Prediction and Analysis of the Grit Blasting Process on the Corrosion Resistance of Thermal Spray Coatings Using a Hybrid Artificial Neural Network

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Abstract: Grit blasting as a pretreatment process for the substrate surface before thermal spraying is of great importance for assuring the service performance of thermal spraying coatings. In this work, a novel hybrid artificial neural network (ANN) was presented to optimize the grit blasting process to improve the structural properties and corrosion resistance performance of thermal spray coatings. Different grit blasting process parameters were combined to pretreat the substrate surface, and the corresponding surface roughness, interface adhesion strength and corrosion resistance performance were obtained. Hence, a backpropagation (BP) neural network model optimized by the genetic algorithm (GA) was presented to address the poor regression roughness and accuracy of the traditional fitting models; the grit blasting processing parameters were utilized as the inputs for the GA–BP model; the structural properties and the corrosion resistance performance were used as the outputs. The correlation coefficient R reached and exceeded 0.90, and three error values were less than 1.75 on the prediction of the service performance of random samples. All these indicators demonstrated convincingly that the obtained hybrid artificial neural network models possessed good prediction performance, and this innovative and time-saving grit blasting process optimization approach could be potentially employed to improve the comprehensive service performance of thermal spraying coatings.

Keywords: grit blasting; surface roughness; corrosion resistance performance; GA–BP

1. Introduction

Thermal spraying technology is widely applied in various industries to protect and improve the surface properties of materials, which is an important technique of material surface modification and strengthening in green remanufacture engineering [1]. Owing to the increasingly complex service environment, higher demands are put forward for the properties of the thermal spray coatings, especially in the corrosion resistance [2,3]. Since the thermal spray coatings are commonly the porous structure, inevitably, during long-term service in complex environments, a variety of corrosive liquids will penetrate into the surface of the metal substrate and induce the failure of the coatings ahead of the designed lifetime. Previous studies had shown that the bubbling of the coating, the interface bonding state of the substrate/coating, and the penetration of the corrosive liquid are the
main factors, which induce the corrosion failure of the coatings. Among these factors, the interfacial adhesion is predominantly dependent on the mechanical bonding between the substrate and the coating; moreover, the cleanliness and roughness of the substrate determine the adhesion strength. In total, 80% to 90% of the premature failure of the coating is caused by improper pretreatment of the substrate surface [4–7]. Therefore, it is necessary to pay special attention to the surface preparation prior to spraying and to conduct further research on the influencing factors and mechanisms of the surface pretreatment process on the corrosion resistance performance of the coating has become the key to solving this problem.

An important prerequisite for ensuring the serviceability of the coating is the quality of the substrate surface after pretreatment. The pretreatment methods for the preparation of functional coatings are currently very diverse, and a series of important advances have also been made [8–10]. As the most common substrate surface pretreatment method, grit blasting is widely employed to preprocess the substrate before thermal spraying, and the mechanical embedding and bonding mechanisms between the coating and the substrate indicate that the substrate surface state after grit blasting is a vital factor affecting the coating service performance [11,12]. The state of the substrate surface will not only affect the interface adhesion strength but also the mechanical properties of the coating, notably the service lifetime. For instance, it can make substrate surface residual compressive stresses after grit blasting to improve the coating’s performance, and the residual stresses can be regulated by adjusting the grit blasting processing parameters [6,13,14]. The surface roughness of the substrate after blasting is the feature parameter to evaluate the surface quality after pretreatment, as residual grit on the substrate surface is the negative product of blasting pretreatment, which will degrade the coatings service performance [11,15,16].

The grit blasting process parameters, including the grit type, the grit blasting parameters (grit grain size, blasting pressure, blasting distance, blasting time and blasting angle) and the cleaning process, codetermine the substrate surface quality after pretreatment [17,18]. In general, larger surface roughness and coating adhesion strength can be obtained by selecting larger blasting pressure, moderate blasting distance, moderate blasting time and moderate blasting angle; however, the actual blasting process is based more on the empirical parameters. Hence, it should optimize the grit blasting process parameters quantitatively by experiment test and data analysis and thereby achieving the appropriate surface quality.

In fact, grit blasting is a complex coupling process involving multiple factors and levels. To further reveal the regulatory mechanism of grit blasting parameters on the coating performance, previous studies have investigated the effect of different blasting parameters on the effectiveness of substrate pretreatment and found that the corrosion resistance performance could be optimized by varying a single blasting parameter [17,19,20]. The data analysis method could be applied to optimize the combination of the blasting parameters. For example, the Taguchi design method is the most generally employed data analysis method to evaluate the influence rank of various preprocessing parameters on the coating’s performance qualitatively [21,22]; the multiple linear regression method is commonly applied to establish the quantitative relationship among the grit blasting process parameters, the substrate surface condition and coating performance [23]. Nevertheless, these traditional analysis and modeling methods cannot meet the higher requirements of the actual grit blasting guidance. Additionally, the prediction accuracy and robustness of these traditional analysis and modeling methods are very poor, owing to the complicated multi-physical coupling behavior of the actual grit blasting process.

In this study, the atmospheric plasma sprayed (APS) alumina coatings deposited on the surface of the R683/IC45e steel substrate were chosen as the research object. The influence of the grit blasting pretreatment process on the surface and interface properties (structure properties, i.e., surface roughness and interface bonding strength) was studied by the controlled variable method. Combining the occurrence time of each characteristic stage in the corrosion failure process, the factors and mechanisms affecting the corrosion
resistance of the coatings were studied. By using the hybrid artificial neural network algorithm, the optimization regression model of the grit blasting pretreatment process parameters was set up for the prediction of structure properties after the grit blasting process and also for the lifetime prediction of the corrosion resistance.

2. Experimental and Modeling

2.1. Sample Preparation and Characterization

The R683/IC45e carbon steel was commonly used in the manufacturing industry, which was chosen as the substrate material for the grit blasting pretreatment experiment in this study. Disc-shaped substrate samples (Ø 25 mm × 3 mm) were prepared by ultrasonic cleaning. The grit material used for grit blasting was the aluminum oxide grit grain (white corundum grit). The grit blasting experiments were carried out using the pressure feed type grit blasting machine (TB1212, Shanghai Liangshi Painting Equipment Co., Shanghai, China). The grits were accelerated by compressed air and sprayed onto the surface of the R683/IC45e carbon steel substrate, which would squeeze and cut the substrate surface material; as shown in Figure 1, a rough surface, which was conducive to coatings deposition, was obtained by grit blasting preprocessing. Microstructural analysis was conducted on the surface of the substrate after sandblasting using a scanning electron microscope in the backscattered and secondary electron (SEM, ZEISS EVO MA15, Carl Zeiss SMT Ltd., Cambridge, UK) modes with an acceleration voltage of 20 kV.

![Figure 1. Surface topography of a R683/IC45e carbon steel substrate after blasting: (a) macro; (b) micro.](image-url)

Grit is the core carrier of sandblasting pretreatment, and the grit characteristics are one of the important factors affecting the quality of sandblasting and coating performance; the process parameters of sandblasting pretreatment are another important factor. Therefore, in this work, different surface pretreatment states were obtained by controlling the various combinations of grit characteristics and blasting process parameters, including the grit size, the blasting pressure, the blasting distance, the blasting time and the blasting angle. Table 1 shows the grit blasting process parameters and their variation range. A three-dimensional surface profiler (InfiniteFocus1 G4, Alicona Imaging, Grambach/Graz, Austria) was used to observe the substrate surface topography after blasting and measure the roughness parameter value. The average roughness Rz was used to effectively characterize the undulation degree of the substrate surface after grit blasting pretreatment.
Table 1. Grit blasting process parameters and variation range.

| Process Parameter     | Range of Value          |
|-----------------------|-------------------------|
| Grit size (mesh)      | 40, 80, 120, 160        |
| Blast pressure (MPa)  | 0.4, 0.5, 0.6, 0.7      |
| Blasting distance (mm)| 50, 100, 150, 200       |
| Blasting time (s)     | 15, 30, 45, 60          |
| Blasting angle (°)    | 45, 60, 75, 90          |

As shown in Table 2, a commercial APS system (APS-2000, Beijing Aeronautical Technology Institute, Beijing, China) was used to prepare the coatings with a certain process parameter combination. The other details of the preparation process could be found in our previous research papers [24,25]; in this work, it was not our focus.

Table 2. APS process parameters.

| Spraying Parameter                           | Value          |
|----------------------------------------------|----------------|
| Spraying distance (mm)                       | 100            |
| Spraying power (KW)                          | 30             |
| Particle size of the alumina powder (μm)     | 25–45          |
| Primary air flow (Ar) (L/min)                | 45             |
| Auxiliary air flow (H₂) (L/min)              | 17.5           |
| Powder feeder speed (r/min)                  | 25             |
| Number of preheating channels                | 2              |

To estimate the interface adhesion strength of the coatings and the substrate, as shown in Figure 2, E7 epoxy adhesive was chosen to bond the coating sample together with the docking piece as a tensile sample. The tensile tests were performed by a tensile testing machine to measure the interface adhesion strength using the bonding tensile method based on the ISO 14916 standard, and the experimental results were averaged via three groups of tensile tests.

Figure 2. Bonding tensile method to measure the adhesion strength.

There are two main methods for testing the corrosion resistance of thermal spray coatings: laboratory corrosion and field corrosion experiments. Among them, the immersion corrosion test in the laboratory corrosion test has the advantages of simple operation, easy control of the corrosion environment, and good reproducibility of the test. The state changes of the coating surface and the relevant characteristics of the corrosion products can be observed by visual observation. Therefore, hydrochloric acid immersion corrosion test and visual method can be combined to evaluate the differences in corrosion resistance of coatings under different blasting conditions. In this work, 5 mass% HCl was used as the corrosion solution to immerse the coating samples for corrosion testing, as shown in Figure 3, to ensure that the corrosion solution only penetrates through the surface of the coating sample. Other fringe regions were edged with E7 epoxy adhesive, so only the coating surface was left in contact with the corrosion solution. Then, the coating corrosion
process was analyzed and counted by macroscopic observation. The coating failure process in a corrosive environment could be divided into four stages: bubbling, cracking, crack propagation and coating flaking. In this work, the coating corrosion life stage under different blasting pretreatment conditions was evaluated by recording the bubbling time, cracking time and flaking time, and the change of crack length (i.e., crack propagation rate) during the corrosion process was also used to evaluate the coating corrosion resistance performance.

Figure 3. Edge treatment of the coating before immersion corrosion.

2.2. BP Neural Network Model Optimized by Genetic Algorithm

The BP neural network is mainly based on the error of the output layer to correct the deviation to achieve the effect of minimum error. At this time, the prediction result of the training model obtained could be as close to the target value as possible. When the BP neural network is trained, the input and output multi-feature parameters cannot be directly trained. The data must be uniformly planned to ensure the validity of the data. Normalization methods are usually used for data preprocessing [26,27]. The formulation of the BP model can be expressed as follows:

$$f(\xi) = W^T \cdot \xi + b$$  \hspace{1cm} (1)

where $\xi$ is the input matrix; $W$ is the weighting matrix; and $b$ is the threshold.

In this work, a typical BP prediction model is chosen, which is composed of an input layer, several hidden layers, and an output layer, as shown in Figure 4. The input signal is fed from the input layer, and it is sent to the output layer after passing through the hidden layer, and the error is transmitted in the opposite direction from it. Generally speaking, a three-layer BP model can resolve the complex nonlinear problem.

Figure 4. The structure of the triple-layer BP neural network.
The genetic algorithm (GA) is a method to find the optimal solution by simulating the natural evolution of organisms. This algorithm uses mathematical techniques and computer simulation to transform the process of problem solving into a process similar to the crossover and mutation of chromosomal genes during biological evolution. Compared with other traditional optimization algorithms, it is more advantageous in solving complex combinatorial optimization problems [28,29]. Owing to the random nature of the initial weights and thresholds in BP neural networks, this leads to high variability in the prediction results of the prediction models built directly using this algorithm. Hence, as shown in Figure 5, the genetic algorithm is used to optimize the initial weights and thresholds of this model, which is implemented in the six steps as follows [30–32]:

1. The basic framework of the BP neural network is set up by setting the number of neurons in the input, hidden and output layers.
2. Coding. The expression of the coding length is given by
   \[ \chi = \chi_{\text{input}} \times \chi_{\text{hidden}} + \chi_{\text{hidden}} \times \chi_{\text{output}} + \chi_{\text{hidden}} + \chi_{\text{output}} \]  
   here \( \chi \) is the code length, \( \chi_{\text{input}} \), \( \chi_{\text{hidden}} \) and \( \chi_{\text{output}} \) are, respectively, the number of the input neurons, hidden neurons and output neurons.
3. Determine the fitness function to estimate the dominance of individuals in the population. In this study, the mean square error of the predictive index of the BP model is chosen to design the fitness function.
4. Set the GA parameters, including the population size, the number of iterations, the mutation probability and the crossover probability, and perform population initialization.
5. Calculate the fitness value mentioned in Step (3) and use this value as the execution basis for population selection, crossover and mutation. If the termination condition is reached, stop the calculation; if the termination condition is not reached, the fitness function is recalculated until the termination condition is met.
6. The optimal individual is decoded into the initial weight and threshold of the BP model. After the training is completed, the BP model is tested, analyzed and obtained.

![Figure 5. Calculation flow of GA–BP algorithm.](image)

The robustness of the hybrid GA–BP model was evaluated via coefficient and various errors: correlation coefficient (\( R \)), mean squared error (\( \text{MSE} \)), mean squared percentage error (\( \text{MSPE} \)) and mean absolute percentage error (\( \text{MAPE} \)). The expression of the four indicators are given as follows:
where $n$ is the number of samples, $Y_i$ is the actual value of structure property or corrosion resistance performance indicator, and $\hat{Y}_i$ is the predicted value of structure property or corrosion resistance performance indicator obtained by GA–BP model.

3. Results and Discussion

3.1. Influence of Grit Blasting Parameters on the Corrosion Resistance

The corrosion process of the coating in hydrochloric acid immersion corrosion is shown in Figure 6. Various grit blasting process parameters were combined together to test the corrosion resistance, as shown in Figure 7. The results were obtained by controlling a single parameter variable while the other variables were kept constant to investigate the influence of substrate blasting pretreatment on corrosion resistance. As can be seen from the experimental results, it can be concluded that the grit size, blasting pressure, blasting distance and blasting time all have a significant impact on the coating corrosion resistance to some different extent, yet such conclusions could only serve as the semi-quantitative guide in practical production applications.

As shown in Figures 8 and 9, the pore structure in the pre-corrosion and post-corrosion stages basically did not change notably; the fracture morphology also had not significantly changed; previous studies had also proved that the component composition of the coating after corrosion treatment had almost no change [33]. To conclude, these factors were not the main reasons for the corrosion failure of the alumina coating. These results also corresponded to the difference in corrosion resistance caused by the various levels of process parameters in Figure 6, which indicated that the substrate surface quality after grit blasting pretreatment was the main factor affecting the corrosion resistance of the alumina coating.
Figure 7. Variation of corrosion crack length under different grit blasting process parameters: (a) grit size; (b) blasting pressure; (c) blasting distance; (d) blasting time; (e) blasting angle.

Figure 8. Pore structure of alumina coating under different corrosion time: (a) 12 h; (b) 48 h.

Figure 9. Fracture morphology of alumina coating under different corrosion time: (a) 12 h; (b) 48 h.

As shown in Table 3, 16 sets of experiments were carried out to obtain the test results of the structural properties and corrosion resistance performance of the alumina coating after grit blasting with various levels of process parameters. It could be seen that the structural properties, as well as the corrosion resistance performance, changed evidently under various combinations of process parameters conditions.
Table 3. Summary of grit blasting process parameter settings and measured results.

| Sample | Grit Size (Mesh) | Pressure (MPa) | Distance (mm) | Time (s) | Blasting Angle (°) | Roughness Rz (μm) | Adhesion Strength (MPa) | Bubbling Time (h) | Cracking Time (h) | Flaking Time (h) |
|--------|-----------------|----------------|---------------|----------|-------------------|-------------------|------------------------|------------------|------------------|-----------------|
| 1      | 40              | 0.7            | 150           | 30       | 75                | 17.28 ± 2.12      | 18.92 ± 1.92         | 15               | 18               | 42              |
| 2      | 80              | 0.7            | 150           | 30       | 75                | 16.48 ± 1.88      | 16.98 ± 1.61         | 18               | 24               | 48              |
| 3      | 120             | 0.7            | 150           | 30       | 75                | 8.86 ± 0.99       | 16.73 ± 1.59         | 13               | 16               | 39              |
| 4      | 160             | 0.7            | 150           | 30       | 75                | 5.62 ± 0.83       | 16.37 ± 1.51         | 7                | 10               | 28              |
| 5      | 80              | 0.4            | 150           | 30       | 75                | 8.16 ± 1.05       | 15.24 ± 1.71         | 9                | 12               | 32              |
| 6      | 80              | 0.5            | 150           | 30       | 75                | 11.98 ± 1.96      | 18.04 ± 1.86         | 12               | 18               | 42              |
| 7      | 80              | 0.6            | 150           | 30       | 75                | 14.06 ± 1.64      | 19.66 ± 2.03         | 15               | 20               | 44              |
| 8      | 80              | 0.7            | 50            | 30       | 75                | 8.34 ± 1.08       | 18.13 ± 1.90         | 10               | 14               | 25              |
| 9      | 80              | 0.7            | 100           | 30       | 75                | 13.22 ± 1.57      | 17.42 ± 1.64         | 15               | 20               | 39              |
| 10     | 80              | 0.7            | 200           | 30       | 75                | 13.6 ± 1.46       | 18.38 ± 1.75         | 16               | 21               | 41              |
| 11     | 80              | 0.7            | 150           | 15       | 75                | 10.9 ± 1.48       | 14.74 ± 1.32         | 13               | 20               | 38              |
| 12     | 80              | 0.7            | 150           | 45       | 75                | 14.48 ± 1.86      | 19.01 ± 1.98         | 17               | 23               | 46              |
| 13     | 80              | 0.7            | 150           | 60       | 75                | 11.13 ± 1.61      | 18.19 ± 1.85         | 19               | 23               | 45              |
| 14     | 80              | 0.7            | 150           | 30       | 45                | 11.32 ± 1.35      | 18.04 ± 1.73         | 16               | 22               | 44              |
| 15     | 80              | 0.7            | 150           | 30       | 60                | 12.11 ± 1.44      | 17.77 ± 1.67         | 18               | 23               | 46              |
| 16     | 80              | 0.7            | 150           | 30       | 90                | 9.33 ± 1.14       | 16.36 ± 1.52         | 17               | 24               | 38              |

As shown in Figure 10, at the early stage of corrosion, the corrosive liquid would preferentially contact the wave peaks of the substrate. When the surface roughness of the substrate was large, the corrosive liquid would mainly make point contact with the substrate. When the roughness was small, the corrosive liquid and part of the wave peaks were in contact, and the reaction area was larger, so more hydrogen was likely to be generated, and bubbling and cracking occurred in advance. In the middle stage of corrosion, for the coating with the larger roughness, the corrosive liquid did not fully penetrate into the surface of the substrate, and the reaction with the coating was limited, and the bonding interface of the substrate/coating was relatively complete. For the coating with the smaller roughness, the overall corrosion had occurred in advance, the substrate completely lost its bearing capacity, and the generation and accumulation of more hydrogen further promoted the propagation of surface cracks in the coating. In the late stage of corrosion, for the coating with the smaller roughness, the corrosive liquid would no longer penetrate into the interior of the substrate, and the coating would peel off. The coating with the larger roughness still had a certain mechanical embedding region to maintain the bonding performance of the substrate/coating interface. Hence, increasing the roughness of the substrate surface could slow down the overall reaction process between the corrosive liquid and the substrate surface. However, the much larger roughness of the substrate would cause the coating thickness to become uneven, and the coating will be preferentially corroded at some parts with lower thickness, and larger roughness would also cause stress concentration at certain bonding parts of the substrate/coating, resulting in a decrease in the corrosion resistance performance.
Figure 10. Schematic diagram of the penetration process of corrosive liquid in coatings with different substrate roughness: (a) 5 μm; (b) 20 μm.

Additionally, as shown in Figure 11, the surface roughness was used as the independent variable to conduct fitting analysis to predict the adhesion strength and the average rate of the corrosion crack propagation by linear fitting and Gaussian fitting. Similar to the above analysis in Paragraph 1, such conclusions could serve us the further quantitative guide in partial practical production applications to choose the proper surface roughness, but the accuracy and reliability of these fitting models were poor in actual application. Not only that, as the analyses mentioned above, the grit blasting process determined the structure property, and the structure property determined the corrosion resistance performance; in other words, there was a progressive relationship among the three, and the grit blasting process was the sufficient condition for the other two. Hence, the quantitative model should be set up to predict the structure property and corrosion resistance performance by using the grit blasting process parameters, and this would be of great significance for guiding actual production, improving coating performance and saving costs.

Figure 11. The fitting analysis results of surface roughness: (a) adhesion strength; (b) average rate of the corrosion crack propagation.

3.2. Analysis of the Training and Prediction Process of BP and GA–BP Model

As shown in Figure 12a–e, the model was trained by selecting eleven random data sets. When the five training models evolved to the 183, 126, 117, 145 and 400 generations, respectively, it could be seen from the fitness evolution curves that the training errors of four parameters reached their minimum values, and the training requirements have been achieved.
Figure 12. Fitness evolution curve: (a) adhesion strength; (b) roughness Rz; (c) bubbling time; (d) cracking time; (e) flaking time.

To test the prediction performance of the BP and GA–BP models, the performances of the BP and GA–BP model were verified via the remaining four random samples. As shown in Figure 13, the black, red and blue symbols represent the experimental and predicted values of the adhesion strength, the roughness, the bubbling time, the cracking time and the flaking time, which were the combinations from the remaining five random samples, and the results show that these comparison results are in good consistency.

Figure 13. The prediction results of the BP and GA–BP regression model: (a) adhesion strength; (b) roughness; (c) bubbling time; (d) cracking time; (e) flaking time.

As shown in Figure 13, it is easy to see that the prediction results of the model built by the BP algorithm have a large gap compared to the experimental values, so the prediction results are not analyzed. To further compare the prediction results of the structural properties and corrosion resistance performance of the five remaining random samples, as shown in Table 4, the prediction performance of the GA–BP model could be seen clearly. The R of GA–BP model on all these structural properties and corrosion resistance performance had reached more than 0.9066, and all the error values (MSE, MSPE, MAPE)
were kept at a low level. All these proved that the proposed GA–BP model had high accuracy and reliability in predicting the structure properties and corrosion resistance performance; therefore, the hybrid machine learning model could meet the optimization requirements in the actual grit blasting process.

Table 4. The prediction performance of the remaining random samples obtained by the GA–BP model.

| Prediction Performance       | R    | MSE   | MSPE  | MAPE  |
|------------------------------|------|-------|-------|-------|
| Adhesion strength            | 0.9552 | 0.1532 | 0.0087 | 0.0131 |
| Surface roughness            | 0.9589 | 0.3400 | 0.0414 | 0.0515 |
| Bubbling time                | 0.9685 | 0.5600 | 0.0434 | 0.0781 |
| Cracking time                | 0.9088 | 1.7421 | 0.1390 | 0.2348 |
| Flaking time                 | 0.9066 | 0.5277 | 0.0250 | 0.0380 |

4. Conclusions

In this study, alumina coating samples preprocessed by different grit characteristics and blasting process parameters were obtained to conduct a corrosion resistance test. It was found that the pore structure and the fracture morphology basically did not change during the corrosion. The main reason that caused the difference of corrosion resistance of various samples was due to the change of their structure properties, notably the surface roughness, and the proper structure properties determined the excellent corrosion resistance performance. Hence, the surface roughness was chosen as the feature parameter to conduct fitting analysis to predict the adhesion strength and the average rate of the corrosion crack propagation, and the results showed that the robustness and accuracy of these fitting models were poor. A BP model was proposed to establish the quantitative relationship to predict the structure property and the corrosion resistance performance of alumina coating after grit blasting pretreatment and optimized by GA algorithm. The hybrid GA–BP model showed its high accuracy and reliability in predicting the structure properties and corrosion resistance performance, so it could be used to guide the actual grit blasting process to obtain excellent surface quality before thermal spraying. Additionally, this novel hybrid machine learning method would be potentially applied in the future to obtain the service life of coatings promoted, develop new coatings and save production costs.

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