Study on optimization of laser cladding process parameters of aluminum alloys using a prediction model of the neural-genetic algorithm

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Abstract: Based on the orthogonal experiment of laser cladding technology on the surface of aluminum alloy, the effect of powder type, laser power, spot diameter and scanning speed on the surface hardness of laser cladding process on aluminum alloy surface was studied using genetic algorithm back-propagation neural network (GA-BPNN), and the process parameters of the laser cladding process test on the aluminum alloy surface were optimized, and the surface hardness under various process parameters was predicted. The predicted results are in good agreement with the actual test results, and the errors are all less than 1%. The results show that the optimal combination of surface hardness influencing parameters is not unique, and this result is closer to the actual production requirements. In addition, no matter whether it is the optimal or various surface hardness predictions, the proposed optimal prediction method can obtain representative results. This paper provides a new method for the selection of the best process scheme for laser cladding of aluminum alloy surface.

1. Introduction

The laser cladding on the aluminum alloy surface has many advantages. It not only utilizes the advantages of low density and light weight of the aluminum alloy, but also improves the comprehensive performance of the aluminum alloy such as hardness and wear resistance. It can fundamentally eliminate the technical disadvantages of aluminum alloy in lightweight, and promote the wide application of aluminum alloy in lightweighting\textsuperscript{[1-4]}. The laser cladding process parameters have a great influence on the properties of the strengthening layer. It is necessary to further study the relationship between the laser cladding process parameters and the properties of the strengthening layer to optimize the process parameters of the laser cladding.

Under different laser process parameters, the change law of the surface hardness of the cladding
layer is consistent with the macroscopic morphology, microscopic cross-sectional morphology, thickness of the cladding layer and dilution rate. Therefore, when the macroscopic morphology is good, and the microscopic cross-sectional morphology has no defects such as pores or cracks, and the thickness of the cladding layer is relatively thick, the surface hardness of the cladding layer is relatively good, whereas the surface hardness is poor.

The BP network model based on MATLAB can effectively analyze the system of multiple variables. In this paper, the aluminum alloy surface laser cladding process test is taken as the research object, and a three-layer BP neural network model is established. The MATLAB software is used to simulate and train the neural network. A new method can be provided for the selection of the optimum process parameters for the aluminum alloy laser cladding process. Taking the surface hardness as the objective, the four main process parameters (powder type, laser power, spot diameter, and scanning speed) that affect the surface hardness were taken as input variables, and the function approximation function of the neural network was used to optimize the design. The combination of process parameters for the best surface hardness was obtained, and the results of the neural network prediction were verified by the process test.

2. Optimization approach

2.1 Theory basis

2.1.1 Back-propagation neural network
Error Back-propagation neural network (BPNN) has become the most extensive application of neural networks\[5\]. It has been reported that a three-layer feed-forward network, showed as Fig.1, can achieve arbitrary precision mapping of the continuous function. It is a good way to use the BPNN to fit the high nonlinear function from input data to corresponding output.

![BPNN topology](image)

The training process of BPNN can be simply categorized as follows: firstly, weights $\omega_{ji}$ and threshold $\theta_j$ are initialized; then, training samples are entered into the net. And the error of each sample $k$ can be obtained by calculating its output state. Based on the error, the next step is to adjust repeatedly the weights and thresholds among layers until the network error $E_1 < \varepsilon_1$ ($\varepsilon_1$ is the setting error) with error back-propagation. After training, we can input the tested samples. If the network error $E_2 < \varepsilon_2$ ($\varepsilon_2$ is the test error), it means that the network can be used for the actual forecast.

At present, for the BPNN model some shortcomings exist, such as poor stability between fitting and prediction, being difficult for determining network architecture, et al \[6,7\]. Therefore, it is necessary to take some improving method into the BPNN model.
2.1.2. Principal component analysis [8]

The essence of Principal Component Analysis (PCA) is an exploratory statistical analysis method, which scatters a group of variables in the information on to a certain number of integrated indicators (Principal components). By doing so, principal components (PC) are to use data to describe the internal structure of the data. In fact, it plays a role of reduced-dimension to data.

The relationship of q PCs to p variables is described as following:

\[
\begin{align*}
    f_1 &= a_{11}X_1 + a_{21}X_2 + \cdots + a_{p1}X_p \\
    f_2 &= a_{12}X_1 + a_{22}X_2 + \cdots + a_{p2}X_p \\
    & \quad \vdots \\
    f_q &= a_{1q}X_1 + a_{2q}X_2 + \cdots + a_{pq}X_p
\end{align*}
\]

(1)

Where \((a_{i1}, a_{i2}, \ldots, a_{ip})'\) are the eigenvectors of q former characteristic roots for the related matrix of variables respectively. The variances from \(\lambda_1, \lambda_2, \ldots, \lambda_q\) are q characteristic roots \((\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_q)\) respectively. And \((a_{i1}, a_{i2}, \ldots, a_{iq})'\) is the load of the ith variable on each PC, called PA’s scores. In fact, the load often means \(a_{i1}, a_{i2}, \ldots, a_{iq}\)' standardized. Then standardized PC’s scores can be obtained accordingly using the least-squares method.

In this paper, in order to improve the structure of BPNN, the learning matrix is dealt with by employing PCA for the BPNN model as such to reduce the dimension and to de-noise. It constructs an initiative approach of low-dimensional learning matrix that reflects fully the relationship between prediction factors \(X_p\) and predictor \(Y_k\). It also tries to improve generalization performance of BPNN to make it suitable for the need of predicting. Meanwhile, actually the new data \(f_q\) is to input into the BPNN model instead of \(X_p\).

2.1.3. Genetic algorithms

Genetic algorithm (GA) simulates Darwin’s natural selection, genetic selection and the process of biological evolution model. It is a search algorithm for global probability of the biological mechanisms based on a genetic variation and a natural selection. It is particularly applicable to solve the nonlinear problems that are complex and difficult for the traditional method [9].

The basic idea for optimizing BPNN with GAs is: it is to find the most appropriate linking weight and network structure using the global search feature of GAs. These years, many scholars over the world have established prediction models using optimizing neural network with the global search capability of GAs [10, 11].

2.2 The proposed optimization approach

According to the delamination of this study, here is an optimization method with the mentioned basic theories. Fig.2 shows the proposed procedure of the method.
The proposed procedure of optimization is summarized as given further.

**Step1.** Collect the input parameters (material or dimension parameters) and corresponding outputs (J-integral value) from the simulation with FEM.

**Step2.** Deal with the input parameters with PCA method.

**Step3.** Building a BPNN model combined GAs to obtain a nonlinear function between the input parameters and corresponding outputs. The well-trained network is seen as a observation tool to optimize the packaging device for next step.

**Step4.** Calculate the effects on the outputs by inputting the changing parameter values into the prediction model; observe the effect and select the optimization value of each input parameter.

**Step5.** Obtain an optimal group of the parameters.

**Step6.** Verify the optimal group results by simulating with FEM. Turn back to step3 if the result is not satisfied.

**Step7.** Obtain the optimal result.

Actually, it uses the $\Phi$ function given as formula (2) which fitted by training GA-BPNN model during the proposed procedure of optimization.

$$Y = \min [ \Phi ( f_1, f_2, f_3, \ldots, f_{q-1}, f_q ) ]$$

It is trying to find out the most excellent parameter combination $f_q$ (corresponded to a group of $X_p$) so as to minimize $\Phi$ function.

### 3. Laser cladding process test

The substrate is 6063 Al, and the cladding powder is a mixture of a Ni60 alloy powder and a rare earth powder (the rare earths are 4% CeO$_2$, 5% Y$_2$O$_3$, and 5% La$_2$O$_3$, respectively). That is, the cladding powders used in this study are Ni60+4%CeO$_2$, Ni60+5%Y$_2$O$_3$, and Ni60+5%La$_2$O$_3$ (hereinafter referred to as Ni60+CeO$_2$, Ni60+Y$_2$O$_3$, and Ni60+La$_2$O$_3$, respectively). Before the cladding, the mixed powder was fully mixed in a ball mill for 24 hours, and then dried in a vacuum heat treatment furnace at 70°C for 12 hours or longer.

The BP neural network has a high requirement for samples. Not all input and output data can get an ideal linear relationship. Therefore, choosing real, reliable, and reasonable data becomes the primary issue. The experiments selected by orthogonal experimental design can fully reflect the laws of the selected system. Although it reduces the number of experiments, the experimental data obtained can also fully reflect the internal relationship between various factors and indicators. The general neural
network model uses orthogonal experiment data as a sample because the combination of experimental factors is representative. Using this result, an efficient and reliable neural network can be established. Through preliminary literature review and a large number of technological trials, the laser power is selected at 3500 W, 4000 W and 4500 W, the spot diameter is selected at 5 mm, 6 mm and 7 mm, the scanning speed is selected at 8 mm/s, 10 mm/s and 12 mm/s, and orthogonal experimental design method was used to arrange the experimental protocol. A CNC machining program was programmed to carry out multi-lap laser cladding processing in accordance with the predetermined laser process parameters, and the lap ratio of all the strengthening layers was 15-25%. The surface hardness of laser cladding of different process parameters (Samples of training neural networks) is obtained as shown in Table 1.

| Cladding materials | Laser power (W) | Spot diameter (mm) | Scanning Speed (mm/s) | Surface Hardness(HV0.1) |
|--------------------|----------------|--------------------|-----------------------|------------------------|
| Ni60+La2O3         | 3500           | 5                  | 8                     | 640                    |
| Ni60+La2O3         | 3500           | 6                  | 10                    | 680                    |
| Ni60+La2O3         | 3500           | 7                  | 12                    | 450                    |
| Ni60+La2O3         | 4000           | 5                  | 10                    | 1050                   |
| Ni60+La2O3         | 4000           | 6                  | 12                    | 620                    |
| Ni60+La2O3         | 4000           | 7                  | 8                     | 1360                   |
| Ni60+La2O3         | 4500           | 5                  | 12                    | 1280                   |
| Ni60+La2O3         | 4500           | 6                  | 8                     | 620                    |
| Ni60+La2O3         | 4500           | 7                  | 10                    | 1260                   |
| Ni60+CeO2          | 3500           | 5                  | 8                     | 740                    |
| Ni60+CeO2          | 3500           | 6                  | 10                    | 810                    |
| Ni60+CeO2          | 3500           | 7                  | 12                    | 525                    |
| Ni60+CeO2          | 4000           | 5                  | 10                    | 1080                   |
| Ni60+CeO2          | 4000           | 6                  | 12                    | 620                    |
| Ni60+CeO2          | 4000           | 7                  | 8                     | 1370                   |
| Ni60+CeO2          | 4500           | 5                  | 12                    | 1300                   |
| Ni60+CeO2          | 4500           | 6                  | 8                     | 660                    |
| Ni60+CeO2          | 4500           | 7                  | 10                    | 1240                   |
| Ni60+Y2O3          | 3500           | 5                  | 8                     | 720                    |
| Ni60+Y2O3          | 3500           | 6                  | 10                    | 820                    |
| Ni60+Y2O3          | 3500           | 7                  | 12                    | 550                    |
| Ni60+Y2O3          | 4000           | 5                  | 10                    | 1050                   |
| Ni60+Y2O3          | 4000           | 6                  | 12                    | 620                    |
| Ni60+Y2O3          | 4000           | 7                  | 8                     | 1320                   |
| Ni60+Y2O3          | 4500           | 5                  | 12                    | 1280                   |
| Ni60+Y2O3          | 4500           | 6                  | 8                     | 690                    |
| Ni60+Y2O3          | 4500           | 7                  | 10                    | 1230                   |

4. Building the optimal model

4.1 Setting the parameters
To construct a GA-BP neural network model, first determine the input and output parameters. According to the principle of parameter selection, combined with the output of the prediction model of surface hardness, the influencing factors identified in this paper are: powder type, laser power, spot diameter and scanning speed. This paper uses the principal component + GA + BPNN integrated analysis model, chooses 4-6-1 neural network model, 4 input nodes, 6 hidden nodes, 1 output, network fitting
training accuracy is 0.0001, training sample number is 82. The weights between nodes are optimized and estimated by genetic algorithm. The genetic algorithm uses a population of 80 and an algebra of 80.

4.2 Selection of data sources and training samples
In this paper, orthogonal tables are used to arrange experiments. Aluminum alloy laser cladding experimental data is used as a neural network training sample (Table 1). A BP neural network is established and the output parameters are training samples. After network training, the fitness of the genetic algorithm is 0.52, and the neural network is much smaller than the required fitting error in 27 training samples. The (MSE) is 8.81e-6, indicating that the training samples obtained from the input orthogonal experiment are very good. Representative, Fig.3 shows the network training convergence and genetic algorithm fitness curve.

![Fitness training convergence curve and genetic algorithm fitness.](image)

Fig. 3. Fitness training convergence curve and genetic algorithm fitness.

5. Results and discussions

5.1 Forecast results
The trained BPNN is used to predict the setting level of each parameter, and the relationship between the process parameters and the surface hardness is predicted. Due to the cross-impact of each parameter, the influence relationship is relatively complex, and the influence of different fixed combinations on changing a certain factor will be different. Each parameter is changed using a fixed combination of 2 different other parameters.

Fig.4 shows the relationship between the predicted laser power and the surface hardness. Fig.5 shows the relationship between the predicted spot diameter and the surface hardness. Fig.6 shows the relationship between the predicted scanning speed and the surface hardness. The relationship between the process parameters and the surface hardness is very important for the engineering application of aluminum alloy laser cladding, and provides important technical support for the promotion and application of this technology. This result also shows that if a better combination of parameters is explored, the optimization combination is likely not to be unique.
Fig.4. The relationship between the predicted laser power and the surface hardness.

Fig.5. The relationship between the predicted spot diameter and the surface hardness.

Fig.6. The relationship between the predicted scanning speed and the surface hardness.

Fig.7 shows the preliminary simulation results of the global simulation using the trained BPNN. It can be seen that the prediction results show singularity and the forecast result is unstable because the data level is subdivided beyond the scope of the original data source, and the negative direction needs to be masked and improved. The following fig.8 shows the final prediction result of shielding negative direction.
5.2 Verification of the process test

For each type of cladding powder, three groups of optimization combinations were selected from the prediction results to develop a process verification test. Table 2 shows the BPNN simulation prediction results and actual process test verification results. The results show that the BPNN simulation prediction results are very close to the results of the process test, and the errors are all less than 1%. This shows that the network model has little difference between the process parameter mapping results and the experimental results. The model can be used to predict the experimental results of aluminum alloy laser cladding.

Fig. 9 shows the cross-sectional topography of 9 groups of actual process tests. It can be seen that the thickness of all the strengthening layers is about 900 μm -1000 μm, and there are no defects such as pores or cracks in the cross-sectional morphology, which further proves the accuracy of the model prediction.

Through technological experiment and BP neural network prediction, the optimal cladding technological parameters of Ni60 alloy + rare earth (4% CeO₂, 5% Y₂O₃, and 5% La₂O₃) laser reinforcement layers were acquired as follows. For Ni60 + 4% CeO₂: power of 4000 W, spot diameter of 7 mm, and scanning speed of 12 mm/s; for Ni60 + 5% Y₂O₃: power of 4500 W, spot diameter of 7 mm, and scan-
ning speed of 10 mm/s; and for Ni60 + 5% La2O3: power of 4000 W, spot diameter of 7 mm, and scanning speed of 10 mm/s.

### Table 2. The BPNN simulation prediction results and actual process test verification results.

| Cladding materials | Laser power (W) | Spot diameter (mm) | Scanning speed (mm/s) | Predict hardness(HV0.1) | Measured hardness (HV0.1) |
|--------------------|----------------|--------------------|-----------------------|-------------------------|---------------------------|
| Ni60+La2O3         | 4000           | 7                  | 10                    | 1457.3                  | 1454                      |
| Ni60+La2O3         | 4000           | 7                  | 12                    | 1444.3                  | 1440                      |
| Ni60+La2O3         | 4500           | 7                  | 12                    | 1450.4                  | 1446                      |
| Ni60+CeO2          | 4000           | 7                  | 12                    | 1658.0                  | 1646                      |
| Ni60+CeO2          | 4500           | 5                  | 10                    | 1598.0                  | 1586                      |
| Ni60+CeO2          | 4500           | 7                  | 12                    | 1574.0                  | 1564                      |
| Ni60+Y2O3          | 4000           | 7                  | 8                     | 1358.7                  | 1366                      |
| Ni60+Y2O3          | 4500           | 7                  | 10                    | 1467.6                  | 1472                      |
| Ni60+Y2O3          | 4500           | 7                  | 12                    | 1317.8                  | 1324                      |

Fig. 9. The cross-sectional topography of 9 groups of actual process tests

### 6. Conclusions

In this paper, a GA-BPNN model is established to optimize the process parameters of laser cladding on the aluminum alloy surface. The results of the optimized prediction are in good agreement with the
experimental results, which shows that the prediction method based on BPNN is feasible. The exploration results show that the combination of process parameters and optimization objectives, the optimal combination of surface hardness impact parameters is not unique, this result is very conducive to the selection of process parameters, and is closer to the actual production needs. In addition, no matter whether it is the optimal or various surface hardness predictions, the proposed optimal prediction method can obtain representative results. This article predicts the laser cladding process parameters of aluminum alloy surface, and provides a good reference method for the optimization of the surface hardness of laser cladding of aluminum alloy surface in engineering practice.

Declaration of Competing Interest
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.

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