Optimization of Plasma Spray Process VIA Orthogonal Test Design Method, SVM, and Improved PSO

Jing Xue and Min Huang

Abstract—**Plasma spray is a widespread thermal spraying technology due to its unique advantages, but control of various defects in the coating is still the major trouble currently faced in the field. The key problem left to be solved is how to determine the optimum combination of input process parameters to achieve the required quality of coating. This research work integrates Orthogonal Test Design Method, Support Vector Machine (SVM), and Particle Swarm Optimization (PSO) algorithm to ascertain the optimal process parameter settings of the plasma spray. Orthogonal Test Design method is used to design a set of representative experiments for reducing the number of tests, simultaneously, accessing to the most valuable sample data. The data obtained from orthogonal test is used as samples for training and testing SVM so as to establish relation model between process parameters and the coating quality. Then, SVM is combined with Improved PSO to find the optimal combination of spraying parameters. In the end, the verification test is implemented to verify the effectiveness of the optimal process parameters.**

In this paper, the proposed method is applied to determine the optimal process parameter settings of aero-engine seal coating formed by plasma spray. The experimental results show that this method can overcome the shortcomings of the traditional orthogonal test which only obtain a discrete optimization and the difficulties to optimizing the complex systems when there are small samples or the high number of dimension, furtherly obtain the optimal ones in the continuous ranges of plasma spray process parameters, which contributes to spraying coatings with the best quality.

Index Terms—**Plasma spray, orthogonal test design method, support vector machine, particle swarm optimization.**

I. Introduction

Plasma spray technique is an effective means to obtain a variety of unusual and superior function coating on the surface of the material, which can strengthen the performance of substrate surface with wear-resistant, corrosion resistance, high temperature oxidation, thermal insulation, sealing and so on. It is a very wide application of thermal spray technology because of its key feature, high internal temperature, which ensures that almost all of the materials can be sprayed [1]. The working principle of plasma spray is that the gas is accelerated under the action of electric field, and the collision with neutral particles, leading to neutral particle ionization, in turn resulting in ion arc. And due to the effect by thermal shrinkage, shrinkage of magnetic and mechanical contraction, plasma arc owns such high speed and high temperature flame flow that the spray material is heated to a molten or semi molten state. Then the spraying material is sprayed onto the surface after coarsening and cleaning to produce plastic deformation and adhered to the surface of the part. The fused drops are connected with each other by plastic deformation, so as to obtain a good layer of compact coating [2]. Although plasma spray has made considerable achievements and also received the substantial economic and social benefits after over 50 years of development, but the control of various defects in the coating is still the major problems currently faced in the plasma spray technique. Pores, cracks and delamination defects often appear in the coating, which bring a lot of adverse effects on coating performance. The coating quality depends on the settings of spray coating process parameters in the manufacturing process, it is unsuitable process parameter settings that cause those production problems [3].

Plasma spray process consists of four phases: the substrate pretreatment (including surface purification, blasting roughened, etc.), clamping, spraying and coating disposition after spraying. Previous studies have shown that plasma spray process related to numerous parameters, including sandblasting rate, the amount of feed powder, powder feed rate, current, power, spraying distance, the proportion of working gas composition, gas pressure, and so on [4]. Coating properties like porosity, adhesive strength, hardness, Young's modulus, and coating residual stresses are the main factors determine the actual performance of coating [5]. Therefore, hardness, porosity, adhesive strength are always chosen as the indicators of the coating quality. Previously, it is experience or trial-and-error method that was used to determine initial process parameter settings for the plasma spray process. However, this method is very time-consuming, cost, especially difficult to obtain optimal results of complex system. Hsu *et al*. [6] researched that it was nearly impossible to search the really optimal parameter settings just by the means of a trial-and-error process.

Many researchers start to explore new ways, subsequently various methods part of Design of Experiment have been employed in optimizing process parameters of plasma spray. Kimswell *et al*. [7] applied the Taguchi method to study the influence of process parameters on coating quality on the vacuum plasma sprayed deposition of, nickel-base alloy, alumina, tungsten cobalt metal ceramic coating; Li *et al.* [8] researched the application of uniform design experimental methods in optimizing plasma spray parameters about deposition efficiency, porosity and micro-hardness in the yttria stabilized zirconia coatings; In the research work of S. Karthikeyan [9], the response surface methodology (RSM)

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was used to estimate the relationship between controllable atmospheric plasma spray process parameters (standoff distance, input power and powder feed rate) and performance characteristics (micro-hardness and porosity) of thermal barrier coatings. However, the orthogonal test or uniform design can only achieve a given level of the optimal combination of several factors. It neither achieve prediction, nor obtain the best process parameters, especially existing a big deficiencies in the multi-objective optimization. It is also difficult for RSM to establish enough precision relation model when the control variable is too much, even the complex relationship is unknown between the input and output. Unreasonable parameter Settings will be a large impact on the quality of spraying coating, therefore, it is quite necessary to find a suitable optimization method.

To meet the challenge, Artificial Neural Network (ANN) has been quoted with more advantages in the aspect of modeling in complex nonlinear system. Through a large number of data samples of training and learning, neural network technology can map the fuzzy function relationship between the input and output. T. A. Choudhury *et al*. [10]-[14] has proposed (ANN) to achieve the process control by establishing correlations between the various plasma condition parameters and in-flight particle characteristics. ANN is often combined with Genetic Algorithms (GA), Particle Swarm Optimization (PSO) to determine the optimal process parameters [15], [16]. Although ANN has a strong nonlinear function approximation capability, but the foundation of the neural network is the contents of the traditional statistical study that is asymptotic theory of infinite sample. On the contrary, the sample data are often limited in the practical problems. Therefore, it is difficult to achieve the desired results by a variety of algorithms based on the assumption that owns an infinite number of sample data [17]. Thus, trained neural network always shows poor generalization ability of the neural network, and it is also likely to fall into local extremum in the optimization process, but the Support Vector Machine (SVM) shows many unique advantages in solving the small sample, nonlinear and high dimensional pattern recognition problems [18].

Based on the above discussion together with the circumstances that the actual process parameters impact on the quality of the coating is too many and the test sample data is extremely limited, this paper proposes an effective approach for plasma spray process parameter optimization which integrates Orthogonal Test Design method, Support Vector Machine (SVM) and Particle Swarm Optimization (PSO) algorithm. Orthogonal Test Design method is used to design a set of representative experiments for reducing the number of tests, simultaneously, accessing to the most valuable sample data. The data obtained from orthogonal test is used as samples for training and testing SVM so as to establish relation model between process parameters and the coating quality. Then, SVM is combined with PSO to find the optimal combination of spraying parameters. In addition, this paper has improved the standard particle swarm optimization algorithm including nonlinear dynamic improvement of inertia weight, nonlinear dynamic adjustment of acceleration factor and introducing adaptive mutation particle three methods to increase the accuracy of the standard PSO algorithm. In the end, the verification test is implemented to verify the effectiveness of the optimal process parameters. The method can overcome the shortcomings of the traditional orthogonal test which only obtain a discrete optimization and the difficulties to optimize the complex systems when there are small samples or the high number of dimension, furtherly obtain the optimal ones in the continuous ranges of plasma spray process parameters, which contributes to spraying the optimal coatings.

II. Optimization Methods

In this paper, Particle Swarm Optimization has been improved due to the shortcomings of standard algorithm. The optimization method including Support Vector Machine and Particle Swarm Optimization are briefly introduced as follows.

A. Standard Particle Swarm Optimization

PSO has been first put forward by James Kennedy and Russell Eberhart in the 1995, whose basic idea is the behavior simulation of migration and accumulation in the foraging process of birds, fish migration, and the biological population model of biologist Frank Heppner was also been utilized [19]. PSO algorithm is a kind of swarm intelligence based on stochastic optimization technique, genetic algorithm relative terms, both of which are based on iterative search group. However, PSO algorithm search for the optimal point through collaboration between individuals solution without crossover and mutation operator like GA. It use the biological population information sharing ideas, thus the concept is so simple, efficient and easy to implement that it has been widely used in different disciplines intelligent optimization.

A group of particles (random solutions) has been first randomly initialized in the PSO algorithm, and particle iterative search optimal solution in the solution space following the current optimal particle. In the D-dimensional search space, assume that the position and velocity of the i-th particle are respectively represented as $X=(x_{i1},x_{i2},...,x_{iD})$ and $\mathrm{V}=(v_{i1},v_{i2},...,v_{iD})$. In each iteration, the particles update themselves by tracking both the optimal solutions that one is the individual optimal solution pbest, the other is the global optimal solution gbest. In the process of looking for the both optimal solutions, the particles update their speed and positions according to the formula (1) and (2) to ensure to gather global optimal solution by searching continuously in the design space.

$$v_i^{k+1}=w\times v_i^k+c_1\times rand_1\times(pbest-x_i^k)+c_2\times rand_2\times(gbest-x_i^k) \tag{1}$$

$$x_i^{k+1}=x_i^k+v_i^{k+1} \tag{2}$$

where v_i^k is the k-th iteration speed of i-th particle, x_i^k is the k-th iteration position of i-th particle, ω is the inertia weight factor, and $rand_1$ and $rand_2$ are two random functions in the range [0,1], c_1 and c_2 are two acceleration factors or called learning factors.

B. Improved Particle Swarm Optimization

The accuracy of PSO algorithm is closely related to the choice of parameters, so that if the selection of parameters is not appropriate, the accuracy of the algorithm will directly decrease. The value range of inertia weight is generally between 0.5 and 2.0, and that of the learning factors c_1 and c_2 are generally from 0 to 4. In the realization process of the whole standard algorithm, the parameters are the fixed value, which ignores the specific optimization model and the iterative process. Inappropriate selection of the parameters will have a serious influence on the results of the optimization [20].

Based on the previous research, this paper has improved the standard particle swarm optimization algorithm including nonlinear dynamic improvement of inertia weight, nonlinear dynamic adjustment of acceleration factor and introducing adaptive mutation particle three methods, especially the improvement of inertia weight has been made further revision and perfection.

1) Nonlinear dynamic improvement of inertia weight

In PSO algorithm, inertia weight determines the extent of the current particle velocity inheritance, and suitable choice can make particles have a balanced global search ability and local search ability. Larger value of ω is helpful to improve the global search ability of the algorithm, while the smaller will enhance the local search ability. In this paper, the form of the incentive function is used to construct the form of the nonlinear automatic adjustment with the objective function value of the particle for the inertia weight. In each iteration, the inertia weight is

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \times \frac{1}{1+e^{-(f-f_{avg})}} \tag{3}$$

As can be seen from the formula (3), inertia weight will continue to increase with the value of target particles tend to be consistent or local optima, assuring that the particle can search better particles at a high speed in the global scope, which enables the algorithm to have a strong ability of search. If the particle target value is scattered or the fitness value is better than the group average of adaptation, the inertia weight will be correspondingly reduced to ensure particle can fine local search and make the algorithm have strong local searching ability. If the particle target value poorer than the average objective function, increase the inertia weight will enable the particles to better search area closer. By nonlinear dynamic adjustment of inertia weight, the global search ability of the algorithm can be enhanced, and the search results can be better than the fixed weight and linear adjustment weights.

2) Nonlinear dynamic adjustment acceleration factor

In the particle swarm optimization algorithm, the acceleration factor c_1 and c_2 make the particles have the ability to self sum up and learn from the group, for the sake of being close to the best advantage in the group or in the field. In order to make the particle in the initial stage of optimization has a strong ability to search, and enhance the ability to converge to the global optimal solution in the optimization of the latter, acceleration factor c_1 and c_2 should be improved nonlinear dynamically in the each iteration.

$$\begin{cases} c_1 = c_{1,start} + (c_{1,end} - c_{1,start}) \ln(\dfrac{(e-1)t}{t_{\max}} + 1) \\ c_2 = c_{2,start} + (c_{2,end} - c_{2,start}) \ln(\dfrac{(e-1)t}{t_{\max}} + 1) \end{cases} \tag{4}$$

where both $c_{1,start}$ and $c_{2,start}$ are the initial value of acceleration factors, both $c_{1,end}$ and $c_{2,end}$ are learning the final iteration value for factor c_1 and c_2, $t_{\max}$ is the maximum number of iterations of particles.

3) The introduction of adaptive mutation particles

In the particle search process, it can make the variation of particle population satisfy the constraints through the introduction of adaptive mutation. The variation occurs in each particle, which can make the particles to find more promising results, and keep the population diversity and effectiveness.

$$\begin{aligned} & x(i,j) = \begin{cases} U \times rand + L, rand \le 0.5 \\ (U-L) \times rand + L, rand > 0.5 \end{cases} \\ & i = 1,2,...,N \\ & j = ceil(D \times rand) \end{aligned} \tag{5}$$

where U and L are respectively the lower and upper bounds of the position of the particle; D is the space variable dimension, namely the number of unknown variations; rand is a random number between 0 and 1; ceil () is the rounding function.

C. Support Vector Machine

Support Vector Machine (SVM) [21] is a new method to solve data classification and regression problems. It is based on the statistical VC dimension theory in the learning theory and structural risk minimization principle, with the stronger generalization ability of the learning machine. Because small error is obtained from limited training sample set and kept continuously on the independent test set, it has stronger theoretical foundation and better generalization performance than ANN learning algorithm that is on the basis of empirical risk principle. In addition, the SVM is a convex two optimization problem, which can ensure that the optimal solution is the global optimal solution. It is suitable for SVM to solve the problem of machine learning with limited samples. The SVM is called support vector regression SVR when it is used to solve the regression problems. Loss function ε-insensitive is employed in regression SVR like the formulate (2.5).

$$L(y - f(x,a)) = L(|y - f(x,a)|_\varepsilon) \tag{6}$$

where,

$$|y - f(x,a)|_\varepsilon = \begin{cases} |y - f(x)| - \varepsilon, & |y - f(x)| \ge \varepsilon \\ 0\ , & \text{0thers} \end{cases} \tag{7}$$

where ε is the difference between the predictive value and the true value, the smaller the ε, the smaller the loss.

The training data in the input space is mapped to a high dimensional feature space F in virtue of the kernel function through nonlinear mapping in the SVM algorithm applied to the multivariate nonlinear fitting. Thus, the nonlinear function estimation problem in the input space X is transformed into the linear function estimation problem in the high-dimensional feature space F. Then, nonlinear fitting effect in the original space is obtained by linear regression in the high dimensional feature space. There are many kinds of kernel function of SVM, such as polynomial and function, Gauss radial basis function, Sigmoid kernel function. Because the prediction model is nonlinear in this research, the kernel function is selected as the radial basis function:

$$k(x_i, x) = esp\left\{-|x - x_i|^2 / (2\sigma)\right\} \tag{8}$$

where, $|x - x_i| = \sqrt{\sum_{k=1}^{n}(x^k - x_i^k)^2}$, σ is the kernel bandwidth.

III. Proposed Research Scheme

Plasma spray process is quite complex with the numerous influence factors, while the most effect factor of the quality of the coating is the process parameter involved in the plasma spray. The key process parameters include: working gases flow, spraying power, feeding gas, powder feed rate, feed powder, spray distance, spraying angle, the movement speed of the spray gun and the workpiece, workpiece temperature control etc. In the process of plasma spray, the change of one or several process parameters will affect the physical, chemical and mechanical properties of the coating. Therefore, it is very important to optimize the process parameters of plasma spray. However, due to the numerous parameters and unknown relationship among parameters, it is difficult to establish the relationship between process parameters and coating quality by simple regression fitting. Taking those factors into account, this paper uses Orthogonal Test design, Support Vector Machine and Particle Swarm Optimization algorithm to optimize the parameters of plasma spray process. Specific process parameter optimization process is as follows,

Step1: Determine the evaluation index of the quality of the plasma spray coating according to the requirements of the actual spraying process;

Step2: Ascertain the key parameters need to be optimized in the plasma spray process associating with the experience and the actual spraying process parameter setting;

Step3: Confirm the level and range of each process parameter and the quality index of the coating in accordance with the actual spraying situation, then select the appropriate orthogonal table to do the orthogonal test under the corresponding factor level;

Step4: Identify the process parameters which have a significant influence on the coating quality by analyzing the results of orthogonal test, in turn to obtain a set of preliminary optimal process parameters;

Step5: Train and verify SVM by using the orthogonal test data, in which the input of SVM is the plasma spray process parameters, the output is the plasma spray quality index value;

Step6: Find the optimal process parameter settings of plasma spray by the improved particle swarm algorithm combined with the relation model between the process parameters and the quality of the coating established by SVM.

Step7: Implement the verification test to verify the optimization results. In addition, the result are compared with that of the orthogonal test design.

The specific optimization flow of plasma spray process parameters has shown in Fig. 1.

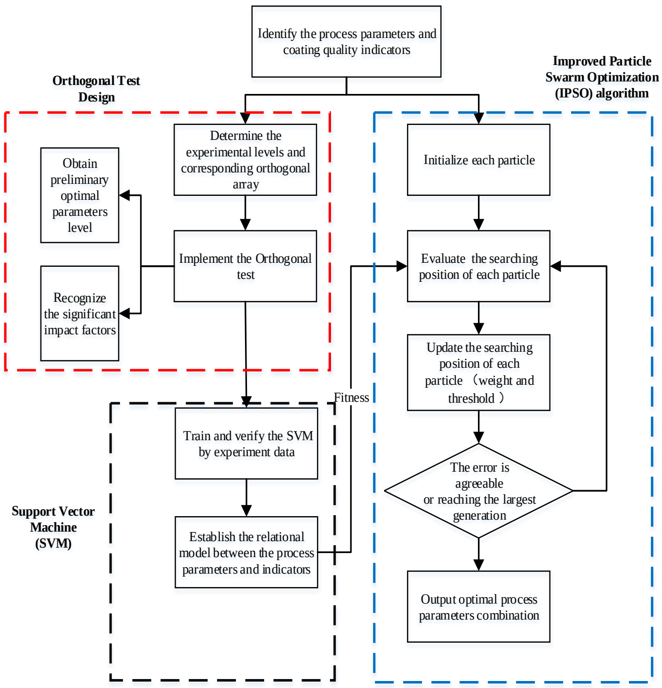


Fig. 1. The optimization flow of plasma spray process parameters.

IV. Application of Method

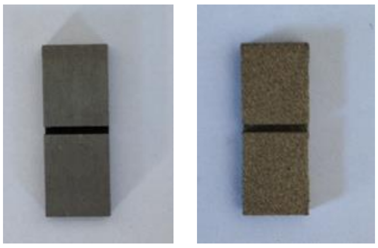
TABLE I: Range of Plasma Spray Process Parameters

Control Factor	Item	Unit	Min Value	Max Value
Argon Pressure	A	psi	65	85
Hydrogen Pressure	B	psi	50	70
Argon Gas Flow	C	SCFH	80	120
Send Powder Gas Pressure	D	bar	3.1	3.9
Send Powder Gas Flow	E	SCFH	7.5	9.5
the Amount of Send Powder	F	%RPM	20	28
Spray Distance	G	mm	120	170
Spray Current	H	A	470	510
Spray Voltage	I	V	60	70

Plasma spray has been widely used in the parts spray of the aircraft engine. Coating quality directly affects the overall performance of the aircraft engine, and good process parameter settings will greatly improve the quality of the coating, on the contrary, the coating quality is poor, which led to the decline in performance of the aviation engine. In this paper, it is aero-engine compressor casing seal coating by plasma spray process to be the research object. Metco 9M plasma spray system is used for preparing nickel-aluminum bonding layer, including 9MB plasma spray gun, Metco TWIN 10-C Powder Feeder and ABB2400-16 six axis manipulator. Nine main processing parameters influence on the quality of coating were selected as the control variable, namely argon pressure, hydrogen pressure, argon gas flow, send powder gas pressure, send powder gas flow, the amount of send powder, spraying distance, spray current and voltage.

Table I shows the range of the nine parameters. According to the actual conditions of the process, the coating hardness is considered as the sole quality index of the coating, measured by the micro-hardness instrument

Firstly, the orthogonal test design is used to arrange the experiments. Three levels of each participating parameters was determined based on engineering experience and practice. The orthogonal table $L_{27}(3^{13})$ was used for nine parameters and three levels orthogonal test. The level of process parameters settings are shown in Table II. A total number of 27 sets of testing and detection of micro-hardness of coatings cooperating were made, and two small pieces have been sprayed in each test. Fig. 2 (a) and (b) show respectively the specimens before and after plasma spray.



(a) (b)

Fig. 2. Specimens before and after plasma spray.

TABLE II: LEVEL OF PLASMA SPRAY PROCESS PARAMETERS

Item	Unit	Level 1 (low)	Level 2 (middle)	Level 3 (high)
A	psi	65	75	85
B	psi	50	60	70
C	SCFH	80	100	120
D	bar	3.1	3.5	3.9
E	SCFH	7.5	8.5	9.5
F	%RPM	20	24	28
G	mm	120	145	170
H	A	470	490	510
I	V	60	65	70

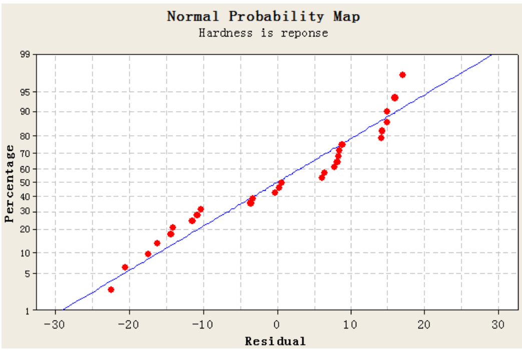


Fig. 3. Normal probability map of the experiment result residuals.

Plasma spray experiment results of orthogonal test design is made analysis of variance. First of all, the normality of the residuals is tested, and the normal probability map (Fig. 3) shows that the residual error follows the normal distribution, which satisfies the basic hypothesis of the analysis of variance. Then the results from analysis of variance illustrate that send powder gas pressure, send powder gas flow and the spray current have a significant influence on the coating quality. The influence trends of the nine process parameters on the hardness obtained by range analysis are respectively shown in Fig. 4. Therefore, the optimal combination of process parameters settings have been got by analyzing the results of the orthogonal experiments, which were shown in Table III.

Then support vector machine was trained relied on the first 22 sets of experimental data obtained by orthogonal test, and checked by the later 5 sets of to confirm the effectiveness of relationship model.

Afterwards the improved particle swarm optimization algorithm was combined with to search the optimal process parameter settings in the continuous range. What's more, the initial position of the particle swarm optimization algorithm depends on the optimal parameters level combination obtained by the orthogonal test design. Optimization results are shown in Table III.

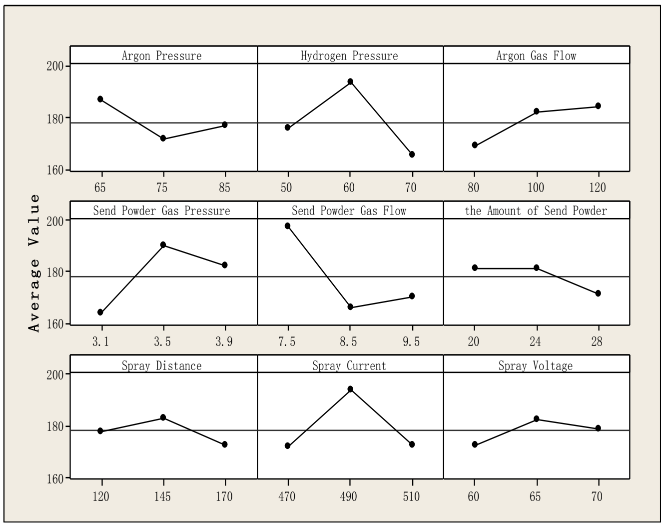
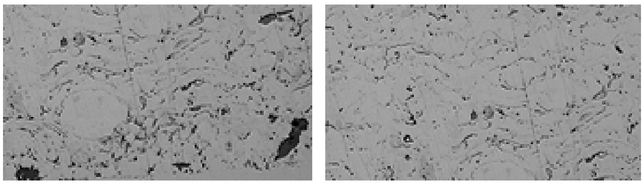


Fig. 4. Normal probability map of the experiment result residuals.

TABLE III: THE OPTIMAL PROCESS PARAMETER SETTINGS

Item	Unit	Optimal Value obtained by the orthogonal test design	Optimal Value obtained by Support Ventor Machine
A	psi	65	63.32
B	psi	60	59.44
C	SCFH	120	121.76
D	bar	3.5	3.55
E	SCFH	7.5	7.43
F	%RPM	20	22.11
G	mm	145	147.82
H	A	490	490.49
I	V	65	66.74

Finally, spray validation experiments were implemented based on the optimal parameter settings attained by the improved particle swarm optimization algorithm combined with support vector machine and the orthogonal test design, furtherly the results were compared with each other. The average value of the hardness of the former is 304.59 HV and the standard deviation is 2.23HV, while the latter respectively 254.06HV, 10.58HV. Fig. 5 also shows the representative microstructure of the coating under the two methods, where (a) shows the result of the Orthogonal Test Design and (b) shows the result of Improved PSO combined with SVM. It is concluded that the optimal process parameters set by the method proposed in this paper conducive to excellent coating quality which owns more dense tissue structure and lower porosity, especially the higher hardness and more stable process than the results of the orthogonal test design.



(a) (b)

Fig. 5. Microstructure pictures of nickel aluminum bonding layer (200 times).

V. CONCLUSION

In this paper, a set of orthogonal test method integrated support vector machine and particle swarm optimization algorithm is proposed to optimize the parameters of plasma spray process to improve the reliability of plasma spray process. The orthogonal test method is used to design a set of representative experiments. In the same time, the most valuable sample data is obtained. The data obtained from the orthogonal test design is utilized to train and test the support vector machine to establish the relationship model between the process parameters and the spraying quality. Then, the support vector machine and particle swarm optimization algorithm are combined to find the optimal spraying process parameter setting. Finally, the verification test is designed to verify the effectiveness of the optimal process parameters. In the application of aero-engine compressor casing seal coating by plasma spray process, indicating that the method can overcome the limitation of traditional orthogonal test which only discrete seeking optimal point as well as the disadvantages of optimization of complex system with small samples and high dimension data modeling, to obtain a set of optimal process parameters in the change continuously interval of plasma spray process parameters, contribute to spray a coating with best quality.

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