Multi-objective numerical simulation of geometrical characteristics of laser cladding of cobalt-based alloy based on response surface methodology

Lu-jun Cui, Meng Zhang, Shi-Rui Guo, Yan-Long Cao, Wen-Han Zeng, Xiao-lei Li and Bo Zheng

Abstract
The objectives of this study are to optimize the key process parameters of laser cladding remanufacturing parts, improve the sealing quality of the hemispherical valve and prolong and improve its service life and reliability. A high-power fiber-coupled semiconductor laser was used to fabricate a single Co-based alloy cladding layer on the pump valve material ZG45 plate. The key process parameters of laser power, scanning speed and powder feeding rate in the process of laser remanufacturing are taken as optimization variables, and the coating width, coating height, coating depth, aspect ratio and dilution rate are taken as response indexes. Based on the response surface analysis method, the central compound experiment is designed using Design-Expert software. The variance analysis of the experimental results is performed, and the regression prediction model of the process parameters relative to the corresponding index is established. Through analysis of the established perturbation diagram and three-dimensional response surface, it is concluded that the main influence factors of melting width and penetration depth are laser power and positive effect, and the main influence factors of melting height are scanning speed and negative effect. The average error of each regression prediction model is lower than 10%. The above research work has important guiding significance for optimizing the process parameters and improving the cladding quality of cobalt-based alloy on ZG45.

Keywords
Laser cladding, cobalt-based alloy, response surface methodology, regression prediction model

Introduction
Pump valve is a device used to realize mechanical energy conversion and control fluid direction, pressure and flow in fluid systems. Its products are widely used in various fields of the national economy and are an important part of general machinery. The quality of the sealing surface determines the service life of the valve, which is often subjected to corrosion, erosion and abrasive wear of many kinds of media in the switching process, which is easy to be damaged. To repair and remanufacture the valve sealing surface, it can be repaired and strengthened, and many scholars have studied it. It is important to note that laser cladding technology is better than the traditional surface technology. As a new remanufacturing technology, laser cladding melts the coating material at the same time with the thin layer on the surface of the substrate after laser irradiation and forms a surface coating with extremely low dilution and metallurgical bonding with the substrate after rapid solidification. The wear resistance, corrosion resistance, heat resistance, oxidation resistance and electrical properties of the base surface should be significantly improved, to achieve the purpose of surface modification or repair. Because the cobalt-based laser cladding layer is widely used in harsh working conditions such as high-parameter valve sealing surface, Co-Cr-W alloy is used for laser cladding in this paper. The performance of laser cladding coating also depends on some process parameters such as laser power, scanning speed, powder feeding rate, spot characteristics and carrier gas flow rate.

Corresponding author:
Meng Zhang, School of Mechanical and Electrical Engineering, Zhongyuan University of Technology, Zhengzhou 450007, China.
Email: zhangmeng@zut.edu.cn

Creative Commons CC BY: This article is distributed under the terms of the Creative Commons Attribution 4.0 License (https://creativecommons.org/licenses/by/4.0/) which permits any use, reproduction and distribution of the work without further permission provided the original work is attributed as specified on the SAGE and Open Access pages (https://us.sagepub.com/en-us/nam/open-access-at-sage).
Large-area cladding is composed of multiple single-pass cladding, and cladding must be carried out under the best process parameters to obtain satisfactory coatings. Therefore, it is particularly crucial to model and optimize the geometric characteristics of the single-pass laser cladding layer.\(^\text{19-22}\)

The empirical statistical model helps to avoid the complex physical phenomena of the analysis process and can help to study the relationship between the geometric characteristics of single coats and key process parameters in laser cladding processes.\(^\text{23-25}\) At present, there are many methods for optimizing process parameters, such as mathematical statistics, the Taguchi method, response surface method (RSM) and artificial neural network.\(^\text{26-29}\) Yu et al.\(^\text{30}\) and others used Taguchi experimental design experiments to convert the response indexes such as coating width, coating height and dilution rate into a single grey relational grade (GRG) for comprehensive evaluation combined with gray correlation theory and obtained the best combination of process parameters. The optimized parameter combination ensures the robustness of the optimization results. Chen et al.\(^\text{31}\) used Taguchi’s method to design experiments, ranked the factors affecting quality characteristics by the signal-to-noise ratio and used analysis of variance (ANOVA) to analyze the influence of important factors on coating quality characteristics. The results show that presetting powder thickness, spot diameter and laser power are the most critical processes. The support vector machine (SVM) model with a correlation coefficient (CC) > 0.94 is established to obtain the optimal process parameters. Onwubolu et al.\(^\text{32}\) and others used the RSM to establish the infiltration angle model of laser power, scanning speed and powder mass flow rate. Discrete search optimization technology was used to determine the optimal process parameters. The adequacy of the prediction model was verified by ANOVA. Ma et al.\(^\text{33}\) modeled the dilution rate and residual stress of laser cladding parameters by the RSM, studied the effect of each parameter on the response, and then used the quadratic model as a constraint function and applied multi-objective quantum. The behavioral particle swarm optimization algorithm was used to find the minimum dilution rate and residual stress. Finally, the optimal process parameters were predicted by this algorithm, and a high-entropy alloy coating was prepared.

In the Design of Experiment (DOE) experimental design, the Box–Behnken experimental design and RSM are applied in the preparation of a mathematical model. The developed model is verified by the ANOVA method. The relationship between process parameters and the output response and the interaction between process parameters are analyzed and discussed in detail.\(^\text{34}\) Therefore, the purpose of this study is to use a regression analysis method to correlate the main processing parameters with the geometric characteristics of a single-pass coating, thereby establishing a statistical model of a cobalt-based alloy coaxial laser cladding system to verify the actual predicted effect of the model. The lap cladding experiment can obtain the optimal process parameter range, and the laser cladding process can be simulated and predicted at a lower cost.

### Experimental principle and research method

#### Experimental equipment

The laser cladding system used in the present experiment is mainly composed of numerical control machining center LDM8060, high-power semiconductor fiber coupling laser, scraping disk powder feeder, water cooler and nitrogen gas protection system. The diameter of the laser spot is 3 mm. The laser processing head uses four coaxial powder feeding ways. The protective gas system is used for laser, powder feeder and laser processing head, respectively (Figure 1).

The base material employed in the present experiment is ZG310-570 (ZG45), which is a common material for pumps and valves. Its size is 100 mm × 50 mm × 15 mm. The surface of the base material is first removed with sandpaper, and then the surface is repeatedly cleaned with ethanol and acetone. Co-Cr-W alloy with a particle size of 53–150 μm is selected for this experiment. Its narrow particle size distribution helps in the formation of dense structures. Before the experiment, the powder is dried in a 120 °C drying box for 1 h to ensure its good fluidity. Figure 2 and Table 1 show the powder morphological characteristics and chemical composition mass fractions, respectively.

#### Experimental principles

RSM is a mathematical and statistical method used to establish the relationship between multiple independent input variables and responses to optimize the target response. To better establish a regression function model between influencing factors and response variables, this experiment uses the Box–Behnken design method to design an experimental scheme. The Box–Behnken design method can extract as much experimental variable effect and overall experimental error information as possible in the least number of runs and it runs efficiently. Therefore, a second-order regression model is used to fit the experimental data. As shown in equation (1)

\[
y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum_{j=1}^{k} \beta_{jj} x_j^2 + \sum_{i<j}^{k} \beta_{ij} x_i x_j + e (1)
\]

Among them, \(y\) is the predicted response value, \(\beta_0\) is the intercept coefficient, \(\beta_j\) is the linear coefficient, \(\beta_{jj}\) is the quadratic coefficient, \(\beta_{ij}\) is the primary coupling relationship coefficient, \(x_j\) is the cladding process parameter, \(k\) is the factor quantity, \(e\) is the correlation error.
To study the effect of laser cladding process parameters on coating quality characteristics, based on RSM, laser power (LP), scanning speed (SS) and powder feed rate (PFR) were used as optimization variables. Coating width ($W$), coating height ($H$), coating depth ($D$), aspect ratio ($W/H$) and dilution rate ($DR$) were the response variables. Therefore, the response surface analysis software Design-Expert was used to establish a three-factor and three-level composite matrix with 12 axial points and 3 replication center points, that is, a 12-factor analysis experiment and 3 central experiments were designed. A total of 15 groups of experiments were designed based on the optimized levels obtained from the single-factor studies of the LP, SS and PFR. Table 2 describes each process parameter and coding level, and Table 3 describes the Box–Behnken experimental design scheme and experimental result.
The quality characteristics of a single coat as a response variable of the process parameters include coat width ($W$), coat height ($H$), coat depth ($D$), aspect ratio ($W/H$) and dilution rate (DR). Figure 3 is a schematic diagram of the locations of the geometric features of the coating cross section. The aspect ratio takes into account the lateral expansion ability of the cladding layer. The larger the aspect ratio, the stronger the lateral expansion ability of the cladding layer. The dilution rate reflects the longitudinal expansion ability of the cladding layer and the dilution degree of the substrate of the cladding material. The smaller, the greater the longitudinal expansion ability, and the lower, the dilution degree of the cladding material of the substrate, so the aspect ratio and the geometric dilution rate can be used to optimize the three-dimensional stacking effect of the cladding layer. The calculation formula of geometric dilution rate is

$$\text{DR} = \frac{D}{H+D} \times 100\%$$

After the preparation of the cladding layer is completed, the wire cutting machine is utilized to cut the block according to the cross-sectional position of Figure 3 to prepare a metallography sample. The cross sections of the samples were polished with 1200 mesh sandpapers and polished with a 0.25-μm diamond polishing agent until there was no scratch on the cross section of the sample, and metallographic corrosion was performed with aqua regia. The morphology of the cross section of the coating was photographed using a Lycra optical microscope (OM), and the geometric characteristics of the cross section illustrated in Figure 3 were measured using image processing software.

After measuring the cross-sectional quality characteristics of the coating, the data obtained were

| Sample no. | Input variables | Output responses |
|------------|-----------------|------------------|
|            | LP (W)          | SS (mm/s)        | PFR (g/min) | $W$ (μm) | $H$ (μm) | $D$ (μm) |
| 1          | 1000            | 5                | 17.5        | 2303.9    | 1843.1 | 25 |
| 2          | 1800            | 5                | 17.5        | 4019.4    | 1836  | 39 |
| 3          | 1000            | 7                | 17.5        | 2424.4    | 1296.5 | 14.8 |
| 4          | 1800            | 7                | 17.5        | 3941.4    | 1654.3 | 27.8 |
| 5          | 1000            | 6                | 15          | 2537.8    | 1318.5 | 18.5 |
| 6          | 1800            | 6                | 15          | 4267.5    | 1545.4 | 37.6 |
| 7          | 1000            | 6                | 20          | 2849.7    | 1474.5 | 12.4 |
| 8          | 1800            | 6                | 20          | 3537.4    | 1623.4 | 26 |
| 9          | 1400            | 5                | 15          | 3828      | 1602.1 | 22.2 |
| 10         | 1400            | 7                | 15          | 3587      | 1304.4 | 23.6 |
| 11         | 1400            | 5                | 20          | 3211.3    | 1885.6 | 13.8 |
| 12         | 1400            | 7                | 20          | 3282.2    | 1566.6 | 14 |
| 13         | 1400            | 6                | 17.5        | 3530.3    | 1793.5 | 17.3 |
| 14         | 1400            | 6                | 17.5        | 3572.8    | 1750  | 18.8 |
| 15         | 1400            | 6                | 17.5        | 3353.5    | 1715.5 | 19.2 |

LP: laser power; SS: scanning speed; PFR: powder feed rate.
The model relative to the unexplained change when the residual mean square, that is, the change explained by the model’s mean square division. With the ratio of the residual mean square less than 5%, then the model or term is considered reliable within the confidence interval. A p value less than 0.05 indicates that this term has a significant effect on the output response.

First, the significance analysis of four response value models of linear, linear and square terms, linear and interaction terms and the complete quadratic model is performed on the experimental data of each group. The model compares with the model p value less than 0.05 and the mismatch term greater than 0.05 to compare the models. The degree of fit of the model determines the better response value model corresponding to the output response. Second, stepwise regression is utilized to eliminate insignificant terms in each model to determine the important influence factor of each parameter of the output response. Quantitative analysis is performed based on the importance of each factor, and the cause of change is analyzed according to the perturbation diagram and an interactive diagram of the response of the input variables. Finally, a quadratic regression equation model is established to quantitatively control and predict the quality characteristics of the cladding layer.

### Experimental results and discussion

**Influence of process parameters on coating geometric characteristics**

The significant analysis was performed on four response value models of linear, linear and square terms, linear and interaction terms and complete quadratic term model. The results are presented in Table 4. When a full quadratic regression model is selected for the coating width, the model p value is 0.0027 and the mismatch term p value is 0.2595, which is the best model among the four. When the linear and the interaction term regression model was selected for the coating depth, the model p value was 0.0008 and the mismatch term p value was 0.0730, which is the best model among the four.

#### Coating width analysis

It can be seen from Table 4 that the coating width should be fitted with a complete quadratic regression model, and the insignificant factors should be eliminated automatically by the stepwise regression method. The variance analysis of the coating width in Table 5 shows that the F value of the model is 54.68 and the F value of the mismatch term is 1.74, indicating that the term in the model is highly related to the response, and the p value of the model is less than 0.0001 and the p value of the mismatch term is 0.4154. It is known that the model has only a 0.01% probability distortion, indicating that the model fits well. The input variables and output responses have a significant impact, and the selected model is reasonable. The $R^2$ is 95.63%, indicating that there is a strong correlation between the experimental results and the predicted results. The $R^2$ (adj) is 93.88%, indicating that the model has a very high degree of the fitting to the response. The $R^2$ (pred) is 84.45%, indicating that the model is effective in predicting the new response value. AdeqPrecision (the ratio of the measured signal to noise) is 22.81, which is much more than 4, indicating that the accuracy of the model meets the requirements and has a high recognition rate. Therefore, equation (3) regression equation can be utilized to replace the real point of the experiment to analyze the experimental results

$$
W = -7208.9933 + 10.62131LP + 297.715PFR
- 0.00153463LP * LP
- 0.0605LP * PFR
$$

(3)

The response model of input variables to W, including linear term LP and PFR, quadratic term LP² and the interaction term LP*PFR, shows that it is the main influence factor of W. According to the value of P, the

| Source          | Linear | Linear + squares | Linear + interactions | Full quadratic |
|-----------------|--------|------------------|-----------------------|----------------|
| Coating width   | Model  | 0.0001           | 0.0009                | 0.0006         | 0.0027         |
| p value         |        | 0.1604           | 0.1687                | 0.1876         | 0.2622         |
| Coating height  | Model  | 0.0053           | 0.0010                | 0.0465         | 0.0028         |
| p value         |        | 0.0739           | 0.1669                | 0.0616         | 0.2595         |
| Coating depth   | Model  | 0.0027           | 0.0008                | 0.0567         | 0.0262         |
| p value         |        | 0.0333           | 0.0730                | 0.0230         | 0.0414         |

Table 4. Significance analysis of the response model.
influence grade of \( W \) is \( LP > LP*PFR > LP*LP > PFR \). Figure 4 shows the perturbation diagram of the input variable on \( W \), which shows that the effect of the LP on \( W \) is positive, while that of PFR on \( W \) is negative. Figure 5 shows the interaction between LP and PFR on \( W \), when the LP is low; PFR has almost no effect on \( W \); when the LP is large; the influence of PFR on \( W \) increases; and the contours are oval, indicating that the interaction is significant. With the increase of the LP, the laser input energy per unit time increases, forming a larger molten pool, which eventually leads to the increase of \( W \); so LP has a positive effect on \( W \). With the increase of PFR, the melting powder per unit time increases, resulting in the reduction of the molten pool and the decrease of \( W \).

Coating height analysis. It can be seen from Table 4 that the coating height should be fitted with a complete quadratic regression model, and the insignificant factors should be eliminated automatically by the stepwise regression method. According to the ANOVA of the coating height in Table 6, the \( F \) value of the model is 38.26, and the misfit term \( F \) value is 1.68, indicating that the term in the model is highly related to the response, and the \( p \) value of the model is less than 0.0001, and the misfit term \( p \) value is 0.4185. It is known that the model has only a 0.01% probability distortion, indicating that the model fits well. The input

### Table 5. Analysis of coating width variance.

| Source          | DF | Adj SS     | Adj MS     | \( F \) value | \( p \) value |
|-----------------|----|------------|------------|---------------|---------------|
| Model           | 4  | 4,711,046  | 1,177,761  | 54.68         | < 0.0001      | Significant   |
| Linear          | 2  | 4,214,521  | 2,107,260  | 97.83         | < 0.0001      |
| LP              | 1  | 3,990,171  | 3,990,171  | 185.24        | < 0.0001      |
| PFR             | 1  | 224,350    | 224,350    | 10.42         | 0.0091        |
| Square          | 1  | 225,084    | 225,084    | 10.45         | 0.0090        |
| LP*LP           | 1  | 225,084    | 225,084    | 10.45         | 0.0090        |
| 2-Way interaction| 1  | 271,441    | 271,441    | 12.60         | 0.0053        |
| LP*PFR          | 1  | 271,441    | 271,441    | 12.60         | 0.0053        |
| Error           | 10 | 215,406    | 21,541     | 1.74          | 0.4154        | Not significant|
| Lack-of-fit     | 8  | 188,353    | 23,544     |               |               |
| Pure error      | 2  | 27,052     | 13,526     |               |               |
| Total           | 14 | 4,926,452  |            |               |               |

\( R^2 = 95.63\% \), \( R^2 \) (adj) = 93.88\%, \( R^2 \) (pred) = 84.45\%, AdeqPrecision = 22.818

DF: degree of freedom, MS: mean square, SS: scanning speed; LP: laser power; PFR: powder feed rate.

![Figure 4. Perturbation plot of the coating width.](image)

![Figure 5. Effect of LP and PFR on W interaction: (a) contour map of LP and PFR interaction on W and (b) 3D response of LP and PFR interaction on W.](image)
variables and output responses have a significant impact, and the selected model is reasonable. The $R^2$ is 96.63%, indicating that there is a strong correlation between the experimental results and the predicted results. The $R^2 (adj)$ is 94.11%, indicating that the model has a very high degree of the fitting to the response. The $R^2 (pred)$ is 88.92%, indicating that the model is effective in predicting new response values. AdeqPrecision (the ratio of the measured signal to noise) is 16.792, which is much more than 4, indicating that the accuracy of the model meets the requirements and has a high recognition rate. Therefore, equation (4) regression equation can be utilized to replace the real point of the experiment to analyze the experimental results

\[
H = -5616.60288 + 0.56521LP - 487.4125SS + 964.76192PFR - 0.000609483LP \times LP + 26.45077PFR \times PFR + 0.22806LP \times SS \quad (4)
\]

The response model of input variables for $H$ includes linear terms LP, SS, PFR; quadratic terms LP$^2$, PFR$^2$; interaction term LP*SS, which are the main influence factors of $W$. According to the value of $P$, the influence grade of $H$ is SS $>$ PFR$^2$ $>$ PFR $>$ LP $>$ LP$^2$ $>$ LP*SS. Figure 6 indicates the perturbation diagram of the input variable to $H$, which shows that the effect of the LP and PFR on $H$ is positive in the first section and negative in the later section. The reason is that with the increase of the LP, the laser input energy increases, the powder melting amount increases and $H$ increases in the unit time of the front section, and the laser input energy continues to increase in the latter section, which leads to the increase of the input energy of the substrate, the increase of $W$ and the decrease of $H$. With the increase of PFR, the melting amount of powder in the front section increases and $H$ increases, while in the latter section, due to gravity and other factors, the molten powder spreads around and $H$ decreases. The effect of SS on $H$ is negative as a whole, which is due to the decrease of laser input energy and powder melting per unit time with the increase of SS. Figure 7 shows the interaction between SS and PFR on $H$, and the contours are oval, indicating that the interaction is significant. When PFR is low, the effect of SS on $H$ is linear. When PFR is large, the effect of SS on $H$ is nonlinear. The influence of PFR on $H$ decreases with the decrease of SS, while the influence of the SS on $H$ increases with the increase of PFR.

Coating depth analysis. It can be seen from Table 4 that the coating depth should be fitted with the linear and square model, and the insignificant factors should be deleted automatically by the stepwise regression method. The variance analysis of the coating depth in Table 7 shows that the $F$ value of the model is 20.84 and the misfit term $F$ value is 12.04, indicating that the item in the model is highly related to the response, and the $p$ value of the model is 0.0001, and the $p$ value of the misfit term is 0.0789. It is known that the model has only a 0.01% probability distortion, indicating that

| Source       | DF | Adj SS | Adj MS | $F$ value | $p$ value |
|--------------|----|--------|--------|-----------|-----------|
| Model        | 6  | 530,319| 88,386 | 38.26     | $< 0.0001$|
| Linear       | 3  | 368,095| 122,698| 53.11     | $< 0.0001$|
| LP           | 1  | 65,975 | 65,975 | 28.56     | 0.0007    |
| SS           | 1  | 226,128| 226,128| 97.88     | $< 0.0001$|
| PFR          | 1  | 75,992 | 75,992 | 32.89     | 0.0004    |
| Square       | 2  | 128,936| 64,468 | 27.90     | 0.0002    |
| LP*LP        | 1  | 35,321 | 35,321 | 15.29     | 0.0045    |
| PFR*PFR      | 1  | 101,511| 101,511| 43.94     | 0.0002    |
| 2-Way interaction | 1  | 33,288 | 33,288 | 14.41     | 0.0053    |
| LP*SS        | 1  | 33,288 | 33,288 | 14.41     | 0.0053    |
| Error        | 8  | 18,483 | 2310   |           |           |
| Lack-of-fit  | 6  | 15,427 | 2571   | 1.68      | 0.4185    |
| Pure error   | 2  | 3056   | 1528   |           |           |
| Total        | 14 | 548,802|        |           |           |

$R^2 = 96.63\%$, $R^2 (adj) = 94.11\%$, $R^2 (pred) = 88.92\%$, AdeqPrecision = 16.792

SS: scanning speed; LP: laser power; PFR: powder feed rate.
the model fits well. The input variables and output responses have a significant impact, and the selected model is reasonable. The $R^2$ is 89.29%, indicating that there is a strong correlation between the experimental results and the predicted results. The $R^2$ (adj) is 85%, indicating that the model has a very high degree of fitting to the response. The $R^2$ (pred) is 72.29%, indicating that the model is effective in predicting the new response value. AdeqPrecision (the ratio of the measured signal to noise) is 14.107, which is much more than 4, indicating that the accuracy of the model meets the requirements and has a high recognition rate. Therefore, equation (5) regression equation can be utilized to replace the real point of the experiment to analyze the experimental results

$$D = 120.74241 - 0.099LP - 2.475SS - 1.785PFR + 0.0000420201LP \times LP$$ (5)

The response model of input variables to $D$ includes linear terms LP, SS and PFR; quadratic term LP$^2$, which are the main influencing factors of $D$. According to the value of $P$, the order of influence on $D$ is $LP > LP^2 > PFR > SS$. Figure 8 shows the perturbation diagram of the input variable to $D$. It can be seen that the influence of LP on $D$ in the front part is small and has a negative impact. The reason is that the increased laser input energy per unit time is used to melt the powder, and the substrate receives less radiation energy, so the effect is not obvious. In the latter part, with the...
increase of the LP, the laser input energy radiates more to the substrate, which leads to the enlargement and deepening of the molten pool and the decrease of \( D \), so the influence of \( D \) varies greatly and shows a positive effect. The effects of SS and PFR on \( D \) are negative. With the increase of SS, the laser input energy, molten pool and \( D \) decrease per unit time. With the increase of PFR, the laser input energy is more used to melt the increased powder, while the input energy to the substrate decreases, resulting in the reduction of the molten pool and the decrease of \( D \). Figure 9 shows the effect of the LP and PFR on \( D \) interaction. The contours are oval, and the interaction is significant on the surface. The influence of LP on \( D \) increases with the decrease of PFR, and the impact of PFR of \( D \) increases with the increase of LP.

**Mathematical statistical model of coating aspect ratio and geometric dilution rate.** From equations (3) and (4), the mathematical-statistical model of aspect ratio can be deduced as

\[
\frac{W}{H} = \frac{-7208.9933 + 10.62131LP + 297.715PFR - 0.00153463LP \times LP}{-5616.60288 + 0.56521LP - 487.4125SS + 964.76192PFR - 0.000609483LP \times PFR} \times 100\% \quad \text{(6)}
\]

From equations (2), (4), (5), the geometric dilution of the coating can be derived

\[
DR = \frac{120.74241 - 0.099LP - 2.475SS - 1.785PFR + 0.0000420201LP \times LP}{-5495.86047 + 0.46621LP - 489.8875SS + 962.97692PFR - 0.0005674629LP \times LP \times 100\%} \times 100\% \quad \text{(7)}
\]

To calculate the fitting effect of the aspect ratio equation and the geometric dilution rate equation for the experimental data, the average error equation is used

\[
e = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - P_i}{A_i} \right| \times 100\% \quad \text{(8)}
\]

where \( e \) is the average error, \( n \) is the total number of experimental groups, \( A_i \) is the actual value, \( P \) is the predicted value of the equation, \( i = (1, 2, 3 \ldots) \). The average error between the predicted value of aspect ratio and the actual value is 4.13%, and the average error between the predicted value of the dilution ratio and the actual value is 9.82%.

**Optimization of process parameters and model prediction verification**

According to the actual engineering requirements, the coating height needs to be greater than 1500 \( \mu \)m. It can be known that \( 5 \text{ mm/s} < \text{SS} < 6 \text{ mm/s} \) and \( \text{PFR} > 15 \text{ g/min} \). The aspect ratio needs to be greater than 2.4 to ensure the good lateral expansion of the cladding layer, so \( W > 3600 \text{ \mu m} \); it can be known that \( \text{LP} \geq 1400 \text{ W} \) and \( \text{PFR} < 20 \text{ g/min} \). The dilution rate needs to be less than 2% to ensure that the cladding layer has a good vertical expansion ability, so \( D < 30 \text{ \mu m} \); it
can be known that LP ≤ 1700 W. Therefore, the optimal process parameter range of a single coat is 1400 W ≤ LP ≤ 1700 W, 5 mm/s ≤ SS ≤ 6 mm/s, 15 g/min < PFR < 20 g/min.

To perform predictive tests on the output response index regression equations (3)–(7), four sets of verification experimental data were selected to compare with the predicted data obtained from the respective regression equations. According to equation (8), the prediction error of each response index is shown in Table 8. According to the table, the average error of the coating width is 4.496%, the average error of the coating height is 1.150% and the average error of the aspect ratio is 3.364%. The average error of the three is less than 5%. It can be seen that the regression model established by response surface analysis and ANOVA has a very beneficial effect on fitting and predicting the width and height of the coating. The average error of the coating depth is 9.403%, and the error of the dilution rate is 8.470%. The average error of the two is below 10%. From the geometric dilution rate formula (2), it can be seen that the larger the value of the coating height, the more. When the depth value is small, a very small change in the predicted value of the coating depth can cause a large increase in the error rate, and the dilution rates in the experimental data are less than 2%, which can meet the actual production requirements. Therefore, the coating depth and the average error of the dilution rate below 10% can meet the actual needs of the project. It can be recognized from the above that the regression prediction model based on the RSM has important guiding significance for the optimization of the process parameters of the high-quality cladding of cobalt-based alloys on ZG45 and the improvement of cladding quality.

Conclusion

1. The laser cladding experiment of Co-based alloy is designed by the Box–Behnken design method. The experimental and analytical results show that the process parameters are closely related to the geometric characteristics of the single-pass coating. LP is the most important factor affecting the width of the coating and has a positive effect on it. SS is the most important factor affecting the height of the coating and has a negative effect on it. LP is the most important factor affecting the depth of the coating and has a positive effect on it in the main range.

2. The range of optimum process parameters for single-pass coating is 1400 W ≤ LP ≤ 1700 W, 5 mm/s ≤ SS ≤ 6 mm/s, 15 g/min < PFR < 20 g/min, which lays the foundation of processing parameters for laser cladding of multi-pass cobalt-based coatings.

3. It is both reasonable and feasible to use response surface analysis and variance analysis to model and analyze the relationship between process parameters and geometric features. The average error of the regression equation of geometric characteristics of a single coating is 4.496%. The coating height is 1.150%, the coating depth is 9.403%, the aspect ratio is 3.364% and the dilution rate is 8.470%.

Declaration of conflicting interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding
The author(s) disclosed receipt of the following financial support for the research, authorship and/or publication of this article: The authors would like to acknowledge the supports from the National Natural Science Foundation (grant no.: 51505506), Henan University’s key scientific research projects (grant nos: 20A460033, 19A460035, 20A460031) and Applied Research Project of Independent Innovation in Zhongyuan University of Technology (grant no.: K2018Y001).

ORCID iD
Meng Zhang https://orcid.org/0000-0001-9007-4086

| Table 8. Prediction error table of each response index. |
|---------------------------------|----------|----------|----------|----------|
| W (μm)                         | H (μm)  | D (μm)  | W/H     |
| Predicted value                | Actual value | Error ratio |
| LP = 1600 W                    | 3474.75 | 1829.805 | 21.83887 | 1.898973 | 0.011794 |
| SS = 5 mm/s                    | 3707.5  | 1864.4  | 25.1     | 1.988575 | 0.013284 |
| PFR = 20 g/min                 | 0.062770| 0.018556| 0.129926 | 0.045058 | 0.112137 |
| LP = 1600 W                    | 3772.462| 1652.626| 21.35137 | 2.282707 | 0.012755 |
| SS = 7 mm/s                    | 3572.8  | 1644.6  | 21.7     | 2.172443 | 0.010323 |
| PFR = 17.5 g/min               | 0.055884| 0.00488 | 0.016066 | 0.050756 | 0.020579 |
| LP = 1600 W                    | 4070.175| 1512.363| 28.28887 | 2.691268 | 0.018362 |
| SS = 6 mm/s                    | 4005.2  | 1495.8  | 24.9     | 2.677631 | 0.016374 |
| PFR = 15 g/min                 | 0.016223| 0.011073| 0.136099 | 0.033636 | 0.084701 |
| Average error ratio (%)        | 4.496   | 1.150   | 9.403    | 3.364    | 8.470    |

W/H: aspect ratio; DR: dilution rate; LP: laser power; SS: scanning speed; PFR: powder feed rate.
References

1. Song B. Welding process properties, microstructure and wear resistance of 1Cr13 hardfacings electrode for valve. Xiangtan, China: Xiangtan University, 2011, pp. 1–3.

2. Liang H-s, Jiang D-g, Zhang C-w, et al. Establishment of alarm value for aging susceptibility point of valve sub-assembly and countermeasures for aging mitigation. Nucl Power Eng 2005; 26(S1): 97–102.

3. Pan L, Gao W-Z, Tao X-I, et al. Evaluation on microstructures and properties of laser cladding layer for WFLC-11 Co-based alloy. Rare Metal Mat Eng 2007; 36(8): 1444–1446.

4. Zhao J, Gao Q, Wang H, et al. Microstructure and mechanical properties of Co-based alloy coatings fabricated by laser cladding and plasma arc spray welding. J Alloy Compd 2019; 785: 846–854.

5. Feng K, Chen Y, Deng P, et al. Improved high-temperature hardness and wear resistance of Inconel 625 coatings fabricated by laser cladding. J Mater Process Tech 2017; 243: 82–91.

6. Shi S, Zheng Q, Fu G, et al. Comparison study on resistance to wear and abrasion of high-temperature sliding strike of laser and plasma spray layer on the stainless steel surface. Nucl Eng Des 2004; 231(1): 121–126.

7. Yang J, Xiao Z, Yang F, et al. Microstructure and magnetic properties of NiCrMoAl/WC coatings by laser cladding: effect of WC metallurgical behaviors. Surf Coat Technol 2018; 350: 110–118.

8. Tanigawa D, Funada Y, Abe N, et al. Suppression of dilution in Ni-Cr-Si-B alloy cladding layer by controlling diode laser beam profile. Opt Laser Technol 2018; 99: 326–332.

9. Liu J, Chen Y and Zhang J. Oxidation behavior of Ni-Mo-Si alloy coatings fabricated on carbon steel by laser cladding. Surf Coat Technol 2019; 375: 903–910.

10. Zhou J and Kong D. Effects of Ni addition on corrosion behaviors of laser cladded FeSiB:Ni coating in 3.5% NaCl solution. J Alloy Compd 2019; 795: 416–425.

11. Liu Y, Wu Y, Ma Y, et al. High temperature wear performance of laser cladding Co06 coating on high-speed train brake disc. Appl Surf Sci 2019; 481: 761–766.

12. Cai ZB, Zhu MH, Lin XZ, et al. Tribological behavior of laser-cladding Ni60 and Co-Cr-W coatings at elevated temperature. Key Eng Mater 2007; 353: 878–881.

13. Liu R, Yao JH, Zhang QL, et al. Microstructures and hardness/wear performance of high-carbon stellite alloys containing molybdenum. Metall Mater Trans A 2015; 46(12): 5504–5513.

14. Zhang Z, Kong F and Kovacevic R. Laser hot-wire cladding of Co-Cr-Mo metal cored wire. Opt Laser Eng 2020; 128: 105998.

15. Mostajeran A, Shoja-Razavi R, Hadi M, et al. Evaluation of the mechanical properties of WC-FeAl composite coating fabricated by laser cladding method. Int J Refract Met H 2020; 88: 105199.

16. Gowardham A, Chaitanya G, Katiyar JK, et al. Experimental Investigations on laser cladding of NiCrBSi + WC coating on SS410. Mater Today: Proc 2019; 27: 1984–1989.

17. Yao J, Zhang J, Wu G, et al. Microstructure and wear resistance of laser cladded composite coatings prepared from pre-alloyed WC-NiCrMo powder with different laser spots. Opt Laser Technol 2018; 101: 520–530.

18. Khamidullin BA, Tsivilskiy IV, Gorunov AI, et al. Modeling of the effect of powder parameters on laser cladding using coaxial nozzle. Surf Coat Technol 2019; 364: 430–443.

19. El Cheikh H, Courant B, Branchu S, et al. Analysis and prediction of single laser tracks geometrical characteristics in coaxial laser cladding process. Opt Laser Eng 2012; 50(3): 413–422.

20. Reddy L, Preston SP, Shipway PH, et al. Process parameter optimisation of laser clad iron based alloy: predictive models of deposition efficiency, porosity and dilution. Surf Coat Technol 2018; 349: 198–207.

21. Lei K, Qin X, Liu H, et al. Analysis and modeling of melt pool morphology for high power diode laser cladding with a rectangle beam spot. Opt Laser Eng 2018; 110: 89–99.

22. Fan P and Zhang G. Study on process optimization of WC-Co50 cermet composite coating by laser cladding. Int J Refract Met H 2020; 87: 105133.

23. Erfanmanesh M, Abdollah-Pour H, Mohammadian-Sennani H, et al. An empirical-statistical model for laser cladding of WC-12Co powder on AISI 321 stainless steel. Opt Laser Technol 2017; 97: 180–186.

24. Nabhani M, Razavi RS and Barekat M. An empirical-statistical model for laser cladding of Ti-6Al-4V powder on Ti-6Al-4V substrate. Opt Laser Technol 2018; 100: 265–271.

25. Aghili SE and Shamanian M. Investigation of powder fed laser cladding of NiCr-chromium carbides single-tracks on titanium aluminum substrate. Opt Laser Technol 2019; 119: 105652.

26. Wu Z, Li T, Li Q, et al. Process optimization of laser cladding Ni60A alloy coating in remanufacturing. Opt Laser Technol 2019; 120: 105718.

27. Shi Y, Li Y, Liu J, et al. Investigation on the parameter optimization and performance of laser cladding a gradient composite coating by a mixed powder of Co50 and Ni/WC on 20CrMnTi low carbon alloy steel. Opt Laser Technol 2018; 99: 256–270.

28. Singh J, Thakur L and Angra S. An investigation on the parameter optimization and abrasive wear behaviour of nanostructured WC-10Co-4Cr TiG weld cladding. Surf Coat Technol 2020; 386; 125474.

29. Aggarwal K, Urbanic R and Aggarwal L. A methodology for investigating and modelling laser clad bead geometry and process parameter relationships. SAE Int J Mater Manuf 2014; 7(2): 269–279.

30. Yu T, Yang L, Zhao Y, et al. Experimental research and multi-response multi-parameter optimization of laser cladding Fe313. Opt Laser Technol 2018; 108: 321–332.

31. Chen T, Wu W, Li W, et al. Laser cladding of nanoparticle TiC ceramic powder: effects of process parameters on the quality characteristics of the coatings and its prediction model. Opt Laser Technol 2019; 116: 345–355.

32. Onewubolu GC, Davim JP, Oliveira C, et al. Prediction of clad angle in laser cladding by powder using response surface methodology and scatter search. Opt Laser Technol 2007; 39(6): 1130–1134.

33. Ma M, Xiong W, Lian Y, et al. Modeling and optimization for laser cladding via multi-objective quantum-behaved particle swarm optimization algorithm. Surf Coat Technol 2020; 381; 125129.

34. Khorraram A, Jamaloei AD, Paidar M, et al. Laser cladding of Inconel 718 with 75Cr32C + 25 (80Ni20Cr) powder: statistical modeling and optimization. Surf Coat Technol 2019; 378: 124933.