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Multi-objective Optimization of the Laser Cladding Process for Cr12MoV die Steel based on RBF–NSGA-II

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ABSTRACT

To rapidly fabricate Cr12MoV die-steel cladding layers with balanced metallurgical and mechanical properties meeting stringent engineering requirements, laser power (P), scanning speed (V), and feeding rate (S) were systematically optimized using surface roughness (Sa), dilution rate (η), and microhardness (HV) as quantitative evaluation metrics. Sixteen orthogonal experiments were conducted to develop a radial basis function (RBF) neural network prediction model, which was subsequently coupled with the non-dominated sorting genetic algorithm II (NSGA-II) for multi-objective optimization. The orthogonal experimental results and model predictions revealed a complex nonlinear relationship between the laser cladding process parameters and cladding-layer properties. Laser power exerted the dominant influence on surface roughness, whereas feeding rate governed both dilution rate and microhardness most significantly; the established RBF model effectively captured these nonlinear mappings. Following Pareto front identification and experimental validation of seven representative parameter combinations, the engineering-optimal solution was determined as follows: $P = 921.07$ W, $V = 2.28$ mm·s⁻¹, and $S = 0.26$ r·min⁻¹, resulting in $Sa = 11.717$ μ m, $\eta = 19.76\%$, and $HV_{0.025} = 671.57$. The results demonstrate that the RBF–NSGA-II multi-objective optimization framework effectively addresses the limitation of orthogonal experimental design associated with discrete factor levels by enabling continuous optimization within the experimentally investigated parameter space, thereby offering a robust, efficient, and scalable methodology for optimizing laser cladding parameters to achieve target-oriented cladding-layer performance fulfilling engineering requirements.

Keywords: Laser cladding; Cr12MoV die steel; RBF neural network; NSGA-II; Multi-objective optimization.

Introduction

Cr12MoV is a high-carbon, high-chromium cold-work die steel widely employed in cold-forming dies owing to its exceptional hardness, outstanding wear resistance, and superior hardenability[1]. Nevertheless, under prolonged cyclic loading and abrasive–adhesive wear conditions, the working surface is prone to progressive wear, fatigue cracking, and localized plastic deformation, leading to premature failure, reduced service life, and elevated maintenance expenditures [2, 3]. Laser cladding is an advanced surface engineering and remanufacturing technique characterized by high energy density, a narrow heat-affected zone, minimal substrate distortion, and metallurgical bonding between the clad layer and the substrate. Consequently, high-performance alloy coatings can be precisely deposited onto material surfaces to enhance wear resistance and service performance [4-6]. Liu et al. [7] fabricated WC-particle-reinforced composite coatings on Cr12MoV steel via laser cladding and demonstrated substantial improvements in microstructure and wear resistance, indicating strong potential for surface strengthening. However, clad-layer quality is highly sensitive to process parameters; improper matching of laser power, scanning speed, and feeding rate may result in unstable surface formation, excessive substrate dilution, and degradation of mechanical properties [8-11]. Accordingly, systematic experimental optimization of process parameters is generally required prior to laser cladding for die repair.

Orthogonal experimental design and response surface methodology (RSM) are currently among the most commonly used methods for optimizing laser cladding parameters. Yuan et al. [12] and Dong et al. [13] used orthogonal experiments to evaluate the effects of laser power, scanning speed, and feeding rate on cladding-layer formation and properties and to identify favorable parameter combinations. For Ni60 and WC-reinforced composite clad layers, related studies have further applied methods such as orthogonal experiments and multi-response evaluation to the experimental process [14, 15], enabling comprehensive parameter screening under different performance criteria. The results indicate that orthogonal experiments can quickly identify the main influencing factors through a small number of representative tests; however, their optimization outcomes are constrained by predefined parameter ranges and discrete levels, making it difficult to achieve further optimization within continuous parameter ranges. To address this limitation, Liu et al. [16] and Feng et al. [17] employed RSM to establish regression models relating process parameters to quality indicators such as cladding geometry, dilution rate, and microhardness and then performed multi-response optimization. Wei et al. [18] further coupled response-surface models with multi-objective optimization to achieve coordinated optimization of laser cladding parameters. Nevertheless, response surface methodology can only use low-order polynomials to describe the relationship between process parameters and performance, making it difficult to fully capture complex nonlinear relationships.

Machine learning has strong potential for handling complex nonlinear relationships. Tyagi et al. [19] and Gao et al. [20] respectively employed machine learning methods such as artificial neural networks, random forests, and BP neural

networks to establish predictive models linking laser cladding process parameters with clad layer properties, achieving good consistency between predicted and experimental results. Compared to traditional BP neural networks, RBF neural networks offer faster learning speeds, stronger nonlinear approximation capabilities, and superior prediction and generalization performance, making them suitable for modeling and predicting complex nonlinear systems under small sample conditions and enabling rapid performance predictions for various parameter combinations [21-23]. Based on these process-performance prediction models, Cai et al. [24] and Huang et al. [25] further integrated the models with multi-objective evolutionary algorithms such as Non-dominated Sorting Genetic Algorithm II (NSGA-II), achieving trade-offs among multiple performance objectives through Pareto non-dominated solutions. NSGA-II is a mainstream algorithm in multi-objective optimization, capable of overcoming the tendency of genetic algorithms to fall into local optima, and is more suitable than particle swarm optimization for handling discrete data [26, 27]. Therefore, this study ultimately adopts RBF neural network to build a predictive model relating process parameters to cladding performance, and combines it with NSGA-II for multi-objective optimization.

In this study, Cr12MoV cold-work die steel was used as the substrate and a Ni-based WC composite powder was used to fabricate laser-cladded layers. The overall workflow is illustrated in Fig. 1. First, orthogonal experiments were conducted to determine the effects of laser power, scanning speed, and feeding rate on surface roughness, dilution rate, and microhardness. Next, an RBF neural network was developed to map the process parameters to cladding-layer properties, and its predictive performance was evaluated. Finally, NSGA-II was employed for multi-objective optimization of the laser cladding parameters to obtain a Pareto non-dominated solution set, from which representative parameter combinations were selected for experimental validation and comprehensive engineering evaluation.

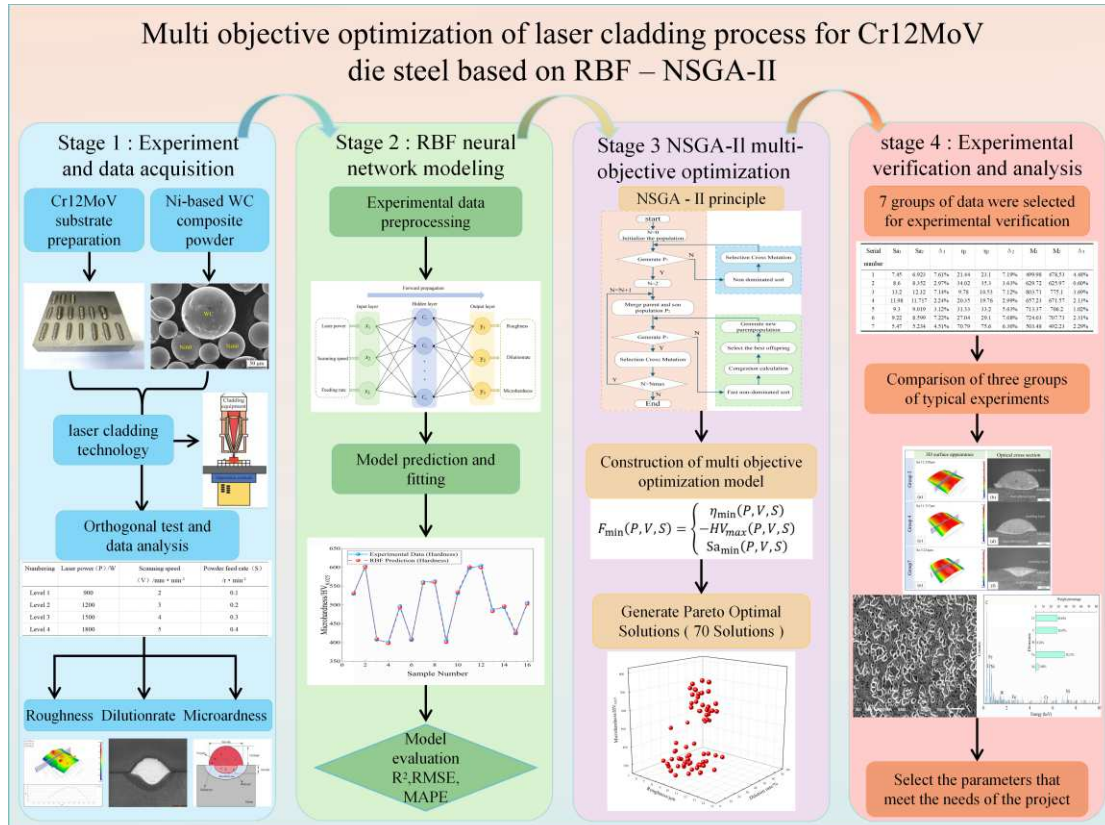


Figure 1 Overall flowchart of multi-objective process optimization for laser cladding of Cr12MoV mold steel based on RBF-NSGA II

1 Orthogonal Experimental Materials and Design

1.1 Materials

The substrate material was Cr12MoV cold-work die steel with dimensions of 100 mm × 100 mm × 15 mm. Before cladding, the workpiece surface was ground and polished to improve flatness and then cleaned with anhydrous ethanol to remove oil and other contaminants. The chemical composition of the substrate is listed in Table 1.

Table 1. Chemical composition of Cr12MoV die steel (wt.%)

Element	Cr	C	Mo	V	Mn	Si	S	P	Fe
wt.%	11.77	1.54	0.45	0.18	0.4	0.11	0.011	0.023	Bal.

The cladding feedstock consisted of a homogeneous mixture of spherical Ni-based alloy powder and tungsten carbide (WC), with a WC content of 15 wt.%. The particle-size ranges of the Ni-based alloy powder and WC were 49.25-116.12 μm and 49.25-159.35 μm, respectively. The morphology of the mixed powder is shown in Fig. 2

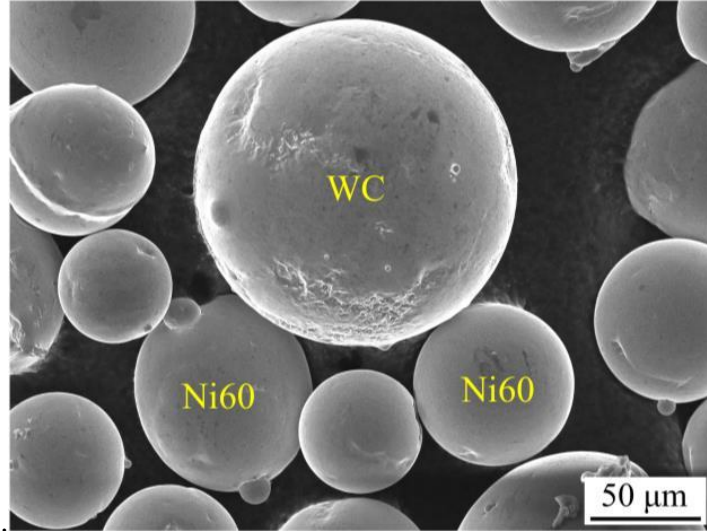


Fig. 2. SEM morphology of the mixed Ni60 and WC powders

The mixed powder was dried in a DZF-6050 benchtop vacuum oven at 60 °C for 60 min. Its chemical composition is given in Table 2.

Table 2. Chemical composition of the Ni-based WC composite powder (wt.%)

Element	Cr	Fe	C	B	Si	W	O	Ni
wt.%	14.58	3.85	0.78	2.55	3.58	14.12	<0.05	Bal.

1.2 Experimental Design

The laser cladding system consisted primarily of a laser emitter, a six-degree-of-freedom robotic arm, a water cooling device, a laser cladding head, a coaxial powder feeding system, a robot control cabinet, a workbench, a PLC controller, and an argon supply, as shown in Fig. 3. The laser system, manufactured by Raycus, was equipped with an RFL-C3000s fiber laser and a coaxial powder feeding system. The maximum output power was 3 kW and the central laser wavelength was 1080 ± 5 nm. A DPSF-2

dual-hopper powder feeder with a 2 L hopper capacity was used; its feeding rate ranged from 0 to 10 r·min⁻¹, and the feeding disk was 16 mm wide and 1 mm deep. Argon was used for both powder delivery and shielding at a gas flow rate of 5 NL/min.

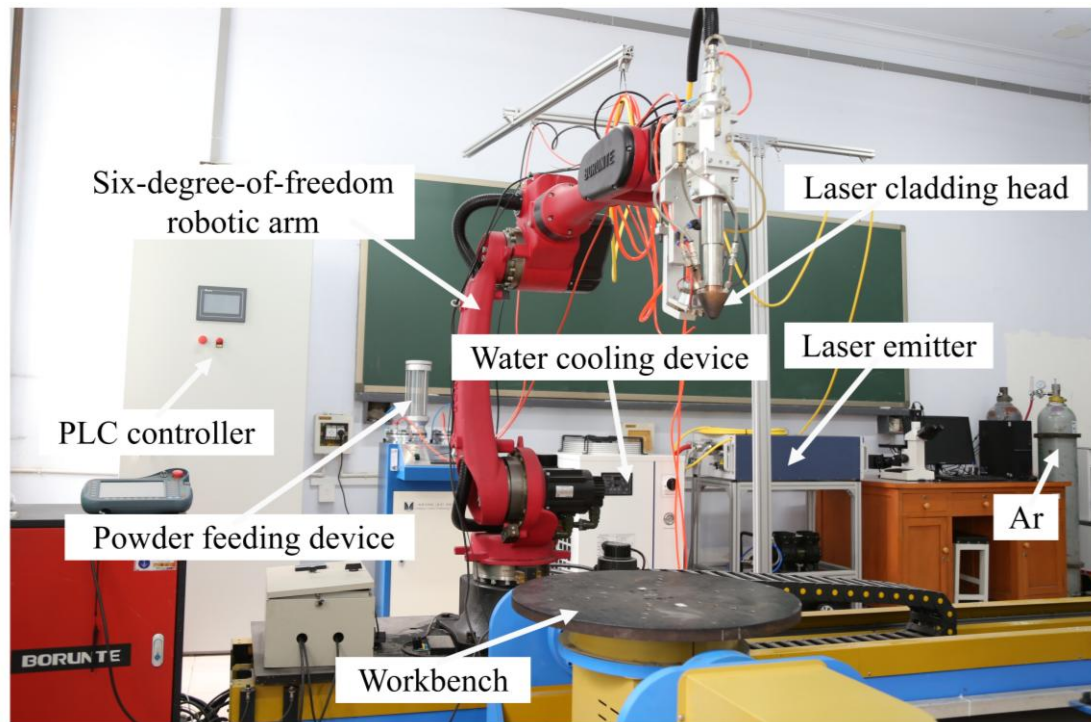


Figure 3 Schematic diagram of the laser cladding system setup

Laser power (P), scanning speed (V), and feeding rate (S) were selected as the three factors for process optimization. Each factor was examined at four levels, resulting in 16 orthogonal experimental runs. The three-factor, four-level design is listed in Table 3.

Table 3. Factors and levels used in the orthogonal experiment

Numbering	Laser power(P)/W	Scanning speed (V)/mm·s ⁻¹	Powder feed rate(S)/r·min ⁻¹
Level 1	900	2	0.1
Level 2	1200	3	0.2
Level 3	1500	4	0.3
Level 4	1800	5	0.4

1.3 Evaluation Metrics

After laser cladding, the specimens were sectioned perpendicular to the cladding direction using wire electrical discharge machining, followed by grinding, polishing, and etching for metallographic examination. The cross section consisted primarily of the cladding layer, the heat-affected zone (HAZ), and the Cr12MoV substrate. Cross-sectional morphology of the cladding layer—including the cladding-layer profile, clad width, clad height, clad depth, molten pool boundary, and HAZ—was examined using

a Leica DMI3000M inverted optical microscope. Obvious defects, such as cracks and pores, were also assessed.

Surface roughness (S_a) is an important indicator of cladding-layer surface quality [28]. A ZYGO white-light interferometer was used to measure the surface roughness. To minimize the influence of fluctuations at the start and end of the cladding track, all measurements were taken from the central region of a single-track cladding layer, and the measured S_a was used to characterize surface quality. Lower surface roughness helps improve the flatness of the clad layer and reduces the machining allowance required in subsequent multi-pass overlapping and mechanical processing.

Dilution rate (η) is an important indicator of metallurgical bonding between the cladding layer and substrate [29]. An appropriate dilution rate not only ensures sound metallurgical bonding but also prevents excessive dilution by the substrate. A schematic of the cladding-layer cross section is shown in Fig. 4. The dilution rate was calculated from the geometric areas of the cross section as follows:

$$\eta = \frac{S_2}{(S_1 + S_2)} \quad (1)$$

where S_1 is the cross-sectional area of the cladding layer and S_2 is the area of the molten pool.

Microhardness (HV) is an important indicator for evaluating the mechanical and wear-resistant performance of the cladding layer [30]. A THV-2MD automatic turret Vickers microhardness tester was used under a test force of 0.245 N (25 gf). Five measurement points were selected in the central region of each cladding layer, and their average value was taken as the microhardness of the corresponding specimen. Higher microhardness improves the resistance of the cladding layer to plastic deformation and wear.

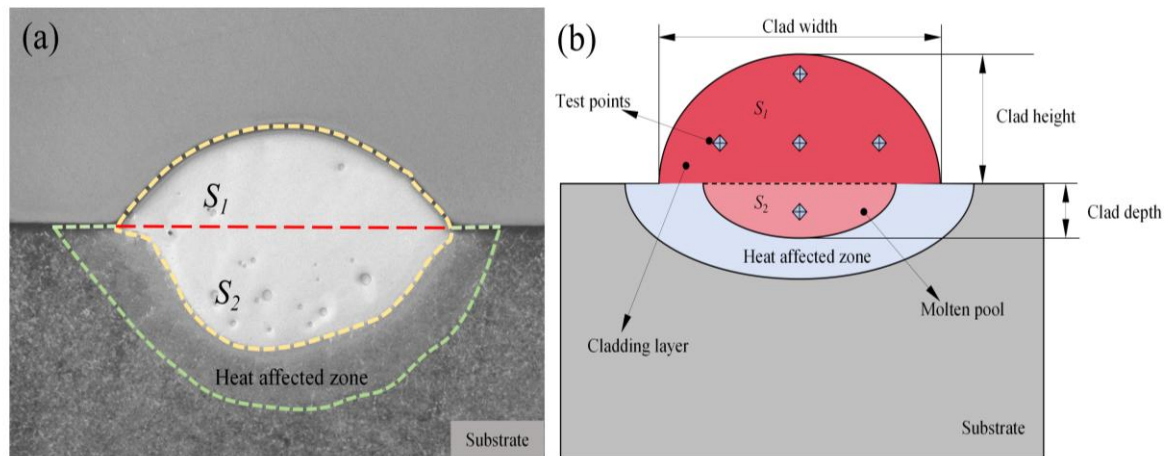


Figure 4 Schematic of the cross-sectional morphology of the clad layer

1.4 Results and Analysis of the Orthogonal Experiments

The orthogonal experimental results are summarized in Table 4, and the corresponding cross-sectional morphologies of the cladding layers are shown in Fig. 5.

Table 4 Orthogonal Experiment Results

Number	Variable			Response		
	Laser power /W	Scanning speed /(mm·s ⁻¹)	Feeding rate /(r·min ⁻¹)	Roughness /μm	Dilutionrate /%	Microhardness /HV _{0.025}
1	900	2	0.1	18.611	51.67	623.46
2	900	3	0.2	13.849	33.54	609.83
3	900	4	0.3	14.623	25.54	383.03
4	900	5	0.4	15.878	17.19	381.21
5	1200	2	0.2	17.486	30.41	502.54
6	1200	3	0.1	12.605	60.55	387.15
7	1200	4	0.4	15.452	42.76	557.61
8	1200	5	0.3	10.454	59.49	557.93
9	1500	2	0.3	11.776	25.99	408.14
10	1500	3	0.4	12.262	28.39	529.98
11	1500	4	0.1	11.426	68.79	589.00
12	1500	5	0.2	13.382	55.84	603.68
13	1800	2	0.4	9.99	25.84	482.81
14	1800	3	0.3	13.273	41.46	490.31
15	1800	4	0.2	9.772	51.59	411.6
16	1800	5	0.1	8.793	78.56	509.15

In the 16 experimental groups, surface roughness, dilution rate, and microhardness showed significant variations with changes in process parameters, indicating that the process parameters have a substantial influence on the properties of the clad layer.

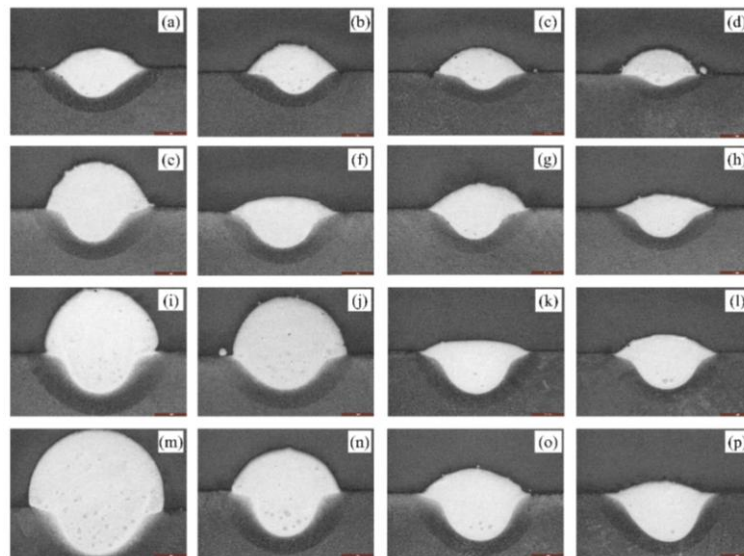


Fig. 5. Cross-sectional morphologies of the cladding layers obtained in the orthogonal experiments

The range value (R) is defined as the difference between the maximum and minimum average response at different levels of the same process factor. A larger R indicates a stronger influence of that factor on the corresponding response. The mean surface roughness, dilution rate, and microhardness at different factor levels are shown in Fig. 6, and the range-analysis results are summarized in Table 5.

Table 5 Range Analysis of Process Parameters on Coating Performance

Factor	Range value	Roughness / μm	Dilutionrate /%	Microhardness /HV _{0.025}
Laser power/W		5.28	17.38	59.23
Scanning speed/(mm·s ⁻¹)	R	2.34	19.29	27.68
Powder feed rate/(r·min ⁻¹)		1.09	36.35	72.06

According to Table 5 and Fig. 6, laser power had the greatest effect on surface roughness, followed by scanning speed and feeding rate, giving the influence order $P > V > S$. Surface roughness decreased with increasing laser power and showed an overall downward trend with increasing scanning speed, whereas feeding rate had a comparatively small effect. Feeding rate exerted the strongest influence on dilution rate, followed by scanning speed and laser power ($S > V > P$). The dilution rate decreased markedly with increasing feeding rate but increased with scanning speed. Laser power had a relatively minor effect on dilution rate, which exhibited an overall increasing trend. Feeding rate also had the greatest effect on microhardness, followed by laser power, while scanning speed had the least influence, yielding $S > P > V$. Microhardness exhibited a nonlinear dependence on the process parameters.

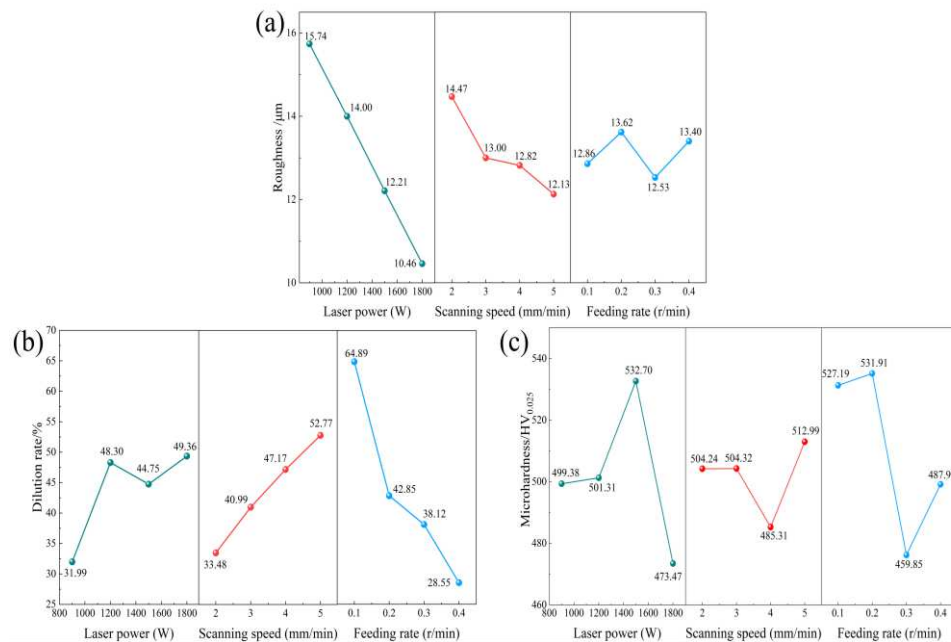


Figure 6: Main effect means of process parameters: (a) surface roughness, (b) dilution rate, (c) microhardness

2 Construction of the RBF Neural-Network Prediction Model

2.1 RBF Neural Network Architecture

The RBF neural network is a typical three-layer feedforward neural network, primarily composed of an input layer, a hidden layer, and an output layer, as shown in Figure 7.

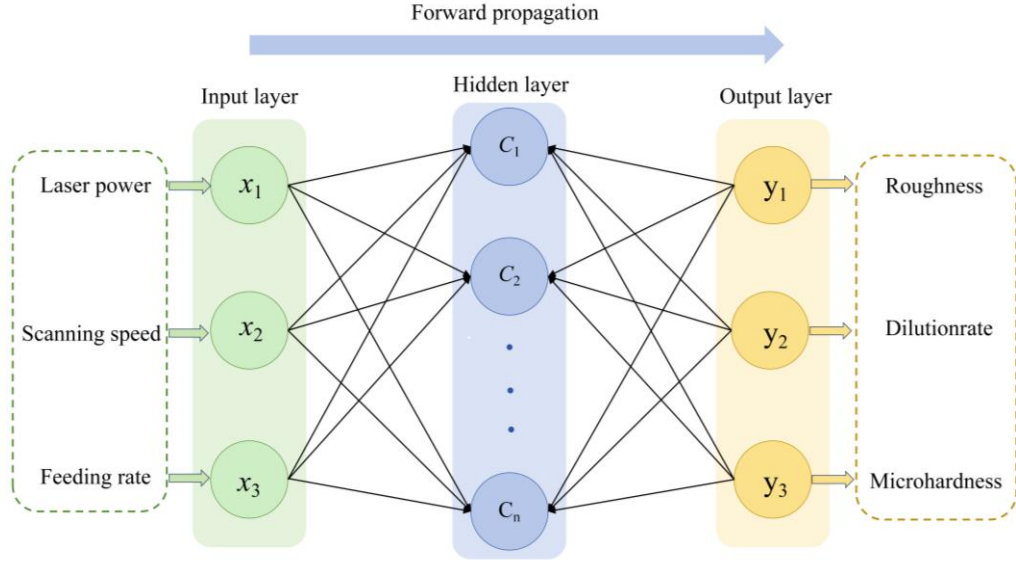


Figure 7 Structure of the RBF neural network

The input-layer nodes correspond to the laser cladding process parameters, namely laser power P , scanning speed V , and feeding rate S , whereas the output-layer nodes correspond to the cladding-layer responses, namely surface roughness (S_a), dilution rate (η), and microhardness (HV). The RBF neural network nonlinearly maps the input variables through radial basis functions in the hidden layer, and the output layer linearly weights the hidden-layer responses to produce the predicted properties. A Gaussian function was adopted as the radial-basis activation function in the hidden layer:

$$\phi(x) = \exp\left(-\frac{\|x - c_i\|^2}{2\sigma_i^2}\right) \quad (2)$$

where x is the input vector; c_i is the center of the i th hidden-layer neuron; σ_i is the radial-basis width; and $\|x - c_i\|$ is the Euclidean distance between the input vector and the center vector.

The network output is expressed as:

$$Y = \sum_{i=1}^n w_i \phi(x) \quad (3)$$

where w_i denotes the connection weight between the hidden and output layers.

Three independent RBF neural network models were constructed using the 16 orthogonal experimental datasets to predict surface roughness, dilution rate, and microhardness, respectively. To reduce the effect of scale differences among the variables on model training, both the input and output data were normalized to the range

of 0–1. The mean squared error goal, spread, and maximum number of neurons were set to 0.01, 1, and 20, respectively. The RBF models were trained using the MATLAB `newrb` function by incrementally adding radial basis neurons according to the fitting error. After training, the models predicted surface roughness, dilution rate, and microhardness for any specified combination of laser power, scanning speed, and feeding rate within the studied range.

To evaluate predictive accuracy, the coefficient of determination (R^2), root-mean-square error (RMSE), and mean absolute percentage error (MAPE) were used as model evaluation metrics [31-33]:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (6)$$

where y_i is the experimental value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the mean experimental value, and n is the number of samples. An R^2 value closer to 1 indicates stronger fitting performance, whereas lower RMSE and MAPE values indicate smaller prediction errors and higher predictive accuracy.

2.2 RBF Neural Network Fitting Results and Analysis

After training, the RBF predictions were compared with the experimental values, as shown in Fig. 8. For surface roughness, dilution rate, and microhardness, the predicted and experimental results exhibited consistent overall trends, indicating that the established RBF model effectively captured the nonlinear relationships between laser power, scanning speed, feeding rate, and cladding-layer properties.

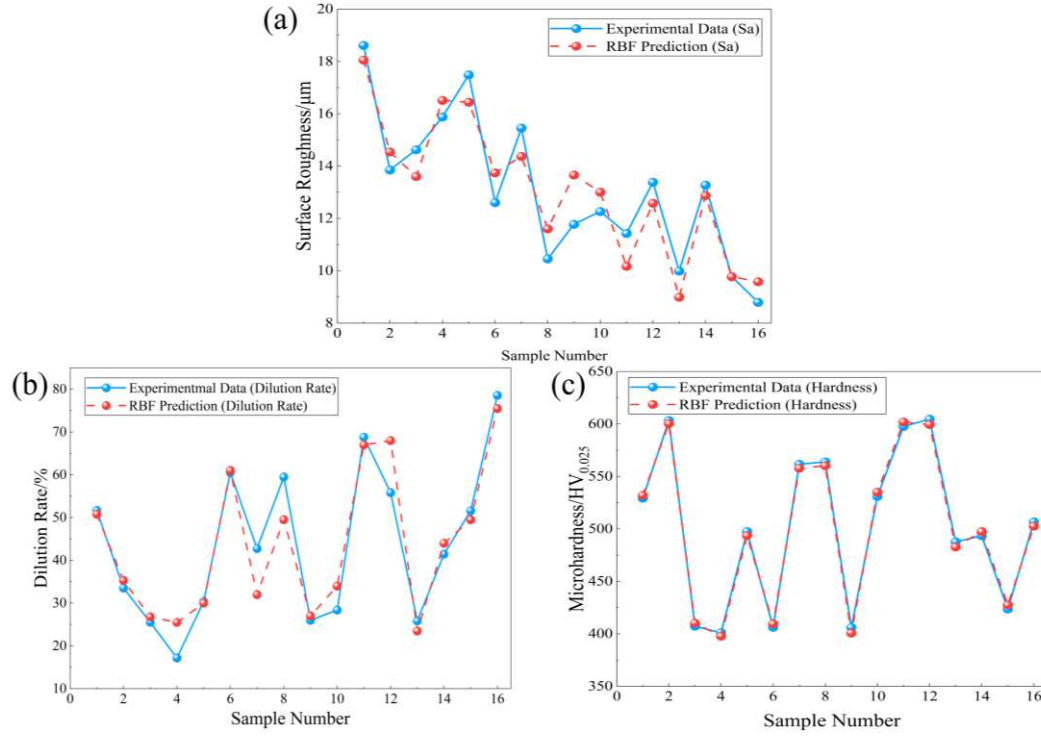


Fig. 8. Comparison between experimental values and RBF predictions

For the dilution-rate model, R^2 , RMSE, and MAPE were 0.8967, 5.5883, and 10.96%, respectively. The corresponding values for the microhardness model were 0.9984, 3.28, and 0.62%, while those for the surface-roughness model were 0.992, 0.97, and 7.06%. The R^2 values of the microhardness and surface-roughness models were both close to 1, indicating strong agreement between predictions and experiments. Although the dilution-rate model showed comparatively lower fitting accuracy, it still reproduced the overall variation trend well.

Taken together, the three evaluation metrics demonstrate that the RBF neural network can effectively model the complex nonlinear relationships between the process parameters and surface roughness, dilution rate, and microhardness. The overall fitting performance is satisfactory, enabling prediction of cladding-layer properties for specified process conditions and providing a reliable surrogate model for subsequent NSGA-II multi-objective optimization.

3 Multi-objective Optimization Based on NSGA-II

3.1 Principle of NSGA-II

The non-dominated sorting genetic algorithm II (NSGA-II) is a genetic-algorithm-based method for multi-objective optimization. For two individuals a and b , a is said to dominate b if a is no worse than b for all objectives and is strictly better in at least one objective. If neither individual satisfies this dominance relation with respect to the other, the two are considered mutually non-dominated.

Fig. 9 illustrates the NSGA-II procedure. The population is first sorted according to the dominance relationships among individuals and divided into Pareto fronts of different ranks, with the first front comprising the non-dominated individuals in the current population. To maintain a uniform distribution of non-dominated solutions in objective space, NSGA-II introduces the crowding distance, which evaluates the local density of solutions around each individual. Among individuals belonging to the same non-dominated rank, those with larger crowding distances are preferentially retained, thereby preventing excessive clustering of the solution set in local regions.

During iteration, the parent population undergoes selection, crossover, and mutation to generate an offspring population. The parent and offspring populations are then merged and subjected again to non-dominated sorting and crowding-distance calculation. Superior individuals are selected according to rank and crowding distance to form a new parent population, while elite individuals from the previous generation are retained. The new parent population continues through crossover and mutation to generate the next generation. This cycle is repeated until the termination criterion is reached, yielding the final set of Pareto non-dominated optimal solutions.

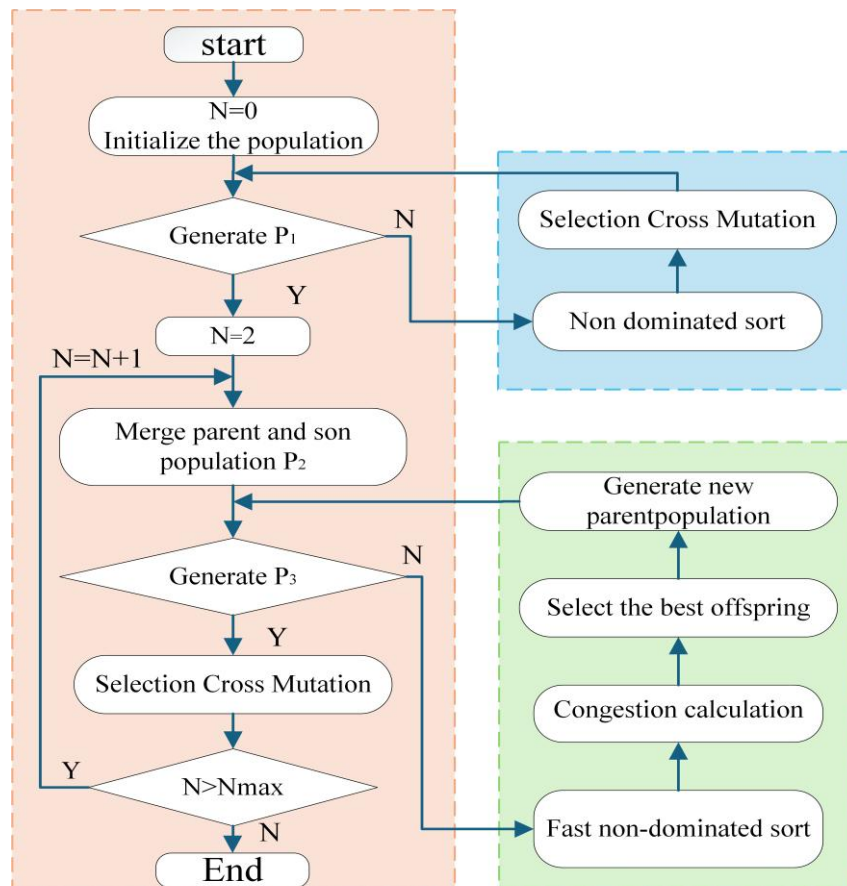


Figure 9 Flowchart of the NSGA-II multi-objective optimization algorithm

3.2 Formulation of the Multi-objective Optimization Model

Dilution rate (η), microhardness (HV), and surface roughness (Sa) were defined as the three optimization objectives. In practical laser cladding, excessive dilution increases the tendency of the cladding layer to crack; hence, the dilution rate should be minimized. Excessive surface roughness reduces the wettability and flatness of the cladding layer and is unfavorable for subsequent multi-track overlapping, so surface roughness should also be minimized. Microhardness is a key indicator of the mechanical performance of the cladding layer; therefore, maximizing microhardness was selected as the third objective to improve the surface-strengthening effect. Accordingly, the multi-objective optimization model for the laser cladding process parameters was formulated as follows:

$$\begin{cases} \eta = RBF_{1min}(P, V, S) \\ HV = RBF_{2max}(P, V, S) \\ Sa = RBF_{3min}(P, V, S) \end{cases} \quad (7)$$

where P is laser power, V is scanning speed, and S is feeding rate.

The constraints refer to the allowable ranges of values for each process parameter during laser cladding, determined by the actual equipment specifications and the orthogonal experimental design. The inequality constraints for each process parameter are as follows:

$$s.t. \begin{cases} 900W \leq P \leq 1800W \\ 2mm \min^{-1} \leq V \leq 5mm \min^{-1} \\ 0.1r \min^{-1} \leq S \leq 0.4r \min^{-1} \end{cases} \quad (8)$$

This study employs the minimization method to optimize each process parameter, requiring the inverse mathematical equation of the microhardness objective model, where $\eta(P, V, S)$, $HV(P, V, S)$, and $Sa(P, V, S)$ are predicted by RBF neural network models. To facilitate unified solving using the NSGA-II algorithm, the multi-objective optimization problem is transformed into a minimization form by taking the negative of the microhardness objective function. The final multi-objective optimization model can be expressed as:

$$F_{min}(P, V, S) = \begin{cases} \eta_{min}(P, V, S) \\ -HV_{max}(P, V, S) \\ Sa_{min}(P, V, S) \end{cases} \quad (9)$$

3.3 Optimization Results

Based on the established RBF prediction model, NSGA-II was employed to perform multi-objective optimization of laser power, scanning speed, and feeding rate. The population size was set to 200, the maximum number of generations to 100, and the Pareto fraction to 0.35. The remaining algorithm parameters were kept at their default values. After iterative optimization, 70 Pareto non-dominated solutions were obtained, as shown in Fig. 10.

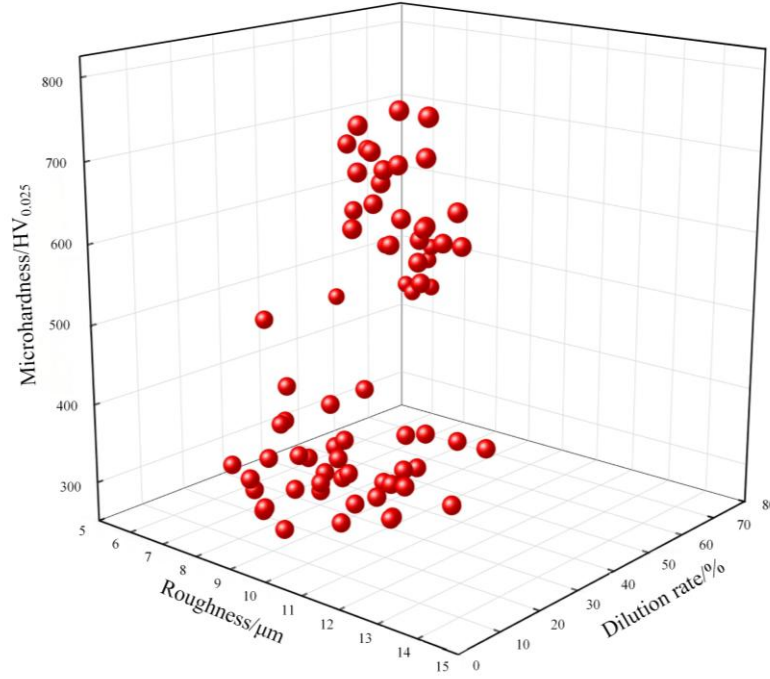


Figure 10: Pareto non-dominated solution set of 70 groups

The 70 Pareto non-dominated solutions obtained by NSGA-II reveal a clear trade-off among the three performance objectives. Solutions favoring different performance attributes are distributed in distinct regions of the Pareto front, providing multiple parameter combinations with different property profiles and thereby supporting process selection for different engineering requirements.

According to the distribution of the Pareto solutions, seven representative parameter combinations were selected from different regions of the front; their process parameters and predicted properties are listed in Table 6. The selected solutions span regions characterized by relatively low surface roughness, low dilution rate, high microhardness, and more balanced combinations of all three responses, thereby providing a representative comparison of alternative process strategies. These results indicate that coupling the RBF prediction model with NSGA-II enables simultaneous exploration of multiple performance objectives within the prescribed parameter space and yields optimized parameter combinations for further screening.

Table 6. Seven representative Pareto parameter combinations and predicted properties

number	Variable			Response		
	Laser power /W	Scanning speed /(mm·s ⁻¹)	Feeding rate/(r·min ⁻¹)	Roughness /μm	Dilution-rate/%	Microhardness/HV _{0.025}
1	1610.35	4.01	0.14	7.45	21.44	499.98
2	1772.15	2.06	0.39	8.6	34.02	629.72
3	931.3	2.29	0.3	13.2	9.78	803.71
4	921.07	2.28	0.26	11.98	20.35	657.23
5	1286.94	4.87	0.36	9.3	31.33	713.37
6	1399.44	4.87	0.36	9.22	27.04	724.03
7	1368.18	4.7	0.14	5.47	70.79	503.48

Because the above results were obtained from model predictions, laser cladding experiments were subsequently conducted using the seven selected parameter combinations. The experimental results were compared with the corresponding model predictions to further evaluate the practical performance of the optimized conditions and to verify the reliability of the RBF-NSGA-II multi-objective optimization framework.

4 Optimization Parameter Experiment Validation and Tissue

Performance Analysis

4.1 Experimental Validation of Pareto-Optimal Parameters

Table 7 compares the experimental results with the model predictions for the seven selected parameter combinations. The three measured responses were generally consistent with the corresponding predictions. The relative errors were 2.24%–7.61% for surface roughness and 2.99%–7.19% for dilution rate, while all microhardness errors were below 5%. These small discrepancies indicate that the RBF model can accurately predict the cladding-layer properties associated with the Pareto-optimal parameters and that the NSGA-II-derived parameter sets exhibit good experimental consistency.

Table 7. Comparison of experimental results and model predictions for the seven parameter combinations

Number	Sa ₁ /μm	Sa ₂ /μm	Δ ₁ /%	η ₁ /%	η ₂ /%	Δ ₂ /%	M ₁ /HV _{0.025}	M ₂ /HV _{0.025}	Δ ₃ /%
1	7.45	6.923	7.61%	21.44	23.1	7.19%	499.98	478.53	4.48%
2	8.6	8.352	2.97%	34.02	35.3	3.63%	629.72	625.97	0.60%
3	13.2	12.32	7.14%	9.78	10.53	7.12%	803.71	775.1	3.69%
4	11.98	11.717	2.24%	20.35	19.76	2.99%	657.23	671.57	2.13%
5	9.3	9.019	3.12%	31.33	33.2	5.63%	713.37	706.2	1.02%
6	9.22	8.599	7.22%	27.04	29.1	7.08%	724.03	707.73	2.31%
7	5.47	5.234	4.51%	70.79	75.6	6.36%	503.48	492.23	2.29%

Note: Sa₁, η₁, and M₁ represent the model-predicted values, whereas Sa₂, η₂, and M₂ represent the corresponding experimental values. Δ₁, Δ₂, and Δ₃ denote the relative errors of Sa, η, and M.

Among the seven experimental conditions, Group 3 exhibited the lowest dilution rate and the highest microhardness but a relatively high surface roughness. Group 7 produced the lowest surface roughness but by far the highest dilution rate and comparatively low microhardness. In contrast, Group 4 showed balance values for all three responses. These three conditions directly illustrate the trade-offs among surface roughness, dilution rate, and microhardness, consistent with the Pareto optimization results.

Groups 3, 4, and 7, which represent distinct property profiles, were selected for further comparative analysis. Their surface formation, cross-sectional morphology, and microstructural characteristics were examined to assess the practical engineering suitability of different performance trade-off strategies and to identify the parameter combination offering the best overall performance for engineering application.

4.2 Analysis of Cladding Layers under Different Optimized Parameters

As shown by the surface and cross-sectional morphologies in Fig. 11, the three cladding layers exhibited markedly different formation characteristics. Group 3 showed pronounced surface undulation and obvious cross-sectional defects; bonding with the

substrate was insufficient, resulting in poor overall formation. Group 4 exhibited stable surface formation, a complete cross-sectional profile without obvious defects, and sound bonding with the substrate, giving a well-balanced overall morphology. Group 7 had a relatively smooth surface, but the substrate was extensively melted, producing a large heat-affected zone and evident substrate erosion.

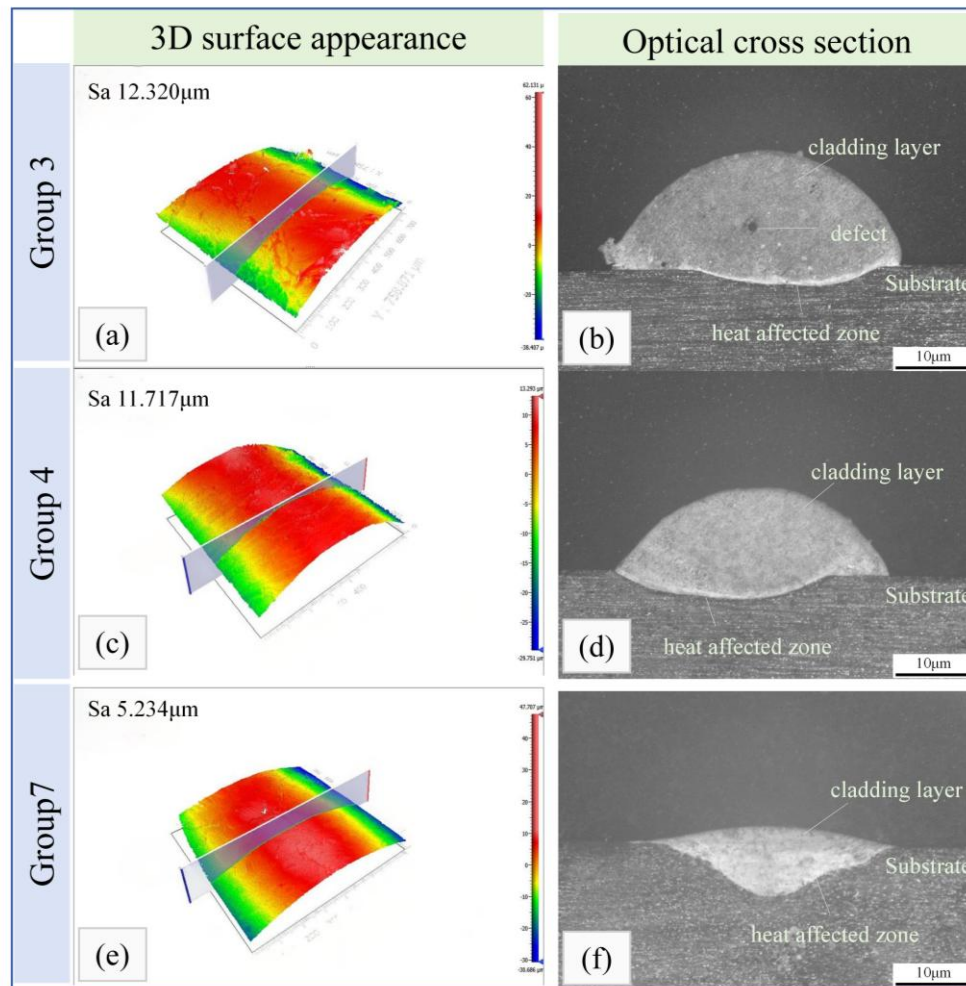


Fig. 11. Comparison of surface and cross-sectional morphologies for Groups 3, 4, and 7

As shown in Fig. 12, the microstructures in the top, middle, and bottom regions of Groups 3 and 4 were broadly similar, with cellular grains, dendrites, and directionally grown columnar dendrites observed in both cases. Compared with Group 3, Group 4 exhibited more uniform grain sizes, a more regular microstructural distribution, and more continuous transitions between different regions. Group 7 differed markedly from the other two conditions, showing more pronounced grain coarsening and directional growth and, consequently, lower microstructural uniformity.

These differences are associated with variations in laser energy input, feeding rate, and molten pool composition. Groups 3 and 4 had similar laser power and scanning speed; however, the lower feeding rate in Group 4 allowed more energy to be delivered per unit amount of powder, helping stabilize the molten pool temperature and composition and promoting a more uniform and continuous solidification microstructure. EDS analyses were performed at points 1-8 in Fig. 12, corresponding

sequentially to Fig. 13(a)-(h). The measurement points in Group 3 exhibited relatively high Cr, C, and Ni contents, whereas the different microstructural regions in Group 4 were distinguished mainly by variations in Cr, C, and Fe contents. This indicates that local elemental distributions remained different between the two groups even under similar thermal conditions, potentially affecting solute redistribution and grain-growth behavior during solidification. In Group 7, the feeding rate was further reduced under higher laser power and scanning speed, increasing the extent of substrate melting. Consequently, the Fe content measured by EDS was higher than that in Group 3, and the variations in Cr, Fe, and Ni among different regions became more pronounced. The increased participation of substrate elements, together with stronger local compositional heterogeneity and a larger temperature gradient, altered the solidification process, promoted columnar-dendrite growth along the heat-flow direction, and intensified local grain coarsening.

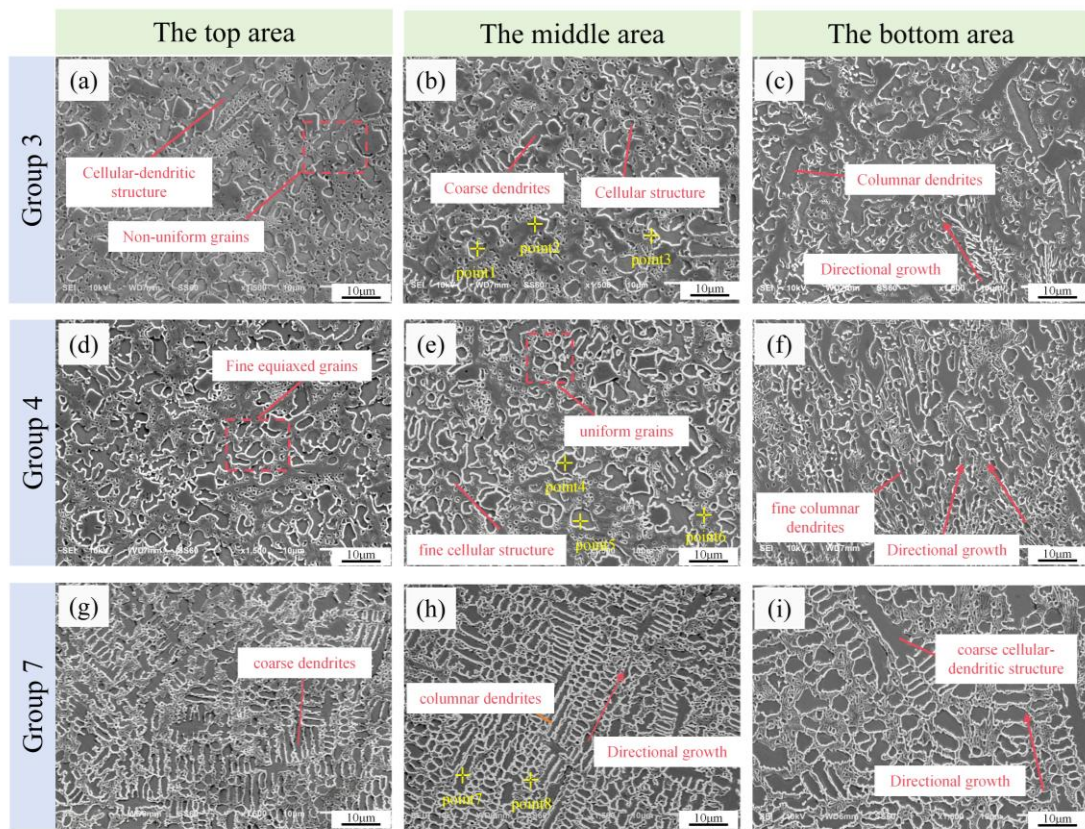


Fig. 12. SEM micrographs of the cladding layers obtained using Groups 3, 4, and 7

A comprehensive evaluation of the macroscopic morphology, microstructure, and elemental distribution across the three cladding layers reveals that Group 4 demonstrates superior microstructural uniformity and process stability, rendering it more suitable for engineering applications.

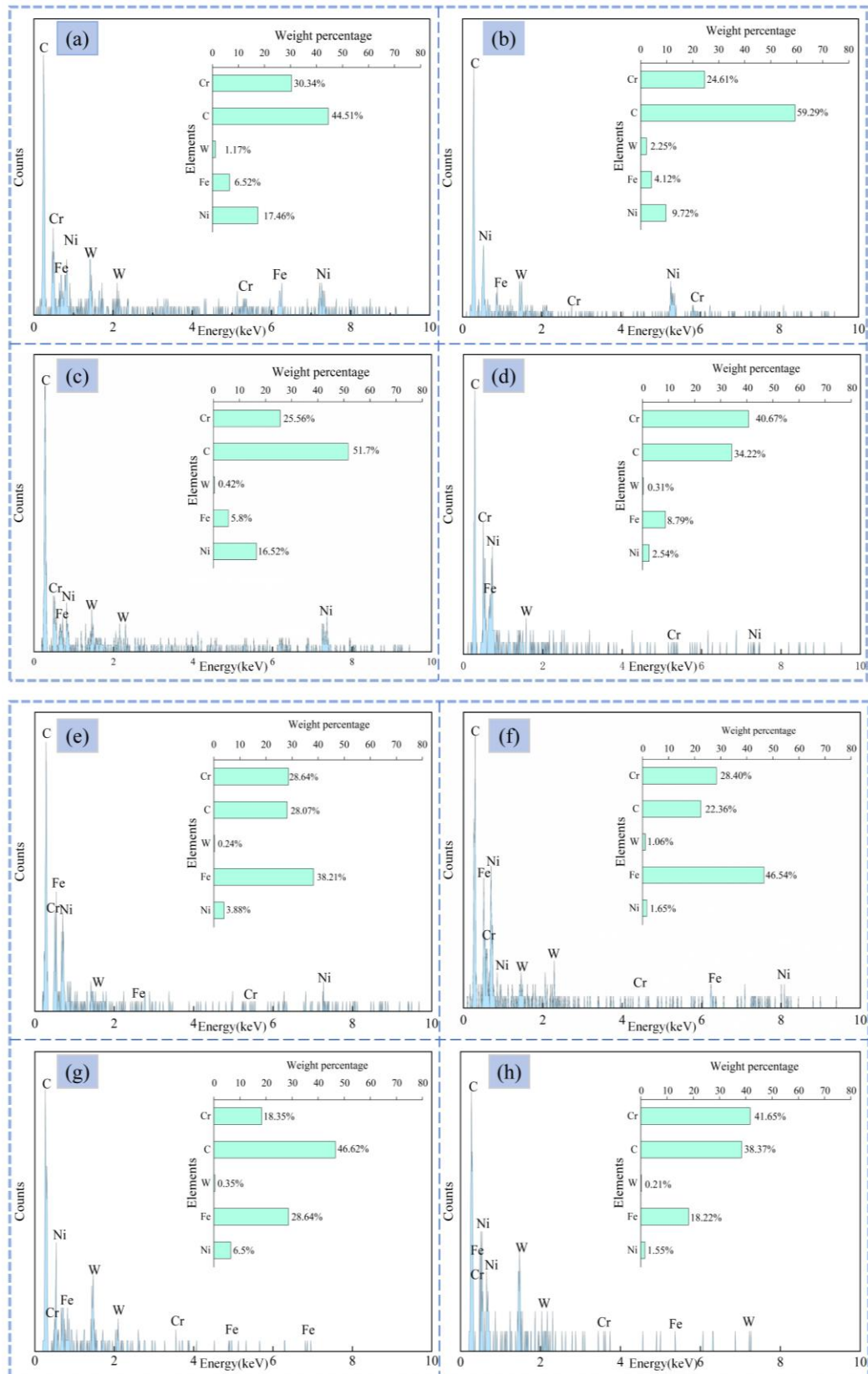


Fig. 13. EDS results for the cladding layers obtained using Groups 3, 4, and 7

5 Conclusion

This study addressed the difficulty of concurrently optimizing surface roughness, dilution rate, and microhardness in laser cladding of Cr12MoV die steel. The effects of process parameters were first analyzed through orthogonal experiments, after which an RBF neural network and NSGA-II were combined for multi-objective optimization and experimental validation. The main conclusions are as follows:

(1) By using an RBF prediction model combined with the NSGA-II algorithm for multi-objective optimization, Pareto-optimal process parameter combinations that met engineering requirements were quickly obtained within a given process range.

(2) Laser power was the dominant factor affecting surface roughness, which decreased markedly with increasing laser power. The feeding rate was the principal factor governing dilution rate and microhardness, and the dilution rate decreased substantially as the feeding rate increased.

(3) Based on the integrated Pareto optimization and experimental validation results, Group 4 was identified as the preferred engineering condition, with a laser power of 921.07 W, a scanning speed of $2.28 \text{ mm}\cdot\text{s}^{-1}$, and a feeding rate of 0.26 r min^{-1} . The corresponding surface roughness, dilution rate, and microhardness were $11.717 \text{ }\mu\text{m}$, 19.76%, and $671.57 \text{ HV}_{0.025}$, respectively. The resulting cladding layer exhibited stable formation, a cross section without obvious defects, sound metallurgical bonding with the substrate, and relatively high microhardness. This parameter combination delivers a well-balanced property profile suitable for engineering applications.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Declaration of competing interests statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contributions

Changlong Zhao: Conceptualization, Funding acquisition, Methodology, Supervision. **Ning Zhang:** Writing—original draft, visualization, validation. **Jiaqiang Wang:** Writing—review & editing. **Jing Wang:** Writing—review & editing. **Yifan Zheng:** Writing—review & editing. **Ye Zheng:** Writing—review & editing. **Junhui Li:** Writing—review & editing. **Chen Ma:** Writing—review & editing.

References

- [1] X. Pei, G. Liu, Y. Zhang, J. He, B. Tang, F. Wu, X. Song, B. Li, Y. Shi, Y. Zhao, Single-solution-treated Fe60 laser cladding coatings for mold repair with sliding wear resistance against Si₃N₄, *Wear*, DOI (2026) 206989.
- [2] M. Liu, C. Duan, G. Li, Y. Cai, F. Wang, Friction property and milling machinability of Ni60 cladding layer in hybrid additive-subtractive manufacturing, *Journal of Manufacturing Processes*, 93 (2023) 162–172.
- [3] X. Miao, M. Wu, H. Wang, Y. Zhao, C. Cui, R. He, D. Jie, Effects of La content on microstructure and tribological properties of laser clad Ni60/WC/La₂O₃ composite coatings on Cr12MoV, *Journal of Materials Research and Technology*, 29 (2024) 2667–2678.
- [4] W. Gui, C. Zhong, J. Gu, Y. Ding, X. Wang, T. Wu, Y. Liang, J. Qin, Y. Qu, J. Lin, Laser-clad Inconel 625 coatings on Q245R structure steel: Microstructure, wear and corrosion resistance, *NPJ Materials Degradation*, 6 (2022) 37.
- [5] W. Sun, X. Huang, J. Zhang, B. Wang, X. Liu, The roles of microstructural anisotropy in tribo-corrosion performance of one certain laser cladding Fe-based alloy, *Friction*, 11 (2023) 1673–1689.
- [6] K. Wang, Y.-Q. Ji, L. Zhao, C. Zhang, L. Liu, X. Liu, Crack-free Fe-based metallic glass coatings by extreme high-speed laser cladding and their phase features correlated toughness: K. Wang et al, *Rare Metals*, 44 (2025) 9263–9270.
- [7] X.-y. Liu, X. Yang, Z.-b. Chen, C.-h. Guo, H.-x. Li, Z.-l. Yang, T. Dong, F.-c. Jiang, Z.-h. Qiao, Microstructure and wear property of laser clad WC particles reinforced CoCrFeNiMo composite coatings on Cr12MoV steel, *Journal of Central South University*, 32 (2025) 49–70.
- [8] R. Feng, Z. Tang, W.-M. Quach, J. Yao, M. Yan, H.-H. Lau, Experimental study on laser cladding forming of 316 L stainless steels based on Response Surface Methodology, *Structures*, Elsevier, 2025, pp. 109495.
- [9] M. Hong, R. Li, X. Bi, D. Shao, B. Liu, Optimization of laser cladding parameters for Y₂O₃-reinforced CoCrNi medium-entropy alloy coatings with enhanced high-temperature wear and corrosion resistance, *Surface and Coatings Technology*, 512 (2025) 132412.
- [10] H. Hosseini-Tayeb, S.M. Rafiaei, Enhanced microstructural and mechanical properties of Stellite/WC nanocomposite on Inconel 718 deposited through vibration-assisted laser cladding, *International Journal of Minerals, Metallurgy and Materials*, 29 (2022) 327–334.
- [11] Q. Deng, P. He, C. Sun, Y. Li, Y. Xing, Y. Wang, J. Li, X. Liang, X. Wang, Y. Zhou, High speed laser cladding as a new approach to prepare ultra-high temperature ceramic coatings, *J. Adv. Ceram*, 13 (2024) 143–154.
- [12] J. Yuan, H. Geng, M. Alfano, Multi-response optimization of M2 steel coatings deposited by co-axial laser cladding on A2 steel tool surfaces, *Journal of Materials Research and Technology*, 29 (2024) 1102–1117.
- [13] Z. Liu, S. Wu, W. Liu, Y. Wu, X. Liang, Optimization of multiple responses in the laser cladding process parameters, *Materials and Manufacturing Processes*, 39 (2024) 2139–2153.
- [14] Z. Yong, Y. Wang, G. Yang, Y. Shi, Q. Zhang, J. Yao, Optimization for furnace-assisted laser cladding process parameter of crack-free ceramic-based coating by response surface methodology, *Ceramics International*, 51 (2025) 11735–11746.
- [15] C. Yan, Y. Cheng, X. Zhu, Q. Zeng, Y. Wang, Tribological properties of the optimized Ni-based laser cladding coating in simulated coal mine water environment, *Optics & Laser Technology*, 191 (2025) 113302.
- [16] F. Liu, S. Ji, T. Shi, S. Shi, G. Fu, Statistical and experimental study of effects of process parameters on Ti-6Al-4V coaxial wire-feed laser cladding, *Chinese Journal of Mechanical Engineering*, DOI (2025) 100041.
- [17] L. Feng, G. Jin, X. Cui, B. Lu, Z. Dong, Y. Guan, X. Li, X. Yan, M. Liu, Optimizing laser cladding process parameters for transformation-induced plasticity FeMnCoCr high entropy alloy: a multi-objective approach, *Surface and Coatings*

Technology, 495 (2025) 131536.

[18] X.-l. Wei, W.-f. Xin, H.-s. Hong, C. Zhang, S. Dosta, Multi-objective optimization and performance improvement of laser cladded Ni–WC-reinforced CoCrNiFeAl composite coatings: XL Wei et al, *Journal of Iron and Steel Research International*, 32 (2025) 1275–1285.

[19] R. Tyagi, S. Kumar, M.S. Raza, A. Tripathi, A.K. Das, Experimental study of laser cladding process and prediction of process parameters by artificial neural network (ANN), *Journal of Central South University*, 29 (2022) 3489–3502.

[20] J. Gao, T. Shan, Y. Yang, Z. Gong, X. Kong, Y. Qin, M. Huang, S. Yang, The process optimization and wear resistance of dual-phase high-entropy alloy coatings by laser cladding based on machine learning, *Tribology International*, 211 (2025) 110907.

[21] R. Kumar, Recurrent context layered radial basis function neural network for the identification of nonlinear dynamical systems, *Neurocomputing*, 580 (2024) 127524.

[22] Y. Yuan, X. Li, Y. Cheng, H. He, Z. Yang, X. Jiang, D. Wu, Acoustic characteristic optimal design for railway steel–concrete composite bridge based on the RBFNN-NSGA-II algorithm, *Railway Engineering Science*, 34 (2026) 333–348.

[23] X. Wang, J. Jiang, L. Hong, J.-Q. Sun, A novel method for response probability density of nonlinear stochastic dynamic systems: X. Wang et al, *Nonlinear Dynamics*, 113 (2025) 3981–3997.

[24] Y. Cai, Y. Wang, H. Chen, J. Xiong, Searching optimal process parameters for desired layer geometry in wire-laser directed energy deposition based on machine learning, *Virtual and Physical Prototyping*, 19 (2024) e2352066.

[25] H. Huang, M. Wu, S. Luo, Z. Chen, Optimization of process parameters in laser cladding multi channel forming using MVBM-NSGA-II method, *Materials and Manufacturing Processes*, 39 (2024) 2226–2235.

[26] Y. Zhang, P. Bai, Z. Li, J. Zhang, Rapid optimization of iron-based alloy laser cladding process based on orthogonal experiment and machine learning for Q345, *Optics & Laser Technology*, 182 (2025).

[27] X. Ji, C. Lu, R. Chen, R. Huang, W. Zhang, J. Zhou, M. Zhang, Y. Yin, H. Yu, Multi-objective optimization of laser cladding parameters for CoCrW coatings using RSM-NSGA-II hybrid methodology, *Surfaces and Interfaces*, DOI (2026) 109399.

[28] P. Gradl, A. Cervone, P. Colonna, Development and experimental evaluation of surface enhancement methods for laser powder directed energy deposition microchannels, *Virtual and Physical Prototyping*, 19 (2024) e2345389.

[29] C. Qiao, J. Yu, S. Zhang, Z. Liu, J. Wang, Combined effect of a laser cladded coating and surface texture on tribological performance under dry sliding and starved lubrication, *Metals and Materials International*, 28 (2022) 666–678.

[30] H. Lin, P. Lv, H. Tan, L. Zhang, T. Long, Y. Long, C. Li, J. Zhou, Microstructure and properties analysis of AlCrFeNiV high entropy alloy coating in situ fabricated by laser cladding, *Advanced Engineering Materials*, 27 (2025) e202500419.

[31] C. Xia, Z. Pan, J. Polden, H. Li, Y. Xu, S. Chen, Modelling and prediction of surface roughness in wire arc additive manufacturing using machine learning, *Journal of Intelligent Manufacturing*, 33 (2022) 1467–1482.

[32] A.M. Chung Baek, T. Kim, M. Seong, S. Lee, H. Kang, E. Park, I.D. Jung, N. Kim, Multimodal deep learning for enhanced temperature prediction with uncertainty quantification in directed energy deposition (DED) process, *Virtual and Physical Prototyping*, 20 (2025) e2474532.

[33] S. Sanchez, D. Rengasamy, C.J. Hyde, G.P. Figueredo, B. Rothwell, Machine learning to determine the main factors affecting creep rates in laser powder bed fusion, *Journal of Intelligent Manufacturing*, 32 (2021) 2353–2373.