PLASMA 2006

21st National Symposium of Plasma Science Society of India Dec, 2006, MNIT, Jaipur

NEURAL NETWORK ANALYSIS FOR DEPOSITION OF NICKEL-ALUMINIDE COATINGS ON STEEL BY PLASMA SPRAYING

M.Chaithanya, Alok Satapathy*, S.C.Mishra
National Institute of Technology, Rourkela

P.V.Ananthapadmanabhan, K.P.Sreekumar
Laser & Plasma Technology Division, B.A.R.C., Mumbai

*corresponding author: aloksatapathy@rediffmail.com

ABSTRACT

Nickel-aluminides are used in thermal spray applications mostly as bond-coat materials, where their function is two-fold: to minimize the thermo-mechanical stresses at the substrate-coating interface arising out of thermal expansion mismatch of the metal substrate and ceramic top layer and secondly to promote coating adhesion. This paper describes the deposition of nickel aluminide coatings on mild steel substrates. A computational technique (ANN analysis) is used to predict the rate of coating deposition under various operational conditions. Prediction of deposition efficiency is significant as it gives an idea about the effectiveness of the spraying technique as well as about the coatability of the material under investigation. This technique involves database training to predict property parameter evolutions in process having large number of interdependent variables such as in the case of plasma spray coating deposition. This paper presents the database construction, implementation protocol and also the set of predicted results related to the deposition efficiency of nickel-aluminide coating. It is seen that the deposition rate depends largely on the plasma arc current, arc voltage etc. The neural network analysis gives an oversight on the parameter inter-dependencies and of the effect of the individual process variable on the efficiency of coating deposition.

INTRODUCTION

Intermetallic compounds find extensive use in high temperature structural applications [1-4]. In particular, these alloys have potential demand in aerospace industry and other high performance applications [3, 4]. In thermal spray applications, nickel aluminides and their derivative alloys are used as bond coat materials, where their function is to minimize the thermo-mechanical stresses at the substrate-coating interface and also to promote coating adhesion [5]. The coefficient of thermal expansion of these alloys is intermediate between those of ceramics and metals and therefore can take care of interface stresses. Moreover, the reaction leading to the formation of the alloy is highly exothermic leading to better coating adhesion. The nickel-aluminide (Ni_3Al) has drawn enormous attention because of its technological and scientific interest. It is the most important strengthening constituent, generally referred to as γ-phase of commercial Ni- base super-alloys used extensively as high temperature structural materials for jet engines and aerospace applications. It is responsible for the high strength and creep resistance of the super-alloys at elevated temperatures. Ni_3Al containing about 25% Al has the ability to form protective aluminum-oxide scales, resulting in excellent oxidation resistance.

Functional coatings have to fulfill various requirements. The deposition efficiency is one the main requirements of the coatings developed by plasma spraying. It is defined as the ratio of the weight of coating deposited on the substrate to the weight of the expended feedstock. Deposition efficiency represents the effectiveness of the deposition process as well as the coatability of the powders under study. In order to achieve certain values of deposition efficiency accurately and repeatedly, the influence parameters of the process have to be controlled accordingly. Since the number of such parameters in plasma spraying is too large and the parameter-property correlations are not always known, statistical methods can be employed for precise identification of significant control parameters for optimization. Neural computation can be used as a tool to process very large data related to a spraying process and to predict any desired coating characteristic the simulation can be extended to a parameter space larger than the domain of experimentation.

EXPERIMENTAL

Nickel and aluminum powders were taken in a ratio of 3:1 by weight and were mixed thoroughly in a planetary ball mill to get homogeneous mixture. This mixture was sprayed on mild steel substrates of dimensions 50×20×3 mm. Spraying is done is using a 40 kW APS (atmospheric plasma spray) system in the thermal plasma laboratory at NIT Rourkela. This is a typical plasma spray system operating in the non transferred mode. The major components of this set up include the plasma torch, power supply, power feeder, plasma gas supply, control console, cooling water and spray booth. Prior to spraying, the substrates were grit blasted by compressed air at the pressure of $3 kgf/cm^2$. A current regulated dc power supply was used. A four stage closed loop centrifugal pump at a pressure of $10 kgf/cm^2$ supplied cooling water for the system. The primary plasma gas (argon) and the secondary gas (nitrogen) were taken from normal cylinders at an outlet pressure of $4 kgf/cm^2$. The plasma torch input power was varied from 10 to 20 kW by controlling the gas flow rate, plasma arc current and the arc voltage. The powder feed rate was kept constant at about 50 gm/min by a turntable type volumetric powder feeder. Weighing method is accepted widely to calculate the deposition efficiency. Weighing of samples is done using a precision electronic balance with $\pm$ 0.1 mg accuracy. Operating parameters used during the spraying are given in table-1.

Parameter	Range
Torch input power	10-20 kW
Current	250-400 Amp
Voltage	40-50 Volt
Plasma gas (Ar) flow rate	20 lpm
Secondary gas (N_2) flow rate	2 lpm
Powder feed rate	50 gm/min
Carrier gas (Ar) flow rate	12 lpm
Torch to base distance	100 mm

Table 1 Operating parameters used during the plasma spraying process

ARTIFICIAL NEURAL NETWORK (ANN) ANALYSIS

Plasma spraying is considered as a non-linear problem with respect to its variables: either materials or operating conditions. To obtain functional coatings exhibiting selected in-service properties, combinations of processing parameters have to be planned. These combinations differ by their influence on the coating properties and characteristics. In order to control the spraying process, one of the challenges nowadays is to recognize parameter interdependencies, correlations and individual effects on coating characteristics. Therefore a robust methodology is needed to study these interrelated effects. In this work, a statistical method, responding to the previous constraints, is implemented to correlate the processing parameters to the coating properties. This methodology is based on artificial neural networks (ANN), which is a technique that involves database training to predict property-parameter evolutions. This section presents the database construction, implementation protocol and a set of predicted results related to the coating deposition efficiency. The details of this methodology are described by Rajasekaran and Pai [6].

NEURAL NETWORK MODEL: Development and Implementation

An ANN is a computational system that simulates the microstructure (neurons) of biological nervous system. The most basic components of ANN are modeled after the structure of brain. Inspired by these biological neurons, ANN is composed of simple elements operating in parallel.

It is the simple clustering of the primitive artificial neurons. This clustering occurs by creating layers, which are then connected to one another. The multilayered neural network has been utilized in the most of the research works for material science. A software package NEURALNET for neural computing developed by Rao and Rao [7] using back propagation algorithm is used as the prediction of coating deposition efficiency at different operating power levels.

Input Parameters for Training	**Values**
Error tolerance	0.01
Learning parameter(ß)	0.001
Momentum parameter(α)	0.02
Noise factor (NF)	0.01
Maximum cycles for simulations	2000,000
Slope parameter (£)	0.6
Number of hidden layer neuron	6
Number of input layer neuron (I)	2
Number of output layer neuron (O)	1

Table 2 Input parameters selected for training

The database is built considering experiments at the limit ranges of each parameter. Experimental result sets are used to train the ANN in order to understand the input-output correlations. The database is then divided into three categories, namely: a validation category, which is required to define the ANN architecture and adjust the number of neurons for each layer. a training category, which is exclusively used to adjust the network weights and a test category , which corresponds to the set that validates the results of the training protocol. The input variables are normalized so as to lie in the same range group of 0-1. To train the neural network used for this work, about 24 data sets on selected substrates are taken. It is ensured that these extensive data sets represent all possible input variations within the experimental domain. So a network that is trained with this data is expected to be capable of simulating the plasma spray process. Different ANN structures (I-H-O) with varying number of neurons in the hidden layer are tested at constant cycles, learning rate, error tolerance, momentum parameter and noise factor and slope parameter. Based on least error criterion, one structure, shown in table 2, is selected for training of the input-output data. The learning rate is varied in the range of 0.001-0.100 during the training of the input-output data. The network optimization process (training and testing) is conducted for 2000,000 cycles for which stabilization of the error is obtained. Neuron numbers in the hidden layer is varied and in the optimized structure of the network, this number is 6. The number of cycles selected during training is high enough so that the ANN models could be rigorously trained. Fig.1 presents the optimized three layer network.

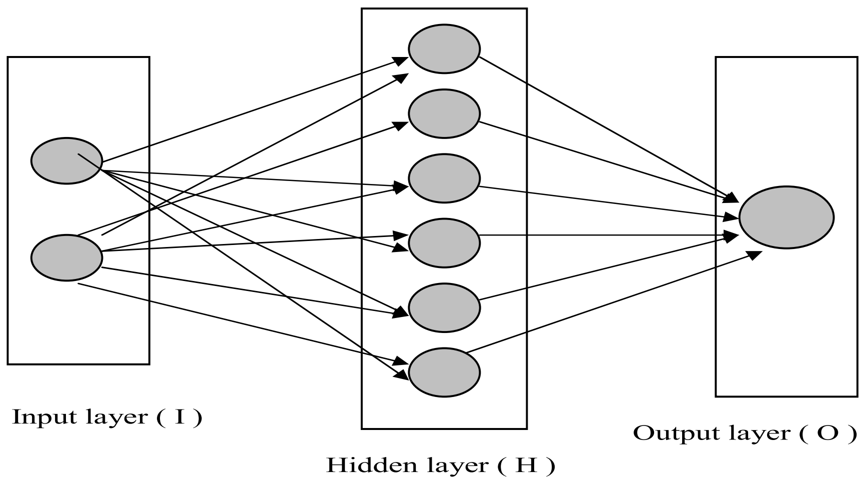

Fig 1. The three layer neural network

ANN PREDICTION OF DEPOSITION EFFICIENCY

The prediction neural network was tested with four data sets from the original process data. Each data set contained inputs such as torch input power and an output value i.e. deposition efficiency was returned by the network. As further evidence of the effectiveness of the model, an arbitrary set of inputs is used in the prediction network. Results were compared to experimental sets that may or may not be considered in the training or in the test procedures. Fig. 2 presents the comparison of predicted output values for deposition efficiency with those obtained experimentally.

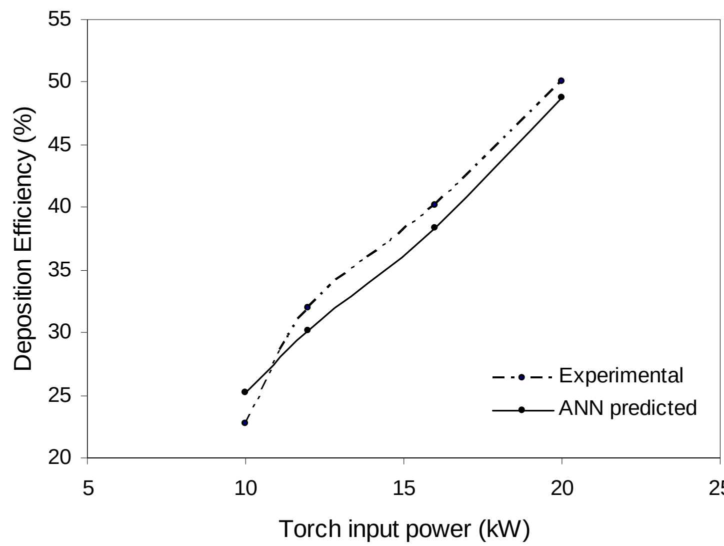

Fig.2 Comparison plot for predicted and experimental values of deposition efficiency of Nickel aluminide coatings on mild steel substrates

It is interesting to note that the predictive results show good agreement with experimental sets realized after having generalizing the ANN structures. The optimized ANN structure further permits to study quantitatively the effect of the considered input power. The range of the chosen parameter can be larger than the actual experimental limits, thus offering the possibility to use the generalization property of ANN in a large parameter space. In the present investigation, this possibility was explored by selecting the torch input power in a range from 6 kW to 24 kW, and a set of prediction for deposition efficiency is evolved. Fig.3 illustrates the predicted evolution of deposition efficiencies of nickel aluminide coatings on mild steel substrates with torch input power.

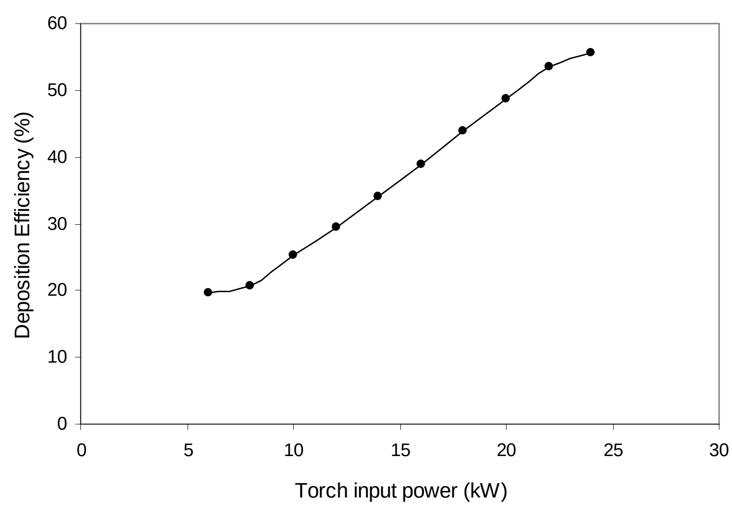

Fig. 3 Predicted Deposition efficiency at different power levels

As seen in fig.3, the deposition efficiency presents a sigmoid-type evolution with the torch input power. As the power level increases, the total and the net available energies increase (the arc current intensity increases from 250A to 400A for operating power increasing from 10 to 20kW).This leads to a better in-flight particle molten state and hence to higher probability for particles to flatten. The deposition efficiency reaches a plateau for the highest current levels due to the plasma jet temperature increasing which in turn increases both the particle vaporization ratio and the plasma jet viscosity.

CONCLUSIONS

Deposition efficiency is one the main requirements of the coatings developed by plasma spraying. In order to achieve certain values of deposition efficiency accurately and repeatedly, the influence parameters of the process have to be controlled accordingly. Neural computation can be gainfully employed as a tool for this purpose. The simulation can be extended to a parameter space larger than the domain of experimentation.

REFERENCES

1. C. T. Liu and C. L. White, in High Temp. Ordered Intermetallic Alloys, ed. by C. C. Koch,C. T. Liu and N. S. Stoloff, Mat. Res. Soc., 39, 365 (1985)

2. R. W. Cahn, Load-Bearing Ordered Intermetallic Compounds- A Historical View, MRS Bulletin, 5, 18 (1991)

3. J. Z. Chen, H. Herman and S. Safai, Evaluation of NiAl and NiAl-B Deposited by Vacuum Plasma Spray, J. Thermal Spray Technology, 2, 357 (1993)

4. C. T. Liu and V. K. Sikka, Nickel Aluminides for Structural Uses, J. of Metals, 38, 13 (1986)

5. Robert B.Hiemann, Plasma-Spray Coating-Principles and Applications, VCH Publishers Inc., New York, NY, USA, (1996)

6. S.Rajasekaran , G. A. Vijayalakshmi Pai --*Neural Networks, Fuzzy Logic And Genetic Algorithms—Synthesis and Applications* -Prentice Hall of India Pvt. Ltd. , New Delhi (2003)

7. V. Rao and H. Rao *'C++ Neural Networks and Fuzzy Systems'* BPB Publications, 2000.

****