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Al_2O_3-TiO_2 WEAR RESISTANT COATINGS: A NEURAL COMPUTATION

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ABSTRACT

Plasma sprayed alumina-titania (Al_2O_3-TiO_2) coatings have many industrial applications. They provide a dense and hard surface coating which are resistant to abrasion, corrosion, cavitation, oxidation and erosion and are therefore regularly used for wear resistance, electrical insulation, thermal barrier applications etc. This work reports the implementation of Artificial Neural Networks (ANN) for analysis and prediction of wear behavior of plasma sprayed alumina titania composite coatings. Alumina pre-mixed with titania powder is deposited on mild steel substances by atmospheric plasma spraying at various operating power level and the coatings are subjected to solid particle erosion. ANNs are excellent tools for complex processes that have many variables and complex interactions. The analysis is made taking into account training and test procedure to predict the dependence of erosion wear behavior on angle of impact and velocity of erodent. This technique helps in saving time and resources for experimental trials.

KEYWORDS: *Plasma Spraying, Alumina-titania coating, Solid particle erosion, Neural Network.*

1. INTRODUCTION

Critical components in high-tech industries operate under extremely hostile conditions of temperature, gas flow, heat flux and corrosive media, which severely limit their sevicelife.This problem, can be overcome by using composite structures consisting of the core material with a suitable surface coating. Plasma spray technology, the process of preparing overlay coating on any surface, is one of the most widely used techniques to prepare such composite structural parts with improved properties and increased life span [1]. Composite coatings are defined as the deposits produced by thermal spraying containing at least two distinctive, intentionally present phases apart from porosity. Al_2O_3–TiO_2 composite coatings are composed of a matrix Al_2O_3 and second TiO_2 phase called reinforcement. The role of matrix is to distribute the stresses homogeneously inside the composite material. The role of the second phase in the coating is mostly to reinforce the material mechanically. These types of coatings can be prepared by blending the matrix powder with reinforcement and by plasma spraying [2, 3]. The use of the composite in preference to pure aluminium oxide has certain advantages. Titanium oxide has a lower melting point and effectively binds alumina grains leading to higher density and wear resistance coating. Al_2O_3 with low wt.%.of TiO_2 coatings provide high electric resistance and are suitable where good insulating properties and high electric strength are required but the coatings of mixtures with high wt.%. TiO_2 possess good electrical conductivity due to its manufacturing process of powder and preparation of coatings. The coating process is based on the creation of a plasma jet to melt a feedstock powder [4]. Powder particles are injected with the aid of a carrier gas; they gain their velocity and temperature by thermal and momentum transfers from the plasma jet. At the surface of the substrate, particles flatten and solidify rapidly forming a stack of lamellae.
Solid particle erosion is a process where particles strike against a surface and cause material loss. During flight, a particle carries momentum and kinetic energy, which is dissipated during impact due to its interaction with a target surface. In case of plasma spray coatings encountering such situations, no

specific model has been developed and thus the study of the erosion behavior has been based on mostly experiment data [5]. Solid particle erosion is considered as a non linear process with respect to its variables: either materials or operating conditions. To obtain the best functional output coatings exhibiting selected in-service properties and the right combinations of operating parameters are to be known. These combinations normally differ by their influence on the erosion wear rate or coating mass loss. In order to control the wear loss in such a process one of the challenges is to recognize parameter interdependencies, co-relations and there individual effects on wear. A robust methodology is often 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 erosion rate. Neural networks have provided a means of successfully controlling complex processes in manufacturing industries [6-10]. The details of this methodology are described by Rajesekaran and Pai [11].

2. EXPERIMENTAL DETAILS

2.1 Coating Deposition

Alumina, 13% Titania used as feed stock for coating is first sieved and size range powder 35 to 80 µm is taken and were mixed thoroughly in a planetary ball mill to get homogeneous mixture. This mixture is sprayed on mild steel substrates of 25mm diameter and 3mm thickness. Spraying is done by using a 40 kW APS (atmospheric plasma spray) system in the thermal plasma laboratory (thermal plasma section, L&PTD, BARC, Bombay). The plasma torch input power is varied from 11 to 21 kW by controlling the gas flow rate, plasma arc current and the arc voltage.

2.2 Erosion Test

Solid particle erosion is usually simulated in laboratory by one of two methods. The ‘sand blast’ method, where particles are carried in an air flow and impacted onto a stationary target and the ‘whirling arm’ method , where the target is spun through a chamber of falling particles. In the present investigation, an erosion apparatus (self-made) of the ‘sand blast’ type is used. It is capable of creating highly reproducible erosive situations over a wide range of particle sizes, velocities, particles fluxes and incidence angles, in order to generate quantitative data on materials and to study the mechanisms of damage. The test is conducted as per ASTM G76 standards.

In this work, room temperature solid particle erosion test on mild steel substrate coated with Alumina +13% titania as feed materials (at 18 kW) is carried out. The coating deposited at 18 kW power level is eroded at 30^0, 45^0, 60^0, $75^0$and 90^0 angle at SOD of 150mm. Here, 400µm size dry silica sand particles are used as erodent with different velocities i.e. of 32m/sec, 45m/sec, 58m/sec and at pressure of 4kgf/cm^2, 5.5kgf/cm^2, 6.5kgf/cm^2 with feed rate 50gm/min, 58gm/min and 62 gm/min. Amount of wear is determined on ‘mass loss’ basis. It is done by measuring the weight change of the samples at regular intervals in the test duration. A precision electronic balance with + 0.01 mg accuracy is used for weighing. Erosion rate, defined as the coating mass loss per unit erodent mass (gm/gm) is calculated. The erosion rates are calculated at different velocities and impingement angles.

3. 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 erosion wear. The details of this methodology are described by Rajasekaran and Pai [11].

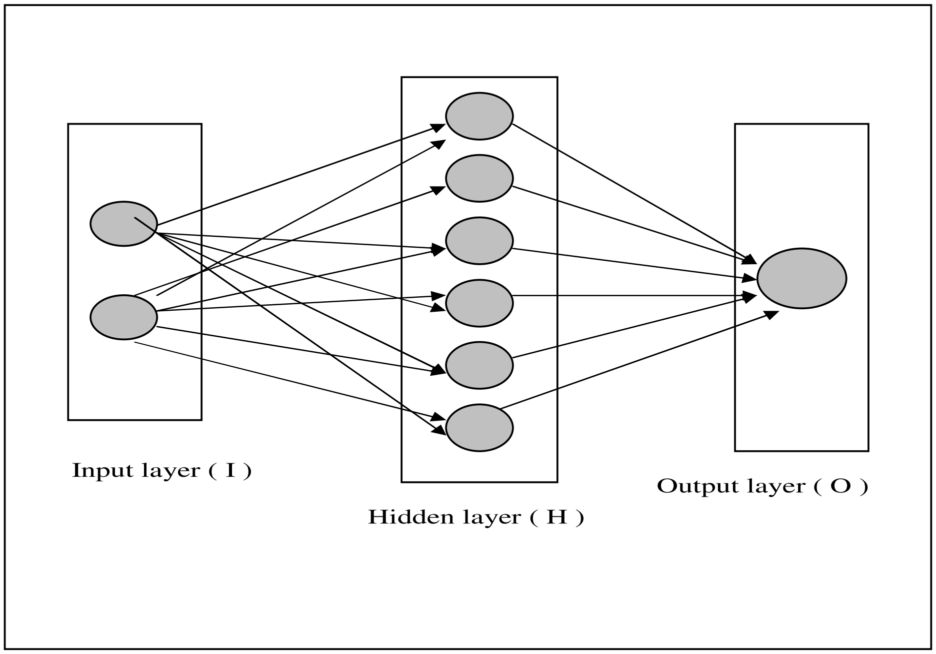
4. NEURAL NETWORK MODEL: Development and Implementation

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 which has been utilized in the most of the research works for material science, reviewed by Zhang and Friedrich [12]. A software package NEURALNET for neural computing developed by Rao and Rao [13] using back propagation algorithm is used as the prediction tool for coating erosion wear rate at different impact angles and impact velocity.

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 15 data sets at different angles and different velocities 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 1, 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 1000,000 cycles for which stabilization of the error is obtained. Here the hidden layer number is 1 and 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.

Table 1 Input parameters selected for training

Input Parameters for Training	**Values**
Error tolerance	0.002
Learning parameter(ß)	0.001
Momentum parameter(α)	0.001
Noise factor (NF)	0.002
Maximum cycles for simulations	1000000
Slope parameter (£)	0.6
Number of hidden layer neuron	6
Number of input layer neuron (I)	2
Number of output layer neuron (O)	1



5. ANN PREDICTION OF EROSION WEAR RATE

The prediction neural network is tested with three data sets from the original process data. Each data set contained inputs such as impact angle and impact velocity and an output value i.e. erosion wear rate is 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 are compared to experimental sets that may or may not be considered in the training or in the test procedures. Fig.2 represents the comparison of predicted output values for erosion wear rate with those obtained experimentally with impact angle of the erodent at different impact velocities i.e. 32m/sec , 45 m/sec and 58m/sec respectively.

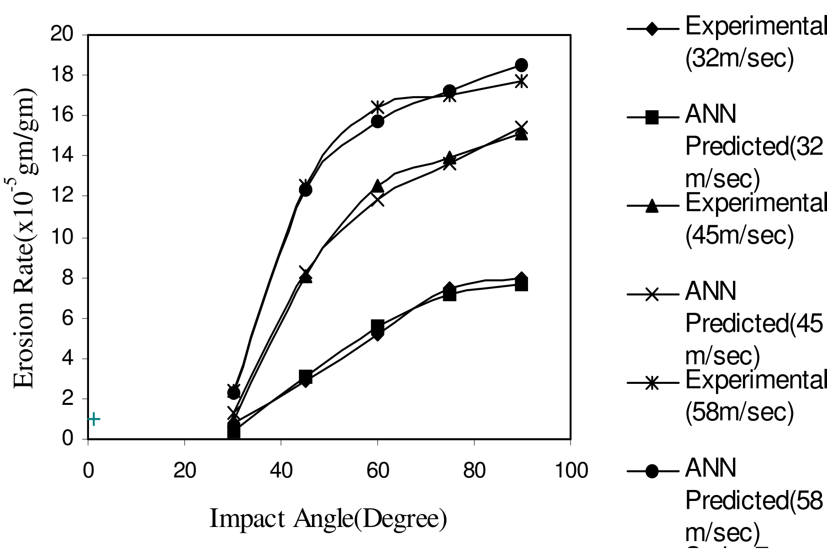


Figure 2. Comparison plot for predicted and experimental values of coating erosion wear rate (Size of the erodent 400µm, time of exposure 6 min, SOD 150mm)

Beside comparison of predicted and experimental values of erosion wear rate Fig.2 illustrates the effect of impact angle (α) on the erosion rate of coatings subjected to solid particle erosion. The erosion results for coatings of materials deposited at 18 kW operating power of the plasma torch at impact angles of 30^0, 45^0, 60^0,75^0 and 90^0 for 32m/sec,45m/sec and 58m/sec respectively at SOD of 150mm for size of the erodent 400μm are shown. Mass loss, then erosion rate (mass loss of coating (gm) per unit wt of erodent (gm)) is measured after the samples are exposed to the erodent stream for 6 minutes. It is seen from the graph that irrespective of the feed material , the erosion mass loss is higher at larger angle of impact and the maximum erosion takes place at $\alpha = 90^0$.

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 impact angle. 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 impact angle in a range from 10^0 to 90^0 for velocities 32m/sec, 45m/sec, 58m/sec and a set of prediction for erosion wear rate is evolved. Fig.3 illustrates the predicted evolution of erosion wear rate of alumina titania coatings on mild steel substrates with the impact angle for velocities 32m/sec, 45m/sec, 58m/sec. From the predicted graph in fig.3 with increasing impact angle erosion rate increases for different impact velocity, and it is maximum at 58m/sec.

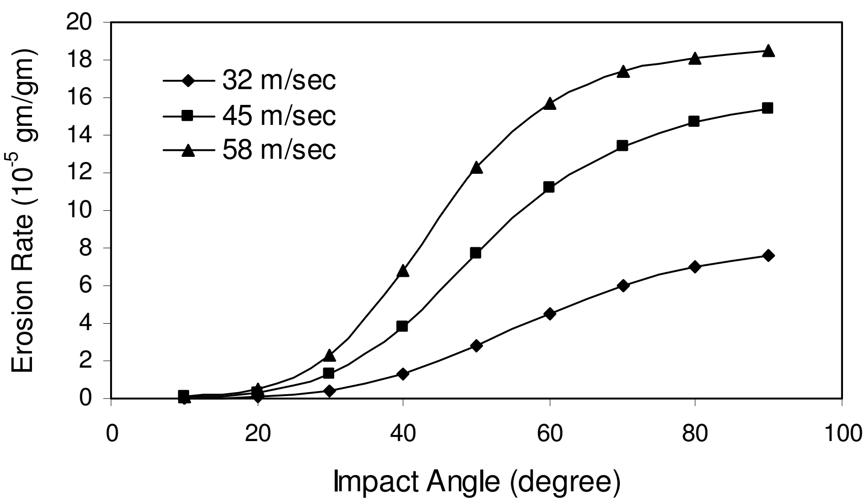


Figure 3 Predicted erosion wear rate of alumina titania coating at different impact angles of the erodent for different impact velocities (for 6 minute time of exposure, SOD150mm, size of the erodent 400μm, for the sample coated at 18 kW power level).

In the present investigation, by selecting the impact velocity in a range from 20 to 70 m/sec at impact angles 30^0 , 60^0 and 90^0 and a set of prediction for erosion wear rate is evolved. Fig.4 illustrates the predicted evolution of erosion wear rate of alumina titania coatings on mild steel substrates with the impact velocity at impact angles 30^0, 60^0 and 90^0.

From the predicted graph in fig.4 with increasing velocity erosion rate increases for different angles. It is obvious that, with increasing velocity the particles will have high kinetic energy which transformed at impact and hence remove more particles from the impacted surface and it is maximum at 90^0 angle. Beside that at low velocity and at low angle there may be one mechanism, so that the slope does not change much, but at high velocity and high angle there may be two mechanisms, so that may be the reason of large slope change.

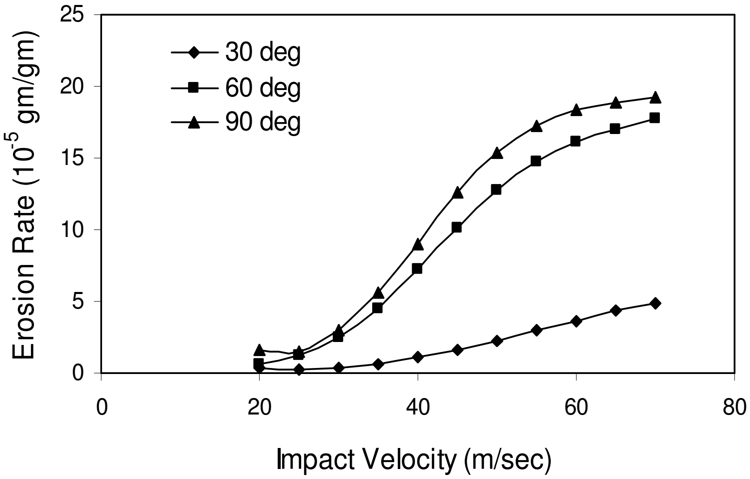


Figure4. Predicted erosion wear rate at different impact velocities impacted at different angles for exposure time 6 min

6. CONCLUSIONS

Alumina titania can be used for depositing plasma spray coatings on metals. The coating sustains erosion by solid particle impingement substantially and there fore alumina titania can be considered as a potential coating material suitable for various tribological applications. Erosion wear behaviour is one of the main requirements of the coatings developed by plasma spraying for recommending specific application. In order to achieve tailored erosion wear rate accurately and repeatedly, the influence of the process parameters are to be controlled accordingly. Neural computation can be gainfully employed as a tool to analyze, optimize and predict the erosion behavior of the coatings purpose. The simulation can be extended to a parameter space larger than experimentation domain.

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