Process Reliability Optimization of Plasma Spray Process Based on Uniform Design, RBF and Improved PSO

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Abstract. Plasma spraying is a kind of thermal spraying technology widely used in parts production. However, the coating performance can’t meet requirements due to process parameters and machining equipment, which caused a bad effect on overall product reliability. It is necessary to study the reliability of plasma spraying process. Firstly, seven controllable process parameters impacting on coating quality were determined, according to engineering experience. The uniform design was selected to find the most contributing factors and primary selection parameter combination was determined. For optimality design, the RBF neural network was trained and verified by sample data. The particle swarm optimization (PSO) algorithm was used to optimize the RBF model. The optimal process parameters were obtained by improved PSO. The optimization of the process improves the process reliability of the plasma spraying and plays an important role in ensuring the reliability of the part.

1. Introduction

The concept of process reliability first appeared in the book of machine reliability written by the Professor Probucol in 1978 [1]. The book defined the process reliability of the equipment as the ability to maintain the required quality level of the process within the specified scope and time. For many years, the research and development of process reliability is in the understanding of concept and connotation, the establishment of parameter index system and so on. At present, the research results of process reliability mainly focus on the modeling and optimization analysis of process reliability.

In terms of plasma spraying, Balan K N and Bapu B R R optimized the technological parameters of spray gun in plasma spraying by Taguchi method in order to obtain the maximum coating hardness [2]. However, the experimental design cannot obtain the optimal results in the continuous space. Thirumalaikumarasamy D, etc. used the response surface methodology (RSM) to establish the relationship between porosity and spray process parameters, and three parameters were optimized for high quality coatings [3]. However, there are still many deficiencies in the research of the reliability of plasma spraying process. On the one hand, the qualitative analysis results in inaccurate optimization; on the other hand, the optimized parameters were less and the optimization was not sufficient.

With the deepening of the research, the combination of experiment of design and intelligent algorithm had become a hot research topic. For example, neural network algorithm and particle swarm optimization algorithm and so on.

This study come out from the actual problems that coating hardness of a parts cannot meet the actual needs and surface defects is serious. It was obvious that the spraying process parameters were closely
related to the quality of the coating. Coating quality reflects the reliability of plasma spraying process. Therefore, the plasma spraying process was studied.

Intelligent algorithms were introduced to solve practical engineering problems. Aiming at the controllable process parameters which have a critical influence on the coating quality in the process of reliability analysis, the optimization scheme of plasma spraying process parameters was proposed based on uniform design, RBF neural network and particle swarm optimization algorithm.

2. Process Analysis Based on Uniform Design
Neat comparability was the most significant feature of orthogonal design, but uniform dispersion was not sufficient. When the number of factors and levels were more, the orthogonal design cannot meet the requirements. Chinese academician Wang Y and Professor Fang K.T have worked out the uniform design [4]. Uniform design was an experimental design method for uniform distribution of test points in the range of test.

The meaning of $U_n(q^s)$ and $U_0(q^s)$ was as follows: $n$: number of trials; $q$: levels of factors; $s$: number of columns.

In general, $U_0(q^s)$ has better uniformity and should be preferred.

In this paper, seven controllable variables were determined by process FMEA analysis based on actual engineering requirements. The coating quality was reflected by coating hardness (HV). The symbols, units and ranges of each process parameter were shown as Table 1:

| Parameter Information | 0 | Sign | Unit | $L$ | $U$ |
|-----------------------|---|------|------|-----|-----|
| Ar pressure           | $X_1$ | psi  | 62   | 88  |
| Hydrogen pressure    | $X_2$ | psi  | 50   | 70  |
| Argon flow rate      | $X_3$ | SCFH | 78   | 125 |
| powder pressure      | $X_4$ | bar  | 2.5  | 4.5 |
| powder flow rate     | $X_5$ | SCFH | 7.0  | 10  |
| Amount of powder     | $X_6$ | %RPM | 18   | 30  |
| Spraying distance    | $X_7$ | mm   | 115  | 175 |

$U_0(12^{10})$ was selected to design based on number and range of factors according to the principle of minimum deviation. Table with $D=0.2768$ was chose. The experiment was carried out according to uniform design table. The experiment were shown in Table 2:

| Table 2. Uniform design experiments |
|-----------------------------------|
| NO. | $X_1$ | $X_2$ | $X_3$ | $X_4$ | $X_5$ | $X_6$ | $X_7$ |
|-----|-------|-------|-------|-------|-------|-------|-------|
| 1   | 65.00 | 51.82 | 98.18 | 3.773 | 8.955 | 26.55 | 170.0 |
| 2   | 66.82 | 55.45 | 120.0 | 2.864 | 8.227 | 24.36 | 162.5 |
| 3   | 68.64 | 59.09 | 94.55 | 4.318 | 7.50  | 22.18 | 160.9 |
| 4   | 70.45 | 62.73 | 116.4 | 3.409 | 9.136 | 20.00 | 156.4 |
| 5   | 72.27 | 66.36 | 90.91 | 2.500 | 8.409 | 27.27 | 151.8 |
| 6   | 74.09 | 70.00 | 112.7 | 3.955 | 7.682 | 25.09 | 147.3 |
| 7   | 75.91 | 50.00 | 87.27 | 3.045 | 9.318 | 22.91 | 142.7 |
| 8   | 77.73 | 53.64 | 109.1 | 4.500 | 8.591 | 20.73 | 138.2 |
| 9   | 79.55 | 57.27 | 83.64 | 3.591 | 7.864 | 28.00 | 133.6 |
| 10  | 81.36 | 60.91 | 105.5 | 2.682 | 9.500 | 25.82 | 129.1 |
| 11  | 83.18 | 64.55 | 80.00 | 4.136 | 8.773 | 23.64 | 124.5 |
| 12  | 85.00 | 68.18 | 101.8 | 3.227 | 8.045 | 21.45 | 120.0 |
The results of the test were shown in Table 3.

| NO. | 1   | 2   | 3   | 4   | 5   | 6   |
|-----|-----|-----|-----|-----|-----|-----|
|     | 190.24 | 183.56 | 195.29 | 193.87 | 194.32 | 203.65 |
| NO. | 7   | 8   | 9   | 10  | 11  | 12  |
|     | 213.58 | 215.72 | 217.33 | 221.42 | 226.94 | 225.05 |

The experimental results were processed by regression analysis with backward. The test index influenced by three factors is hardness. Let $\alpha = 0.05$. After six elimination, small contributory factors were cut. The final regression equation was obtained, as following:

$$y = 41.25 + 2.207 \times X_1$$

The correlation coefficient of regression was 0.9661. The significance test showed that the regression equation was significant. Model trustworthiness analysis proves that the model was credible.

The regression analysis showed that $X_1$ had the greatest contribution to the target, and it was a positive correlation. The method of uniform analysis was simple and easy to be realized, which guided the worker to choose the parameter. Because of the influence of uncontrollable factors, the uniform test results basically show such a trend. Test No. 11 and No. 12 were analysed based on practical experience and experiment. The combination of the better process plan No. 12 was selected. The greatest contributory factor was found and the process was chosen.

The results showed that $X_1$ had great contribution, but the influence of other factors couldn't be ignored. The experimental point of uniform design analysis optimization was discrete. There are many uncertainties in the experiment, and the better results need to be obtained through more accurate methods and more test data. Based on more experiments, it is necessary to carry out continuous optimization. The algorithm of PSO combined with RBF was implemented to optimize.

3. The Algorithm of PSO Combined with RBF

3.1. RBF ANN model

RBF ANN (Radical Basis Function Artificial Neural Network) model is widely used to fitting nonlinear function. In this passage, RBF ANN model is used to fitting accurate nonlinear model on the basis of the original model. In the RBF ANN model, there are three layers of network structure: input layer, hidden layer and output layer. The activation function is Gaussian function, which is defined as:

$$g_i(x_k) = \exp \left( \frac{\|x_k - c_i\|^2}{\sigma_i^2} \right)$$

Among them: $x_k (1 \leq k \leq n)$ is the $Kth$ input vector; $c_i (1 \leq i \leq c)$ is the basis function center, $\sigma_i$ is the expansion constant, $n$ is the number of samples, $c$ is the number of hidden layer nodes, and the network output is:

$$o(x_k) = \sum_{i=1}^{c} \omega_i g_i(x_k)$$
Among them: $\omega_i$ is the connection weight of the $i$th hidden node.

The essence of the training process of RBF ANN was the optimization of the basis function centers, expansion constants and connection weights, that is, optimizing three parameters of $c_i, \sigma_i, \omega_i$. Therefore, this paper first improves the standard PSO algorithm, introduced adaptive weight adjustment strategy of chaos, diversity assessment of population entropy and convergence and divergence strategy, and proposes an improved PSO algorithm. Then, the improved PSO algorithm was applied to RBF ANN. Three sets of parameters were optimized to obtain the optimal combination of parameters, which was designed to improve the predictive performance.

3.2. PSO algorithm optimization

3.2.1. PSO algorithm. The PSO algorithm was a group evolution algorithm proposed by scholars Eberhart and Kennedy. The standard PSO algorithm updates the velocity and position of particles by the following formula.

$$v_{i,d}^{k+1} = \omega v_{i,d}^k + c_1 (p_{i,d}^k - x_{i,d}^k) + c_2 (p_{g,d}^k - x_{i,d}^k)$$

$$x_{i,d}^{k+1} = x_{i,d}^k + v_{i,d}^{k+1}$$

Among them: $i = 1, ..., m$; $\omega$ was called inertia weight factor; $c_1$ and $c_2$ were learning factors; $v_{i,d}^k$ and $x_{i,d}^k$ were the velocity and position of the $d$th dimension of particle $i$ in the $k$th iteration, respectively; $p_{i,d}^k$ was the position of particle $i$ in the dimensional individual extremum; $p_{g,d}^k$ was the position of the global extremum of the population in the $d$th dimension. It can be seen that the particle velocity was determined by the inertia weight factor $\omega$, cognitive factor $c_1$ and exploring factor $c_2$.

3.2.2. Optimize RBF with PSO. From 1.1, the parameters of RBF model are $c_i, \sigma_i, \omega_i$. Therefore, in order to make the RBF model fit more accurately, the PSO algorithm was used to search the three parameters in the range. The particle structure was defined as follows:

$$particle(i) = [w_{h,o}, b_{h,o}, c_h]$$

Among them, $w_{h,o}(1 \leq h \leq c), (1 \leq o \leq p)$ was the weight matrix of hidden layer node and output node. $b_{h,o}(1 \leq h \leq c), (1 \leq o \leq p)$ was the hidden layer node and output deviation matrix of nodes. $c_h$ was the basis function center; $p$ was the number of output nodes.

Through the optimization of PSO algorithm, RBF ANN model based on PSO algorithm was obtained, and then the model was tested. In order to evaluate the performance of the model, this paper used the prediction mean square error $RMSEP$ as the evaluation index of the model, defined as:

$$RMSEP = \sqrt{\frac{1}{N} \sum_{i=1}^{n} (y_i - \bar{y}_i)^2}$$
In this formula, \( N \) was the number of data samples, \( \bar{y}_i \) was the predicted value, \( y_i \) was the experimental value. Through particle swarm optimization algorithm, \( \text{RMSEP} \) was used to find the optimal fitting parameters of \( c_i, \sigma_i \) and \( w_i \) for fitting the RBF ANN model to the actual nonlinear model.

### 3.3. Optimize parameter values with PSO

From 1.2, a good fit of the RBF ANN model was obtained. The ultimate goal of this paper was to obtain the hardness index of the optimized plasma spray, so the PSO model was reused to optimize the parameter values during the plasma spray process. In this optimization, the PSO particle structure was defined as:

\[
\text{particle}(i) = [p_a]
\]

In this formula: \( n \) was the number of design parameters in the plasma spraying process.

In this PSO model, the RBF ANN model in 1.2 was used as fitness function. Through iterative optimization, the optimal value of the design index and the corresponding parameter value combination were obtained.

### 4. Model Establishment

The experimental data of this paper comes from experimental operation of the author. The RBF ANN model of this paper used three layers structure, namely input layer, hidden layer and output layer. The model structure shown in Fig.1.

![RBF ANN prediction model](Image)

**Figure 1.** RBF ANN prediction model

The input layer of the model indicated the influencing factors of the model object of study. In this paper, there are 7 nodes in the input layer, and the output layer was composed of Ar pressure, hydrogen pressure, argon flow rate, powder pressure, powder flow rate, amount of powder and spraying distance, which was the surface hardness of the spray process, so there was one node in the output layer. In this paper, a neural network modeling method based on precise radial basis was used. The number of nodes...
in the hidden layer was the number of samples, that is, the hidden layer has 99 nodes.

5. Results and Analysis

5.1. PSO algorithm optimization

This paper established a 3-layer RBF ANN model with a structure of 7-99-1, in which the input nodes represent 7 parameters related to the plasma spraying process: Ar pressure, hydrogen pressure, argon flow rate, powder pressure, powder flow rate, amount of powder and spraying distance; 99 hidden nodes, and 1 output node representing the surface hardness of the coating. Fig. 2 was a comparison chart of the deviation of the prediction values in the RBF ANN model after PSO-optimized RBF ANN model and without PSO optimization.

It can be seen from the figure above that the deviation between the predicted value and the actual value was remarkable in the prediction of the model of the RBF ANN which was not optimized by the PSO. After the optimization of the PSO, the deviation ratio between the predicted value and the actual value of the RBF ANN model before optimization had been significantly reduced. It can be seen that the surface hardness of plasma sprayed by PSO optimized RBF ANN model was in good agreement with the actual value, and the prediction was accurate and reliable. Table 4 showed the statistical values of the $\text{RMSEP}$ evaluation parameters of the prediction model during testing.

|                   | $\text{RMSEP}$ |
|-------------------|----------------|
| Before optimization | 8.4568         |
| After optimization | 6.8873         |

As can be seen from the data in Table 4 before and after optimization, the PSO-optimized RBF ANN model had a smaller fitting deviation from the original model, and the $\text{RMSEP}$ was relatively reduced by 25%. The above results confirmed that the optimized model had excellent predictive performance and can be used to predict the surface hardness of the plasma spray process.

5.2. PSO algorithm optimization

The PSO model was established to optimize the parameters of the spray process to obtain a higher hardness plasma sprayed surface. In this model, the parameters involved in the spraying process are taken as the particle structure, the surface hardness of the spraying process as the fitness of the PSO
optimization model, and the RBF ANN model mentioned above as its fitness function. After 500 iterations, the optimal value can basically got a better result. The model optimization results were shown in Table 5.

Table 5. Optimized parameter and hardness values

| Parameter          | Values |
|--------------------|--------|
| Ar pressure        | 82.10  |
| Hydrogen pressure | 58.77  |
| Argon flow rate    | 95.70  |
| powder pressure    | 3.75   |
| powder flow rate   | 8.74   |
| Amount of powder   | 21.73  |
| Spraying distance  | 151.14 |
| Surface hardness   | 241.26 |

In this model of PSO optimization process parameters, a set of optimized plasma spray parameters were obtained and the plasma spray surface hardness was obtained when RBF ANN was used as a fitness function.

6. Conclusion

In this paper, two optimization methods were used. Firstly, RBF ANN model was optimized by using PSO algorithm to get a more accurate fitting model. The relationship between process parameters and indexes was accurately simulated by the model. Then, Indicators, the use of PSO algorithm to optimize the process parameters, get the surface hardness was relatively large parameter combinations.

The actual experiment, using the data obtained in this paper model can get a higher surface hardness of plasma spraying, plasma spraying process optimization put forward guiding opinions.

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