatic welding machine in the era of intelligent manufacturing

Qiangqiang Wang[1,], Ziyang Shi[1], Ruzhi Hao[1], Jianguo Wu[1], Mingli Guo[1], Lei Qin[1] and Biao Li[1]*

[1] State Grid Shanxi Transmission and Transformation Engineering Co., Ltd. Taiyuan, Shanxi, 030000, China

SUMMARY: *The current research focuses on the problem of ensuring quality and efficiency control of the automatic welding machine's welding process. Taking into account the characteristics of analysis of welding experimental data, the orthogonal experiment technique is used for obtaining sample data, and the variance analysis is utilized for finding parameters that have the largest impact on the results of the experiments. Using the mentioned findings, the three-layer BP neural network structure was developed. In terms of genetic algorithms, real-number coding was chosen as a method of encoding the individuals, and the optimization problem became the extreme value problem of the objective function, thus developing the GA-based BP neural network. Depending on the optimal combinations of process parameters found using orthogonal experiments in the cases of flash butt welding and welding joint stretching, the number of individuals involved in the iterative process is equal to 80. Using the GA-based BP neural network, one can find optimal combinations of process parameters of the weld time-value transformation in the range between 1.0 and 9.0. With the use of such neural networks, welding quality is guaranteed, since its error prediction performance falls within the range of (-0.03; 0.02). The optimal combinations of welding process parameters are found automatically.*

KEYWORDS: *orthogonal test; analysis of variance; genetic algorithm; BP neural network; welding process parameter optimization*

1 Introduction

The global manufacturing sector has entered an intelligent era due to the depth of the fourth industrial revolution, which will make traditional processes more intelligent. Welding is a crucial industrial process, and aerospace, transportation, and electric energy will all benefit from intelligent management over its process parameters and quality [1, 2]. The traditional welding process is based on the builder's experience, with variable welding quality and low productivity, which is difficult to meet the welding needs of aerospace and transportation vehicles, etc. [3]. In the context of intelligent manufacturing, automatic welding machines are put into use, and the selection of its welding process parameters determines the quality of the final welded joint, while the selection process is difficult [4]. The rapid development of modern industrial production requires continuous innovation in technology, and methods have been researched and many research results have been achieved in the technology of optimizing welding process parameters.

*15234086862@163.com
https://doi.org/10.65102/is2026421
Published: 30 April, 2026

In recent years, scientists have introduced mathematical methods, statistics and experimental methods into the optimization of welding process parameters and achieved good results. The principle of this is mainly through the rational arrangement of experiments, and then build the appropriate mathematical models to analyze and derive the optimization results. Srivastava and Garg [5] applied response surface methodology to experimental data collected from the arc welding process and established a mathematical model to optimize welding process parameters, with the aim of minimizing weld width and height while maximizing melt-in and melt-area. Ahmad et al [6] carried out experimental design for optimizing submerged arc welding parameters through signal-to-noise ratio analysis and analysis of variance, and introduced statistical optimization techniques to determine the optimal process parameter settings under constant quality and within the specified standards. Chen et al [7] employed computational fluid dynamics and finite volume method based models to optimize the arc welding process by simulating welding procedures under different parameter settings and comparing the simulation outcomes so as to improve welding performance. However, these approaches are relatively inefficient and their optimization capacity is limited. Moreover, because of the uncertainty, complexity, and multivariable coupling characteristics of the welding process, establishing a mathematical model for it remains highly difficult, which has become a major challenge in the welding field [8].

Along with the development of Artificial Intelligence (AI) technique, optimization algorithms including Artificial Neural Network algorithms (ANN), Genetic Algorithm (GA), and Deep Learning (DL) have also been applied in the field of welding process parameter optimization and quality control. Rocha et al [9] further enhanced the capability of the ANN algorithm by applying differential evolution together with cross-validation and data enhancement procedures, which made it possible for ANN to optimize process parameters in accordance with the weld shape based on limited experimental data. Mengistie and Bogale [10] proposed a hybrid algorithm combining the advantages of ANN and GA to develop an automated orbital pipe welding process. The proposed model is able to estimate the tensile strength limit and Rockwell hardness of the pipe so as to predict and optimize welded steel pipe process parameters. By establishing a mathematical model of submerged arc welding process parameters with linear regression and ANOVA, then optimizing the welding parameters via GA and particle swarm optimization algorithms, Choudhary et al [11] proposed an efficient hybrid optimization algorithm. Wang et al [12] optimized process parameters and achieved welding quality control via improving a back-propagation neural network with GA, considering the melt depth and width as input variables and the welding parameters as output variables. An intelligent design algorithm of welding robot process parameters was designed and applied based on DL and machine learning to predict welding parameters and weld geometry parameters under different production demands and to guarantee the welding quality, as proposed by Zhang et al [13]. Furthermore, Biber et al [14] proposed a robotic welding system for automatic gas metal arc welding, which combined a six-axis industrial robot, welding power source, black-and-white vision camera, and process controller to automatically adjust welding parameters. Neural network algorithms show remarkable advantage compared to other optimization algorithms since neural networks are capable of modeling quickly based on limited experimental samples and perform better as the sample numbers become large enough.

Traditional welding quality control mostly uses manual inspection and sampling assessment, which is inefficient and difficult to standardize the assessment criteria. While Gong et al [15] introduced machine intelligence into welding visual inspection, processed welding images in real time by machine learning algorithms, and developed a low-cost portable embedded device for welding quality control. Gyasi et al [16] integrated AI technology and infrared thermography equipment to build an intelligent welding system for realizing adaptive weld attribute prediction and adaptively adjusting the control function for weld quality even in offline environments. Madhav et al [17] extracted feature information from welding process images with the help of deep convolutional neural network to identify missing or incomplete parts in the welding process and to accurately detect visual defects so as to evaluate and improve the accuracy of welding. Barot and Patel [18] deployed sensors in welding process environments to monitor welding environment parameters in real time and identify welding defects through sensor signal data, while also constructing an Internet of Things (IoT)-based welding expert system to overcome the difficulties of adaptive control and achieve reliable online quality control. Liu et al [19] clarified the relationship between welding process parameters and quality, introduced feature dimension reduction methods to determine the key elements of the welding process, and employed a hybrid model to build a welding quality prediction model for early warning of welding quality. Khan et al [20] designed a real-time closed-loop control system for adaptive assurance of welding quality under different conditions through real-time adjustment of welding parameters, normal and defect classification, and the identification of melt-through phenomena.

This paper applies orthogonal experimental design in the process of parameter determination, and ANOVA will be used in the analysis of experimental data. In such a way, the experiment analysis framework can be built. After the completion of the process of parameter determination, the neural network model is developed using those parameters. With the help of the parameter determination results, taking into account the encoding strategy of the genetic algorithm and the use of the fitness function, genetic algorithm-based neural network welding algorithm is suggested. As for the welding equipment, the automatic flash butt welder for band saw blades is taken as the study subject, and the best combinations of parameters are determined experimentally. The viability of that parameter combination is proved by the values of two indicators – flash amount and slag pile height. While taking into account the result of one-factor ANOVA concerning the strength of the welding joints, further optimization of parameters is conducted in order to collect all the combinations of parameters. Welding process quality control will be performed with the use of both BP neural network and genetic algorithm.

2 Orthogonal experimental design for welding process parameter identification

The process of weld formation is the result of a combination of factors and is a highly nonlinear fitting process. It is necessary to choose a reasonable method for the selection of sample data, and to minimize the time and cost of the experiment while ensuring the sufficient amount of data.

2.1 Selection of experimental methods

The welding process involves many factors, and each factor contains a variety of levels, if the use of comprehensive experimental method to collect sample data need to carry out a large number of experiments, the cost and labor is too much. If the sample data are selected arbitrarily, there is a lack of reasonable basis, which can easily lead to a large error in the experimental results. Therefore, the design of the experiment needs to take into account the cost of the experiment and manpower, and the selection of samples should be representative, to a certain extent, can represent the overall distribution.

In the welding experiment process, through the analysis of its rationality and feasibility, it was decided to use orthogonal experimental method to carry out experimental research, which is based on the principle of probability theory and mathematical statistics, through the data obtained in the orthogonal test results, it can be very clear and fast to get which factors for the experimental results of the impact of the size. Orthogonal test method can ensure that the quality of the experiment can be completed at the same time can carry out the minimum number of experiments, but also to ensure that the results of the experiment and the full-scale experiment is equivalent to bring the convenience of the experiment and improve the efficiency of the work, in summary, this experiment choose orthogonal test method to arrange the experiment of the factors and the distribution of the level.

2.2 Principles of orthogonal experimental design

The orthogonal table is usually denoted as $L_n(S^r)$. Where n represents the number of experiments to be conducted, i.e., the total number of samples, S denotes the number of levels for each factor, and r denotes the maximum number of factors that can be selected for level S. If the existence of interactions between factors is not taken into account, the value of S obtained from the analysis in the orthogonal table should be consistent with the number of level factors measured in the experiment, and the value of the maximum number of factors that can be selected should theoretically be greater than the actual number of factors. Take $L_9(3^4)$ as an example, this orthogonal table needs to arrange 9 experiments to get a total of 9 samples, and the maximum number of factors to be selected is 4, and the maximum number of levels to be selected for each factor is 3.

2.3 Methods of analyzing experimental results

Generally speaking, there are two ways to analyze the experiment results of orthogonal test, and the first one is the maximum difference analysis method, which is to analyze the process of experimental parameters that influence the results based on the calculation of the results of the extreme difference level of each factor, and this method is easy and quick, but normally used for the experiments with the relatively complex number of experiments and factors level; the other way is the variance analysis method, which analyzes the results based on the decomposition of total variation of the factor level to obtain the variance value of the experimental level of the factors. The other way is ANOVA, which is to analyze the results of experiments by analyzing the parameters influencing the results, based on the total variation decomposition to obtain the variance of each factor level, and the results will be analyzed based on ANOVA in this experiment. The specific calculation steps are as follows:

(1) Calculate the sum of squares: the sum of squares is divided into the total sum of squares SS_T, intra-group sum of squares SS_E and inter-group sum of squares SS_A.

The sum of squares is divided into total sum of squares SS_T calculated as in equation (1):

$$SS_T = \sum X^2 - \left(G^2 / N\right) \tag{1}$$

In equation (1) where G denotes the sum of all data values and N denotes the overall number of data, there is an in-group sum of squares SS_E calculated as in equation (2):

$$SS_E = \sum\{n_i(\bar{X} - \bar{G})^2\} = \sum T_i^2 / n_i - G^2 / N \tag{2}$$

In equation (2) $\bar{G}$ is the total mean of the data, T_i is the sum of the data in each group, n_i is the number of data in the group, and there is an intergroup sum of squares SS_A calculated as in equation (3):

$$SS_A = SS_T - SS_E \tag{3}$$

(2) Calculation of degrees of freedom: due to the differences in the number of levels between the samples so that the variance value in the results will produce a change, in order to eliminate this effect, the introduction of degrees of freedom to improve the ability to make the deviation sum of squares of the factors can be compared with each other. The df_T, df_E, df_A in Eqs. (4), (5), and (6) are the total degrees of freedom, error degrees of freedom, and degrees of freedom of each factor, respectively. Where k is the number of levels of the factor.

$$df_T = N - 1 \tag{4}$$

$$df_E = df_T - \sum\left(df_A\right) \tag{5}$$

$$df_A = k - 1 \tag{6}$$

(3) Calculate the mean square as in equations (7)-(8):

$$MS_E = SS_E / df_E \tag{7}$$

$$MS_A = SS_A / df_A \tag{8}$$

(4) Calculation of F-value: In ANOVA, to determine the degree of influence of each factor on the experimental indicators is obtained by comparing the calculated F-ratio with the size of the corresponding critical value in the F-distribution table. The F value is calculated as in equation (9).

$$F = MS_E / MS_A \tag{9}$$

(5) Test the significance of the factors: set the confidence level as $1-\alpha$ (α is usually taken as 0.01, 0.05, 0.1), get the critical value of F_0 by checking the distribution table of F, and compare the computed F with F_0 to analyze the degree of influence of the levels of the factors on the results of the experiments during the experimental process.

3 Optimized network design for welding process parameters

3.1 BP neural network modeling

Using MATLAB software to run the neural network program, a three-layer BP neural network model is established in this paper, and four input layer neurons are selected, which are preheating time, heating time, wire feeding speed, and wire feeding length. In the selection of transfer function, the S-type transfer function lansig is used as the conduction function between the input and the implied layer, and the linear transfer function purelin is used as the transfer function equation between the implied layer and the output layer. The number of neurons in the output layer is two, which are tin filling angle σ. The structure of the model is shown in Fig. 1.

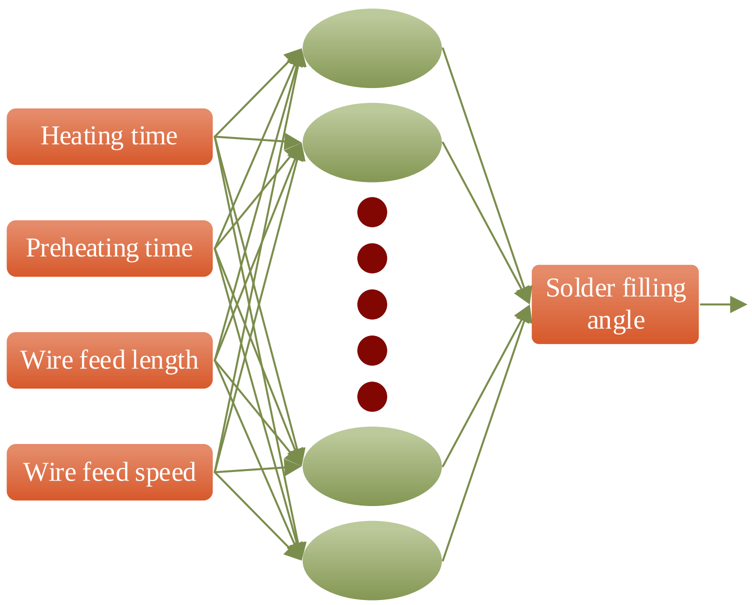

Figure 1: Neural network model for solder joint quality

The sample values are normalized. Based on the tansig type transfer function properties, the target value is made to vary according to equation (10):

$$d' = \frac{d - d_{\min}}{d_{\max} - d_{\min}} \times 0.9 + 0.05 \tag{10}$$

where d : input value of the sample; d' : output value of the sample after normalization.

3.2 Basic Principles and Applications of Genetic Algorithms

3.2.1 Coding methods

Genetic Algorithm (GA) aims to identify the best solution to a problem by encoding individuals, continuously searching for individuals with greater fitness, and progressively increasing the proportion of highly fit individuals within the population. Encoding is a transformation process that maps the feasible solution space of a problem into a search space that can be processed by the genetic algorithm.

Another problem that must be solved in genetic algorithms is to choose an appropriate coding scheme; this is also an important phase during the design of GAs. The chromosome representation of an individual depends on the encoding scheme selected, and the mapping from genotype in search space to phenotype in solution space is also decided upon through the same coding scheme. Moreover, genetic operators, such as crossover and mutation, are somewhat dependent on the coding scheme chosen. As a result, the performance of the population during genetic evolution operations and also the efficiency of evolution itself greatly depend on the coding scheme used. The decoding process is the inverse of the encoding process, whereby the optimal string generated by the GA is mapped to real values using the adopted encoding scheme.

A number of different encoding methods have been proposed, which can be categorized into three main groups: binary encoding methods, floating-point encoding methods, and symbolic encoding methods.

(1) Binary encoding methods

Binary coding is one of the most commonly used coding methods in genetic algorithms, and the binary symbol set $\{0,1\}$ composed of binary symbols 0 and 1 is its coding symbol set, and a binary coding symbol string constitutes an individual chromosome in this coding method.

The accuracy of the solved problem is closely related to the length of the binary encoded symbol string designed in this paper. If the value range of a parameter is $[U_{\min}, U_{\max}]$, and a binary encoded symbol string of length l is utilized to represent the parameter, then 2^l different encodings can be generated.

Such as the use of binary coding corresponds to the equation (11):

$$\begin{array}{ccccc} 00000000 & \cdots & 00000000=0 & & \rightarrow U_{\min} \\ 00000000 & \cdots & 00000001=1 & & \rightarrow U_{\min}+\delta \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 11111111 & \cdots & 11111111=2^l-1 & & \rightarrow U_{\max} \end{array} \tag{11}$$

Then the coding accuracy of the binary code is equation (12):

$$\delta=\frac{U_{\max}-U_{\min}}{2^l-1} \tag{12}$$

Assuming that a particular body is encoded as $X: b_l b_{l-1} b_{l-2} \cdots b_2 b_1$, the corresponding decoding formula is equation (13):

$$x=U_{\min}+\left(\sum_{i=1}^{l} b_i \cdot 2^{i-1}\right) \cdot \frac{U_{\max}-U_{\min}}{2^l-1} \tag{13}$$

Binary encoding and decoding are straightforward and easy to implement. Genetic operations such as crossover and mutation can be conveniently carried out during GA execution, and this encoding form follows the principle of minimum character set coding. Moreover, the algorithm can be theoretically analyzed through pattern theorem under binary encoding. However, when continuous variables are discretized for coding, serious mapping errors may occur. If the length of the coding string is designed too short, the required precision cannot be achieved; by contrast, increasing the length of the coding string to improve precision will cause the search space of the genetic algorithm to expand sharply. In addition, under binary encoding, the structural characteristics of the problem itself cannot be directly represented.

(2) Real number coding

The real number coding method uses decimal coding for individual chromosomes, which can directly carry out the relevant genetic operations on the solution space. This encoding method is mostly used in solving complex optimization problems and high-dimensional problems. Experiments have proved that, through the introduction of specially designed genetic operators, the average efficiency of using real number coding to solve most numerical optimization problems is higher than that of the algorithm when using binary coding, so this paper selects the real number coding method for the optimization study of welding process parameters.

3.2.2 Adaptation function

In the evolutionary process of a genetic algorithm, the algorithm only needs the value of the objective function for the target problem to obtain the search information required for the next step, and by evaluating the fitness of individuals in the population, the corresponding objective function value can be derived.

The biological fitness of organisms in nature is applied in genetic algorithms to quantify the level of excellence of every individual in the optimization problem. Individuals that have a higher ability to move toward or find the best possible answer to the problem have greater fitness scores. The evolution of populations is based on their fitness scores through iterative processes. In the process of iteration, individuals with high fitness scores will probably be chosen for propagation in the next generation, while those with low fitness scores are less likely to propagate. Over the course of repeated computations, individuals with high fitness scores are increasingly selected, resulting in an optimal answer from the design.

For this work, the total squared error between the real and desired outputs of the neural network is chosen to be the objective function. The problem of numerical optimization, by translating the objective function optimization problem into searching for the extreme value of the objective function, can be solved by determining the minimum value of the objective function.

When dealing with genetic algorithms, after translating the value of the objective function to the fitness function value, the value of the fitness function is positive, and its optimization direction translates to maximizing or minimizing the fitness function value.

Optimization tasks can generally be divided into two categories: finding the global maximum of the objective function and finding the global minimum of the objective function. For these two types of problems, the transformation from the objective function value $f(X)$ at a point in the solution space to the corresponding individual fitness value $F(X)$ in the search space is expressed as follows:

For the problem of finding the global minimum, the conversion is made as in equation (14):

$$Fit\left(f(x)\right)=\begin{cases} c_{\max}-f(x), & f(x)<c_{\max} \\ 0, & \text{Other} \end{cases} \tag{14}$$

For the problem of finding the global maximum, make the transformation as in equation (15):

$$Fit\left(f(x)\right)=\begin{cases} f(x)+c_{\max}, & f(x)+c_{\max}>0 \\ 0, & \text{Other} \end{cases} \tag{15}$$

3.2.3 Application of Genetic Algorithms to Neural Networks

Parameters such as the number of network layers, the number of units per layer, and the way the units are connected to each other are usually utilized to describe the structure of a neural network model. And the essence of designing the structure of a neural network is to determine the combination of parameters suitable for solving a certain problem or a certain class of problems according to some performance evaluation criterion. For large-scale, multilayer, nonlinear networks with complex problems to be solved, it is difficult to design neural networks by manual methods, and there are no strict design rules. In the case of satisfying a reasonable structure and proper weights, Kosmogorov's theorem holds that an arbitrary continuous function can be approximated using a three-layer feedforward network, but the method for determining this reasonable structure is not given in Kosmogorov's theorem, and the designer can only rely on experience to design the structure of the neural network. The standard engineering design methods usually used are powerless when it comes to neural network design. It is also not feasible to decompose the complex distributional interactions between neurons in a neural network using modular design methods. There are no applicable direct analytical design techniques for this complex structure of neural networks, and to make matters more difficult, even if a network capable of accomplishing a particular task is found, there is no certainty that a better performing network has not been lost. The use of manual design methods for large-scale, complex neural networks can no longer meet the design requirements, in response to the above situation this paper proposes a more efficient and automated neural network design method based on genetic algorithms see Fig. 2.

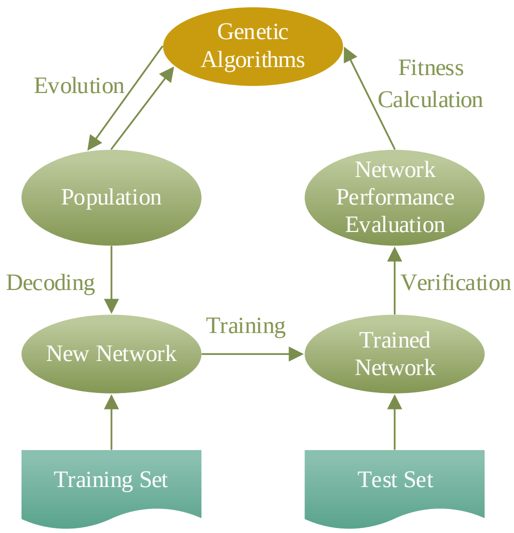

Figure 2: Genetic algorithm and neural network combination

4 Optimization of welding process parameters by combining BP network and GA algorithm

4.1 Acquisition of combinations of welding process parameters

4.1.1 Orthogonal test for optimization of flash butt welding process parameters

Flash butt welding, as a highly automated welding method, has been more and more widely used due to its stable welding quality and high efficiency. This subsection to the band saw blade automatic flash butt welding machine as an experimental sample, for its welding process parameters to design orthogonal test program, for different specifications of the band saw blade should be used in different parameter levels of the test, to 35mm * 1.3mm specifications of the saw band as the main object of the study for welding test.

First of all, the object to be welded to carry out the appropriate end face cutting, in order to ensure the coherence of the teeth after welding, and then end face cleaning, in the control side of the welding machine to adjust and set up a good preparation for the test parameters can start the test. Test selected for the 4 factors: (S1) flash speed setting value (ω / s), (S2) welding voltage setting value, (S3) top forging pressure setting air pressure (gear), (S4) welding time value setting, as well as 5 levels of process parameter factor level, the specific process parameter factor level settings are shown in Table 1.

Table 1: Factor level

Level	S1	S2	S3	S4
1	45	1	1.4	4.0
2	50	2	1.7	5.0
3	55	3	2.0	6.0
4	60	4	2.3	7.0
5	65	5	2.7	8.0

After each welding of a group of test objects, immediately score the flash phase of its welding process, and measure the height of its welding slag pile, complete the statistical record of the score of its test indexes, cut and retain the sample. The results of orthogonal experiments on the completion of saw blade welding polar analysis to obtain the optimal level of different parameters, the degree of influence of each parameter on the quality of welding, so as to derive the optimal combination of levels under each parameter. A total of 20 sets of experiments were carried out as shown in Table 2, i.e., a total of 20 combinations of welding parameters.

Table 2: Orthogonal analysis

Level	S1	S2	S3	S4	Score
1	60	2	1.4	6.0	2.20
2	50	3	1.4	6.0	3.50
3	55	3	1.4	6.0	4.40
4	60	3	2.0	5.0	2.90
5	60	3	1.4	7.0	3.60
6	45	3	1.7	5.0	4.70
7	65	2	2.7	6.0	4.70
8	60	3	1.4	8.0	8.10
9	45	1	2.3	6.0	6.20
10	45	1	2.0	4.0	5.70
11	55	5	2.3	6.0	5.80
12	65	2	1.7	7.0	6.40
13	50	1	1.7	5.0	7.10
14	65	3	2.0	8.0	7.20
15	55	4	1.7	7.0	3.30
16	55	5	2.0	6.0	5.60
17	65	4	2.7	5.0	8.80
18	65	1	2.7	6.0	2.40
19	50	3	2.7	4.0	3.80
20	55	4	2.3	4.0	2.50

Using ANOVA method based on a total of 20 parameter combinations in Table 2 to calculate the optimal level and optimal level of each factor, to obtain the optimal process parameter settings, in which (S1) the flash speed setting value (ω/s) should be 55 ω/s, (S2) the welding voltage setting value should be 3 gears, (S3) the top forging pressure setting pressure (gears) should be 2.3 gears, (S4) the welding time value should be set at 6.0. At the same time, based on the orthogonal experimental data, the impact of four factors on the amount of welding flash, slag heap height two quality indicators is shown in Figure 3. Orthogonal experimental data, drawing four factors on the amount of welding flash, slag pile height of two quality indicators of performance in Figure 3, where the flash speed between 45 ~ 65 for the amount of flash has little effect, basically at the same level, while the slag pile height is a small upward trend, reaching the optimum value (6.14) at 60, and then reduced. The effect of welding voltage was more obvious, showing that the higher the voltage selected the more intense the flash, with a maximum rating of 9.35. The stacking height of welding slag reaches its peak at the 3rd and 4th grades. The variation of the top forging pressure has a negligible effect on the flash quantity. The slag stack height gradually increases within the range of 1.4 to 2.3 with the increase of the top forging pressure (4.92 to 6.43). Moreover, when the top forging pressure further increases, due to the excessive top forging pressure corresponding to a shorter top forging time, under the condition of a fixed top forging distance with power, Excessive speed leads to an earlier power-off time and insufficient melting volume, resulting in a decrease in the height of the slag pile. The welding time value has almost no effect on the amount of flash, and the effect on the slag height does not show a significant trend, but 6.0 is preferred.

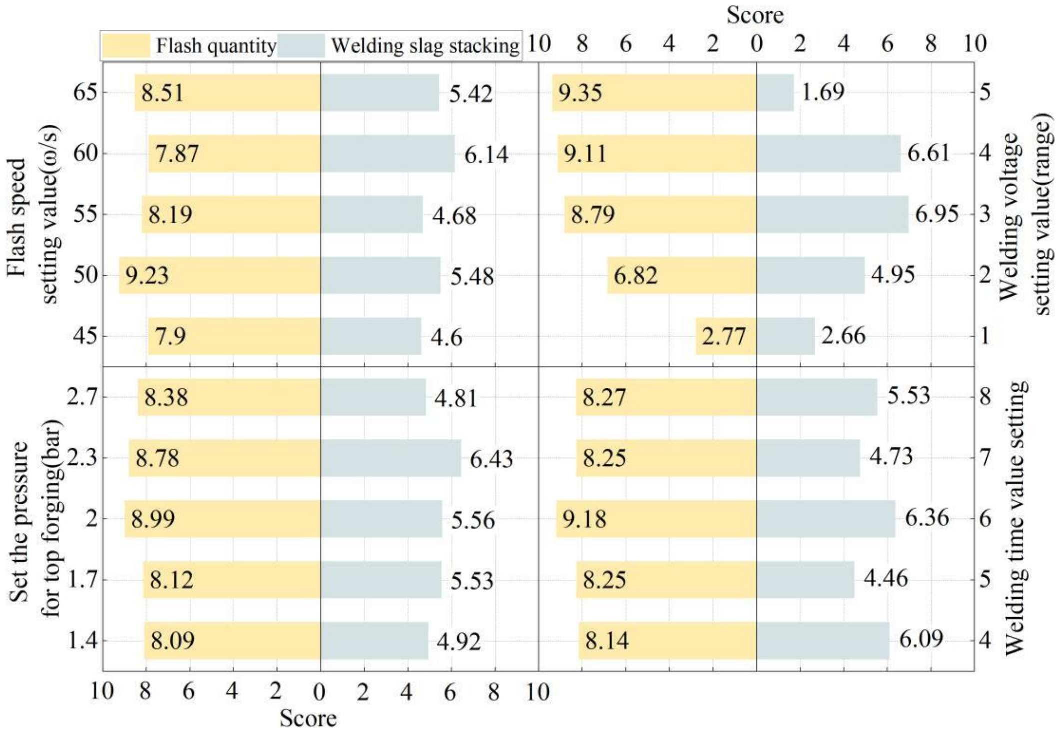

Figure 3: The influence of various factors on flash welding

4.1.2 Orthogonal tests for stretching of welded joints

In order to enhance the tensile strength of welded joints with band saw blade automatic flash butt welder, the optimum combination of process parameters is still sought through orthogonal tests with breaking force (N) as the specific evaluation index.

It is planned to complete the tensile test of 9 groups of samples (01-09), first complete a single tensile test, analyze (S1) flash speed setting value, (S2) welding voltage setting value, (S3) top forging pressure setting barometric pressure, (S4) weld hourly value setting of the four factors on the performance of the welded joints of the influence of the law, and then carry out repetitive tensile tests. The welding parameters of 10 of these welded joint specimens are organized in Table 3.

Table 3: The individual tensile test results of DOE welded joints

Sample number	S1	S2	S3	S4
01	45	1	2.0	4.0
02	45	1	2.0	4.0
03	45	1	2.0	4.0
04	55	2	2.3	5.0
05	55	2	2.3	5.0
06	55	2	2.3	5.0
07	65	3	2.7	6.0
08	65	3	2.7	6.0
09	65	3	2.7	6.0

The experimental results presented in Table 3 were analyzed using the ANOVA method in the orthogonal test analysis method, and the parameters (S1) flash speed setting value (ω/s), (S2) welding voltage setting value and (S3) top forging pressure setting air pressure (gear) were regarded as constants to analyze the effect of (S4) welding time value setting on the fracture force of the welded joints as shown in Table 4, where the optimal process parameters were obtained by the ANOVA method. Accordingly, the optimum process parameters are obtained by ANOVA as follows: (S1) flash speed setting (ω/s) is 55, (S2) welding voltage setting is 1, (S3) top forging pressure setting is 2.7, and (S4) welding hourly value setting is 4.0.

Table 4: DOE range analysis data

Sample number	S1	S2	S3	S4	Breaking force
01	45	1	2.7	4.0	519.5
02	45	2	2.3	6.0	227.7
03	45	2	2.3	5.0	260.3
04	55	1	2.3	6.0	477.9
05	55	3	2.0	5.0	495.3
06	55	1	2.7	4.0	555.5
07	65	1	2.0	4.0	255.5
08	65	2	2.0	5.0	337.9
09	65	3	2.7	4.0	252.7
K_1	1007.97	1253.17	1414.07	1268.37	1007.97
K_2	1528.67	1061.07	958.17	1039.17	1528.67
K_3	847.27	1069.67	1011.97	1076.37	847.27
K_1	339.77	421.5	475.14	426.57	339.77
K_2	513.34	357.47	323.17	350.17	513.34
K_3	286.2	360.24	341.1	362.57	286.2
Range (R)	232.81	69.7	157.64	81.17	232.81
Factor dominant	S1>S3>S4>S2				
Excellent level	S12	S21	S33	S41	
Excellent combination	S12S21S33S41				

The one-trial ANOVA process for the data in Table 3 is shown in Table 5, which yielded SS_{S1} = 84,662.896, T = 3445.5, and SS_T = 143,943,131.869.

Table 5: Variance analysis process for individual test

Factor	S1	S2	S3
Repeat 1	518.9	476.4	254.9
Repeat 2	226.4	494.4	337.3
Repeat 3	259.7	554.9	252.1
And	1003.2	1523.9	842.5
	K_1	K_2	K_3

The results of analysis of variance (ANOVA) of the single test based on the data in Table 5 are shown in Table 6, which shows that the calculations to find SS_{S1} = 84,662.895, SS_{S2} = 7,928.416, SS_{S3} = 4,1492.976, and SS_{S4} = 10,165.289, which verifies the optimal level combination as S12S21S33S41.

Table 6: Variance analysis data for individual test

Sample number	S1	S2	S3	S4	Test data	
					X_i	X_i^2
01	6.3	2.9	2	4	519.5	269880.25
02	6.3	3.2	1	2	227.7	51847.29
03	6.3	3.5	1	3	260.3	67756.09
04	7.2	2.9	3	4	477.9	228388.41
05	7.2	3.2	1	3	495.3	245322.09
06	7.2	3.5	2	2	555.5	308580.25
07	8.1	2.9	3	2	255.5	65280.25
08	8.1	3.2	2	3	337.9	114176.41
09	8.1	3.5	1	4	252.7	63857.29
K_{1j}	1007.97	1253.17	1414.07	1268.37		
K_{2j}	1528.67	1061.07	958.17	1039.17		
K_{3j}	847.27	1069.67	1011.97	1076.37		
K_{1j}^2	1016003.521	1570435.049	1999593.965	1608762.457		
K_{2j}^2	2336831.969	1125869.545	918089.7489	1079874.289		
K_{3j}^2	717866.4529	1144193.909	1024083.281	1158572.377		
SS_j	84662.895	7928.416	41492.976	10165.289		

4.2 Welding Quality Control Based on BP and GA

4.2.1 Analysis of BP neural network fitting effect

Based on Chapter 3 of the paper, a 3-4-2 BP neural network structure is used in the research. The total number of layers in the architecture includes 3, which are made up of 4 and 2 neurons in the input and output layers respectively. In order to enable the BP neural network to study the experimental effects associated with predicting the residual height, melting depth, and melting width, a total of 15 experiments were carried out, and the network's prediction error performance in the prediction is shown in Fig. 4. Overall the network's prediction error for the three items presents a fluctuating The overall prediction error of the network on the three elements shows fluctuation, but in 15 experiments are controlled in the (-0.03,0.02) interval, the prediction error is very small, the accuracy is high, and the fitting effect is excellent.

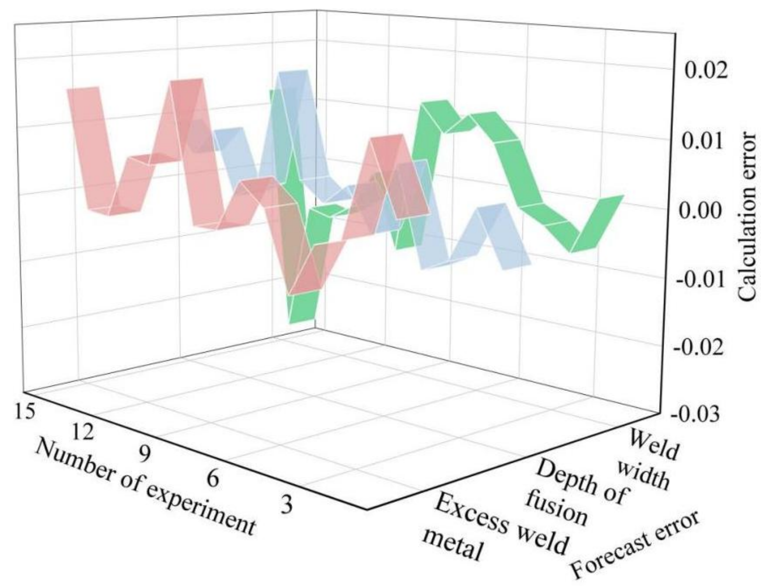

Figure 4: Indication of network fitness error

4.2.2 Design of the genetic algorithm

The values of the initial population size of 20, 40, 60, 80, and 100 and the welding parameters obtained through the optimization process of search results, which include (S1) flash speed setting value (ω/s), (S2) welding voltage setting value, (S3) top forging pressure setting air pressure (gear), and (S4) welding hourly value setting, along with the values of the four performance indicators, are summarized in Table 7. From the results shown in Table 7, it can be observed that for the case of randomly generating the initial individuals, an increase in the population size is favorable for enhancing the performance of the optimization process. The mean square error of performance decreases to 0.08 mm^2 as the number of individuals increases. Nevertheless, as the number of individuals exceeds a certain value, a significant improvement in performance cannot be observed, whereas the computational cost of the optimization process becomes significantly higher. Hence, taking into account the computer processing speed, the population size chosen in this study for the genetic algorithm iterative process must be 100.

Table 7: Optimization results of different initial popluation

Population size	20	40	60	80	100
S1	45	55	55	65	45
S2	3	2	3	2	1
S3	1.7	2.0	1.7	1.4	2.3
S4	8.0	5.0	6.0	7.0	4.0
Mean square error of performance(mm^2)	0.055	0.049	0.037	0.026	0.008

4.2.3 Optimization of welding process parameters under effect prediction

Since the BP neural network for process parameter design can not independently search for the best process parameters, and it is difficult to carry out evolutionary calculations when using only genetic algorithms. Therefore, in this paper, genetic algorithm is used for global optimization of welding parameters, and BP neural network is used to provide the required performance indexes for evolutionary calculations. In turn, a large-scale optimization calculation was carried out under the conditions of initial population size of 100 and crossover factor of 0.80, and some of the welding parameter optimization search results (1-15) are listed in Table 8. When the value of (S4) welding time is set to be transformed in the interval of 1.0~9.0, the trend of other variables can be clearly seen, reflecting the effectiveness of accurate optimization of welding process parameters under the combination of BP neural network and genetic algorithm.

Table 8: Welding parameter optimization results

Number	S1	S2	S3	S4
1	24	2	3.7	3.0
2	35	2	2.9	3.0
3	33	5	4.7	8.0
4	32	3	1.6	5.0
5	33	4	4.3	9.0
6	40	3	3.7	7.0
7	25	2	1.4	6.0
8	38	3	1.9	8.0
9	26	2	3.8	6.0
10	23	2	1.6	5.0
11	25	1	2.4	1.0
12	30	3	1.3	8.0
13	35	3	1.6	9.0
14	38	2	1.6	8.0
15	36	4	2.2	4.0

5 Conclusion

In this paper, the orthogonal test method to obtain the flash butt welding process and welding joint stretching parameter combinations, and multiple parameter combinations for ANOVA analysis to obtain its optimal parameter combinations. When the flash speed is 55ω/s, welding voltage is 3, top forging pressure is 2.3, welding time value is 6.0, the welding flash amount of influence amplitude is small, and the slag pile height score can reach a high point, determined as the optimal process parameter combination of automatic flash butt welding machine. For the stretching of its welded joints, the optimal combination of process parameters is obtained as flash speed = 55ω/s, welding voltage = 1 grade, top forging pressure = 2.7 grades, and welding hour value = 4.0.

A 3-4-2 BP network with strong fitting ability and prediction performance in the range of (-0.03~0.02) is constructed for predicting welding quality and performance under different welding process parameters. The population size for the iterative operation of the genetic algorithm is set to 100, and the BP neural network is integrated with the genetic algorithm to perform intelligent optimization of the welding process parameters for the automatic welding machine, thereby achieving quality and efficiency control of the automatic welding machine in the context of intelligent manufacturing.

Funding

This work was supported by State Grid Shanxi Transmission and Transformation Engineering Co., Ltd..

About the Author

Qiangqiang Wang was born in Linfen, Shanxi, P.R. China, in 1988. I obtained a bachelor's degree from Tianjin University in China. I am currently working at State Grid Shanxi Transmission and Transformation Engineering Co., Ltd. My main research direction is Primary Substation Installation.

Ziyang Shi was born in Linfen, Shanxi, P.R. China, in 1996. I obtained a bachelor's degree from North China Electric Power University in China. I am currently working at State Grid Shanxi Transmission and Transformation Engineering Co., Ltd. My main research direction is Primary Substation Installation.

Ruzhi Hao was born in Linfen, Shanxi, P.R. China, in 1996. I obtained a bachelor's degree from North China Electric Power University in China. I am currently working at State Grid Shanxi Transmission and Transformation Engineering Co., Ltd. My main research direction is Primary Substation Installation.

Jianguo Wu was born in Taiyuan, Shanxi, P.R. China, in 1970. I obtained a bachelor's degree from North China Electric Power University in China. I am currently working at State Grid Shanxi Transmission and Transformation Engineering Co., Ltd. My main research direction is Primary Substation Installation.

Mingli Guo was born in Taiyuan, Shanxi, P.R. China, in 1989. I obtained a bachelor's degree from Shaanxi University of Science & Technology in China. I am currently working at State Grid Shanxi Transmission and Transformation Engineering Co., Ltd. My main research direction is Primary Substation Installation.

Lei Qin was born in Xinzhou, Shanxi, P.R. China, in 1990. I obtained a bachelor's degree from Taiyuan University of Technology in China. I am currently working at State Grid Shanxi Transmission and Transformation Engineering Co., Ltd. My main research direction is Primary Substation Installation.

Biao Li was born in Taiyuan, Shanxi, P.R. China, in 1990. I obtained a bachelor's degree from PLA Nanjing Institute of Politics in China. I am currently working at State Grid Shanxi Transmission and Transformation Engineering Co., Ltd. My main research direction is Primary Substation Installation.

References

[1] Zakharova, I. (2024). Welding processes in the restoration of industrial and energy facilities. Machinery & Energetics, 15(1).

[2] Kepka, M., & Kepka Jr, M. (2021). Consideration of random loading processes and scatter of fatigue properties for assessing the service life of welded bus bodyworks. International Journal of Fatigue, 151, 106324.

[3] de Resende, A. A., & Duarte, C. A. R. (2025). The role of sustainability in the welding process: Context, technologies and challenges. Environment, Development and Sustainability, 1-28.

[4] Park, M. H., Jin, B. J., Yun, T. J., Son, J. S., Kim, C. G., & Kim, I. S. (2018). Control of the weld quality using welding parameters in a robotic welding process. Journal of Achievements in Materials and Manufacturing Engineering, 87(1), 32-40.

[5] Srivastava, S., & Garg, R. K. (2017). Process parameter optimization of gas metal arc

welding on IS: 2062 mild steel using response surface methodology. Journal of Manufacturing Processes, 25, 296-305.

[6] Ahmad, M. A., Sheikh, A. K., & Nazir, K. (2019). Design of experiment based statistical approaches to optimize submerged arc welding process parameters. ISA transactions, 94, 307-315.

[7] Chen, F. F., Xiang, J., Thomas, D. G., & Murphy, A. B. (2020). Model-based parameter optimization for arc welding process simulation. Applied mathematical modelling, 81, 386-400.

[8] Buang, A. S., Bakar, M. S. A., & Rohani, M. Z. (2024). A review of trend advanced welding process and welding technology in industries. International Journal of Technical Vocational and Engineering Technology, 5(1), 133-145.

[9] Rocha, V. R., Lobato, F. S., de Assis, P. A. Q., Ribeiro, C. R., da Cunha Jr, S. S., Vilarinho, L. O., ... & dos Santos Paes, L. E. (2025). Parametric optimization of artificial neural networks and machine learning techniques applied to small welding datasets. Processes, 13(9), 2711.

[10] Mengistie, A. K., & Bogale, T. M. (2023). Development of automatic orbital pipe MIG welding system and process parameters' optimization of AISI 1020 mild steel pipe using hybrid artificial neural network and genetic algorithm. The International Journal of Advanced Manufacturing Technology, 128(5), 2013-2028.

[11] Choudhary, A., Kumar, M., Gupta, M. K., Unune, D. K., & Mia, M. (2020). Mathematical modeling and intelligent optimization of submerged arc welding process parameters using hybrid PSO-GA evolutionary algorithms. Neural Computing and Applications, 32(10), 5761-5774.

[12] Wang, H., Li, J., & Liu, L. (2021). Process optimization and weld forming control based on GA-BP algorithm for riveting-welding hybrid bonding between magnesium and CFRP. Journal of manufacturing processes, 70, 97-107.

[13] Zhang, Y., Xiao, J., Zhang, Z., & Dong, H. (2022). Intelligent design of robotic welding process parameters using learning-based methods. Ieee Access, 10, 13442-13450.

[14] Biber, A., Sharma, R., & Reisgen, U. (2024). Robotic welding system for adaptive process control in gas metal arc welding. Welding in the World, 68(9), 2311-2320.

[15] Gong, Y., Lin, Z., Wang, J., & Gong, N. (2018). Bringing machine intelligence to welding visual inspection: development of low-cost portable embedded device for welding quality control. Electronic Imaging, 30, 1-4.

[16] Gyasi, E. A., Kah, P., Penttilä, S., Ratava, J., Handroos, H., & Sanbao, L. (2019). Digitalized automated welding systems for weld quality predictions and reliability. Procedia Manufacturing, 38, 133-141.

[17] Madhav, M., Ambekar, S. S., & Hudnurkar, M. (2025). Weld defect detection with convolutional neural network: an application of deep learning. Annals of Operations Research, 350(2), 579-602.

[18] Barot, R. S., & Patel, V. J. (2021). Process monitoring and internet of things feasibility for submerged arc welding: State of art. Materials Today: Proceedings, 45, 4441-4446.

[19] Liu, J., Cheng, Y., Jing, X., Liu, X., & Chen, Y. (2024). Prediction and optimization method for welding quality of components in ship construction. Scientific Reports, 14(1), 9353.

[20] Khan, A., Hussain, S., Jawad, M., Ahmad, W., & Jahanzaib, M. (2025). A real-time closed-loop control system for adaptive robotic welding: a step toward intelligent welding. The International Journal of Advanced Manufacturing Technology, 1-23.