Determination of the effect of plasma spray parameters on in-situ reaction intensity by experimental method and by means of artificial neural networks techniques

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Abstract

In the present work, mechanically alloyed Al-12Si and SiO_2 powder was deposited onto an aluminium substrate by atmospheric plasma spraying (APS) to obtain a composite coating consisting of in-situ formed alumina reinforced hypereutectic Al-18Si matrix alloy. The effects of spray parameters and in-flight particle characteristics on reaction intensity between selective powders were investigated. Obtained results are tested by artificial neural network (ANN) techniques. An ANN model is built, trained and tested. Multilayer perception model has been constructed with back propagation algorithm using the input parameters of arc current, spray distance, in-flight particle velocity and temperature. The ANN model was found able to predict the coating hardness, substrate temperature, alumina intensity and silicon intensity in the range of input parameters considered. This study demonstrates that ANN is very efficient for predicting output parameters of experimental studies.

Key words: artificial neural network, in-situ plasma spray, composite coating, in-flight particle, Al-Si

1. Introduction

Recently, a new processing method, in-situ plasma spraying (IPS), has been developed where thermodynamically favourable phases can be in-situ formed by the reaction between selective powders. Composite coatings with in-situ formed Al_2O_3 [1], Al_2O_3-TiB_2 [2], Mg_2Si, $MgAl_2O_4$, $NiAl_3$ [3], and Ni-Al [4] phases have been successfully fabricated by using HVOF, DC and RF plasma spraying methods.

However, due to rapid processing time in IPS, in-situ reaction strongly depends up on in-flight particle surface temperature and velocity upon impact onto the substrate. The effect of plasma spray parameters on in-flight particle characteristics has been a major research subject, and there is a tremendous interest in on-line measurements of particle temperature and velocity in-flight characteristics [5–12].

However, plasma spraying is a complex process and involves a large number of intrinsic and extrinsic operating parameters ("effective" factors). Therefore, a robust design is required to optimise process parameters and produce coatings with desired properties. Artificial neural network (ANN) appears to be an efficient predictive concept and has been widely used to model the complex plasma spray processes [13–15]. On the other hand, the reaction between selective powders during in-situ reactive plasma spraying multiplies the complexity of the process, and therefore, the correlations between spray parameters, in-flight particle characteristics and in-situ reaction need to be well established.

This paper aims to integrate the artificial intelligence methodology in order to control in-flight particle temperature and velocity by optimising process parameters to achieve the desired amount of in-situ reaction product through the reaction between selective powders during atmospheric plasma spraying.

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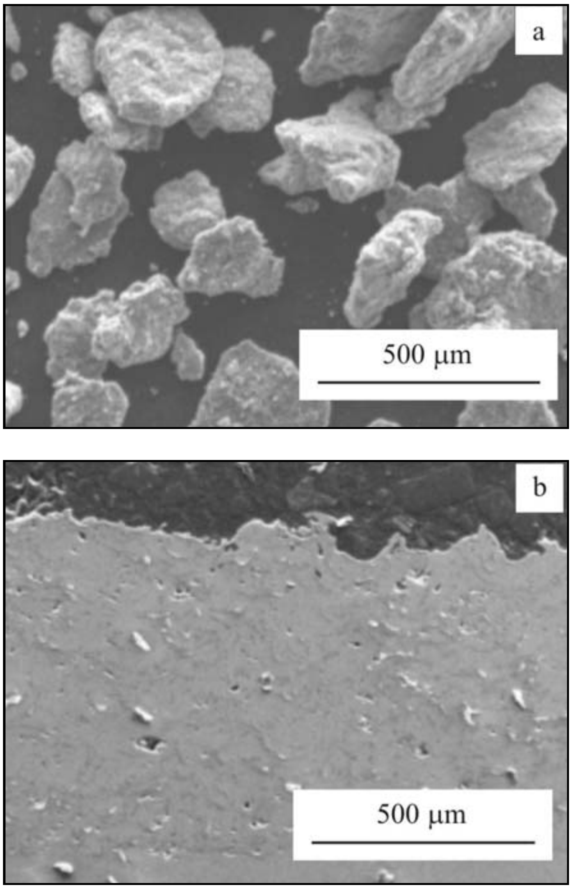

Fig. 1. (a) powder morphology after mechanical alloying, (b) typical microstructure of the coating.

Table 1. Plasma spray conditions

Plasma current (A)	300–700
Primary gas flow rate (l min^{-1})	Ar: 40
Secondary gas flow rate (l min^{-1})	H_2: 10
Carrier gas flow rate (l min^{-1})	Ar: 4
Feeder rotation rate (rpm)	10
Spray distance (mm)	100–125–150

2. Experimental studies

The material design for in-situ alumina formation is based on reaction (1) and the powder composition was designed through stoichiometric calculations to obtain a hypereutectic Al-18Si matrix alloy. The powder morphology of the mechanical alloying process is given in Fig. 1a. The composite powder was mechanically alloyed prior to the coating spraying. Coating experiments were carried out by using atmospheric plasma spraying (APS) (Sulzer Metco 9MB) under conditions given in Table 1. In order to determine the effect of some plasma operating parameters on in-situ reaction intensity, plasma current and spray distance were selected as variables. Also, during the coating process, substrate temperature was monitored by using a computer-aided thermocouple, and the peak temperature was used for ANN studies. Typical microstructure of the coating is given in Fig. 1b. The details of composite powder preparation and coating process were published in a previous study [1].

$$\text{Al-12Si} + \text{SiO}_2 \rightarrow \text{Al}_2\text{O}_3 + \text{Al-18Si}. \qquad (1)$$

In-flight particle average velocity (V_p) and surface temperature (T_p) measurements were performed using an Accuraspray-g3 system, which is based on time-shift cross-correlation between signals and twin wavelength pyrometer principle, respectively [16]. Relative intensity values of alumina and silicon were calculated through the XRD intensity ratios by using the strongest peaks (Si(111)/Al(111) and γ-Al_2O_3(440)/Al(111)) measured by X-ray diffractometer (XRD) with Co Kα radiation. Microhardness measurements were carried out by using a HSV-30 Shimadzu Vickers hardness tester under 200 g load. The details of in-flight particle diagnostic and microstructural characterization of the coating are given in the previous study [1].

3. Modelling with neural networks

The artificial neural networks are a relatively new modelling technique in plasma spraying.

Neurocomputing architectures can be built into physical hardware (or machine) or neurosoftware languages (or programs) that can think and act "intelligently" like simplified human beings would behave. The neural network based modelling process involves five main aspects: (a) data acquisition, analysis and problem representation; (b) architecture determination; (c) learning process determination; (d) learning of the networks; and (e) testing of the trained network for generalization evaluation [17]. During the training process, the network adjusts its weights to minimize the error between the predicted and actual outputs [18].

Since the ANN is a non-linear statistical technique, they can be used to solve problems that are not eligible for conventional statistical methods [19]. In the past few years there has been a constant increase in interest of neural networks modelling in different fields of materials science. Most common algorithm for adjusting the weights is back propagation algorithm [20].

The weighted sums of input components are calculated as:

$$\mathrm{Net}_j = \sum_{i=1}^{n} w_{ij} x_i, \qquad (2)$$

where Net_j is the weighted sum of the j^{th} neuron for the input received from the preceding layer with n neurons, w_{ij} is the weight between the j^{th} neuron and the i^{th} neuron in the preceding layer and x_i is the output of the i^{th} neuron in the preceding layer. The output of the j^{th} neuron out_j is calculated with a sigmoid function as follows:

$$\mathrm{out}_j = f(\mathrm{Net}_j) = \frac{1}{1+\exp\left(-k\mathrm{Net}_j\right)}, \tag{3}$$

where k is a constant used to control the slope of the semi-linear region. The sigmoid function has no linearity and activates in every layer except the input layer [17].

The system has three layers of neurons: an input layer, a hidden layer and an output layer. The neurons or units of the network are connected by the weights. The input factors, information from the input layer are then processed through a hidden layer, and following output vector incomputed in the output layer [21].

In the present work, an ANN program is designed on the basis of improvement upon back propagation (BP) learning algorithms. The input variables A_1, A_2, A_3, and A_4 represent the values of arc current, spray distance, average velocity (V_p) and temperature (T_p). Output variables C_1, C_2, C_3, C_4 are average hardness value, substrate temperature, alumina intensity and silicon intensity (Fig. 2).

In neural network applications, input or output values can be reduced to the values of 0–1, which is called the normalization process. Suitable networks have been tried for the values. Networks that permitted to obtain the lowest error have been selected in this study. Hidden layers were 5 : 5. Therefore, four input variables and four output variables have been used in our application. The ANN used architecture is a 4 : 5 : 5 : 4 multi-layer architecture as shown in Fig. 2. 13 values were selected for learning phase and 2 values were selected for test phase.

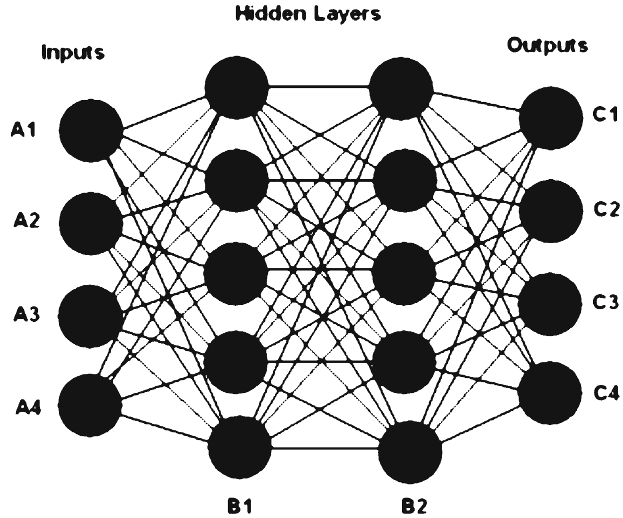

Fig. 2. The ANN architecture.

Iteration number was selected as 10000. The learning rate and momentum values were selected as 0.9 and 0.7, respectively. These values were found from the result of pre-trials. The learning was made once for test phase.

4. Analysis results

Experimental values used at the learning phase are given in Table 2. The mean errors calculated from the training phase were found to be: 1.38 % for hardness, 1.77 % for substrate, 1.56 % for alumina intensity and 3.4 % for silicon intensity for the learning phase. These mean error values were good for this experimental study.

Iteration number versus mean square error (MSE) is shown in Fig. 3.

Table 2. Experimental input values for ANN learning phase

Sample number	Spray dist. (mm)	V_p (m s^{-1})	T_p (℃)	Hardness HV
1	100	111	2293	155
2	125	111	2293	187
3	150	111	2293	197
4	125	125	2586	190
5	150	125	2586	201
6	100	135	2773	155
7	125	135	2773	185
8	100	153	2894	152
9	125	153	2894	180
10	150	153	2894	188
11	100	188	2321	145
12	125	188	2321	165
13	150	188	2321	182

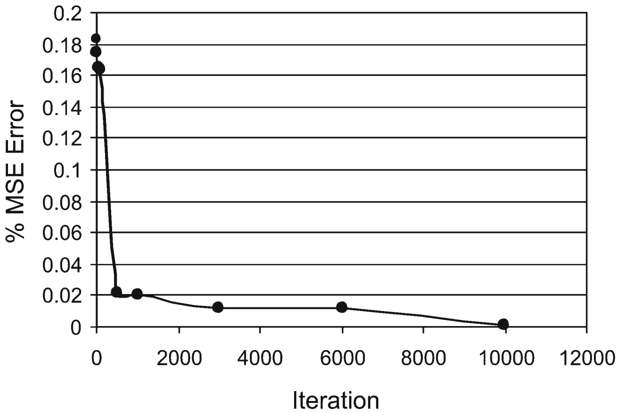

Fig. 3. Iteration number versus mean square error.

The ANN model developed in this study is used to predict hardness, substrate temperature, alumina intensity and silicon intensity. Experimental results and the performance of the proposed ANN model were compared in Fig. 4a,b,c,d. The test results are given in Table 3. The effect of plasma parameters and in-flight particle characteristics on in-situ reaction intensity and coating properties has been discussed in detail in the previous study [1].

5. Conclusions

In the recent years the application of ANN is tremendous in virtually all fields of engineering. ANN modelling is necessary for understanding and control of experimental results. In this study, ANN has been used to predict the experimental results. The results obtained in ANN application are close to experimental test results. Therefore, by using trained ANN values, the intermediate results that were not obtained in the test phase can be calculated. Experimental studies will be increased and research with ANN will continue. Testing results were found to be reasonably good. ANNs have the potential to minimize the need for expensive and difficult experimental investigations. As a conclusion, the ANN system is effective and successful for predicting hardness, substrate temperature, alumina intensity and silicon intensity.

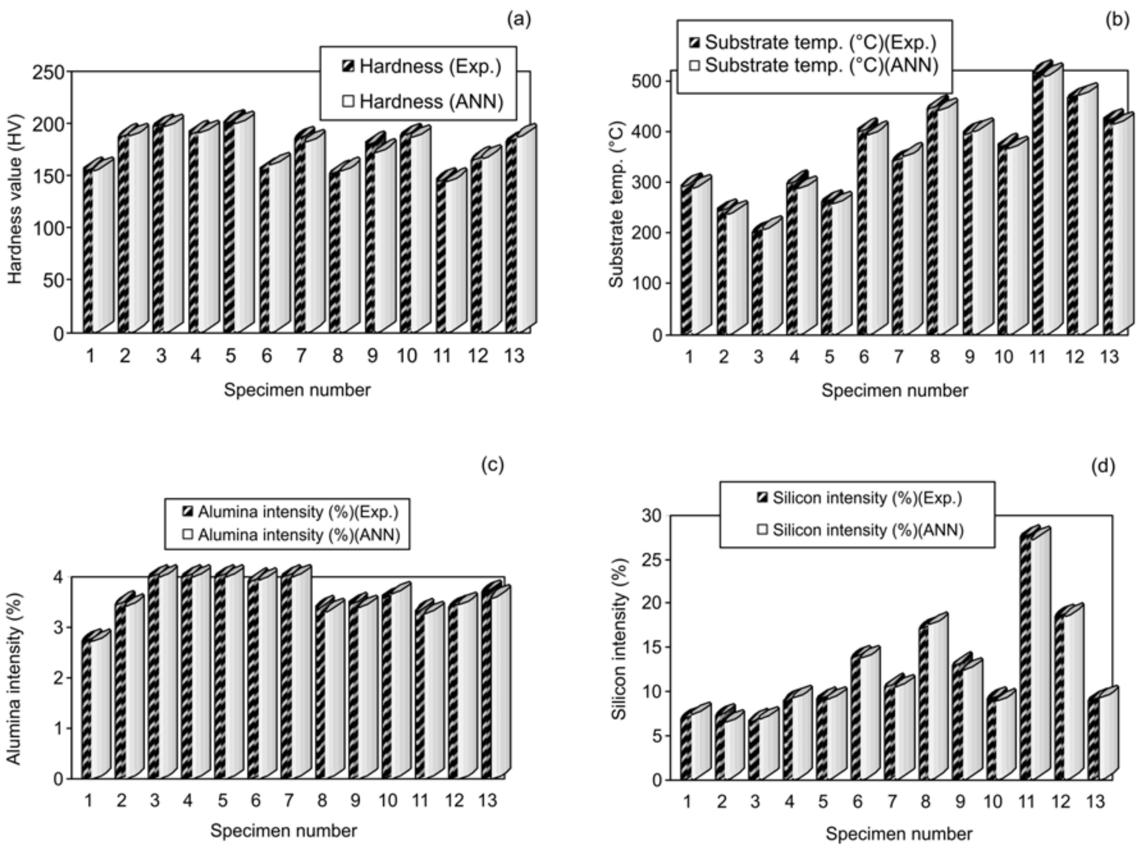

Fig. 4. The comparisons of experimental values with ANNs results at learning phase: (a) hardness, (b) substrate temperature, (c) alumina intensity, (d) silicon intensity.

Table 3. Experimental and ANN test phase results

Test specimen number	Properties	Experimental results	ANN results
Test specimen 1 Current: 400 A Spray distance: 100 mm V_p: 125 m s^{-1} T_p: 2586 °C	hardness HV substrate temp. (°C) alumina intensity (%) silicon intensity (%)	158 350 4.3 11.3	160 355 4.2 11.01
Test specimen 2 Current: 500 A Spray distance: 150 mm V_p: 135 m s^{-1} T_p: 2773 °C	hardness HV substrate temp. (°C) alumina intensity (%) silicon intensity (%)	196 310 4.5 9.27	199 304 4.5 9.27

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