ADVANCED PLASMA SPRAY APPLICATIONS

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Analysis of Experimental Results of Plasma Spray Coatings Using Statistical Techniques

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1. Introduction

Surface modification is a generic term applied to a large field of diverse technologies that can be gainfully harnessed to achieve increased reliability and enhanced performance of industrial components. The incessant quest for higher efficiency and productivity across the entire spectrum of manufacturing and engineering industries has ensured that most modern-day components are subjected to increasingly harsh environments during routine operation. Critical industrial components are, therefore, prone to more rapid degradation as the parts fail to withstand the rigors of aggressive operating conditions and this has been taking a heavy toll of industry's economy. In an overwhelmingly large number of cases, the accelerated deterioration of parts and their eventual failure has been traced to material damage brought about by hostile environments and also by high relative motion between mating surfaces, corrosive media, extreme temperatures and cyclic stresses. Simultaneously, research efforts focused on the development of new materials for fabrication are beginning to yield diminishing returns and it appears unlikely that any significant advances in terms of component performance and durability can be made only through development of new alloys.

As a result of the above, the concept of incorporating engineered surfaces capable of combating the accompanying degradation phenomena like wear, corrosion and fatigue to improve component performance, reliability and durability has gained increasing acceptance in recent years. The recognition that a vast majority of engineering components fail catastrophically in service through surface related phenomena has further fuelled this approach and led to the development of the broad interdisciplinary area of surface modifications. A protective coating deposited to act as a barrier between the surfaces of the component and the aggressive environment that it is exposed to during operation is now globally acknowledged to be an attractive means to significantly reduce/suppress damage to the actual component by acting as the first line of defense. Coating is a layer of material formed naturally or synthetically or deposited artificially on the surface of an object made of another material with the aim of obtaining required technical or decorative properties.

The increasing utility and industrial adoption of surface engineering is a consequence of the significant recent advances in the field. Very rapid strides have been made on all fronts of

science, processing, control, modeling, application developments etc. and this has made it an invaluable tool that is now being increasingly considered to be an integral part of component design. Surface modification today is best defined as "the design of substrate and surface together as a system to give a cost effective performance enhancement, of which neither is capable on its own". The development of a suitable high performance coating on a component fabricated using an appropriate high mechanical strength metal/alloy offers a promising method of meeting both the bulk and surface property requirements of virtually all imagined applications. The newer surfacing techniques, along with the traditional ones, are eminently suited to modify a wide range of engineering properties. The properties that can be modified by adopting the surface engineering approach include tribological, mechanical, thermo-mechanical, electrochemical, optical, electrical, electronic, magnetic/acoustic and biocompatible properties.

The development of surface engineering has been dynamic largely on account of the fact that it is a discipline of science and technology that is being increasingly relied upon to meet all the key modern day technological requirements: material savings, enhanced efficiencies, environmental friendliness etc. The overall utility of the surface engineering approach is further augmented by the fact that modifications to the component surface can be metallurgical, mechanical, chemical or physical. At the same time, the engineered surface can span at least five orders of magnitude in thickness and three orders of magnitude in hardness.

Driven by technological need and fuelled by exciting possibilities, novel methods for applying coatings, improvements in existing methods and new applications have proliferated in recent years. Surface modification technologies have grown rapidly, both in terms of finding better solutions and in the number of technology variants available, to offer a wide range of quality and cost. The significant increase in the availability of coating process of wide ranging complexity that are capable of depositing a plethora of coatings and handling components of diverse geometry today, ensures that components of all imaginable shape and size can be coated economically.

Although there are different techniques available for the deposition of materials on suitable substrates, thermal spraying process is being widely used for depositing thick coatings for various industrial applications. The type of thermal spraying depends on the type of heat source employed and consequently flame spraying (FS), high velocity oxy-fuel spraying (HVOF), plasma spraying (PS) etc. come under the umbrella of thermal spraying. Plasma spraying utilizes the exotic properties of the plasma medium to impart new functional properties to conventional and non-conventional materials and is considered as one highly versatile and technologically sophisticated thermal spraying technique instead of having relatively high price of the sprayable consumables.

Plasma spraying, one of the thermal spraying processes, is increasingly popular owing to its versatility in spraying a large number of materials and is being researched well. It is a very large industry with applications in corrosion, abrasion and temperature resistant coatings and the production of monolithic and near net shapes [1]. The process can be applied to coat on variety of substrates of complicated shape and size using metallic, ceramic and /or polymeric consumables. The production rate of the process is very high and the coating adhesion is also adequate. Since the process is almost material independent, it has a very

wide range of applicability, e.g., as thermal barrier coating, wear resistant coating etc. Thermal barrier coatings are provided to protect the base material, e.g., internal combustion engines, gas turbines etc. at elevated temperatures. Zirconia (ZrO_2) is a conventional thermal barrier coating material used as the top coat, over a bond coat. As the name suggests, wear resistant coatings are used to combat wear especially in cylinder liners, pistons, valves, spindles, textile mill rollers etc. alumina (Al_2O_3), titania (TiO_2) and zirconia (ZrO_2) are the some of the conventional wear resistant coating materials [2].

Plasma spraying is a surface modification technique that combines particle melting, rapid solidification and consolidation in a single process. Because of their higher strength-to-weight ratio and superior wear-resistant properties, ceramics are preferred in most tribological applications. The ceramic materials can be applied for the overlay coating due to the higher gas enthalpy of the thermal plasma jet. The suitability of a ceramic coating on metal substrates depends on (i) the adherence strength at coating-substrate interface, and (ii) stability at operating conditions.

Critical components in high-tech industries operate under extremely hostile conditions of temperature, gas flow, heat flux and corrosive media, which severely limit their service life. This problem can be minimized by using composite structures consisting of the core material to with stand the load and with a suitable surface coating to improve the component life span at operating environment. Plasma spray technology, the process of preparing overlay coating on any surface, is one of the most widely used techniques to prepare such complex structural parts with improved properties and increased life span [3].

Alumina–titania coating, which is one of the material largely manufactured, used the atmospheric plasma sprayed (APS) process. This material is known for its wear, corrosion and erosion resistance applications. These types of coatings can be prepared by blending the matrix powder with reinforcement and by plasma spraying [4, 5]. The coating process is based on the creation of a plasma jet to melt a feedstock powder [3]. 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.

The use of the composite in preference to pure aluminum oxide has certain advantages. TiO_2 is a commonly used additive in plasma sprayable alumina powder. TiO_2 has a relatively low melting point and it effectively binds the alumina grains leading to higher density and wear resistance coating [6]. However, a success of an Al_2O_3 - TiO_2 coating depends upon a judicious selection of the arc current, which can melt the powders effectively. This results in a good coating adhesion along with high wear resistance [7]. 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 [8]. 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 [9].

A qualitative analysis of the experimental results with regard to erosion wear rate using statistical techniques is presented. The analysis is aimed at identifying the operating variables/factors significantly influencing the erosion wear rate of alumina titania on metals. Factors are identified in accordance to their influence on the coating erosion wear rate. A prediction model based on artificial neural network is also presented considering the

significant factors. Neural computation is used since plasma spraying is a complex process that has many variables and multilateral interactions. This technique involves construction of a database, training, and validation and then provides a set of predicted results related to the coating adhesion strength and erosion wear rate at various operating parameters.

During plasma spraying, various operating parameters are determined mostly based on past experience. It therefore does not provide the optimal set of parameters for a particular objective. In order to obtain the best result with regard to any specific coating quality characteristic, accurate identification of significant control parameters is essential. 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/i.e. 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. This chapter is devoted to analyze the experimental results of the erosion wear behavior of alumina titania coatings made at different operational conditions on mild steel and cupper substrates. For this purpose, a statistical technique i.e. Taguchi experimental design is used. Factors are identified according to their influence on the coating erosion rate. The most significant parameter is found. A prediction model using artificial neural network (ANN) is presented considering the significant factors. Beside that, this analysis is made taking into account of training and test procedure to predict the dependence of coating adhesion strength of the coatings made at different operating power levels on different substrate materials.

2. Taguchi experimental design

Taguchi method of experimental design is a simple, efficient and systematic approach to optimize designs for performance and cost effectiveness [10]. In the present work, this method is applied to the process of plasma spraying for identifying the significant process variables/interactions influencing coating erosion wear rate. The levels of these factors are also found out so that the process variables can be optimized within the test range.

Experiments are carried out to investigate the influence of the four selected control parameters. The code and levels of control parameters are shown in table 1. This table shows that the experimental plan has two levels. A standard Taguchi experimental plan with notation **L16 (2^{15})** is chosen as outlined in table 2. In this method, experimental results are transformed into a signal-to-noise (S/N) ratio. It uses the S/N ratio as a measure the quality characteristics deviating from or nearing to the desired values. There are three categories of quality characteristics in the analysis of the S/N ratio, i.e. the lower-the-better, the higher-the-better, and the nominal-the-better. To obtain optimal spraying parameters, the lower-the-better quality characteristic for erosion wear rate is taken.

2.1 Analysis of control factor

Table 2 shows experimental lay out and results with calculated S/N ratios for erosion wear rate of the coatings made at 18Kw power level. Analysis of the influence of each control factor on the coating efficiency is made with a signal-to-noise (S/N) response table, using

MINITAB computer package. The response data of the testing process is presented in table 3. The S/N response graph for coating erosion wear rate is shown in Fig.1.The influence of interactions between control factors is also analyzed in the response table. The control factor with the strongest influence is determined by differences values. The higher the difference, the more influential is the control factor or an interaction of two controls. The strongest influence on coating erosion wear rate is found out to be of impact angle (A) followed by impact velocity (B) and stand off distance (C) then size of the erodent (D) respectively.

Parameter	Code	Level 1	Level 2
Impact Angle(Degree)	A	30	90
Impact Velocity(m/sec)	B	32	58
Stand Off Distance(mm)	C	100	150
Erodent Size(μm)	D	200	400

Table 1. Control factors and selected test levels.

Exp. No.	A	B	C	D	Coating erosion wear rate	S/N Ratio
1	1	1	1	1	10.00	-20.0000
2	1	1	1	2	11.00	-20.8279
3	1	1	2	1	11.5	-21.2140
4	1	1	2	2	12.20	-21.7272
5	1	2	1	1	14.40	. -23.1672
6	1	2	1	2	12.50	-21.9382
7	1	2	2	1	18.10	-25.1536
8	1	2	2	2	19.80	-25.9333
9	2	1	1	1	.6	4.4370
10	2	1	1	2	.8	1.9382
11	2	1	2	1	2.10	-6.4444
12	2	1	2	2	2.41	-7.6403
13	2	2	1	1	6.10	-15.7066
14	2	2	1	2	8.00	-18.0618
15	2	2	2	1	17.10	-24.6599
16	2	2	2	2	17.74	-24.9791

Table 2. Experimental lay out and results with calculated S/N ratios for coating erosion wear rate.

Level	A	B	C	D
1	-11.39	-11.43	-14.17	-16.49
2	-22.50	-22.45	-19.72	-17.40
Diff.	11.11	11.02	5.5	0.91
Rank	1	2	3	4

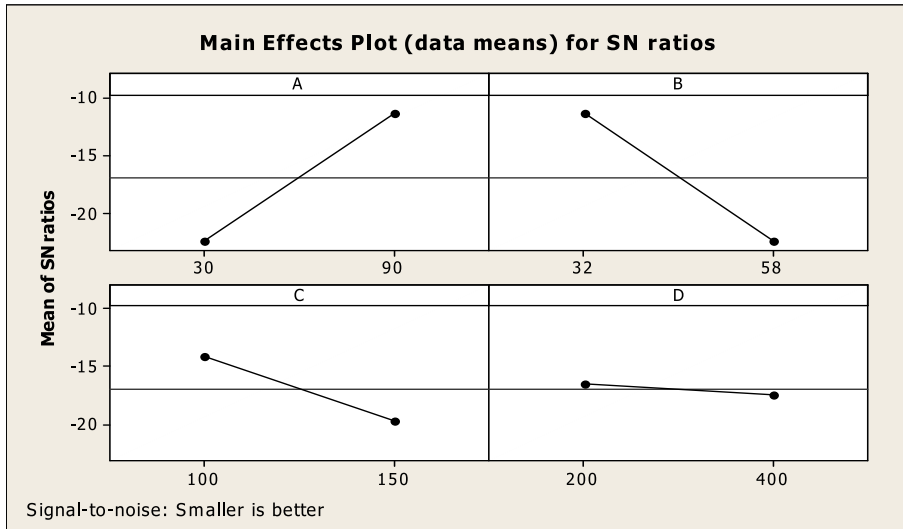Table 3. The S/N response table for coating erosion wear rate.

Fig. 1. The S/N response graph for coating erosion wear rate.

It is interesting to note that the Taguchi experimental design method identified impact angle and impact velocity as the most powerful factor influencing the erosion wear rate of the alumina titania coatings. The stand off distance, size of the erodent emerge as the other significant factors affecting the coating erosion wear rate. The impact angle, thus is a significant process variable and in this work, is rightly taken as the basis for studying its effect on the coating erosion wear characteristics.

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. 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 and the dependence of coating adhesion strength on different operating power levels on different substrates. This technique helps in saving time and resources for experimental trials. The details of this methodology are described by Rajasekaran and Pai [11].

3.1 Neural network model: Development and Implementation (for coating erosion wear rate)

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 25 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 4, 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.

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

Table 4. Input parameters selected for training (Coating erosion).

The impact angles and impact velocity have already been identified (from the outcome of Taguchi analysis) as the parameter significantly affecting the coating erosion wear rate. Each of these parameters is characterized by one neuron and consequently the input layer in the ANN structure has two neurons and the output layer in the ANN structure has one neuron. The optimized three-layer neural network having an input layer (I) with two input nodes, a hidden layer (H) with six neurons and an output layer (O) with one output node employed for this work is shown in Fig. 2.
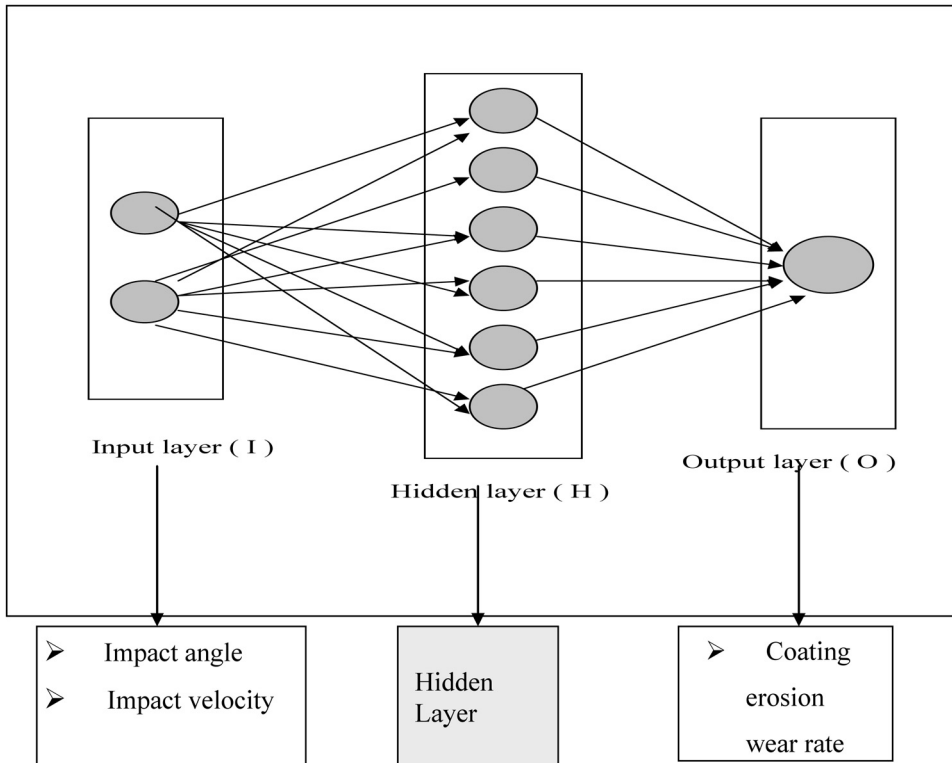

Fig. 2. The three Layer Neural network.

3.2 ANN prediction of erosion wear rate

The prediction neural network is tested with four 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. 3 represents the comparison of predicted output values for erosion wear rate with those obtained experimentally at different impact angles of the erodent at different impact velocities i.e. 32m/sec, 45m/sec and 58 m/sec respectively.
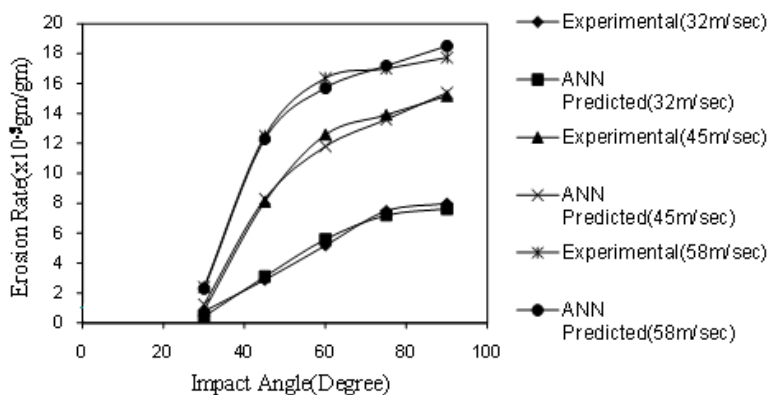
Fig. 3. Comparison plot for predicted and experimental values of coating erosion wear rate at different impact angles of the erodent at impact velocity 32m/sec, 45m/sec and 58m/sec (time of exposure 6 min, SOD 150mm, size of the erodent 400μm for the sample coated at 18 kW power).

Beside comparison of predicted and experimental values of erosion wear rate Fig.3 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 $\alpha = 90^0$. Such trend in generally observed for brittle materials.

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 selected impact angles. 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.4 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.4 with increasing impact angle erosion rate increases for different impact velocity, and it is maximum at 58m/sec.

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.5 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.5 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.
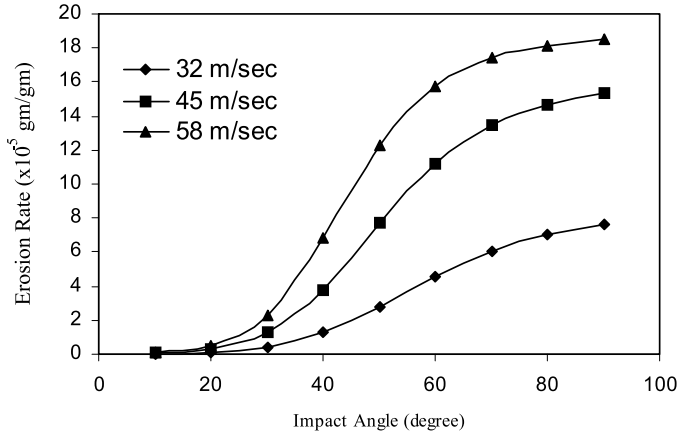

Fig. 4. Predicted erosion wear rate of the coating at different impact angles of the erodent for different impact velocities (for 6 minute time of exposure, SOD150mm, size of the erodent 400μm for the sample coated at 18 kW power level).

3.3 Neural network model: Development and implementation (for coating adhesion strength)

A software package NEURALNET for neural computing developed by Rao and Rao [13] using back propagation algorithm is used as the prediction of coating adhesion strength at different operating power levels for different substrates. To train the neural network used for this work, about 8 data sets at different operating power levels for different substrates are taken. Based on least error criterion, one structure, shown in table 5, is selected for training of the input-output data.

Input Parameters for Training	Values
Error tolerance	0.001
Learning parameter(ß)	0.002
Momentum parameter(α)	0.002
Noise factor (NF)	0.001
Maximum cycles for simulations	1000,000
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 5. Input parameters selected for training (for coating adhesion strength).
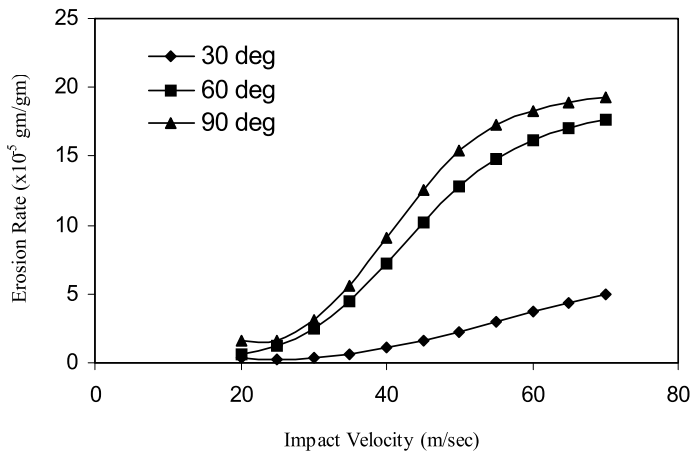
Fig. 5. Predicted erosion wear rate at different impact velocities impacted at different angles (for exposure time 6 min, SOD150mm, size of the erodent 400μm, for the sample coated at 18 kW power level).

The operating power levels and substrate materials are taken as the parameter significantly affecting the coating adhesion strength. Each of these parameters is characterized by one neuron and consequently the input layer in the ANN structure has two neurons and the output layer in the ANN structure has one neuron. The optimized three-layer neural network having an input layer (I) with two input nodes, a hidden layer (H) with six neurons and an output layer (O) with one output node employed for this work is as shown in Fig. 2.

3.4 ANN prediction of coating adhesion strength

The prediction neural network was tested with three data sets from the original process data. Each data set contained inputs such as torch input power, substrate material and an output value i.e. coating adhesion strength 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.6 presents the comparison of predicted output values for coating adhesion strength with those obtained experimentally with different torch input power on different 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 plasma torch input power in the range from 7 kW to 25 kW, and a set of prediction for coating adhesion strength is evolved. Fig.7 illustrates the predicted evolution of coating adhesion strength of alumina titania coatings on copper and mild steel substrates with torch input power.
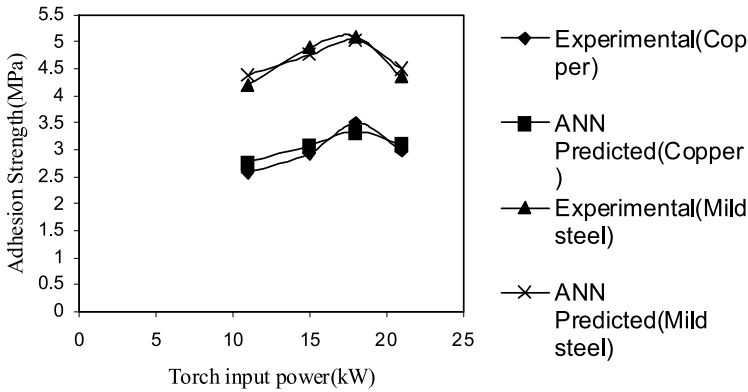
Fig. 6. Comparison plot for predicted and experimental values of coating adhesion strength with different torch input power on different substrates.

From the figure it can be visualized that, the interface bond strength increases with the input power of the torch up to a certain power level and then shows a decreasing trend in coating adhesion, irrespective of the substrate material. This might be due to the fact that, when the operating power level is increased, larger fraction of particles attain molten state as well as the velocity of the particles also increase. Therefore there is better splat formation and mechanical inter-locking of molten particles on the substrate surface leading to increase in adhesion strength [14]. But, at a much higher power level, the amount of fragmentation and vaporization of the particles increase. There is also a greater chance to fly off of smaller particles during in-flight traverse during plasma spraying and results in poor adhesion strength of the coatings. Coating adhesion strength is more in case of mild steel substrate than that of copper substrate may be due to the dependence of thermal conductivity for melted particle, dissipation of heat at metal interface and also may be due to thermal expansion coefficient mismatch at the ceramic metal interface [15].
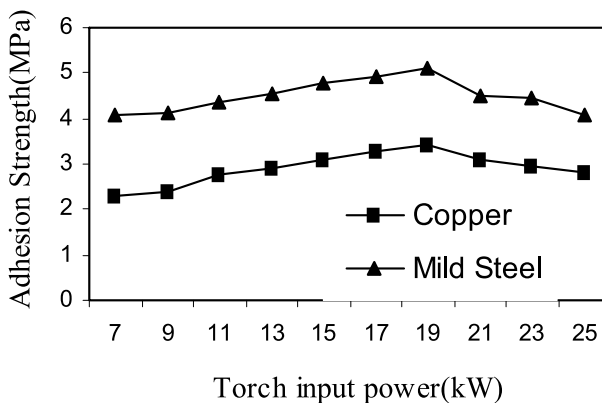

Fig. 7. Predicted values of coating adhesion strength of alumina titania coatings on copper and mild steel substrates at different torch input power.

4. Remarks

Functional coatings have to fulfill various requirements. The less erosion wear rate is one the main requirements of the coatings developed by plasma spraying. Solid particle erosion is considered as a non-linear process with respect to its variables: either materials or operating conditions. In order to achieve certain values of erosion rate 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 like coating erosion wear rate and coating adhesion strength and to predict any desired coating characteristic the simulation can be extended to a parameter space larger than the domain of experimentation.

5. Conclusions

The conclusions drawn from the present work are as follows:

- Commercial grade alumina & titania mixed powders in the size range 40 to 100μm can be coated on metal substrates employing thermal plasma spray technique. Coatings made with alumina titania possess desirable coating characteristics comparable to those of other conventional plasma sprayed ceramic coatings.
- Adhesion strength of the coating varies with operating power. Maximum adhesion strength of 5.1 MPa on mild steel substrate and of 3.5Mpa on copper substrate is recorded at 18 kW. It is noted that invariably in all cases the interface bond strength increases with the input power of the torch up to a certain optimum power level and then shows a decreasing trend. Coating adhesion is higher in case of mild steel substrate than of copper substrate.
- Operating power level of the plasma torch influences the coating adhesion strength, deposition efficiency, coating thickness and coating hardness to a great extent. The coating morphology is also largely affected by the torch input power.
- It is observed that, the erosion wear rate is dependent on erodent dose, angle of attack, velocity of erodent, stand off distance and size of the erodent. Cumulative coating mass loss varies with time of erosion. Maximum amount /rate of erosion occur at 90^0 impact angle. The trend of erosion of the coatings seems to follow the mechanism predicted for brittle materials. Coating deposited at 18 kW power level shows a higher erosion rate than that of the sample deposited at 11kW power level.
- Erosion wear behavior 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. The coating sustains erosion by solid particle impingement substantially and therefore alumina titania can be considered as a potential coating material suitable for various tribological applications.
- Impact velocity, impact angle, stand off distance and size of the erodent significantly affect the erosion wear rate of coating. Identification of these factors and their significance on the coating erosion wear rate is possible by statistical techniques like Taguchi experimental design. Artificial neural networks can be gainfully employed to simulate property-parameter correlations in a space larger than the experimental

domain. Neural computation can be gainfully employed as a tool to analyze, optimize and predict the erosion behavior, adhesion strength of the coatings purpose. It is evident that with an appropriate choice of processing conditions a sound and adherent ceramic coating is achievable using alumina and titania .

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