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Process Parameter Optimization of Plasma Sprayed Nanostructured Al_2O_3-13 % TiO_2 Coating Based on Genetic Algorithm†

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The process parameters of plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings were optimized based on a genetic algorithm. A BP neural network was applied to compute the suitability of the genetic algorithm and a model was established. Four process parameters inputs were spraying distance, spraying electric current, primary gas pressure and secondary gas pressure. The bonding strength of the coating was the output. The network was trained by orthogonal test data. The BP neural network was tested by design of the orthogonal optimization and the margin of error was less than 5 %. It proved that the BP neural network could be applied to predict the bonding strength of plasma-sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings. Process parameters of the coatings were optimized based on the genetic algorithm. The results showed that the maximal bonding strength of the coatings was 32.7 MPa. The process parameters obtained were: spraying distance of 107.51 mm, spraying electric current of 854.07A, primary gas pressure of 0.24 MPa and secondary gas pressure of 1.03 MPa. The results were superior to the design of the orthogonal optimization and provided a definite reference for selecting the best process parameters for plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings.

Keywords: Plasma spraying, Nanostructured coating, BP Neural network, Genetic algorithm, Process parameter optimization.

INTRODUCTION

Plasma spraying is widely used in the fields of atomic energy, aviation, petrochemical, metallurgy and machinery manufacturing for advantages such as rapid deposition and high coating quality[1,2]. Relative to conventional plasma spray coatings, nanostructured coatings are more resistant to corrosion and wear and possess higher strength and hardness. They are the research focus of both amateur and expert scientists because of the low cost[3-5].

A plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coating not only retains a certain percentage of its nanostructure, but also retains an appropriate melting degree of the powder to ensure the adhesive strength of the coating[6,7]. Compared to conventional plasma sprayed coatings, the optimum process parameters of plasma sprayed nanostructured coatings are in a narrow range, so the selection of the process parameters is very important. Plasma spray process parameters have a vital influence on the bonding strength of nanostructured coatings[8] and are one of the main research topics in regards to plasma sprayed coatings.

Currently, the orthogonal test method is widely used to optimize plasma spraying process parameters[9], but this method can only obtain a better factor combination. That means it can neither predict quality of the coating nor can it get the best process parameters. There is still insufficient in actual use. A genetic algorithm is a global optimization method that imitates the natural biogenetic and evolutionary processes. It has a high degree of parallelism and randomness. The objective function value can be treated directly as searching information. It evolves through selection, crossover and mutation operations. After that, the approximate optimal solution can be obtained[10]. The orthogonal test results were input and a BP neural network model was established. The process parameters of the inputs were spraying distance, spraying electric current, primary gas pressure and secondary gas pressure and the bonding strength was the output. Spray process parameters were optimized based on a genetic algorithm. The maximal bonding strength of the coating was obtained. Meanwhile, spraying distance, spraying electric current, primary gas pressure and secondary gas pressure were obtained at the same time. It can provide a clear basis for selecting the process parameters of

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plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings.

EXPERIMENTAL

γ-TiAl-based alloy (TAC-2) smelted by the Iron and Steel Research Institute was used as the test substrate material and its measurements were Φ 25 × 8 mm. In order to reduce the physical performance difference between ceramic and the substrate material, KF-113A powder was selected as a buffer layer produced by the metal materials research branch of Beijing Research Institute of Mining and Metallurgy. Nanox S2613P agglomerated powder produced by the US Inframat company using the spray drying method was selected as the nanostructured ceramic powder, the nominal composition was Al_2O_3-13 % TiO_2 (mass fraction), the size distribution extent was in the range of 10-50 μm and its morphology captured by a scanning electron microscope are shown in Fig. 1.

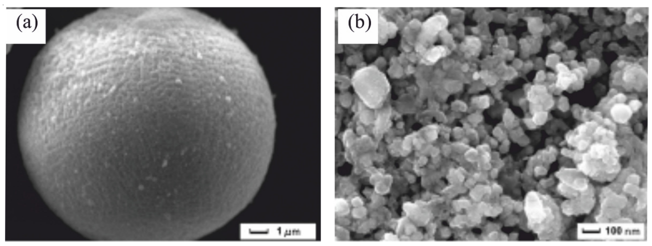


Fig. 1. Morphologies of nanostructured agglomerated powder (a) over morphology; (b) internal morphology

The spraying was carried out on a Praxair 3710 plasma spraying system. The specimen was polished, degreased and sandblasted before spraying. The main parameters that influenced the performance of the coatings according to earlier experiments were the spraying distance, spraying electric current, primary gas pressure and secondary gas pressure. So these four process parameters were selected as the experimental factors. The factors and levels are shown in Table-1. The bonding strength was selected as the optimization objective. The $L_9(3^4)$ orthogonal test program table was applied according to the level. The process parameters were fixed except the spraying voltage, which changed with the spraying electric current, primary gas pressure and secondary gas pressure. The speed of the spray gun was 100 mm/min, the carrier gas pressure was 0.31 MPa (Ar), the powder feed rate was 3 g/min^{-1} and the thickness of the ceramic coating was 350 μm.

TABLE-1
ORTHOGONAL DESIGN OF PROCESS PARAMETERS

Factor	Level		
	1	2	3
Spraying distance L (mm)	90	110	130
Spraying electric current I (A)	820	870	920
Primary gas pressure (Ar) P_A (Mpa)	0.24	0.28	0.31
Secondary gas pressure (He) P_H (Mpa)	0.86	0.97	1.07

Bonding strength tests were performed using the B method of the GB/T 8642-2002 standard. The average value was obtained through three tests. A diagram of the tensile test specimens is shown in Fig. 2(a). The specimen was placed in a pair of coupled parts, bonded by E-7 glue (Shanghai Institute of Synthetic Resins, tensile strength greater than 70 MPa) and afterward placed in a drying oven. Fixture fixed coupled parts are shown in Fig. 2(b). This guaranteed that the coupled parts were coaxial with the specimen. The stretching equipment is shown in Fig. 2(c), which is a WE-100 hydraulic universal testing machine. The entire loading process of the tensile testing in the machine was slow and continuous (loading speed was 10 kN/min^{-1}) and the separation load was recorded until the coupled parts were opened. The average bonding strength of the coating was obtained according to the specimen surface area and the measured load.

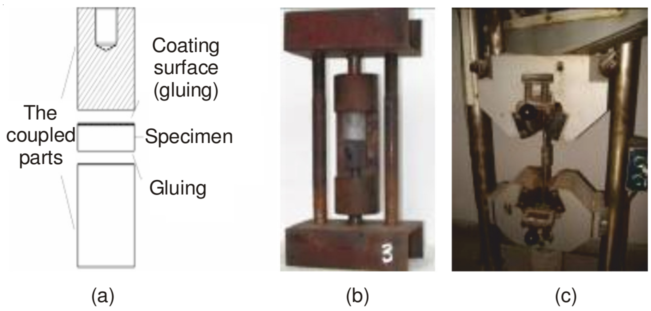


Fig. 2. Tensile test of specimen (a) Schematic of tensile test specimen; (b) Clamping process; (c) Tensile setup

RESULTS AND DISCUSSION

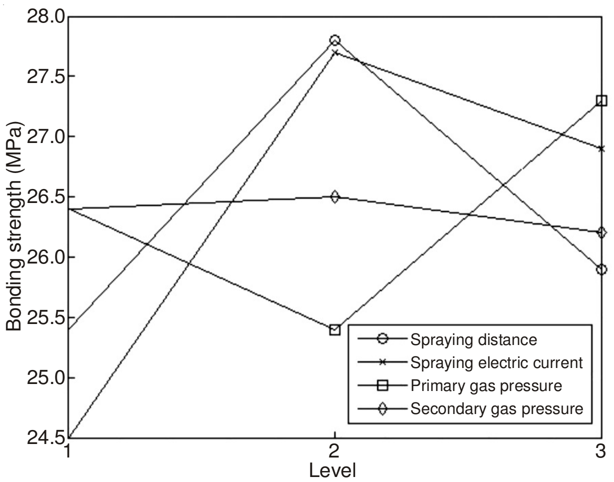
Analysis of orthogonal test: Results of the orthogonal test are shown in Table-2. The range of spraying distance, spraying electric current, primary gas pressure and secondary gas pressure were 2.4, 3.2, 1.9 and 0.3, respectively. The factors were spraying electric current, spraying distance, primary gas pressure and secondary gas pressure in decreasing order to influence the bonding strength. It is clear from Table-1 that the optimization level of spraying distance, spraying electric current, primary gas pressure and secondary gas pressure were 2, 2, 3 and 2, respectively. Then, the optimized process condition was a spraying distance of 110 mm, spraying electric current of 870 A, primary gas pressure of 0.31 MPa, secondary gas pressure of 0.97 MPa.

The effect diagram of the four factors is shown in Fig. 3. When the spraying distance changed from 90 to 130 mm, the bonding strength of the coating increased and then decreased. This is explained as follows: When the spraying distance was short, the heating time was also short and the powder was not sufficiently melted, resulting in a weak bond. When the spraying distance was increased, the powder melted better and retained a certain proportion of organization in the nanostructure. When the spraying distance was 110 mm, the bonding strength was the highest. However, when the spraying distance was too long, the powder melted completely and lost nanostructure organization due to the heating time being too long and resulting in a decreased bonding strength.

The electric current of the spray changed from 820 to 870 A and then to 920 A, with bonding strengths measured at 24.5, 27.7 and 26.9 MPa, respectively. Its trend was similar to the spraying distance which first increased and then decreased. The electric current of the sprayer affected the plasma flame temperature where the greater electric current would generate a higher plasma flame temperature. So nanostructured agglom-

TABLE-2
RESULTS OF ORTHOGONAL TEST AND RANGE ANALYSIS

Test No.	Spraying distance	Spraying electric current	Primary gas pressure	Secondary gas pressure	Bonding strength (Mpa)
# 1	1	1	1	1	23.6
# 2	1	2	2	2	25.9
# 3	1	3	3	3	26.7
# 4	2	1	2	3	24.8
# 5	2	2	3	1	30.1
# 6	2	3	1	2	28.5
# 7	3	1	3	2	25.1
# 8	3	2	1	3	27.2
#9	3	3	2	1	25.4
1 level	25.4	24.5	26.4	26.4	
2 levels	27.8	27.7	25.4	26.5	
3 levels	25.9	26.9	27.3	26.2	
Range	2.4	3.2	1.9	0.3	
Optimization scheme	2	2	3	2	
Order of factors	2	1	3	4	



Spraying distance	90 mm	100 mm	130 mm
Spraying electric current	820 A	870 A	920 A
Primary gas pressure	0.24 MPa	0.28 MPa	0.31 MPa

Fig. 3. Factor-effect diagram

erated powder changed from less melting, proper melting to excessive melting along with the increase of the sprayer's electric current. Bonding strength first increased and then decreased, which followed the trend of the other factors.

The primary gas pressure was changed from 0.24 to 0.31 MPa. During this course, the bonding strength of the coating first decreased and then increased. Plasma flame temperature monotonically decreased and powder speed monotonically increased[11] during the increase of the primary gas pressure. Lower temperatures of the plasma plume were not conducive to melting the powder and it resulted in a reduction of the bonding strength. When powder speed was increased and the heating time was reduced, it was not beneficial to melting the powder. On the other hand, it did assist in increasing the bonding strength due to improved ductility during the powder deposition phase. When the primary gas pressure was increased, the bonding strength of the coating was mainly influenced by the lower stream temperature and shorter heating time, which meant the bonding strength decreased. However, the bonding strength of the coating was vastly increased because it was influenced by the powder speed.

The changing range of the secondary gas pressure was small. Fig. 3 showed that the range of the bonding strength was also relatively small. Plasma plume temperature first increased rapidly, then increased slowly and the powder speed monotonically increased[11] when the secondary gas pressure increased. During this course, it might cancel each other out in a certain degree that influence of powder melting, powder speed and the rest of the nanostructure on the bonding strength. It was determined that the influence of the secondary gas pressure on the bonding strength of the coating was relatively small.

Optimization results analysis: The process parameters of plasma spray derived from the orthogonal optimization were used to prepare samples of nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings. The average bonding strength of the nanostructured coating was 31.5 MPa and the performance of the nanostructured coating had an obvious improvement over the example in Table-2. Morphology of the #1 sample and morphology of the optimized nanostructured coating can be seen in Fig. 4. Both morphologies were constituted with a partially melted zone and a completely melted zone and were a two-phase structure. However, there were significant differences. The partially melted zone of the first example had a higher proportion, which indicates inadequate powder melting and higher porosity. Organization in the nanostructure of the optimized coating was denser and retained an appropriate proportion.

BP Neural networks: A BP neural network was introduced to predict the bonding strength of the plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coating, because a BP neural network can solve non-linear problems and can approach any continuous function. If a hidden layer contains sufficient neurons, it can approach any non-continuous function with finite breakpoints. A BP neural network identifies a system model by learning input and output data of a system, minimizes the function errors and sums up the implication relations in input and output data.

A BP neural network model of a plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coating was established. The same parameters were set as the inputs: the spraying distance, spraying electric current, primary gas pressure

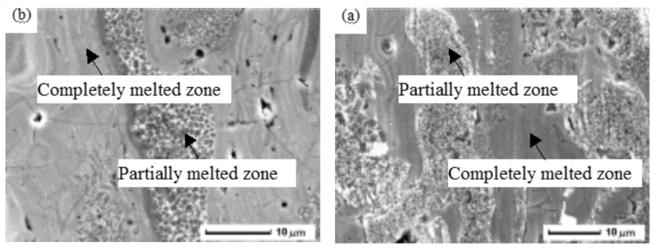


Fig. 4. SEM images of plasma sprayed nanostructured Al_2O_3-13 % TiO_2 coating (a) before optimization (#1 specimen); (b) after optimization

and secondary gas pressure; the bonding strength was the output. The network topology is shown in Fig. 5. The BP neural network contained a single hidden layer. There were four input parameters, so the input layer had four nodes. The hidden layer nodes were determined according to the Kolmogorov theorem[12]:

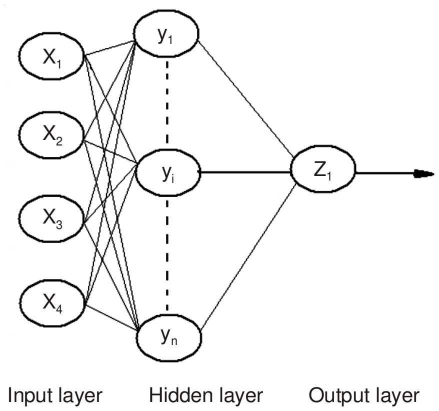


Fig. 5. Model of BP neural network

$$A = 2B + 1 \quad (1)$$

where A is the number of hidden layer nodes and B is the number of input layer nodes, then the number of hidden layer nodes is 9. The output layer has only one parameter, so the number of output layer node is 1. So the BP neural network contained three layer structure of $4 \times 9 \times 1$.

The orthogonal optimization result was predicted based on the BP neural network model. The bonding strength was 31.9 MPa and the margin for error was less than 5 % compared to the experimental results. It proved that the BP neural network model was accurate and could predict the bonding strength of plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings.

Genetic algorithms: Genetic algorithms can imitate reproduction, crossover and mutation that occur in the natural selection and genetic process. It can produce a group of individuals which are more acclimatized to environmental demands by selection, crossover and mutation operations according to any initial population. Consequently, the group evolves to the space and eventually develops into a group of individuals which can best acclimatize to environmental demands through constant reproduction and evolution and then the optimal solution is obtained. Therefore, the performance of plasma sprayed nanostructured coatings can be optimized based on genetic algorithms. The genetic algorithm flow chart is shown in Fig. 6. The solving process is shown as follows[13-16]:

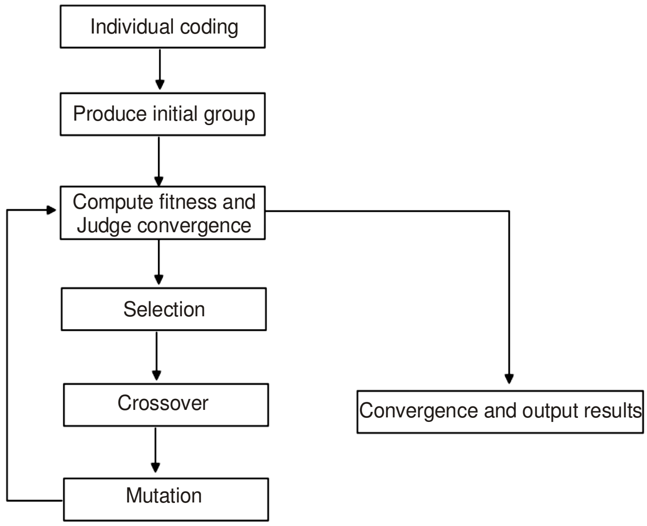


Fig. 6. Flow chart of genetic algorithm

Individual coding is obtained by: A genetic algorithm cannot directly handle data in a solution space which must be expressed as an individual symbol string in a genetic space.

In order to produce the initial population: The larger population size will increase the diversity of individuals and reduce the possibility of falling into the local optimal solution. But if the population size is too large, it will increase the computing workload and extend the computing time of convergence.

The fitness function is calculated as follows: The genetic algorithm evaluates individual fitness values to determine their genetic opportunities. According to the requirements of the actual situation, the parameters are composed of spraying distance, spraying electric current, primary gas pressure and secondary gas pressure of plasma sprayed coatings as the inputs and the bonding strength is the output. A BP neural network model is established to achieve the mapping from input space to output space.

According to each individual's fitness value, some exceptional individuals are moved to the next generation group which is selected from a previous generation group in accordance with certain rules or methods. Crossover operation the genetic algorithm basically exchanges a part of a chromosome of two individuals in a certain probability. The purpose of mutation operation is to increase an individual's diversity in a group, prevent the loss of an individual's diversity in a group during the genetic evolution process and lead to premature convergence of genetic processes.

Process parameters optimization based on genetic algorithm: The number of individuals selected was twenty. The crossover probability was selected as 0.4. The mutation probability was selected as 0.1. The number of evolutional generations was selected as 100. The evolutional curve of the genetic algorithm is shown in Fig. 7. The maximal bonding strength of plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings was obtained based on the genetic algorithm and the value was 32.7 MPa. At this time, the optimized process condition was a spraying distance of 107.51mm, spraying electric current of 854.07 A, a primary gas pressure of 0.24 MPa and a secondary gas pressure of 1.0 MPa.

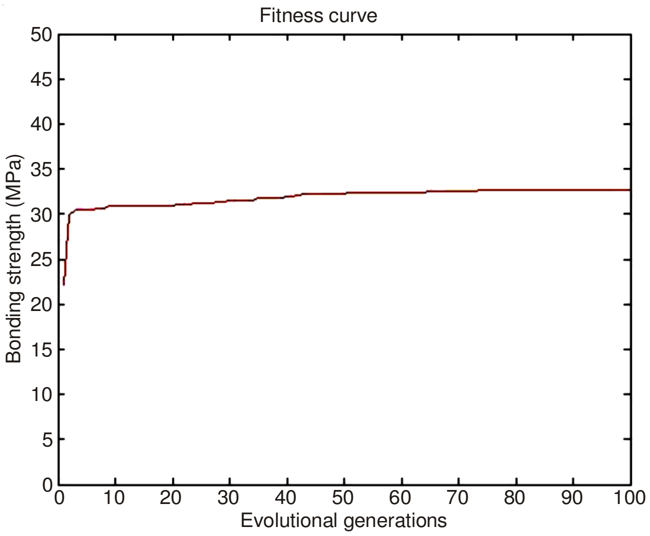


Fig. 7. Evolutional curve of the genetic algorithm

The maximal bonding strength obtained based on the genetic algorithm (32.7 MPa) was significantly better than the bonding strength obtained by orthogonal optimization (31.9 MPa). Meanwhile, the process parameters of the plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings were obtained when the maximal bonding strength was achieved. It provided a clear basis for selecting the best process parameters of plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings.

Conclusion

A BP neural network model was established between the bonding strength as the output of plasma spraying nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings with input parameters set as: spraying distance, spraying electric current, primary gas pressure and secondary gas pressure. It was trained by the orthogonal test data in order to achieve the nonlinear mapping relationship between the coating properties with the spray process parameters. It was validated by the orthogonal optimization result with a margin for error of less than 5 %. It proved that the BP neural network model was accurate and it was able to predict the bonding strength of plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings.

The maximal bonding strength of the plasma sprayed nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings was optimized based on the genetic algorithm and was determined to be 32.7 MPa, which was significantly better than the orthogonal optimization result. The optimized process conditions were a spraying distance at 107.51 mm, spraying electric current of 854.07 A, a primary gas pressure of 0.24 MPa and a secondary gas pressure of 1.0 MPa. It provided a clear basis for selecting the best process parameters of plasma spraying nanostructured Al_2O_3-13 % TiO_2 (mass fraction) coatings.

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