

Study on the Process and Multi-Objective Optimization of Laser Cleaning Anodic Oxide Film on 2024 Aluminum Alloy

wei Wang

wangwei_me@sut.edu.cn

Shenyang University of Technology

huiyuan Li

Shenyang University of Technology

yanlai Wang

Shenyang University of Technology

xiaopeng Li

Shenyang University of Technology

weijun Liu

Shenyang University of Technology

hongyou Bian

Shenyang University of Technology

po Du

Shenyang University of Technology

Research Article

Keywords: laser cleaning, aluminum alloy, cleaning quality, prediction model, multi-objective optimization

Posted Date: August 13th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-9995133/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Version of Record: A version of this preprint was published at Applied Physics A on September 22nd, 2026. See the published version at <https://doi.org/10.1007/s00339-026-10227-8>.

Study on the Process and Multi-Objective Optimization of Laser Cleaning Anodic Oxide Film on 2024 Aluminum Alloy

Wei Wang^{1,2}, Huiyuan Li^{1,2}, Yanlai Wang^{1,2}, Xiaopeng Li^{1,2}, Weijun Liu^{1,2}, Hongyou Bian^{1,2}, Po Du^{1,2}

1 School of Mechanical Engineering, Shenyang University of Technology, Shenyang, 110870, China

2 Liaoning Provincial Key Laboratory of Laser Surface Engineering Technology, Shenyang 110870, China

Corresponding author:

Name: Wei Wang

Email: wangwei_me@sut.edu.cn (Wei. Wang)

Abstract

The process parameters of laser cleaning the anodic oxide film on 2024 aluminum alloy surface are numerous and have a wide adjustable range. The selection of its optimal parameters to achieve a dual improvement in cleaning quality and efficiency has become a critical technical bottleneck restricting engineering applications. To address this problem, this study designed a Box-Behnken design (BBD) response surface experiment with laser power, travel speed, and scanning speed as input variables, and post-cleaning surface roughness, oxygen content, and self-corrosion potential as response indicators. Response surface models and a BP neural network model optimized based on the MOEA/D-DE hybrid algorithm were established, and the prediction accuracy and generalization ability of the two models were compared and analyzed. In addition, this study proposed an improved multi-objective firefly algorithm (IMO-FA) integrating Latin hypercube initialization, adaptive variable step-size detection, and a strict crowding distance selection mechanism to solve the problems of traditional algorithms being prone to local clustering, premature convergence, uneven Pareto front distribution, and boundary shrinkage. Subsequently, the entropy weight-TOPSIS method was used to determine the optimal process parameter combination from the optimal Pareto solution set: average power 184.28 W, scanning speed 2447.10 mm/s, and travel speed 2.86 mm/s. The results show that compared with the optimal specimen in the BBD experiment, the surface roughness of the optimized specimen was reduced by 5.63%, the oxygen content was reduced by 21.43%, and the self-corrosion potential was increased by 2.12%. The optimized process parameters are beneficial to the improvement of cleaning surface quality.

Keywords: laser cleaning; aluminum alloy; cleaning quality; prediction model; multi-objective optimization

0 Introduction

Due to its low density, high strength, low cost, simple processing technology, and strong corrosion resistance, 2024 aluminum alloy is utilized as an indispensable structural material in the aerospace field^[1-4]. As the service life of an aircraft increases, defects such as cracks and holes are easily generated on the airframe surface under the long-term influence of routine service wear and natural aging of protective coatings. Furthermore, aircraft are operated for long periods in complex marine environments characterized by high humidity and salt spray. Chloride ions in the marine atmosphere penetrate into the interior of the airframe through surface cracks and pores, and electrochemical reactions are induced between these ions and the aluminum alloy matrix. Consequently, corrosion damage to the matrix is triggered, by which the service safety and overall performance stability of the aircraft are seriously affected^[5,6]. Therefore, periodic

maintenance and inspection are required for the aircraft surface, where the removal of the surface anodic oxide film is designated as the primary procedure. Laser cleaning, as an emerging green remanufacturing cleaning technology, has obvious advantages in cleaning accuracy and process flexibility compared with traditional methods for removing anodic oxide films, and has become a new favorite in the field of industrial cleaning^[7,8]. During the laser cleaning of the anodic oxide film on 2024 aluminum alloy, the surface quality of the cleaned aluminum alloy is significantly influenced by different parameter configurations^[9,10]. To protect the substrate from damage to the greatest extent possible while the anodic oxide film is removed from the surface of the 2024 aluminum alloy, appropriate process parameters for laser cleaning must be selected. Traditional methods for selecting laser cleaning parameters are based on extensive experimental data combined with empirical knowledge from engineering practice, which requires a large investment of time and resources. Therefore, to enhance the cleaning quality and efficiency in the laser cleaning process, the process parameters are required to be coordinated and optimized, by which the high-precision and high-standard processing requirements are satisfied.

Multi-objective optimization of process parameters for laser processing is currently investigated both domestically and internationally. A hybrid algorithm combining the response surface methodology (RSM) and NSGA-II-MOPSO was adopted by Luo et al.^[11] to perform multi-objective optimization on the process parameters (laser power, scanning speed, powder feeding rate, and overlapping rate) of 17-4PH/B4C multi-layer laser cladding. The depth of the heat-affected zone is significantly reduced, while the cladding layer thickness and microhardness are increased, and the validity of the model is verified through experiments. Based on RSM and the multi-objective desirability function method, the process parameters (laser power, scanning speed, and powder feeding rate) for repairing pipelines via laser cladding were optimized by Li et al.^[12]. The optimal match between a low dilution rate and high microhardness is achieved, and the performance of the repaired coating is rendered close to that of the substrate, which is applicable to the pipeline repair of aviation fuel systems. For the laser-induced hybrid hardening process (laser quenching combined with electromagnetic induction heating) of wind turbine bearings, experiments were designed using the Box-Behnken method by Zhang et al.^[13]. An RSM model and a backpropagation neural network model optimized by the whale optimization algorithm (WOA-BPNN) were established to predict and optimize the depth and hardness of the hardened layer. It is demonstrated by the research that the RSM model is significantly outperformed by the WOA-BPNN model in terms of prediction accuracy, with R^2 values exceeding 0.995, and the root mean square errors (RMSE) are determined to be 0.099 mm for depth and 1.734 HV_{0.3} for hardness. A highly efficient and reliable optimization framework is provided by this model for the deep hardening process of 42CrMo steel, by which production efficiency is effectively improved and component lifespan is extended. A method combining principal component analysis (PCA) and a BP neural network optimized by a genetic algorithm (GABP) was proposed by Zhang et al.^[14] for the real-time prediction of weld bead appearance during high-power disk laser welding. Molten pool shadow images were acquired through a high-speed visual sensing system, and four features, namely area, maximum distance, maximum width, and inclination, were extracted. After the redundancy of the feature data is reduced using PCA, a non-linear mapping model between the morphological features of the molten pool (the principal components processed by PCA) and the weld height and width was established using the GABP network. Good prediction accuracy and robustness are exhibited by this model in experimental verifications under two different welding speeds of 4.5 m/min and 3 m/min, where the mean absolute percentage error (MAPE) is restricted to approximately 5%. An effective approach is thus provided for the online evaluation of laser welding quality and process automation. An artificial neural network (ANN) model optimized by the particle swarm optimization (PSO) algorithm was proposed by Ren et al.^[15] to predict laser cutting quality (such as

kerf width and heat-affected zone width). The network structure, activation function, initial weights, and biases were optimized simultaneously in this study, by which the prediction accuracy of the model was improved. Furthermore, the non-dominated sorting genetic algorithm II (NSGA-II) was employed by the authors to perform multi-objective optimization on the process parameters, whereby processing efficiency is enhanced by more than 40% while processing quality is guaranteed. It is indicated by the experimental results that the prediction error of the model is limited to below 10%, representing strong reliability and practicality.

In summary, existing studies mainly apply intelligent optimization algorithms to traditional laser processing fields such as laser cladding, welding, and cutting, by which significant achievements—including the reduction of heat-affected zones, the enhancement of hardness and cladding layer thickness, the optimization of dilution rates, and the improvement of processing efficiency—are obtained. However, most of these studies are concentrated in the fields of additive manufacturing and surface modification of metallic materials. Regarding laser cleaning technology, fewer investigations are conducted on the optimization of process parameters, particularly for removing anodic oxide films from the surfaces of materials such as aluminum alloys. Therefore, 2024 aluminum alloy is selected as the research object in this paper. A Box-Behnken design experiment is implemented, and an RSM model as well as a BP neural network optimized by the MOEA/D-DE hybrid algorithm are established. The predictive capabilities and generalization performance of the two models are compared. After the optimal model is selected, an improved multi-objective firefly algorithm is employed for resolution to obtain the optimal combination of cleaning process parameters, whereby the laser cleaning quality is enhanced. Finally, the optimal parameter combination is verified through process experiments, where the surface roughness, oxygen element content, and free corrosion potential are tested. It is demonstrated by the results that the surface roughness is reduced by 5.63%, the oxygen element content is decreased by 21.43%, and the free corrosion potential is increased by 2.12%, by which the cleaning quality is improved. The reliability of the method proposed in this paper is confirmed, and theoretical support is provided for subsequent research on the laser cleaning of anodic oxide films on 2024 aluminum alloy.

1. Design of Experiments

1.1. Experimental Materials and Selection of Parameters

A 2024 aluminum alloy sheet with a thickness of 2 mm is selected as the experimental material, and the mass fractions of each elemental component are presented in Table 1. The specimens are cut into square blocks with dimensions of 10 mm × 10 mm × 2 mm via wire electrical discharge machining (WEDM). Anodic oxidation treatment is performed on each specimen, by which an anodic oxide film with a thickness of approximately 4 μm is coated on the surface, as illustrated in the cross-sectional view of the specimen (Fig. 1).

Table 1 Nominal chemical composition of 2024 aluminum alloy

Element	Cu	Mn	Mg	Cr	Si	Zn	Al
Mass fraction (%)	3.8-4.9	0.3-1.0	1.2-1.8	0.1	0.5	0.25	Bal.

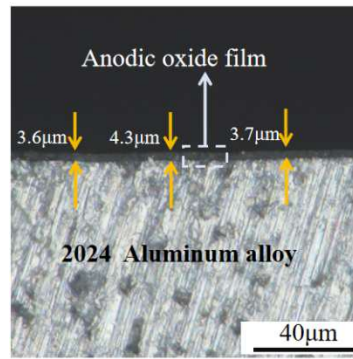


Fig. 1 Cross-sectional view of the specimen

The laser cleaning experimental platform is illustrated in Fig. 2, and the schematic diagram of the experimental platform operation is shown in Fig. 3, which includes: an IPG YLPN-100 pulsed fiber laser, an X/Y two-dimensional galvanometer system, a computer control system, and a focusing system. The laser power and pulse frequency are adjusted by controlling the laser via the computer, and the scanning speed of the laser is adjusted by controlling the galvanometer system. In this study, fixed cleaning parameters are set: the laser wavelength is 1064 nm, the pulse width is 30 ns, the pulse frequency is 30 kHz, and the scanning width is 15 mm.

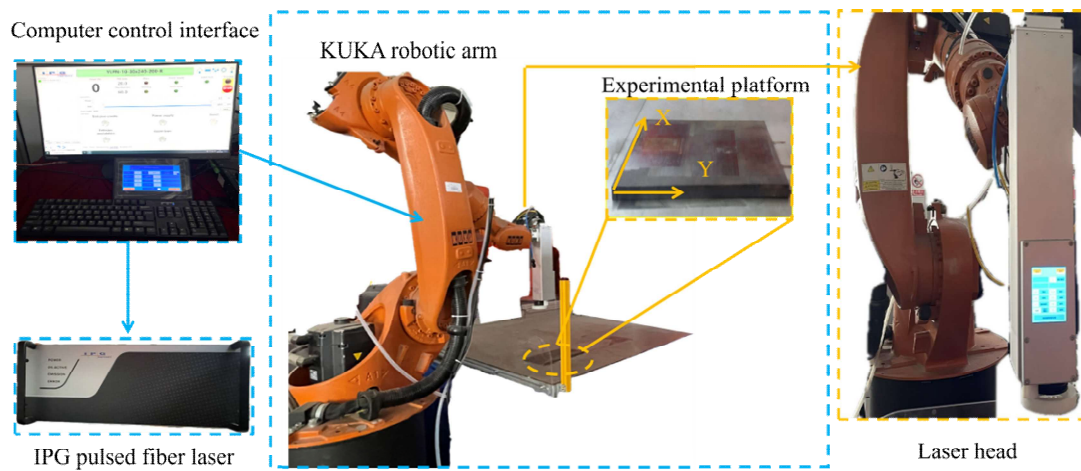


Fig. 2 Experimental platform of laser cleaning equipment

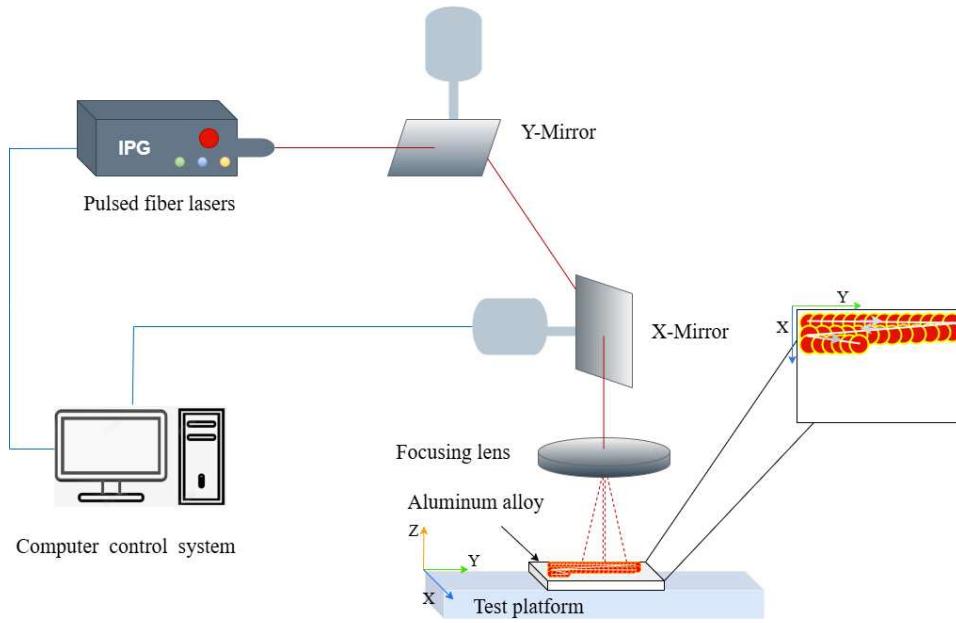


Fig. 3 Schematic diagram of the test platform

In the laser cleaning experiment of the aluminum alloy anodic oxide film, laser power, scanning speed, and travel speed are identified as critical cleaning parameters. A significant enhancement in the cleaning quality and efficiency of the anodic oxide film is achieved through a reasonable combination of parameters, whereas incomplete removal of the oxide film and damage to the substrate surface are caused by an inappropriate parameter combination. Therefore, these three laser cleaning process parameters are selected in this study to conduct the laser cleaning experiments.

1.1. Experimental Methods

Through a finite number of experimental designs conducted on a set of sample points within a specified design space, the functional relationship between response targets and design variables is regressively fitted by response surface methodology (RSM), whereby the optimal combination of design variables is obtained to achieve the optimum of the objective function^[16-18]. To investigate the non-linear fitting relationship between the cleaning quality of the 2024 aluminum alloy anodic oxide film and the laser cleaning parameters, a total of 17 groups of laser cleaning experiments on the 2024 aluminum alloy anodic oxide film are designed using the Box-Behnken Design (BBD) within the response surface methodology, which comprises three factors, three levels, and five center replication points. The factor levels for the BBD experimental design are presented in Table 2.

Table 2 Factor and level table for the BBD experimental design

No.	Factor	Level		
		-1	0	1
A	Laser power /W	170	185	200
B	Scanning speed /(mm/s)	1000	2500	4000
C	Travel speed/ (mm/s)	1	2.5	4

1.2. Measurement of Experimental Results

The common defects in laser cleaning of aluminum alloy oxide films are illustrated in Fig. 4. As can be seen from Fig. 4(a), a large area of the oxide film remains after laser cleaning, and the surface is uneven, indicating a poor cleaning effect. From Fig. 4(b), it can be observed that the surface height variance and

roughness are relatively large after cleaning, which indicates that damage may have been caused to the substrate surface. As shown in Fig. 4(c), the self-corrosion potential of the substrate surface after cleaning is low, resulting in poor corrosion resistance and high susceptibility to corrosion; the corrosive liquid will cause damage to the substrate surface, thereby affecting the continuous safety and performance stability of the aircraft.

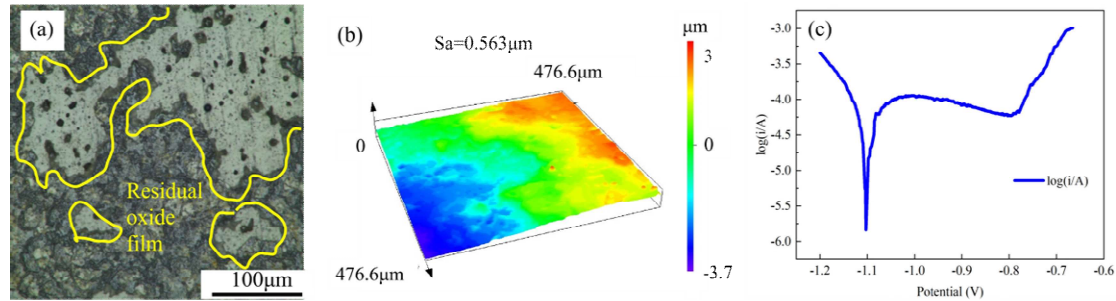


Fig. 4 Common defects in laser cleaning of aluminum alloy oxide films: (a) residual surface oxide film; (b) large surface roughness; (c) poor corrosion resistance

The oxygen content on the specimen surface can directly reflect the removal state of the surface oxide film. Therefore, a Hitachi S-3400 scanning electron microscope (SEM) is employed to observe the surface micromorphology of the specimens after laser cleaning, and an energy dispersive spectrometer (EDS) is utilized to detect the surface oxygen content. Since surface roughness is an important indicator reflecting the surface micro-irregularity and surface finish of the specimen, a DSX1000 ultra-depth-of-field microscope (OLYMPUS, Japan) is used to examine the macromorphology and surface roughness of the specimen surface. The self-corrosion potential can be used to evaluate the corrosion resistance of the specimen surface; thus, a CHI660E electrochemical workstation manufactured by Shanghai Chenhua Instrument Co., Ltd. is adopted to measure the self-corrosion potential of the specimens.

In summary, taking laser power, scanning speed, and travel speed as the input variables, and oxygen content, surface roughness, and self-corrosion potential as the response indicators, the BBD experiments were conducted. The experimental results are presented in Table 3.

Table 3 Design and results of BBD experiments

No.	Cleaning parameters			Results		
	Average power /W	Scanning speed /(mm/s)	Travel speed /(mm/s)	Surface roughness/ μm	Oxygen content /%	Self-corrosion potential/V
1	170	1000	2.5	0.293	6.2	-1.128
2	185	2500	2.5	0.213	5.6	-1.04
3	185	2500	2.5	0.234	5.5	-1.027
4	200	2500	1	0.297	8.1	-1.142
5	170	2500	4	0.223	7.5	-1.169
6	185	4000	1	0.359	9.8	-1.095
7	200	4000	2.5	0.213	8.9	-1.149
8	185	2500	2.5	0.207	5.3	-1.042
9	200	2500	4	0.234	7	-1.194
10	185	2500	2.5	0.219	5.4	-1.046
11	185	4000	4	0.278	8.1	-1.115
12	170	4000	2.5	0.264	9	-1.092

13	200	1000	2.5	0.288	6.7	-1.143
14	185	2500	2.5	0.226	5.1	-1.031
15	185	1000	4	0.256	6.4	-1.146
16	170	2500	1	0.423	8	-1.151
17	185	1000	1	0.485	7.5	-1.102

2. Construction of the Prediction Model

The establishment of the prediction model aims to reveal the mapping relationship between the cleaning process parameters and the macroscopic cleaning effects^[19], thereby providing theoretical guidance and precision assurance for the selection of process parameters in practical engineering applications. In this study, a response surface methodology (RSM) model and a BP neural network optimized by a hybrid MOEA/DE algorithm were established to map the relationship between laser cleaning parameters and output responses. By comparing the errors between the predicted and experimental values of these two models, the model with the best fitting performance was selected and subsequently utilized for further parameter optimization.

2.1. Response Surface Regression Model

Response Surface Methodology (RSM) has been widely applied in process parameter optimization, serving as an analytical approach that combines rational experimental design with scientific statistical analysis^[20,21]. By obtaining empirical data through a limited number of experiments, a regression equation can be fitted and visually represented via coordinate plots to establish an approximate model. This model can thereby predict the effects of different conditions on the response values^[22]. The model is expressed as follows:

$$y = \alpha_0 + \sum_{i=1}^k \alpha_i x_i + \sum_{i=1}^k \alpha_{ii} x_i^2 + \sum_{i=1}^k \sum_{j=1}^k \alpha_{ij} x_i x_j + \varepsilon \quad (1)$$

In the above equation, y represents the response value; k is the number of input variables; x_i denotes the i -th cleaning parameter; α_0 , α_i , α_{ii} , α_{ij} and α_{ij} represent the constant coefficient, linear coefficient, quadratic coefficient, and interaction coefficient, respectively; and ε is the error term.

Based on the BBD experimental data in Table 3, response surface fitting was performed for surface roughness, oxygen content, and self-corrosion potential. The resulting response surface equations for each corresponding response value are presented as follows:

$$\begin{aligned} S_a = & 1.14083 + 6.11 \times 10^{-4} P - 6.9 \times 10^{-5} V_x - 0.542083 V_y \\ & - 5.11111 \times 10^{-7} P \cdot V_x + 1.522 \times 10^{-3} P \cdot V_y + 1.6 \times 10^{-5} V_x V_y \\ & - 1.2 \times 10^{-5} P^2 + 2.11 \times 10^{-8} V_x^2 + 3.4322 \times 10^{-2} V_y^2 \end{aligned} \quad (2)$$

$$\begin{aligned} O_c = & 158.60944 - 1.62756 P - 7.61 \times 10^{-4} V_x - 1.76667 V_y \\ & - 6.66667 \times 10^{-6} P \cdot V_x - 6.667 \times 10^{-3} P \cdot V_y - 6.7 \times 10^{-5} V_x V_y \\ & + 4.489 \times 10^{-3} P^2 + 5.82222 \times 10^{-7} V_x^2 + 0.56 V_y^2 \end{aligned} \quad (3)$$

$$\begin{aligned} E_{corr} = & -12.14699 + 0.116736 P + 1.31 \times 10^{-4} V_x + 0.177944 V_y \\ & - 4.66667 \times 10^{-7} P \cdot V_x - 3.78 \times 10^{-4} P \cdot V_y + 2.66667 \times 10^{-6} V_x \cdot V_y \\ & - 3.12 \times 10^{-4} P^2 - 9.17778 \times 10^{-9} V_x^2 - 2.5178 \times 10^{-2} V_y^2 \end{aligned} \quad (4)$$

In the above equations, S_a , O_c and E_{corr} represent the surface roughness, oxygen content, and self-corrosion potential, respectively; P , V_x and V_y denote the laser power, scanning speed, and travel speed, respectively.

The Analysis of Variance (ANOVA) results for the three response surface models are presented in Tables

4, 5, and 6. It can be observed that the F-values of the respective models are 65.06, 48.34, and 52.23, and the p-values for all three models are less than 0.0001. The lack-of-fit values are 0.2425, 0.1304, and 0.2366, while the signal-to-noise ratios (Adeq Precision) are 27.6770, 20.7668, and 21.9722, respectively. These results indicate that each response surface model is highly significant, and their lack-of-fit values are all non-significant, demonstrating that the three models can well reflect the relationships between the cleaning parameters and each response^[23].

Table 4 ANOVA of surface roughness

Source	Sum of Squares	df	Mean Square	F-Value	p-value	
Model	0.0972	9	0.0108	65.06	<0.0001	significant
A-Laser Power	0.0037	1	0.0037	22.02	0.0022	
B-Canning Speed	0.0054	1	0.0054	32.58	0.0007	
C-Marching Speed	0.0410	1	0.0410	247.23	<0.0001	
AB	0.0005	1	0.0005	3.19	0.1174	
AC	0.0047	1	0.0047	28.27	0.0011	
BC	0.0055	1	0.0055	32.99	0.0007	
A ²	0.0000	1	0.0000	0.1953	0.6719	
B ²	0.0095	1	0.0095	57.17	0.0001	
C ²	0.0251	1	0.0251	151.26	<0.0001	
Residual	0.0012	7	0.0002			
Lack of Fit	0.0007	3	0.0002	2.10	0.2425	not significant
Pure Error	0.0005	4	0.0001			
Cor Total	0.0984	16	R ²	0.9882		
Standard deviation	0.0129		Adjusted R ²	0.9730		
Mean	0.2772		Predicted R ²	0.8771		
Coefficient of variation	4.65%		Adequate precision	27.6770		

Table 5 ANOVA of O content

Source	Sum of Squares	df	Mean Square	F-Value	p-value	
Model	33.13	9	3.68	48.34	<0.0001	significant
A-Laser Power	0.0000	1	0.0000	0.0000	1.0000	
B-Scanning Speed	10.12	1	10.12	132.97	<0.0001	
C-Marching speed	2.42	1	2.42	31.78	0.0008	
AB	0.0900	1	0.0900	1.18	0.3130	
AC	0.0900	1	0.0900	1.18	0.3130	
BC	0.0900	1	0.0900	1.18	0.3130	
A ²	4.30	1	4.30	56.41	0.0001	
B ²	7.23	1	7.23	94.90	<0.0001	
C ²	6.68	1	6.68	87.79	<0.0001	
Residual	0.5330	7	0.0761			
Lack of Fit	0.3850	3	0.1283	3.47	0.1304	not significant
Pure Error	0.1480	4	0.0370			
Cor Total	33.66	16	R ²	0.9842		

Standard deviation	0.2759	Adjusted R ²	0.9638
Mean	7.06	Predicted R ²	0.8101
Coefficient of variation	3.91%	Adequate precision	20.7668

Table 6 ANOVA of self-corrosion potential

Source	Sum of Squares	df	Mean Square	F-Value	p-value	
Model	0.0440	9	0.0049	52.23	<0.0001	significant
A-Laser Power	0.0010	1	0.0010	10.34	0.0147	
B-Scanning Speed	0.0006	1	0.0006	6.17	0.0419	
C-Marching speed	0.0022	1	0.0022	23.98	0.0018	
AB	0.0004	1	0.0004	4.71	0.0666	
AC	0.0003	1	0.0003	3.09	0.1223	
BC	0.0001	1	0.0001	1.54	0.2548	
A ²	0.0207	1	0.0207	221.33	<0.0001	
B ²	0.0018	1	0.0018	19.18	0.0032	
C ²	0.0135	1	0.0135	144.34	<0.0001	
Residual	0.0007	7	0.0001			
Lack of Fit	0.0004	3	0.0001	2.15	0.2366	not significant
Pure Error	0.0003	4	0.0001			
Cor Total	0.0447	16	R ²	0.9853		
Standard deviation	0.0097		Adjusted R ²	0.9665		
Mean	-1.11		Predicted R ²	0.8463		
Coefficient of variation	0.8743%		Adequate precision	21.9722		

To further validate the models, the response diagnostic results need to be analyzed, as illustrated in Fig. 5. Figs. 5(a)–(c) present the normal probability plots of residuals for surface roughness, oxygen content, and self-corrosion potential, respectively. The characteristic that the data points are substantially distributed along the straight line indicates a good fit with the models. To further analyze the fitting accuracy of the response surface models, the predicted results of the RSM models were plotted against the experimental values from Table 3, as shown in Fig. 6. It can be observed that the predicted results of the response surface models are in close agreement with the actual experimental values, demonstrating high fitting accuracy.

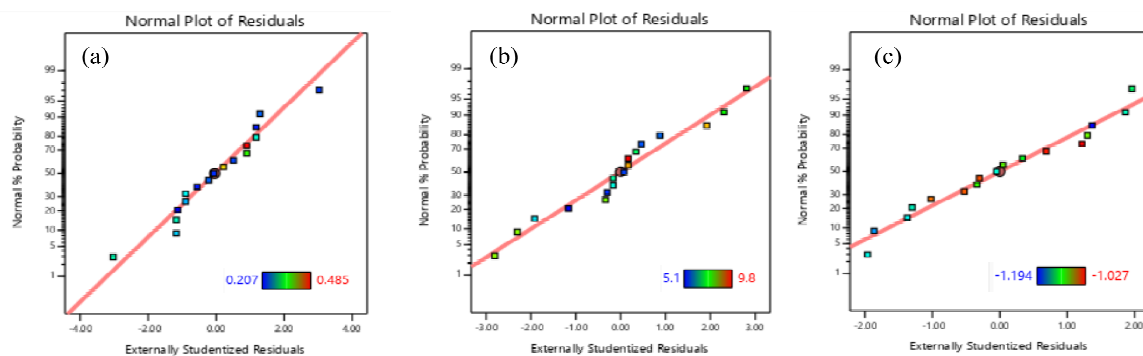


Fig. 5 Diagnostic plots: (a) surface roughness; (b) oxygen content; (c) self-corrosion potential

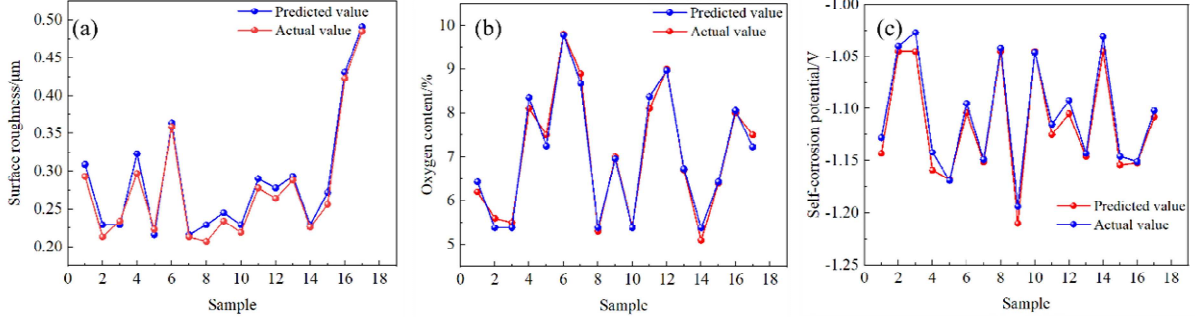


Fig. 6 Predicted results of the RSM models: (a) surface roughness; (b) oxygen content; (c) self-corrosion potential

2.2. BP Neural Network Optimized by Hybrid MOEA/D-DE Algorithm

The BP neural network is a multi-layer feedforward neural network that continuously drives the predicted output to approximate the desired output by leveraging the characteristics of forward signal propagation and backward error propagation^[24,25]. However, when applied to multi-performance index prediction, the traditional BP neural network is prone to falling into local optima and struggles to simultaneously guarantee prediction accuracy across multiple performance indicators. To address this issue, this study takes the MOEA/D algorithm as the overall framework and integrates the global search advantages of the DE algorithm with the efficient local gradient optimization capability of the LM algorithm. This integration compensates for the inherent deficiencies of the traditional model, thereby constructing the MOEA/D-DE-BP neural network prediction model.

Meanwhile, when constructing a BP neural network, the number of neurons in the hidden layer also significantly affects its prediction accuracy. If the number is too small, the network cannot acquire sufficient information to resolve the problem. Conversely, if the number is too large, it not only increases the training time but also leads to an excessively long learning process; furthermore, the resulting error is not necessarily optimal, and an increase in the test error may occur, leading to a decline in generalization capability^[26]. Therefore, the number of hidden layer nodes is determined according to the empirical formula (5).

$$K = \sqrt{m+n} + \alpha (1 \leq \alpha \leq 7) \quad (5)$$

In the equation, K represents the number of nodes in the hidden layer, while m and n denote the number of nodes in the input and output layers, respectively.

Subsequently, BP neural networks with varying numbers of hidden layer nodes were constructed, with the maximum number of training epochs set to 1000, the learning rate set to 0.001, and the target training error set to 1e-6. The average power, scanning speed, and travel speed were employed as the input parameters of the BP neural network, while the surface roughness, oxygen content, and self-corrosion potential were utilized as the output responses; thus, the number of nodes in both the input and output layers of the model was 3. Based on the data in Table 3, an additional 100 datasets randomly generated through Eqs. (2)–(4) were incorporated to train the neural network. After completing the training, the networks were used to perform predictive simulations on the training dataset, and the mean square error (MSE) between the simulation results and the actual outputs for the networks with different numbers of hidden layer nodes was calculated. The calculation formula is as follows:

$$MSE = \frac{1}{n \cdot k} \sum_{i=1}^n \sum_{j=1}^k (y_{i,j} - y_{i,j}^*)^2 \quad (6)$$

In the equation, n represents the number of samples, k is the dimension of the output variables, $y_{i,j}$ denotes the j-th actual output value of the i-th sample, and $y_{i,j}^*$ signifies the j-th simulated output value of the i-th

sample.

The MSE results of the BP neural networks with different numbers of hidden layer nodes are illustrated in Fig. 7. It can be observed that the mean square error reaches its minimum when the number of hidden layer nodes is 5, indicating that the structural configuration of the BP neural network is 3-5-3.

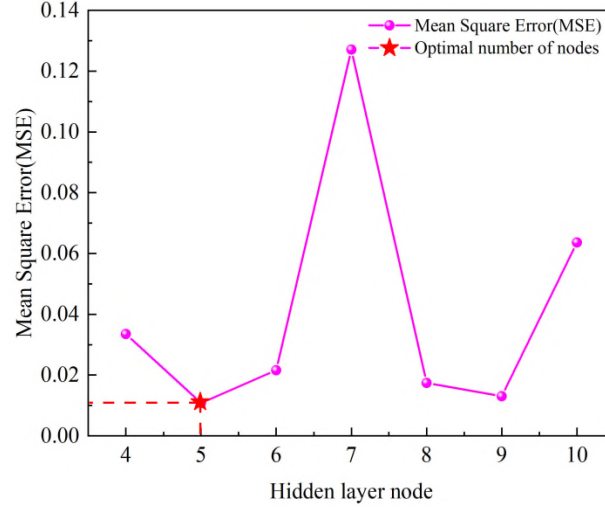


Fig. 7 Mean square error under different numbers of hidden layer nodes

However, traditional BP neural networks usually rely on empirical formulas to determine the number of hidden layer nodes during design, which limits their capability to fit the complex non-linear relationships between laser process parameters and performance indicators. To enhance the prediction accuracy of the model, the hybrid MOEA/D-DE algorithm possessing global optimization capability was introduced in this study to optimize the network weights. This evolutionary algorithm can effectively search within high-dimensional weight spaces and prevent the network from falling into local optima, thereby allowing for the utilization of a network structure with larger capacity. Consequently, the number of hidden layer nodes for the BP neural network optimized by the hybrid MOEA/D-DE algorithm was set to 15 in this study, constructing a 3-15-3 network topology.

In the MOEA/D-DE-BP model, the initial weights and thresholds of the neural network are optimized through iterative optimization of the fitness function. Therefore, prior to training, the construction of the fitness function must be completed, as expressed in Eq. (7).

$$f_{Fit} = \frac{\sum_{i=1}^n \left(\left| \frac{x_i}{x_i^{\wedge}} - 1 \right| + \left| \frac{y_i}{y_i^{\wedge}} - 1 \right| + \left| \frac{z_i}{z_i^{\wedge}} - 1 \right| \right)}{n \cdot T} \quad (7)$$

In the equation, f_{Fit} represents the fitness value, where a smaller value indicates a smaller relative error between the experimental and predicted values; x_i and $x_i^{\wedge}$ represent the experimental and predicted values of surface roughness, respectively; y_i and $y_i^{\wedge}$ represent the experimental and predicted values of oxygen content, respectively; z_i and $z_i^{\wedge}$ represent the experimental and predicted values of self-corrosion potential, respectively; n is the number of experimental data groups; and T signifies the number of output parameters.

The parameters of the hybrid MOEA/D-DE algorithm were set as follows: a population size of 100, a maximum number of iterations of 200, a neighborhood size of 20, a scaling factor of 0.5, a local search trigger

probability of 0.1, and the number of local fine-tuning steps of 2. The laser power, scanning speed, and travel speed were employed as the input parameters of the MOEA/D-DE-BP neural network, while the surface roughness, oxygen content, and self-corrosion potential were utilized as the output responses. The schematic diagram of this process is illustrated in Fig. 8.

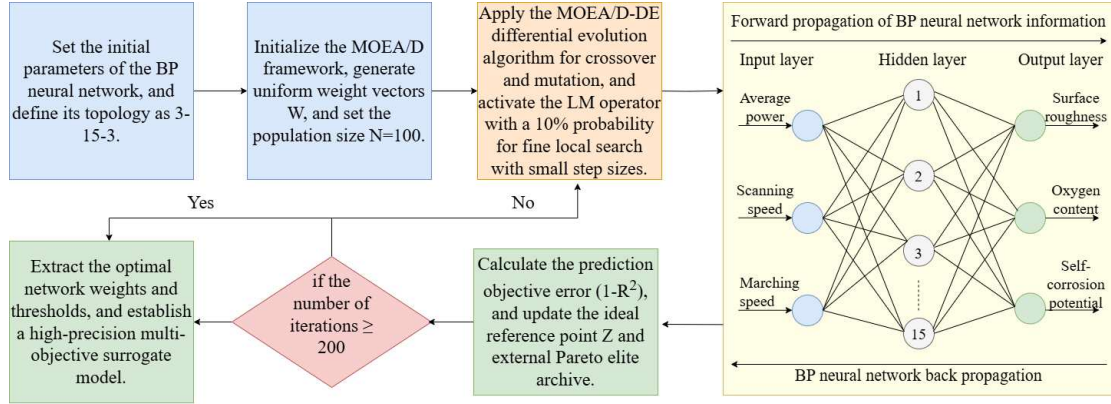


Fig. 8 Schematic diagram of the BP neural network optimized by the hybrid MOEA/D-DE algorithm

In summary, the fitting curves comparing the predicted and experimental values of the optimized BP neural network based on the parameters in Table 3 are shown in Fig. 9. It can be seen that the prediction errors of the three responses of the MOEA/D-DE-BP model are all within a reasonable range, indicating that the model has relatively high accuracy.

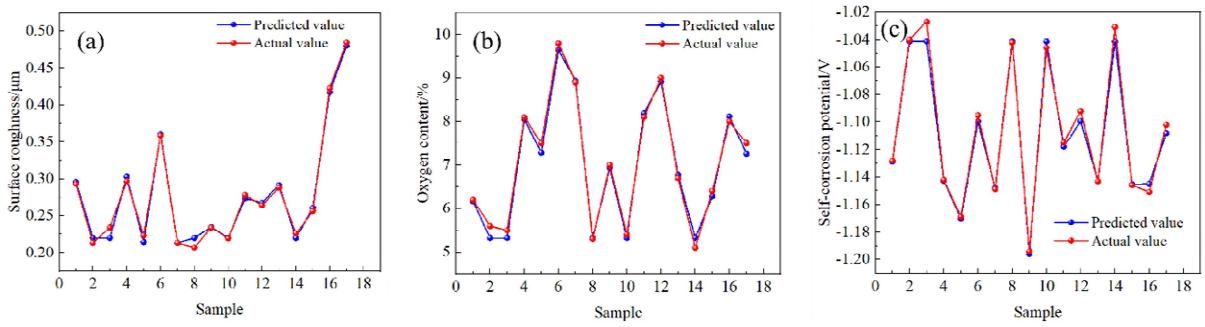


Fig. 9 Predicted results of the MOEA/D-DE-BP model: (a) surface roughness; (b) oxygen content; (c) self-corrosion potential

2.3. Comparative Analysis of the Models

The correlation between the predicted and experimental values of a model can be evaluated by its coefficient of determination R^2 ; the closer the R^2 value is to 1, the higher the prediction accuracy of the model. Its mathematical expression is given in Eq. (8):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - y_i^*)^2}{\sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

In the equation, y_i represents the experimental value, y_i^* denotes the predicted value of the model, and $\hat{y}_i$ signifies the mean of the experimental values.

The relationship between the predicted and experimental values for both the RSM and MOEA/D-DE-BP models is shown in Fig. 10. It can be observed that for the predictions of surface roughness, oxygen content, and self-corrosion potential, the coefficients of determination R^2 of the MOEA/D-DE-BP model are all slightly higher than those of the RSM model. From an overall perspective, however, the R^2 values of both

models are extremely close to 1, with a negligible discrepancy and a similar degree of variance. In conclusion, both models exhibit favorable fitting performance in predicting cleaning parameters and output responses.

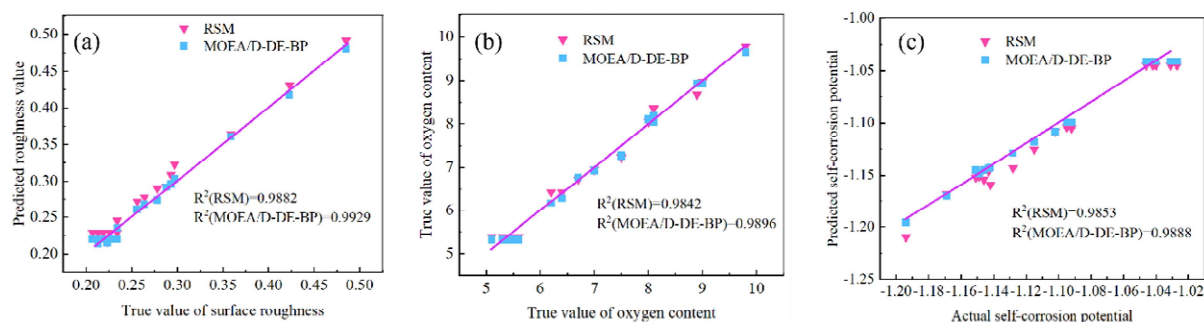


Fig. 10 Residual plots comparing experimental and predicted values of RSM and MOEA/D-DE-BP models: (a) surface roughness; (b) oxygen content; (c) self-corrosion potential

To further investigate the generalization capability of the response surface methodology (RSM) model and the MOEA/D-DE-BP neural network model, five validation groups of laser cleaning parameters were randomly generated within the range of the Box-Behnken Design (BBD) parameters to conduct the cleaning experiments, and the corresponding results were tested. Concurrently, taking these five groups of cleaning parameters as inputs, the RSM model and the MOEA/D-DE-BP model were employed to predict the output responses, which were subsequently compared with the experimental values. The predicted and experimental values of each model are summarized in Table 7.

Table 7 Predicted and experimental values of each response indicator based on RSM and MOEA/D-DE-BP models

Average power/W	Scanning speed/mm/s	Travel speed/mm/s	Surface roughness/ μm			Oxygen mass fraction/%			Free corrosion potential/V		
			Actual value	RSM	MOEA/D-DE-BP	Actual value	RSM	MOEA/D-DE-BP	Actual value	RSM	MOEA/D-DE-BP
170	1000	1	0.422	0.53	0.5234	7.1	7.937	7.8258	1.116	1.185	-1.174
180	2000	2	0.212	0.289	0.2906	6.1	5.538	5.6064	1.068	1.056	-1.0579
185	2500	2.5	0.207	0.229	0.2238	5.8	5.381	5.3773	1.034	1.045	-1.0383
190	3000	3	0.32	0.209	0.2117	6.6	5.92	5.9412	1.089	1.070	-1.0705
200	4000	4	0.517	0.29	0.2591	7.8	9.083	8.7366	1.132	1.227	-1.1995

To visually compare the generalization capabilities of the two models, the relative closeness between the experimental values and the predicted values of both models was calculated, as illustrated in Fig. 11. It

can be observed that, compared with the RSM model, the MOEA/D-DE-BP model generally yields predictions that are closer to the experimental values for surface roughness, oxygen content, and self-corrosion potential across the validation groups, thereby demonstrating a superior generalization capability.

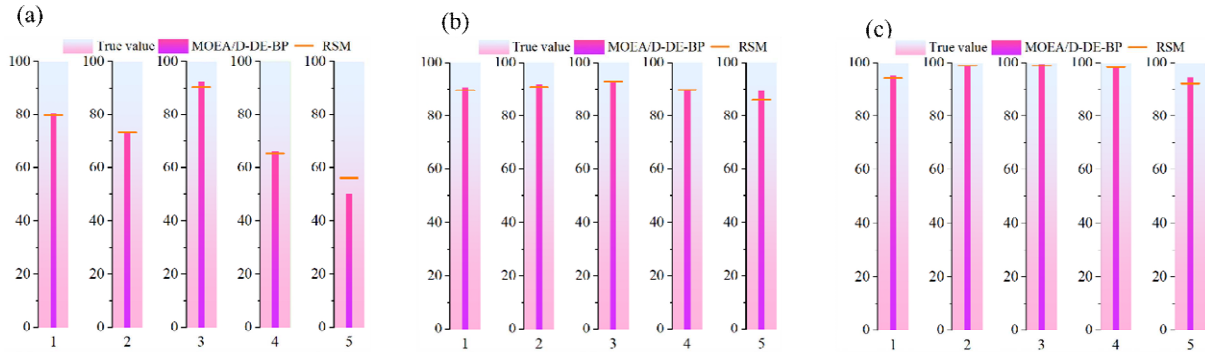


Fig. 11 Predictive performance of RSM and MOEA/D-DE-BP models: (a) surface roughness; (b) oxygen content; (c) self-corrosion potential

In summary, compared with the RSM model, the MOEA/D-DE-BP model not only exhibits excellent fitting performance on the training dataset but also demonstrates stronger generalization capability in practical testing. Therefore, the MOEA/D-DE-BP model is selected as the predictive model in this study.

3. Improved Multi-Objective Firefly Algorithm (IMO-FA)

3.1. Algorithm Design

During the laser cleaning process of anodic oxide films on aluminum alloys, minimizing the surface roughness may lead to a decrease in cleaning efficiency or a reduction in self-corrosion potential. Pronounced optimization conflicts exist among the various objective functions, making it impossible to achieve simultaneous optimality for all targets. Consequently, the only viable approach is to optimize each objective as much as possible to obtain a superior non-dominated (Pareto-optimal) solution set for this multi-objective problem.

To address the aforementioned problems, multi-objective optimization algorithms are commonly employed. The firefly algorithm (FA)^[27] was proposed by Yang in 2008; as a metaheuristic algorithm based on swarm intelligence, FA possesses the advantages of a simple structure, few parameter settings, and strong self-organizing and self-learning capabilities. In 2013, Yang extended the FA to the domain of multi-objective optimization and proposed the multi-objective firefly algorithm (MOFA)^[28], which established the theoretical foundation for research on FA in multi-objective fields. Due to its minimal parameter settings and robust self-organizing and self-learning abilities, MOFA has currently been successfully applied to various engineering optimization problems. However, owing to inherent algorithmic limitations, MOFA still faces numerous challenges that need to be resolved during the optimization process. Therefore, this study proposes an improved multi-objective firefly algorithm—integrating Latin hypercube sampling initialization, an adaptive variable step-size exploration strategy, and a strict crowding distance selection mechanism—to solve multi-objective optimization problems.

Latin hypercube sampling (LHS) is employed to generate the initial population, ensuring a uniform distribution of individuals within the decision space and enhancing the quality of initial solutions. On this basis, non-dominated sorting and crowding distance strategies are introduced to improve the distributional uniformity of the solution set, thereby satisfying the diversity requirements of multi-objective optimization. A lower light absorption coefficient is specified to expand the global search range, strengthening the algorithm's capability to avoid premature convergence. Concurrently, the variable step-size perturbation and elite guidance mechanisms in the firefly position update formula are modified, improving the efficiency of

the algorithm in escaping local extrema as well as its optimization precision.

3.2. Improved Algorithm

3.2.1. Generation of Initial Solutions Based on Latin Hypercube Sampling

In traditional multi-objective evolutionary algorithms, the initial solutions are often generated randomly. However, randomly generated initial individuals usually exhibit low fitness values, which to some extent adversely affects the convergence speed and optimization performance of the algorithm. Therefore, generating an initial population with high superiority and quality is of paramount importance for the algorithm. When the initial solutions of a population are generated randomly, their distribution tends to be non-uniform, making the algorithm prone to falling into local optima and consequently affecting the optimization results^[29]. Furthermore, the traditional Firefly algorithm typically employs pseudo-random methods to generate the initial population, which leads to a chaotic and highly disordered arrangement of the initial individuals within the decision space, easily creating blind zones or overlapping clusters in localized regions. Based on this, to enhance the quality of the initial population, the Latin hypercube sampling (LHS) method is introduced in this study to initialize the firefly population. LHS can divide the decision space of each dimension with equal probability, ensuring that sample points are uniformly distributed across the entire interval of process parameters. The formula for generating the initial population is expressed as Eq. (9):

$$X_i = L_b + (U_b - L_b) \cdot \text{rand}_{\text{LHS}}(N, D) \quad (9)$$

Where L_b and U_b denote the lower and upper bounds of the process parameters, respectively; N represents the population size; D is the dimension of the decision variables; and rand_{LHS} is a uniformly distributed matrix within the interval of $[0, 1]$ generated based on the Latin Hypercube Sampling (LHS) mechanism. The integration of LHS ensures a highly uniform distribution of the initial population, thereby substantially enhancing population diversity during the early stages of iteration.

When the population size is 150, the distributions of the randomly generated initial population and the LHS-generated initial population within the three-dimensional $[0, 1]$ interval are illustrated in Fig. 12.

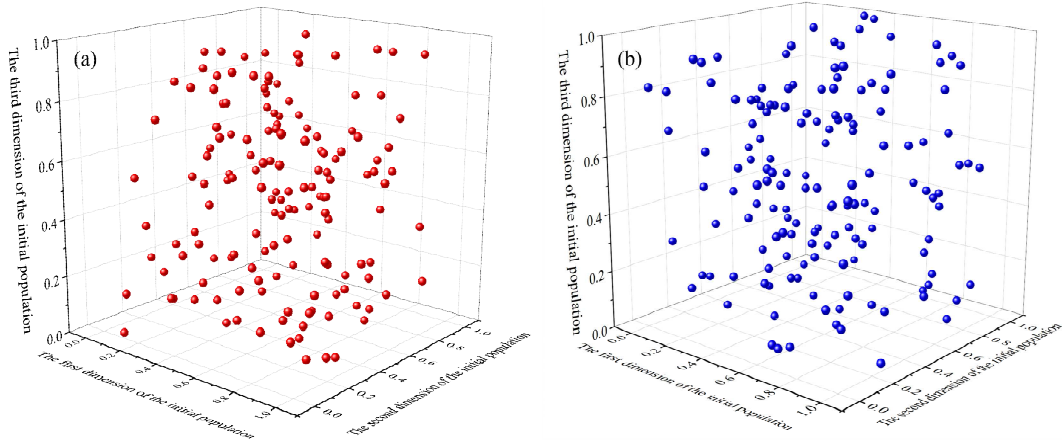


Fig. 12 Distribution plots of the initial population: (a) randomly generated initial population; (b) LHS-generated initial population

By comparing Fig. 12(a) with (b), it can be observed that, compared to the conventional random generation method, which leads to local clustering and search blind zones, Latin Hypercube Sampling (LHS) exhibits superior space-filling capability. LHS enables the initial population to achieve a more uniform coverage within the three-dimensional process parameter space, effectively avoiding the waste of computational resources in the early stages and significantly enhancing the global diversity and quality of

the initial population.

3.2.2. Multi-objective search algorithms

The conventional Firefly Algorithm (FA) relies solely on a single fitness value ($f_j < f_i$) to determine the direction of position updates, making it incapable of directly handling multi-objective conflict problems such as surface roughness, oxygen content, and self-corrosion potential in laser processing. To address this limitation, this study introduces a Pareto dominance strategy to reconstruct the attraction triggering mechanism of individual fireflies. Specifically, the original scalar comparison is upgraded to a vector dominance comparison: individual i is attracted and shifts toward individual j if and only if individual j is non-inferior to individual i in all objective dimensions i ($f_{j,m} \leq f_{i,m}$), and is strictly superior to individual i in at least one dimension i ($f_{j,k} < f_{i,k}$) (i.e., $f_j < f_i$). This expansion of the search mechanism enables the algorithm to effectively preserve high-quality non-dominated trade-off solutions, thereby guiding the population to accurately approach the Pareto front within the three-dimensional objective space.

3.2.3. Adaptive global exploration and variable-step position update

In the conventional Firefly Algorithm (FA), the relative attractiveness β between fireflies is severely restricted by the light absorption coefficient γ . In the traditional algorithm, γ is typically set to a large value, which limits the "horizon" of the fireflies (causing myopia) and forces them to cluster only toward local extrema, thereby inducing premature convergence. To address this issue, this study proposes a global exploration strategy that reduces the absorption coefficient to $\gamma=0.1$. This reduction mitigates the attenuation of light intensity with distance and maintains long-range attraction, ultimately enhancing the global span-search capability of the algorithm.

Furthermore, to enhance the capability of escaping from local extrema, a variable-step perturbation improvement is applied to the position update formula of the fireflies, and its iterative formula is expressed as Eq. (10):

$$X_i^{t+1} = X_i^t + \beta_0 \exp(-\gamma r_{ij}^2) (X_j^t - X_i^t) + \alpha^t \cdot \epsilon_i \quad (10)$$

Where β_0 is the maximum attractiveness; γ_{ij} represents the spatial distance between fireflies i and j ; ϵ_i denotes a random vector uniformly distributed within $[-0.5, 0.5]$; and α^t is the perturbation step size that adaptively decreases with the number of iterations, as expressed in Eq. (11):

$$\alpha^t = \alpha_0 \left(1 - \frac{t}{Iter_{\max}} \right) \quad (11)$$

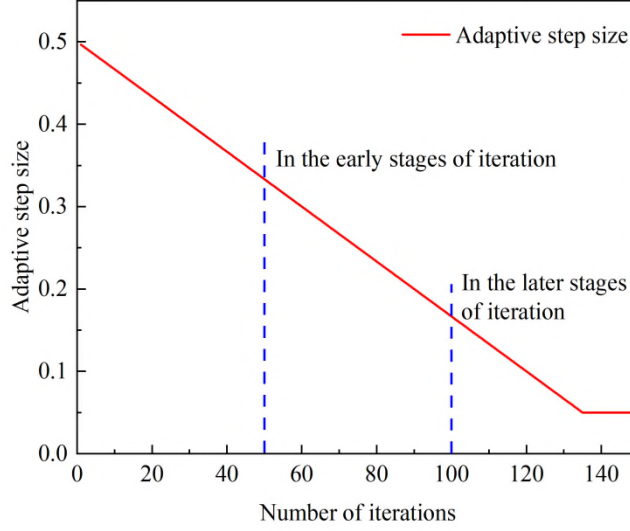


Fig. 13 Adaptive evolutionary curves of the improved variable-step perturbation factor

As illustrated in Fig. 13, the adaptive step size parameter exhibits a dynamically decreasing trend with the increase of iterations. In the early stages of iteration, the step size remains within a relatively high numerical range, which grants the fireflies a larger random-walk step size. This enables the population to have sufficient capability to explore unknown domains within the three-dimensional process space, effectively preventing the algorithm from trapping in local extrema during the initial phase. As the iteration enters the middle and later stages, the step size smoothly decreases with the number of iterations, thereby suppressing the drastic fluctuations during individual position updates. Consequently, the focus of the algorithm smoothly transitions from "global exploration" to "local exploitation," accelerating the population's convergence toward the Pareto front. Furthermore, a safety threshold lower limit of 0.05 is established in the final stage of iteration to prevent population stagnation caused by the attenuation of the step size to zero.

During the update process, a probability-based large-step jumping mechanism (reminiscent of the Lévy flight concept) is additionally introduced: when a random number exceeds a predefined threshold, the step size is forcibly doubled. Concurrently, for the global optimal leader firefly that is not attracted by any other individuals, it is compelled to perform a random walk around its current position. This strategy continuously broadens the physical boundaries of the Pareto front and effectively prevents population stagnation.

3.2.4. Strict elitism preservation strategy based on crowding distance

To address the drawbacks of the conventional Firefly Algorithm, which is limited to single-objective optimization and prone to local clustering, this study introduces a dual environmental selection mechanism combining non-dominated sorting and a strict crowding distance metric.

After each iteration, the population is first classified into different non-dominated levels according to the mutual dominance relationships among individuals. To ensure the distribution uniformity of the Pareto front, the crowding distance CD_i in each objective function dimension is calculated for individuals situated at the same level, as expressed in Eq. (12):

$$CD_i = \sum_{m=1}^M \frac{f_m^{i+1} - f_m^{i-1}}{f_m^{\max} - f_m^{\min}} \quad (12)$$

Where M represents the number of objective functions; $f_m^{\max}$ and $f_m^{\min}$ denote the maximum and minimum values of the m -th objective function within the current level, respectively. To prevent the

contraction of the front, the crowding distances of the boundary extreme points are assigned to infinity. When generating the next-generation population, the algorithm prioritizes selecting individuals with the top Rank sorting; if the Ranks are identical, individuals with larger crowding distances CD_i are preferentially retained. This mechanism completely eliminates the clustering deficiency of the conventional FA, making the obtained Pareto solution set as smooth and uniform as a grid.

3.3. Solution steps of the improved multi-objective firefly algorithm

The flowchart of the improved multi-objective firefly algorithm is illustrated in Fig. 14. The specific implementation steps are detailed as follows:

1. Population initialization. Set the fundamental parameters and reduce the light absorption coefficient ($\gamma=0.1$). Utilize Latin Hypercube Sampling (LHS) to generate a uniformly distributed initial population, and evaluate the initial multi-objective fitness of each individual via the BP neural network.
2. Pareto dominance determination. Enter the main loop and perform pairwise comparisons of individual fitness. If individual j strictly Pareto-dominates individual i ($f_j < f_i$) across the multiple objectives, a position update is triggered.
3. Adaptive attraction update and Lévy jumps. The dominated individual i moves toward individual j based on their spatial distance and relative attractiveness. During the movement, an adaptive step size α^t that decreases with iterations is adopted, and a Lévy flight large-step jump that doubles the step size is triggered with a certain probability to escape from local extrema.
4. Random walk of leader individuals. If individual i is not dominated by any other individuals (i.e., a front leader), it is compelled to perform a random walk around its current position with a step size of α^t , thereby actively broadening the search boundaries of the Pareto front.
5. Boundary violation protection and re-evaluation. Apply decision space boundary constraints to all individuals that have completed position updates, and input them into the BP neural network again to recalculate the latest three-objective fitness values.
6. Double-elite environmental selection. Perform non-dominated sorting on the merged population to classify the Rank levels, and calculate the crowding distance of individuals within the same layer. Give priority to retaining N excellent individuals with top ranks and larger crowding distances to enter the next generation, completely eliminating clustering.
7. Termination and optimal solution decision-making. Upon satisfying the maximum number of iterations, output the final solution set and extract the absolute Pareto front where Rank = 1. Finally, utilize the TOPSIS method to calculate the distance from each solution to the positive ideal point and output the comprehensive optimal process parameters with the shortest distance.

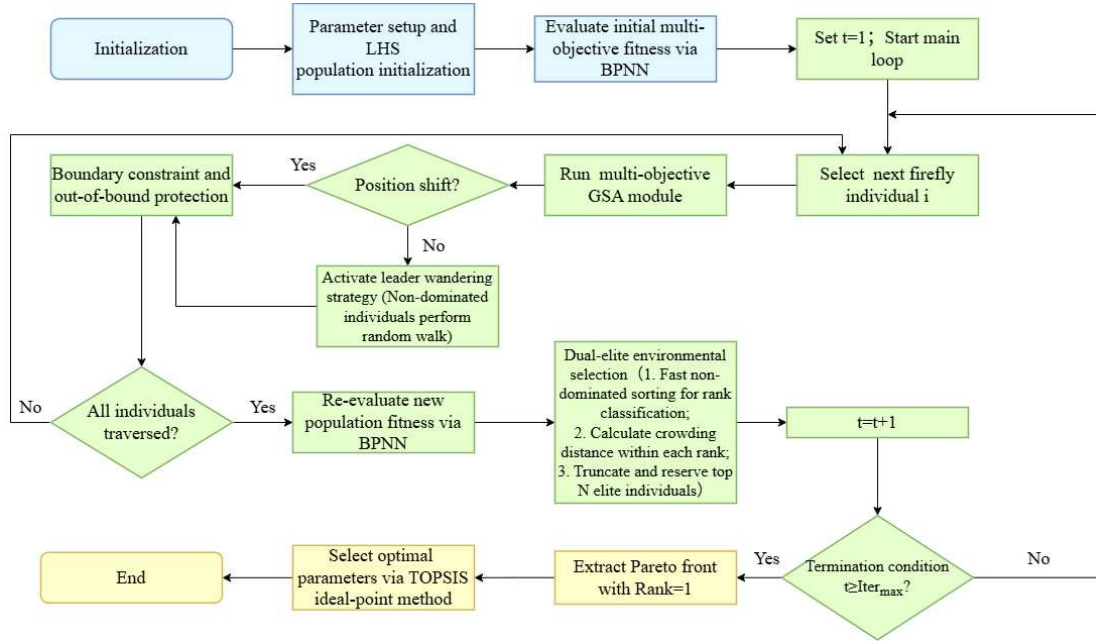


Fig. 14 Flowchart of the improved multi-objective firefly algorithm

3.4. Selection of the Pareto-optimal solution based on TOPSIS

In multi-objective process optimization, the IMO-FA algorithm ultimately outputs a Pareto solution set containing multiple non-dominated solutions (i.e., the entire frontier surface in the objective space). To satisfy the demand for a unique optimal process in practical manufacturing, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is employed in this study for final decision-making within the Pareto solution set.

First, the optimal boundary values of each objective function (surface roughness, oxygen content, and self-corrosion potential) are extracted to construct a "virtual positive ideal point." Subsequently, the range normalization method is applied to the Pareto solution set, and the Euclidean distance from each alternative to the positive ideal point is calculated, as expressed in Eq. (13):

$$D_i^* = \sqrt{\sum_{j=1}^M (Z_{ij} - Z_j^*)^2} \quad (13)$$

Where Z_{ij} represents the normalized objective value for each alternative; Z_j^* denotes the corresponding coordinate of the positive ideal point. The individual with the minimum distance D_i^* constitutes the optimal compromise solution after comprehensively balancing various performance indicators. This method objectively and effectively coordinates the conflicts among process objectives, directly outputting the optimal combination of laser processing parameters.

4. Empirical analysis and verification

4.1. Objective functions and constraint conditions

In the laser cleaning experiments of anodic oxide films on aluminum alloy surfaces, the surface roughness of the laser-cleaned aluminum alloy workpieces exerts a significant impact on their subsequent processing performance. An excessively high roughness value will drastically degrade the wear resistance of the specimen surface; hence, the surface roughness of the cleaned workpieces must be controlled at a level as low as possible. The cleaning efficiency is a core indicator for evaluating the laser cleaning effect and the

equipment's removal capability, where the oxygen element content on the substrate surface can serve as an important reference for determining the cleaning efficiency—a lower oxygen content signifies a higher laser cleaning efficiency. Concurrently, the self-corrosion potential is utilized to evaluate the corrosion resistance of the material, with a larger self-corrosion potential indicating superior corrosion resistance. In summary, the multi-objective optimization problem in this study can be described as follows: pursuing a maximized self-corrosion potential while ensuring that the surface roughness and oxygen element content are minimized as much as possible, as formulated in Eq. (14).

$$F(P, V_x, V_y) = (\max \{E_{corr}\}, \min \{S_a\}, \{O_c\}) \quad (14)$$

The constraint conditions of the multi-objective model are defined by the variation ranges of each process parameter, which are determined by the physical specifications of the actual equipment and the operational conditions [29]. The process parameter constraints selected in this study are given as follows:

$$s.t. \begin{cases} 170W \leq P \leq 200W \\ 1000mm/s \leq V_x \leq 4000mm/s \\ 1mm/s \leq V_y \leq 4mm/s \end{cases} \quad (15)$$

4.2. Algorithmic optimization and performance analysis

To evaluate the optimization efficacy of different algorithms in resolving the multi-objective problem formulated in this study, the Multi-Objective Firefly Algorithm (MO-FA), the Improved Multi-Objective Firefly Algorithm (IMO-FA), the NSGA-II algorithm, the Multi-Objective Sparrow Search Algorithm (MOSSA), the Multi-Objective Whale Optimization Algorithm (MOWOA), the Multi-Objective Grasshopper Optimization Algorithm (MOGOA), and the Multi-Objective Particle Swarm Optimization (MOPSO) are executed for comparative resolution. The Pareto solution sets yielded by each algorithm are illustrated in Fig. 15(a), and a detailed comparison of the Pareto fronts obtained specifically by the MO-FA and the proposed IMO-FA is depicted in Fig. 15(b).

The specific parameter configurations for each algorithm are outlined as follows: For the proposed Improved Multi-Objective Firefly Algorithm (IMO-FA), the light absorption coefficient is scaled down to 0.1, and a large-step Lévy flight mechanism with a mutation jumping probability of 0.2 is incorporated. For the conventional Multi-Objective Firefly Algorithm (MO-FA), the light absorption coefficient is set to 1.0 without any jumping mechanism. The parameters of the NSGA-II algorithm are configured with a crossover probability of 0.85 and a retention ratio of 1.0. For the Multi-Objective Particle Swarm Optimization (MOPSO), the personal cognitive coefficient and social learning coefficient are assigned as 1.0 and 2.0, respectively. For the Multi-Objective Sparrow Search Algorithm (MOSSA), the proportion of discoverers is set to 0.2 with a safety threshold of 0.8. The Multi-Objective Whale Optimization Algorithm (MOWOA) utilizes a helical shape constant of 1. For the Multi-Objective Grasshopper Optimization Algorithm (MOGOA), the maximum and minimum parameters for the comfort zone are quantified as 1 and 0.00004, respectively. To ensure the strict fairness of the comparative evaluation, the identical baseline parameters for all algorithms are unified as follows: a population size of 150 and a maximum iteration count of 150.

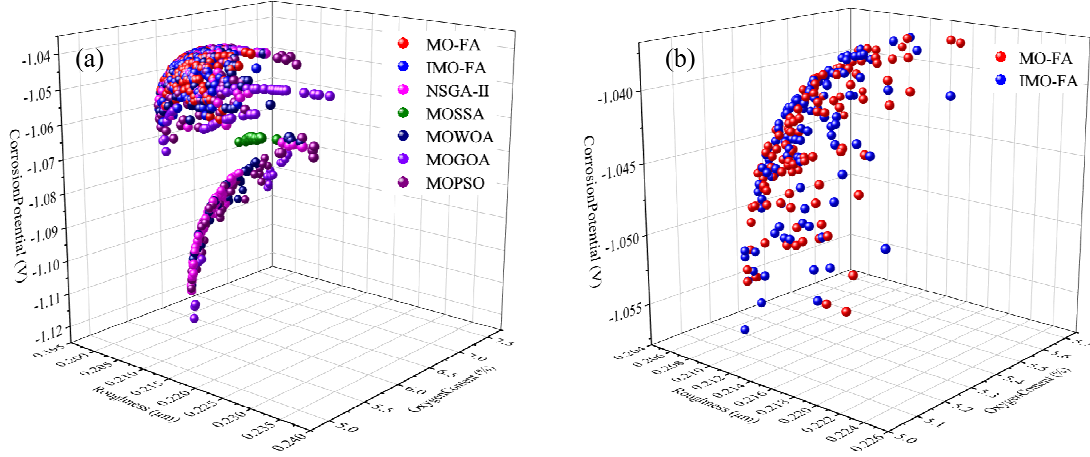


Fig. 15 Comparison of Pareto fronts obtained by different algorithms: (a) Comparison of Pareto fronts among seven algorithms; (b) Comparison of Pareto fronts between MO-FA and IMO-FA.

Based on the aforementioned Pareto solution sets, the optimization performance of the algorithms is quantified and analyzed using four multi-objective evaluation metrics^[30]: Generational Distance (GD), Inverted Generational Distance (IGD), Hypervolume (HV), and Spacing (SP). GD and IGD denote the generational distance and inverted generational distance, respectively; smaller values of GD and IGD indicate that the optimization results are closer to the true Pareto-optimal front, signifying superior convergence and diversity of the algorithm. HV represents the hypervolume metric, where a larger HV value implies a broader distribution of the solution set within the objective space, reflecting enhanced comprehensive performance of the algorithm. SP stands for the spacing indicator; a smaller SP value demonstrates a more uniform distribution of the Pareto solution set in the objective space.

$$GD = \frac{\sqrt{\sum_{x \in X} \text{dis}(P, x)^2}}{|X|} \quad (16)$$

$$IGD = \frac{\sum_{p \in P} \text{dis}(p, X)}{|P|} \quad (17)$$

$$HV = \delta(U_{x \in X} V(x, P)) \quad (18)$$

$$SP = \sqrt{\frac{\sum_{i=1}^{|X|} (\bar{x} - x_i)^2}{|X| - 1}} \quad (19)$$

Where X is the solution set obtained by the algorithm, P represents the reference set, and $|X|$ denotes the number of solutions in X . $\text{dis}(P, x)$ represents the Euclidean distance from a point x in X to the reference set P , while $|P|$ is the number of solutions in P . $\text{dis}(p, X)$ signifies the Euclidean distance from a point p in P to the solution set X . δ represents the Lebesgue measure, and $V(x, P)$ denotes the hypervolume of the space formed between the point x in X and the reference set P . $\bar{x}$ represents the mean value of all x_i .

To ensure the credibility of the multi-objective evaluation metrics, Fig. 16 illustrates the average values

of GD, IGD, HV, and SP obtained over 20 independent runs of each algorithm. It can be observed that the IMO-FA significantly outperforms other alternative algorithms in terms of the comprehensive evaluation metric IGD. Regarding the convergence metric GD, although the MOSSA achieves lower GD values in certain operational batches, its larger box height indicates a highly unstable convergence performance. In contrast, the entire box of the IMO-FA algorithm is situated within an extremely low data interval and remains the most compact among all competing algorithms. In terms of the hypervolume metric HV, the median value of the IMO-FA not only ranks within the top tier among all algorithms but also exhibits an exceptionally flat box with minimal dispersion. As for the spacing indicator SP, although the MOSSA displays a notably low lower bound and median value, its box span is extremely wide and accompanied by numerous high-altitude outliers, demonstrating that this algorithm is highly unstable during the evolutionary search and prone to massive stochastic fluctuations in optimization performance. Comparatively, the median SP value of the IMO-FA algorithm consistently maintains a globally low level; more critically, its box plot demonstrates the smallest degree of dispersion and the highest compactness among all evaluated algorithms. This convincingly demonstrates that the Pareto solution set resolved by applying the IMO-FA to the mathematical model of this study achieves optimal efficacy regarding convergence accuracy, diversity, distribution uniformity, and comprehensive optimization performance.

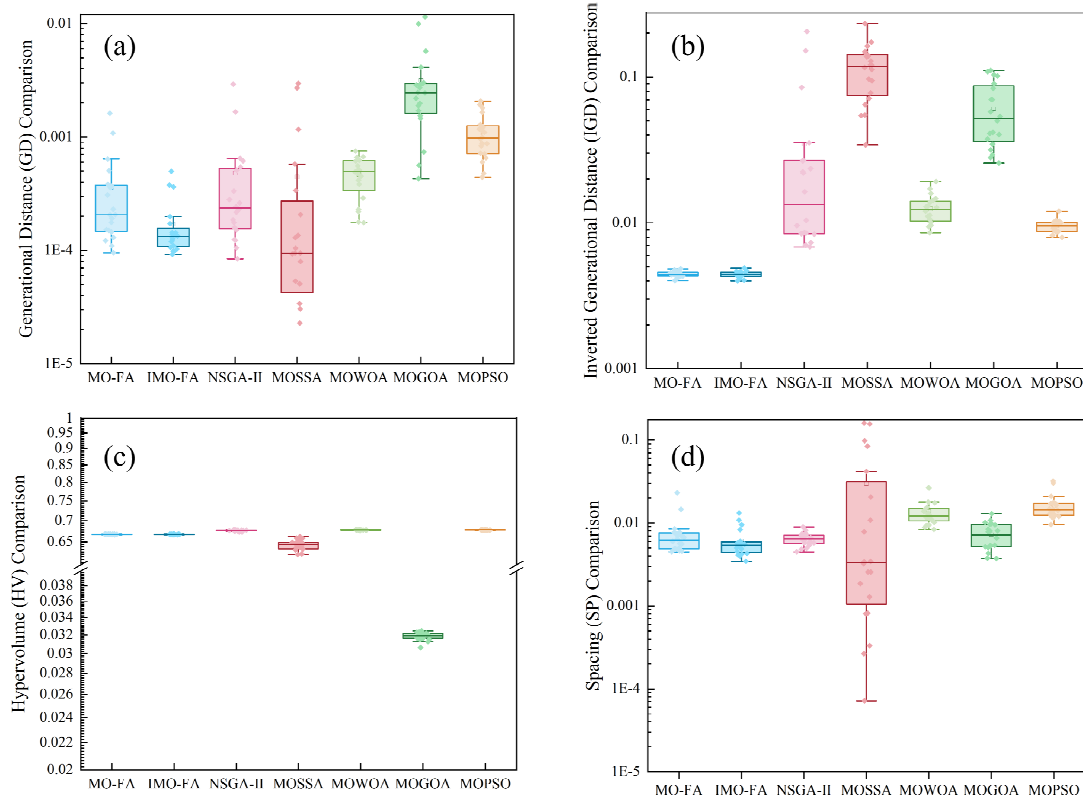


Fig. 16 Statistical comparison of multi-objective evaluation metrics among different algorithms. (a) GD, (b) IGD, (c) HV, (d) SP

4.3. Optimization results and analysis

The Entropy Weight Method (EWM) is applied to assign weight coefficients to the three performance indicators proposed in this study: surface roughness, oxygen element content, and self-corrosion potential. The resulting weights are determined as 0.3760, 0.3661, and 0.2579, respectively. Combined with the TOPSIS method, the Pareto solution set resolved by the proposed IMO-FA algorithm is evaluated and analyzed; the partial analysis results are tabulated in Table 8.

Table 8: Relative closeness coefficients of different alternatives.

Average power /W	Scanning speed /(mm/s)	Travel speed /(mm/s)	Surface roughness/ μm	oxygen element content/%	self-corrosion potential/V	Relative closeness Ki	Ranking
184.28	2447.10	2.86	0.206	4.82	-1.015	0.9398	1
184.47	2488.60	2.85	0.205	4.85	-1.014	0.9356	2
183.71	2485.67	2.80	0.206	4.85	-1.012	0.9312	3
.....							

As can be seen from Table 8, the maximum closeness coefficient calculated based on the TOPSIS method is 0.9398, and the determined optimal cleaning process parameters are: an average power of 184.28 W, a scanning speed of 2447.10 mm/s, and a travel speed of 2.86 mm/s. Utilizing this specific set of parameter configurations for laser cleaning can achieve a highly desirable and well-balanced optimization outcome.

5. Experimental validation

To investigate the feasibility of the proposed optimization model, experiments were conducted using the optimal set of process parameters decoded by the TOPSIS decision-making method. The model-predicted values and the corresponding experimental verifications are summarized in Table 9. The results indicate that the relative errors for surface roughness, oxygen element content, and self-corrosion potential are 2.43%, 8.71%, and 0.30%, respectively. Crucially, all calculated relative errors are restricted to a mere 10%, which is well within the acceptable engineering allowance threshold. The validity of the optimization results was verified.

Table 9 Comparison between model-predicted and experimentally measured values of optimized process parameters.

Evaluation metrics	Predicted values	Experimentally measured values	Relative error
Surface roughness (μm)	0.206	0.201	2.43%
Oxygen element content (%)	4.82	4.4	8.71%
Self-corrosion potential (V)	-1.015	-1.018	0.30%

To comprehensively investigate the quality of the optimization outcomes, analyses encompassing surface morphology, surface roughness, elemental compositions, self-corrosion potential, and overall corrosion resistance were systematically conducted. These characterizations were performed on three distinct representative groups: the uncleaned pristine aluminum alloy specimen, a randomized sample (No. 2) from the Box-Behnken Design (BBD) matrix, and the experimental validation specimen treated under the optimized laser cleaning parameters.

5.1. Surface morphology and roughness analysis

To observe the surface morphology and micro-geometric deviations of the specimens, an ultra-depth-of-field microscope was employed to conduct an in-depth analysis of the surface topographies and roughness of the uncleaned, randomized BBD contrast group (No. 2), and optimized specimens. The two-dimensional (2D) and three-dimensional (3D) surface morphologies of the uncleaned specimen are illustrated in Fig. 17. As shown in Fig. 17a, the surface of the uncleaned specimen is covered with a continuous and intact anodic oxide film. Distinct strip-like textures extending along the rolling direction can be observed on the surface. This phenomenon is attributed to the presence of banded microstructures within the substrate along the rolling direction during the preparation of the anodic oxide film. Because the material properties of these regions differ from those of the matrix, minor variations in the local growth rate and compactness of the film layer

are induced during its growth, ultimately forming the strip-like textures on the surface. The 3D morphology of the uncleaned specimen is presented in Fig. 17b. The uneven color distribution indicates a non-uniform thickness profile across the primitive oxide film. Furthermore, a small portion of red island-like protrusions and a few green strip-like ridgetop topographies are distributed on the surface. Through quantitative calculation, the initial surface roughness S_a of the uncleaned specimen is determined to be $0.461\ \mu\text{m}$.

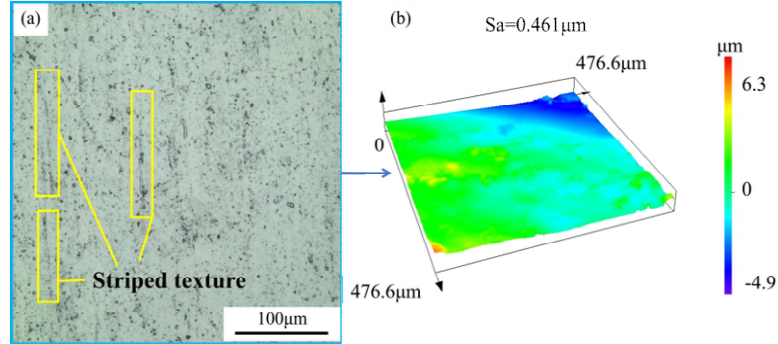


Fig. 17 Surface morphology and roughness analysis of the uncleaned specimen: (a) 2D surface morphology, (b) 3D surface topography.

The 2D surface morphology and 3D topography of the randomized trial specimen (No. 2) are illustrated in Fig. 18. As observed from the surface morphology in Fig. 18a, the laser-cleaned surface appears highly uneven and rugged. Furthermore, the localized high-magnification view in Fig. 18b clearly discloses a small amount of remelted metallic appendages (denoted as P1) and minor residual chunks of the anodic oxide film (denoted as P2). The formation mechanism of the remelted clusters in region P1 stems from the pronounced thermophysical property mismatch between the initial oxide scale and the underlying 2024 aluminum alloy substrate. Crucially, the melting range of the 2024 aluminum alloy (approximately 775–911 K) is significantly lower than that of the surface oxide layer, while the matrix simultaneously possesses an exceptionally high thermal conductivity ($140\ \text{W}\cdot\text{m}^{-1}\cdot\text{K}^{-1}$)^[31]. During the transient laser cleaning process, a fraction of the laser energy penetrates through the micropores of the oxide layer or propagates via thermal conduction into the subsurface. This sequence causes the underlying aluminum alloy to reach its melting point prior to the surface oxide film, thereby inducing a localized micro-molten pool. Upon the termination of laser irradiation, the molten aluminum liquid fast quenches and solidifies rapidly at ambient temperature, eventually producing the metallic remelted features observed in region P1 (Fig. 18b). Concurrently, owing to the non-uniform thickness distribution of the initial anodic oxide film, the delivered laser energy density under this specific recipe is insufficient to completely vaporize the thicker regions of the film layer. Consequently, this threshold deficiency leads to the formation of isolated island-like morphologies in region P2 (Fig. 18b). As depicted in the 3D topography of Fig. 18a1, the color distribution across the surface is relatively uniform, indicating a generally flat macro-profile. However, prominent protrusions can still be detected in both the central and marginal zones. The central protrusions directly correspond to the residual "island-like" oxide films, whereas the marginal bumps are indexed to the metallic remelted aggregates. The measured surface roughness (S_a) is $0.213\ \mu\text{m}$. Collectively, these comprehensive characterizations demonstrate that the cleaning quality yielded by this set of process parameters is highly undesirable.

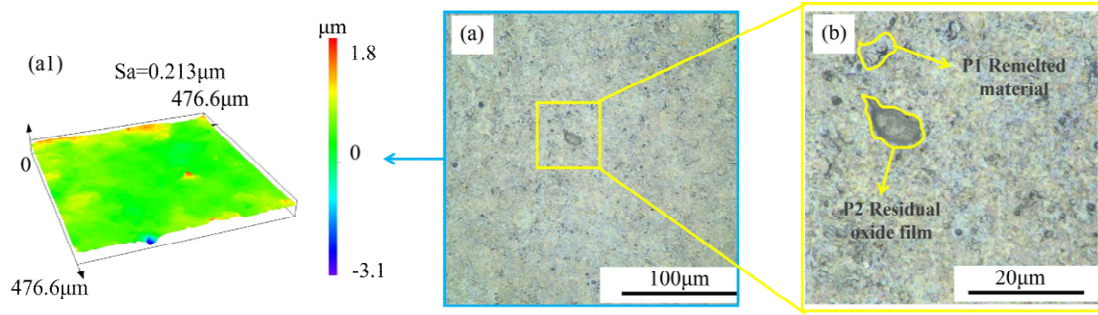


Fig. 18 Surface morphology and 3D topography of the randomized BBD trial specimen (No. 2): (a) 2D surface morphology, (a1) 3D surface topography, (b) localized high-magnification view.

The 2D surface morphology and 3D topography of the specimen treated under the optimized laser cleaning parameters are illustrated in Fig. 19. As shown in Fig. 19a, the cleaned surface appears relatively smooth and uniform, with no detectable residual anodic oxide film, while the laser scanning tracks remain faintly visible on the substrate. Further inspection via the localized high-magnification view in Fig. 19b discloses the existence of "crater-like" molten pools (denoted as P1)^[32] and minor micropores (denoted as P2). The formation of the "crater-like" molten pools in region P1 is fundamentally governed by the hydrodynamic effects during laser irradiation. Specifically, the intense and rapid vaporization/expansion of the surface anodic oxide film generates a massive downward vapor recoil pressure. This immense pressure forces the localized liquid aluminum matrix, which has just reached its melting point, to displace outward toward the periphery of the laser beam. Subsequently, the extruded molten aluminum alloy is instantly solidified under an extremely high temperature gradient, ultimately constructing the unique "crater-like" molten pool architectures in region P1. During the laser cleaning process, the localized high energy density stemming from the non-uniform spot distribution induces micro-melting on the substrate surface, whereby ambient gases are inevitably entrapped within the transient molten pool. Upon the termination of laser irradiation, the molten pool undergoes rapid solidification; consequently, the engulfed gas bubbles have insufficient time to escape, thereby yielding the micropores observed in region P2. As depicted in the 3D topography of Fig. 19a1, the highly uniform color distribution indicates a significantly diminished surface fluctuation with no pronounced macroscopic protrusions. The overall flatness is markedly superior to that of the randomized trial specimen (No. 2). The measured cleaning surface roughness S_a was 0.201 μm, which was reduced by 5.63% compared with that of the test specimen (NO.2), and were all smaller than those of the comparative group test specimens, indicating good surface quality.

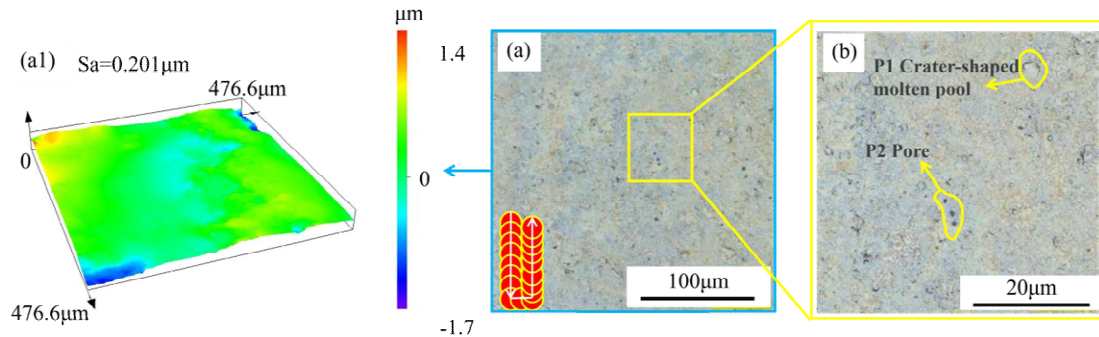


Fig. 19 Surface morphology and 3D topography of the optimized specimen: (a) 2D surface morphology, (a1) 3D surface topography, (b) localized high-magnification view.

5.2. SEM micro-morphology and elemental composition analysis

Furthermore, scanning electron microscopy (SEM) and energy dispersive spectroscopy (EDS) were utilized to sequentially analyze the surface micro-morphology and elemental concentrations of the uncleaned, randomized BBD trial (No. 2), and optimized specimens. The refined microstructural features and elemental compositions of the uncleaned benchmark are illustrated in Fig. 20. As captured by the SEM micrograph in Fig. 20a, the primitive surface is characterized by the distribution of several irregular micropores. This phenomenon is principally governed by the acidic nature of the selected electrolyte during the fabrication of the anodic oxide film, which exerts a simultaneous chemical dissolution effect on both the aluminum alloy matrix and the newly generated oxide scale. Consequently, this competitive growth-dissolution mechanism induces the formation of unique rod-like pores on the external surface^[33], as further detailed in the high-magnification view (Fig. 20a1). The quantitative elemental spectrum is presented in Fig. 20b. The empirical data register that the mass fractions of oxygen (O) and sulfur (S) on the uncleaned specimen surface reach up to 46.1% and 5.5%, respectively. Based on this, it is judged that the specimen surface has been covered with a layer of anodic oxide film.

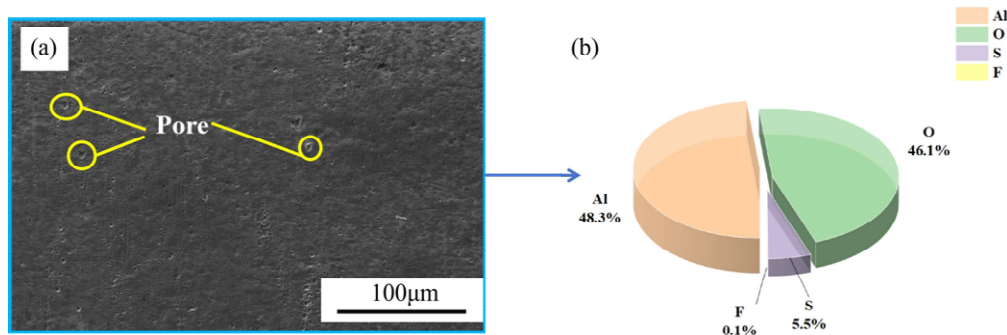


Fig. 20 SEM micro-morphology and elemental content of the uncleaned specimen surface: (a) SEM micrograph, (b) EDS elemental spectrum.

The surface micro-morphology and elemental compositions of the randomized BBD trial specimen (No. 2) are illustrated in Fig. 21. As observed from the low-magnification view in Fig. 21a, the cleared surface appears generally flat. Combined with the broad-area EDS elemental spectrum in Fig. 21a1, the overall oxygen (O) content on the processed surface dramatically drops to 5.6% compared to that of the raw anodic film, indicating a preliminary cleaning effect. However, a noticeable amount of bright white microparticles remains scattered across the matrix. Further inspection via the localized high-magnification SEM micrograph (Fig. 21b) reveals that besides these white microparticles (denoted as P1), pitting defects (denoted as P2) and minor island-like residual fragments (denoted as P3) coexist on the surface. The localized EDS analysis corresponding to region P1 is presented in Fig. 21b1. The aluminum (Al) mass fraction reaches up to 93.98%, which convincingly indexes these bright white microparticles as the remelted products of the aluminum alloy substrate. The underlying physical mechanism stems from the lower melting window of the subsurface aluminum alloy relative to the oxide layer, which triggers localized micro-melting and the formation of a transient molten pool during laser scanning. Upon the termination of laser irradiation, the liquid aluminum fast quenches at ambient temperature, producing the remelted white aggregates in region P1. Regarding region P2, the localized EDS spectrum (Fig. 21b2) exhibits an Al content of 94.29% and an O content of merely 5.3%, demonstrating that this specific pit belongs to a typical micropore defect. This structural imperfection is intrinsically governed by the precipitation of hydrogen gas naturally accumulated within the aluminum alloy during its manufacturing stage^[34]. When the coverage of the passive oxide scale is successfully stripped away, these pre-existing hydrogen-induced micropores inside the bare substrate are

subsequently exposed and detected. For the localized fragment in region P3, the EDS analysis (Fig. 21b3) quantifies a heavily enriched O content of 50.74% and an Al content of 44.55%, confirming that this feature constitutes un-cleared oxide film remnants. This threshold deficiency is driven by the non-uniform thickness distribution of the initial anodic scale, which prevents the laser energy from completely vaporizing the thicker zones under this improper energy input recipe, thereby yielding isolated island-like debris. In summary, the surface micro-morphology of the aluminum alloy cleaned under these process parameters still has many defects, failing to achieve a desirable cleaning effect.

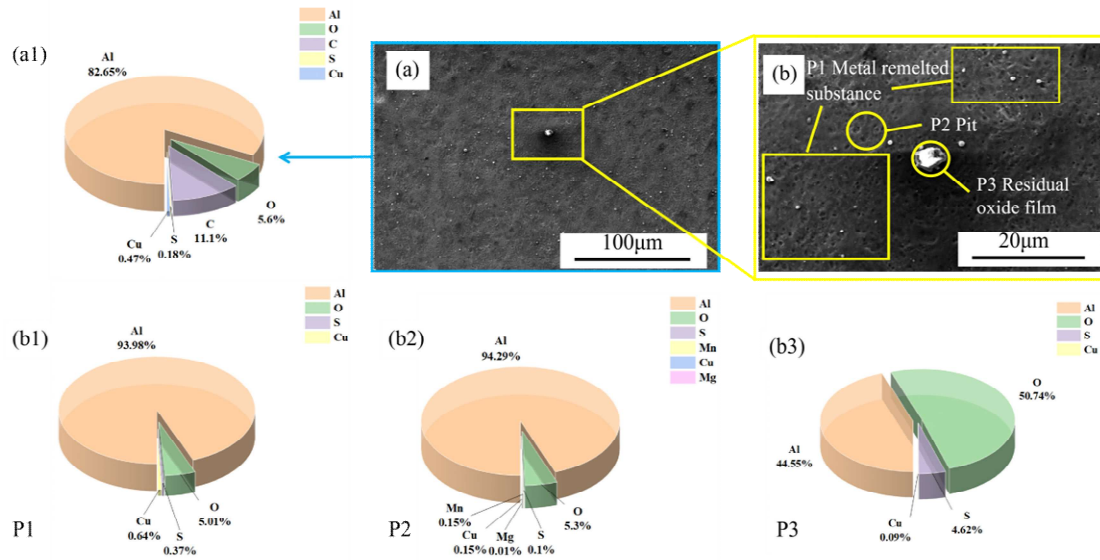


Fig. 21 SEM micro-morphology and elemental content of the randomized BBD trial specimen (No. 2): (a) low-magnification SEM micrograph, (b) localized high-magnification view; (a1) overall surface elemental spectrum, (b1) localized EDS spectrum of region P1, (b2) localized EDS spectrum of region P2, and (b3) localized EDS spectrum of region P3.

The surface micro-morphology and elemental compositions of the specimen treated under the optimized laser cleaning parameters are structurally illustrated in Fig. 22. As clearly observed from the low-magnification SEM micrograph in Fig. 22a, the optimized surface presents a remarkably flatter macro-profile with an absence of pronounced defects compared to the randomized BBD trial specimen (No. 2). Crucially, combined with the broad-area EDS elemental spectrum in Fig. 22a1, the overall oxygen (O) mass fraction on the optimized surface is restricted to a mere 4.4%. This represents a significant reduction of 21.43% relative to the randomized BBD candidate (No. 2) and remains strictly lower than all other candidate combinations within the contrast matrix, convincingly demonstrating an enhanced cleaning efficiency and superior surface quality. Further inspection via the localized high-magnification SEM view (Fig. 22b) discloses that the optimized surface only exhibits a sparse scattering of trace bright white microparticles. As quantified by the corresponding localized EDS spectrum presented in Fig. 22b1, these tiny microparticles possess an O content of 3.87% and an aluminum (Al) content of 93.77%. The quantitative elemental composition confirms that these microparticles constitute resolidified matrix features. In summary, the cleaning effect on the oxide film using the optimized process parameters is better than the cleaning effect of the process parameters used in the BBD (NO. 2) trial.

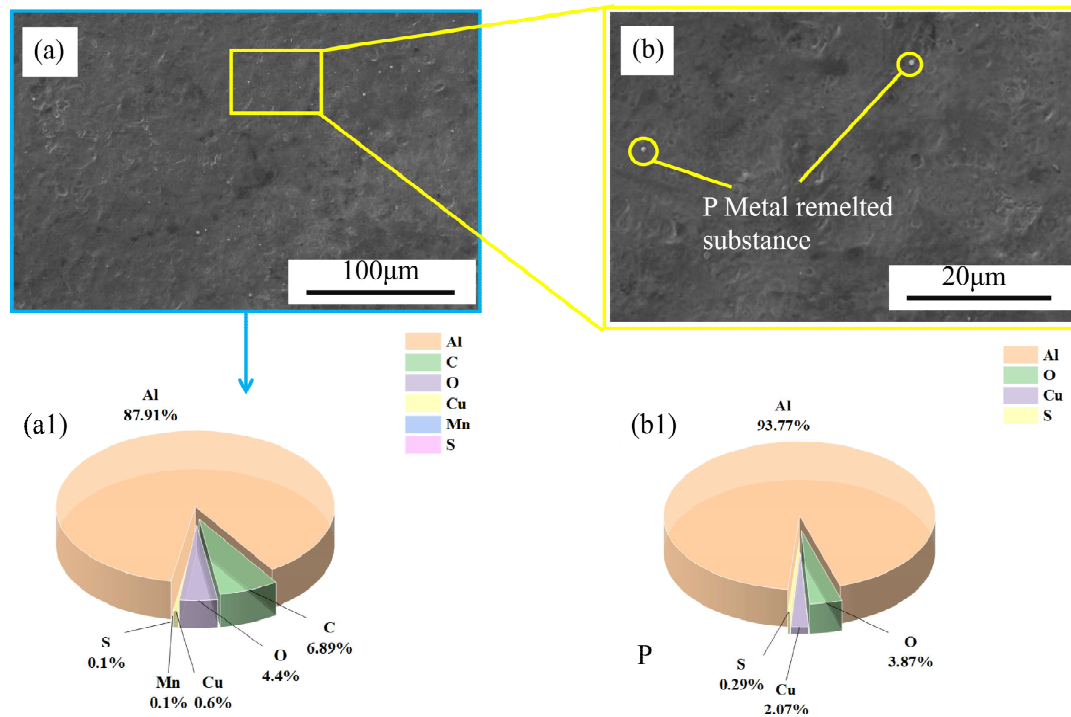


Fig. 22 SEM micro-morphology and elemental content of the optimized specimen surface: (a) low-magnification SEM micrograph, (b) localized high-magnification view; (a1) overall surface elemental spectrum, and (b1) localized EDS spectrum of region P.

5.3. Corrosion resistance validation

To comprehensively investigate the corrosion resistance of the specimens, electrochemical corrosion tests were systematically performed on the surfaces before and after laser cleaning using an electrochemical workstation. Among various electrochemical techniques, potentiodynamic polarization curves characteristically describe the functional relationship between the current density and the electrode potential. This approach serves as a widely accepted and robust methodology for evaluating the electrochemical corrosion behavior of metallic materials. Crucially, the corrosion resistance of the processed surface can be fundamentally evaluated by the magnitude of the corrosion potential; that is, a higher (more noble) corrosion potential implies a lower thermodynamic corrosion inclination, thereby indicating a superior corrosion resistance^[35].

The corrosion resistance validation of the specimens is organized in Fig. 23. As disclosed by the potentiodynamic polarization curves (or corrosion potential statistics) in Fig. 23a, the corrosion potential of the uncleaned baseline specimen is registered at -1.086 V. For the randomized BBD trial specimen (No. 2), the value shifts positively to -1.04 V, whereas the specimen processed under the optimized parameter window exhibits a further noble drift, reaching up to -1.018 V. This distinct and progressive positive shift trend convincingly demonstrates that the optimized laser cleaning process effectively elevates the corrosion resistance of the aluminum alloy substrate. Physically, the surface of the uncleaned pristine specimen is loosely covered with a native oxide scale, manufacturing oil stains, and potential corrosion products. These hybrid substances possess high electrochemical activity, which highly triggers localized micro-galvanic corrosion. Laser cleaning removes these physical defects and chemical contaminants, drastically reducing corrosion initiation sites and thereby increasing the corrosion potential of the matrix metal. Regarding the randomized BBD candidate (No. 2), minor fragments of the anodic film fail to be stripped away, leaving a relatively rugged topography. A coarser surface provides a larger effective reaction area than a smooth profile.

More importantly, the work function required for electrons to escape from the bulk material to the external surface locations typically increases with diminished roughness, meaning that a rougher profile lowers the energy barrier for electronic emission and thereby accelerates the corrosion inclination^[36]. The specimen with optimized parameters exhibits the maximum corrosion potential. The primary reason is that after the laser removes the surface anodic oxide film, the remaining energy causes grain refinement and dislocation deformation on the substrate surface. Grain refinement can significantly improve the passivation behavior, thereby blocking the Cl⁻ enriched in the solution from developing into the grain interiors. At this time, the thermal oxide layer formed on the surface is denser, leading to the lowest corrosion inclination and enhanced corrosion resistance^[37]. The corrosion potential of the specimen after process parameter optimization is increased by 2.12% compared to that of the BBD trial specimen (NO. 2), and both are less than the comparison group trial specimens. This proves that the optimization effect is better.

To further validate the corrosion resistance of the optimized specimen, the electrochemical impedance spectroscopy (EIS) characteristics are structurally evaluated. As illustrated by the Nyquist plots in Fig. 23b, the geometric configurations recorded for all tested specimens exhibit highly similar profiles, which are predominantly composed of high-frequency capacitive loops. In electrochemical theories, a larger high-frequency capacitive loop radius directly reflects a higher charge transfer resistance of the superficial scale, thereby indicating an elevated anti-corrosion capacity^[38].

Empirically, the uncleaned baseline specimen presents the smallest high-frequency capacitive loop radius. In sharp contrast, both the randomized BBD candidate (No. 2) and the optimized specimen yield significantly expanded the High-frequency capacitive loop dimensions relative to the uncleaned benchmark. This expansion convincingly demonstrates that the secondary thermal oxide film generated on the 2024 aluminum alloy surface after stripping the primitive anodic scale under appropriate laser metrics possesses enhanced corrosion-retarding properties. Most notably, among the three configurations, the optimized specimen demonstrates the maximum high-frequency capacitive loop diameter, confirming that the thermal oxide scale formed under this tailored recipe is the most compact and homogeneous, thus providing the highest corrosion immunity. Concurrently, the corresponding Bode profiles depicted in Figs. 23c and d serve as auxiliary criteria to evaluate the localized corrosion dynamics, where the magnitude of the impedance modulus ($|Z|$) and the phase angle are scrutinized. Specifically, a larger impedance modulus value in the low-frequency regime fundamentally correlates with superior total corrosion resistance. Meanwhile, the phase angle reflects the physical barrier performance of the surface layer against electrolyte infiltration^[39]; a higher and broader phase angle peak implies a superior blocking effect and an enhanced corrosion resistance. Overall, the phase angle evolutions of the three specimens exhibit an identical trend, characterized by a well-defined peak emerging in the medium-frequency domain, which typically corresponds to the response of the surface passive film. Crucially, the optimized specimen yields the highest phase angle peak, demonstrating the reconstruction of a substantially denser and more stable passive film on its surface. Conversely, both the uncleaned benchmark and the randomized BBD candidate (No. 2) exhibit noticeably depressed phase angles, reflecting their relatively weaker superficial protective capabilities. Further analysis of the impedance curves reveals that the uncleaned specimen registers the lowest impedance modulus, whereas the optimized specimen achieves the highest impedance modulus, demonstrating the best corrosion resistance.

Synthesizing the comprehensive insights from the Bode and Nyquist plots, the evolution of the impedance modulus and phase angle exhibits a high degree of consistency with the characteristics of the high-frequency capacitive loop radius; specifically, the specimen treated under the optimized process window simultaneously yields the maximum impedance modulus, the highest phase angle peak, and the largest high-frequency capacitive loop dimension. Concurrently, when cross-referenced with the

potentiodynamic polarization curves, the optimized specimen presents the most noble (positive) corrosion potential. Consequently, during the electrochemical corrosion process, the experimentally validated optimal specimen demonstrates a substantially superior corrosion-shielding capability compared to both the uncleaned benchmark and the randomized BBD candidate (No. 2). Thus, during the electrochemical corrosion process, the optimized test specimen exhibits superior corrosion resistance compared to both the uncleaned specimen and the BBD test specimen (No. 2), thereby validating the feasibility of the optimization scheme.

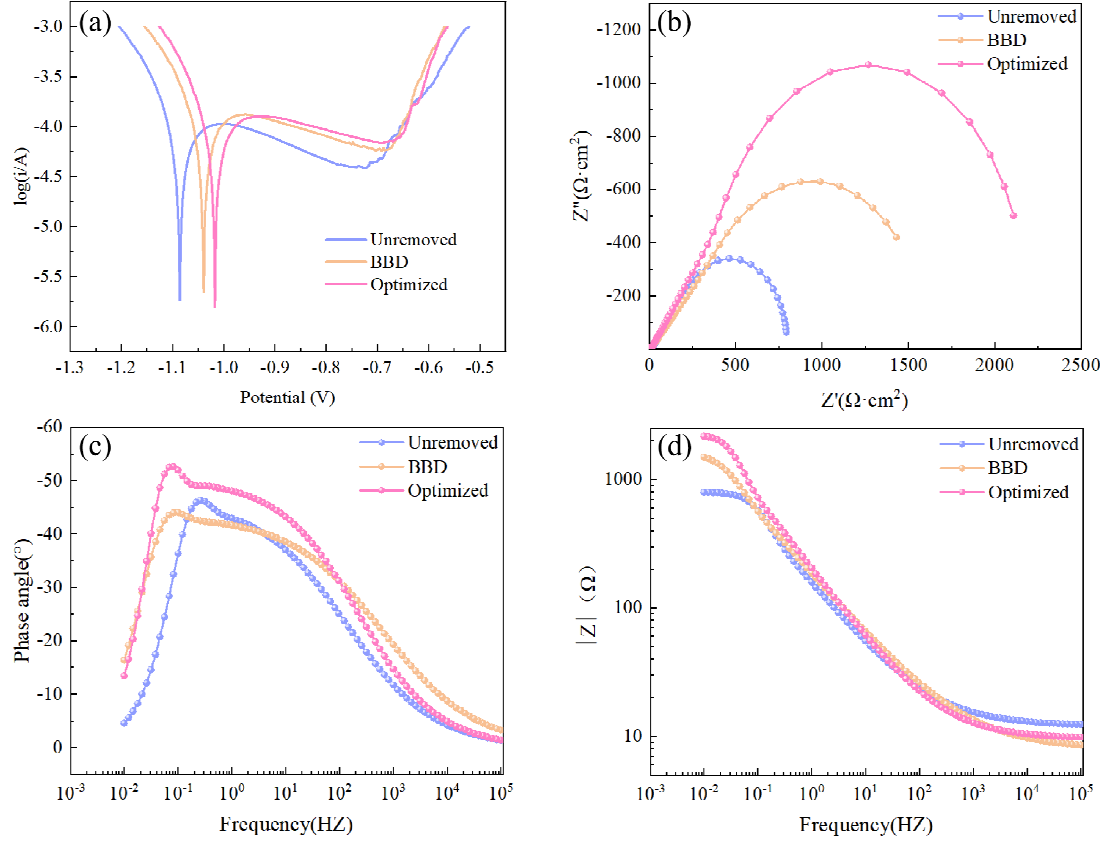


Fig. 23 Corrosion resistance analysis of the specimens: (a) potentiodynamic polarization curves, (b) Nyquist plots, (c) Bode plots of impedance modulus, and (d) Bode plots of phase angle.

6. Conclusions

This study conducted experiments and multi-objective optimization methods for laser cleaning of the anodized film on the surface of 2024 aluminum alloy, and obtained the following conclusions:

1. Both the RSM model and the BP neural network model optimized based on the MOEA/D-DE hybrid algorithm have good fitting effects on the laser cleaning data in this paper, and the generalization ability and prediction accuracy of MOEA/D-DE-BP are significantly stronger than RSM, making it more suitable for solving subsequent multi-objective algorithms.
2. An improved multi-objective firefly algorithm (IMO-FA) was proposed, which integrates Latin hypercube initialization, adaptive variable step-size detection, and a strict crowding screening mechanism, to solve the problems of local clustering, premature convergence, uneven Pareto front distribution, and boundary shrinkage in traditional multi-objective firefly algorithms. It was applied to solve the MOEA/D-DE-BP model, and the optimal parameter combination selected by Topsis was: average power 184.28W, scanning speed 2447.10mm/s, and travel speed 2.86mm/s.
3. By comparing the BBD test sample (NO.2) with the optimized sample, it was verified that the

optimized sample had a 5.63% reduction in surface roughness, a 21.43% reduction in oxygen content, a 2.12% increase in self-corrosion potential, and a significant improvement in cleaning quality compared to the optimal BBD test sample (NO.2). This provides a reference for optimizing the process parameters of laser cleaning aluminum alloy anodized film.

Author contribution

All authors contributed to the study conception and design. Wei Wang: Writing-review & editing, Methodology, Data curation. Huiyuan Li: Writing-original draft, Resources, Conceptualization. Yanlai Wang: Data curation, Supervision. Xiaopeng Li: Validation. Weijun Liu and Hongyou Bian: Funding acquisition, Po Du: Supervision.

Funding This work was supported by the National Natural Science Foundation of China (52375456) and Scientific Research Fund of Liaoning Provincial Education Department (LJ232510142004).

Declarations

Competing interests The authors declare no competing interests.

Data availability All the data is provided in the manuscript.

References

- [1] Guan Renguo, Lou Huafen, Huang Hui, Liang Xiaopeng, Xiao Xiang, Li Huizhong, Li Fang, Wang Jianjun, Yun Xinbing, Zeng Libin. Development Status, Trends, and Prospects of Aluminum Alloy Materials [J]. Strategic Study of CAE, 2020, v.22(05).
- [2] Yang Shoujie, Dai Shenglong. Review and Prospect of the Development of Aviation Aluminum Alloys [J]. Materials Review, 2005(02).
- [3] T. Kim; J.M. Lee; S.H. Cho; T.H. Kim. Acoustic emission monitoring during laser shock cleaning of silicon wafers[J]. Optics and Lasers in Engineering, 2004, 43(9).
- [4] Dong Lihong, Wang Haidou, et al. Research Progress on Corrosion Fatigue of Aerospace Aluminum Alloys [J]. Surface Technology, 2021, 50(07): 106-118.
- [5] Li Faguo, Yang Li, Zhou Yichun. Research Progress on Marine Atmospheric Corrosion Resistance of Aero-engine High-temperature Coatings [J]. Thermal Spray Technology, 2019, 11(04): 1-9+15.
- [6] Wang W ,Kou J ,Zhong J , et al.Effect of Scanning Speed on Surface Quality and Corrosion Resistance of 7075 Aluminum Alloy in Laser Cleaning[J].Metals and Materials
- [7] CHEN G X, KWEE T J, TAN K P, et al. Laser cleaning of steel for paint removal[J]. Applied Physics A, 2010, 101 : 249-253.
- [8] Wang W ,Jiang Q ,Liu W , et al.Effect of laser fluence on the cleaning quality and surface properties of TA15 titanium alloy surface paint layer[J].Optics and Laser Technology, 2025, 181(PC): 112032-112032. DOI:10.1016/J.OPTLASTEC.2024.112032.

- [9] Li Qiang, Zhao Ziming, Liu Weijun, Bian Hongyou, Wang Wei, Wang Huiru. Effect of Laser Paint Removal on Surface Quality of Aluminum Alloy Substrate [J]. Surface Technology, 2024, v.53(03).
- [10] Xia Peiyun, Yin Yuhuan, Cai Aijun, Huang Zheng, Li Dan, Bao Yunfeng, Feng Xiaosong. Research on Laser Cleaning Process of 2219 Aluminum Alloy Anodic Oxide Film Before Welding [J]. Chinese Journal of Lasers, 2019, v.46; No.505(01).
- [11] D. Luo, C. Liu, C. Wang, Y. Wang, X. Wang, J. Zhao, and S. Jiang, "Optimization of multilayer laser cladding process parameters based on NSGA-II-MOPSO algorithm," Opt. Laser Technol., vol. 176, p. 111025, 2024.
- [12] Z. Li, M. Chen, F. Ding, D. Xie, K. Zhou, S. M. R. Naqvi, J. Gu, Y. Liu, X. Gao, D. Wang, M. A. Nasir, and L. Shen, "Hybrid multi-objective optimization based on response surface methodology for laser-cladding repair and remanufacturing technology," Opt. Laser Technol., vol. 183, p. 112347, 2025.
- [13] Q. Zhang, J. Ling, Z. Chen, G. Wu, Z. Yu, Y. Wang, J. Zhou, and J. Yao, "Optimization of laser-induced hybrid hardening process based on response surface methodology and WOA-BP neural network," Appl. Sci., vol. 15, no. 4, p. 1975, 2025.
- [14] Y. Zhang, X. Gao, and S. Katayama, "Weld appearance prediction with BP neural network improved by genetic algorithm during disk laser welding," J. Mater. Process. Technol., vol. 221, pp. 214–224, 2015.
- [15] X. Ren, J. Fan, R. Pan, and K. Sun, "Modeling and process parameter optimization of laser cutting based on artificial neural network and intelligent optimization algorithm," The International Journal of Advanced Manufacturing Technology, vol. 127, pp. 1177–1188, 2023, doi: 10.1007/s00170-023-11543-6.
- [16] Wu Yanwei, Liu Huixia, Li Pin, et al. Experimental Study on Laser Transmission Welding of Polycarbonate and Polyphenylene Oxide [J]. Chinese Journal of Lasers, 2015, 42(5): 0503010.
- [17] Algin H M. Optimised design of jet-grouted raft using response surface method[J].Computers and Geotechnics,2016,74:56-73.
- [18] Pan Lijian, Chen Weifang, Zhou Yanfeng, et al. Optimization of Experimental Apparatus Parameters for Laser-Induced Breakdown Spectroscopy Based on Response Surface Methodology [J]. Chinese Journal of Lasers, 2020, 47(09): 341-347.
- [19] Dai Zongfang. Research on Quality Characteristics and Multi-objective Optimization of Laser Cleaning Process [D]. Jiangsu University, 2021. DOI: 10.27170/d.cnki.gjsuu.2021.000794.
- [20] Qin Haofeng, Cao Lei, Gao Jianguo, et al. Service Life of PTFE Coating on Iron Surface Based on Response Surface Methodology [J]. Surface Technology, 2017, 46(2): 133-137.
- [21] Pang Yifan, Fu Geyan, Wang Mingyu, et al. Parameter Optimization of High Deposition Rate Laser Cladding Based on Response Surface Methodology and Genetic Neural Network Model [J/OL]. Chinese Journal of Lasers: 1-16 [2021-01-13].
- [22] Chu Zhentao, Yu Zhishui, Zhang Peilei, et al. Prediction of Weld Seam Morphology and Optimization of Process Parameters for T-joint Laser Deep Penetration Welding Based on Response Surface Methodology [J]. Chinese Journal of Lasers, 2015, 42(2): 100-108.
- [23] Gao Q, Liu H, Chen P, Liu X, Yang H, Hao J (2023) Multi-objective optimization for laser cladding refractory MoNbTiZr high-entropy alloy coating on Ti6Al4V. Opt Laser Technol 161: 109220.
- [24] Huang Shansong, Du Jihong, Feng Yuankun. Processing Capacity and Generalization Measures of Feedforward Neural Networks [J]. Journal of Tsinghua University (Science and Technology), 1999(07): 54-57.

- [25] Yang S R, Bai H Q, Bao J, et al. Prediction of cladding layer morphology based on BPneural network optimized by regression analysis and genetic algorithm[J/OL]. Laser & Optoelectronics Progress: 1-12[2022-02-04].
- [26] Shen Huayu, Wang Zhaoxia, Gao Chengyao, et al. Determination of the Number of Hidden Layer Units in BP Neural Network [J]. Journal of Tianjin University of Technology, 2008, (05): 13-15.
- [27] Xin-She Yang. Multiobjective firefly algorithm for continuous optimization[J]. Engineering with Computers, 2013, 29(2).
- [28] N. Srinivas, Kalyanmoy Deb. Multiobjective Optimization Using Nondominated Sorting in Genetic Algorithms. [J]. Evolutionary Computation, 1994, 2(3).
- [29] Chen Zhiyuan, Wu Zhangjun, Tong Shanshan. Multi-objective Dynamic Software Project Scheduling Based on Improved Dual-archive Evolutionary Algorithm [J]. Computer Integrated Manufacturing Systems, 2021, 27(9): 2565-2574.
- [30] Li Z (2021) Research on Multi-objective Optimization of Laser Cladding Process Parameters. Harbin Institute of Technology.
- [31] Liang Tianliang. Experimental and Mechanism Research on Pulsed Laser Cleaning Process of 2024 Aluminum Alloy Oxide Film [D]. Shenyang University of Technology, 2023. DOI: 10.27322/d.cnki.gsgyu.2023.000176.
- [32] WANG A, FENG A, GU X, et al. Effect of picosecond laser cleaning on surface morphology and properties of stainless steel[J]. Optics & Laser Technology, 2023, 159 : 109041.
- [33] Wang Wei, Li Xiaoxu, Liu Weijun, et al. Modeling of Cleaning Quality and Multi-objective Optimization of Laser Cleaning 7075 Aluminum Alloy [J]. Journal of Mechanical Engineering, 2025, 61(03): 422-439.
- [34] WANG X, LONG S. Study on hereditary of pores in laser remelting of die casting AZ91D magnesium alloy[J]. Acta Metall Sin, 2012, 48(12) : 1437-1445.
- [35] Li Xiaoxu. Research on Laser Cleaning Process Experiment and Multi-objective Optimization of 7075 Aluminum Alloy [D]. Shenyang University of Technology, 2024. DOI: 10.27322/d.cnki.gsgyu.2024.000535.
- [36] Xu M H, Zhang Q, Yang X X, et al. Impact of surface roughness and humidity on X70 steel corrosion in supercritical CO₂ mixture with SO₂, H₂O, and O₂[J]. The Journal of Supercritical Fluids, 2016, 107: 286-297.1
- [37] Wang P J, Ma L W, Cheng X Q, et al. Influence of grain refinement on the corrosion behavior of metallic materials: A review[J]. International Journal of Minerals, Metallurgy and Materials, 2021, 28: 1112-1126.
- [38] HUANG X, WANG L T, SONG Y F, et al. Effect of Al₂O₃ nanoparticles on the corrosion behavior of aluminum alloy in simulated vehicle coolant[J]. Journal of Alloys and Compounds, 2021, 874: 159807.
- [39] Feng Xiaotian, Gu Hong, Zhou Shengfeng, et al. Microstructure and Electrochemical Corrosion Behavior of Powder-Feeding Laser Additive Manufactured TC4 Titanium Alloy Cladding Layer [J]. Chinese Journal of Lasers, 2019, 46(03): 44-53.