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Application of Neural Network Analysis to Correlate the Properties of Plasma Spray Coating

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ABSTRACT

Thermal spray coatings are more often being demanding process at the recent stages of industrial design processes to become fundamental element of the engineering system. The aim of the present paper is to develop a model-based estimation and control for regulating the coating adhesion strength, by using neural network. This proposed model permits cost reduction by the possibility of adjusting the parameter of the process for each of the desired properties, which can directly act as a quality control process. By this artificial neural network (ANN) technique, the possibility of adhesion strength of the mixture of fly-ash, quartz and illmenite (which is deposited on the mild steel and copper substrates) can be predicted as well as adhesion strength, merits of ease of fabrication, and high quality deposits, which optimize the amount of specified coating materials to achieve the desired properties. This technique involves database training to optimize the property parameter evolutions in processes having a large number of interdependent variables such as plasma current, voltage, powder feed rate and travel speed in this plasma spray coating deposition. By this neural network, it is observed that the coating adhesion strength largely depends on arc current, voltage, torch to base distance, powder size, etc.

Keywords: *ANN, adhesion strength, plasma spraying, power level*

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1. INTRODUCTION

The best way to obtain the desired surface properties for enhancing substrate usability is to coat the surface by using suitable coating material. In particular, atmospheric plasma spraying exhibits attracted considerable attention as a process for applying protective coatings. Atmospheric plasma spraying (APS) is a part of thermal spraying process, in which powdered materials of particle size distribution ranging usually from 40 to 100 μm are injected within the plasma or the plasma jet, where particles are accelerated and melted (molted) or partially melted (semi-molten) before they flatten and solidify onto the substrate [1–5], the coating being built by the layering of splats. For analysis of result for coating adhesion strength, there are three responsible fundamental mechanisms, which are related to the binding mechanical, chemical and physical forces [6].

The coating adhesion strength depends on the characteristics of the substrate (topology, chemistry, etc.) and the impacting particle state (quantity, velocity, impact angle, viscosity, degree of melting, etc.). The particle state is related to particle injection (quantity of momentum, etc.) and to the plasma flow characteristics (mass enthalpy, velocity, coefficient of thermal transfer, etc.) [7, 8]. The

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properties are hence directly or indirectly related to the operating parameters. These operating parameters and variables are intimately interrelated via complex nonlinear relationships (shown in Figure 1).

For better coating adhesion strength, it is necessary to understand and control these interrelated relations. It is possible by using a robust quality control process. Among known approaches, statistical experiments are one of the best for empirically discovering cause-and-effect relationships. For making the experiment more economical, these experiments also require the least number of trials; a well-planned set of experiments, in which all parameters of interest are varied over a specified range, is a much better approach to obtain systematic datum. Artificial neural networks can be used as a tool for processing a 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 [8, 9].

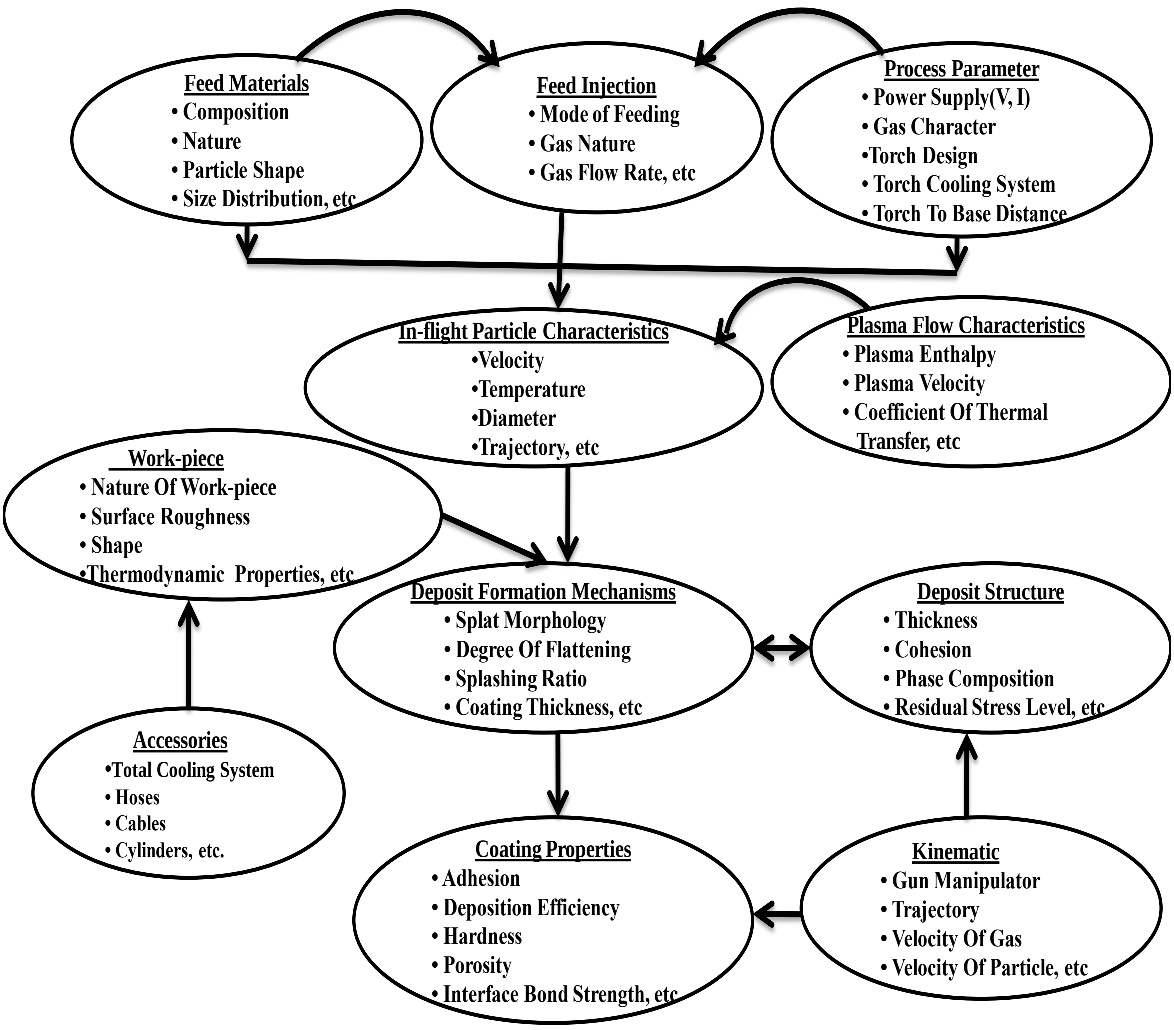

Fig. 1: *Interrelated Parameters and Variables Describing Plasma Spray Process.*

2. EXPERIMENTAL PROCEDURE

The powder mixture of fly-ash, quartz and illmenite was taken with their weight percent ratio of 60:20:20, and plasma sprayed on the mild steel and copper substrates. The size range of the powder mixture was 40 to 100 µm. The powder mixture was mechanically milled in a planetary ball mill for 3 h to get a homogeneous mixture. The substrates were having dimensions 1 in diameter and 3 mm thickness. The surface roughness of the substrate was increased up to ~ 5.00 Ra by grit blasting at a pressure of 3 kg/cm^2 using alumina grit. Substrate surface was cleaned by acetone after grit blasting, then plasma spray process was carried out immediately. The coating process was made by using a 40 kW plasma spray system at the Laser & Plasma Technology Division, BARC, Mumbai. The plasma input power level was varied from 11 to 21 kW. The gas flow rate and arc current are controlled by plasma spraying gun accessories. This is a typically atmospheric plasma spray process, which is working in the non-transferred arc mode. A current-regulated DC power supply was used. The powder mixture was deposited perpendicularly with respect to the substrate. The major subsystems of the setup included the power supply, plasma spray torch, powder feeder, plasma gas supply, distance between torch and substrate, control console, cooling water and spray booth. Operating parameters used for coating deposition are given in Table I. Water cooling of the system was done by a four-stage closed-loop centrifugal pump at a pressure of 10 kg/cm^2 supply. An important role for plasma spray coating is the adhesion strength of interface of the coating powder and the substrate. Interface bond strength is the main characteristic that proves the coating efficiency. The interface bond strength can be measured by coating pull-out test, which was carried out using the setup Instron 1195 at a crosshead speed of 1 mm/min. The test was performed as per ASTM-633 [10, 11].

Table I: *Operating Parameters during Deposition of Fly-ash + Quartz + Illmenite Coatings.*

Operating Parameters	**Values**
Plasma arc current(amp)	270–420
Arc voltage (volt)	40–50
Torch input power (kW)	11,15,18,21
Plasma gas (argon) flow rate (IPM)	28
Secondary gas (N_2) flow rate (IPM)	3
Carrier gas (Ar) flow rate (IPM)	12
Powder feed rate (gm/min)	12–18
Powder size (µm)	40–100
Torch to base distance (TBD)(mm)	100–140

3. ARTIFICIAL NEURAL NETWORK (ANN)

An artificial neural network (NN) is a software [12], which copies the functional principle of the human brain. ANNs are a comparatively new modeling technique composed of simple elements operating in parallel. They can be used to solve problems that are difficult for conventional techniques or for human reasoning [13–16]. ANN calculation is also faster than that of finite element modeling or any other modeling [17, 18]. In ANN optimization process, the parameters are connected by weights which are the numbers, translating the strength of neuron connections. Input variables are taken as number fluxes which feed the network structure and are obtaining the output pattern. ANN is based on a training procedure to decrease the error between ANN response and experimental response for a given set of input variables. Such optimization considers neuron number and weight updates [8]. ANN bibliography is very rich with learning models, like the popular back propagation and the quick propagation, the Hebbian algorithm, the ADALINE model or the Kohonen learning rule and other models [19–24].

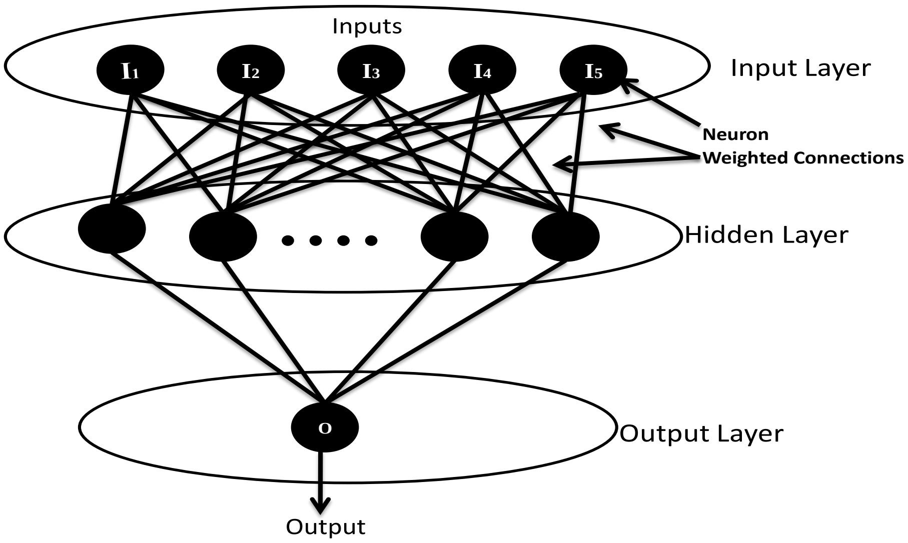

Fig 2: *The Three Layer Neural Network.*

4. RESULTS AND DISCUSSION

For prediction of coating adhesion strength, a software NEURALNET was used, which is developed for neural computing by Rao and Rao [12]. Operation of database undergoes in three categories steps. The first is validation category, which is required to define the ANN architecture, understand the input-output correlations and adjust the number of neurons for each layer. The second is training category, which is exclusively used to adjust the network weights. And, the third is test category, which corresponds to the set that validates the results of the training protocol. About 12 data sets (includes power level, i.e., voltage and current, torch to base distance, powder feed rate, powder size) are taken to train the neural network used for predicting adhesion strength. Varying numbers 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 II, is selected for training of the input-output data. The learning rate is varied in the range of 0.002–0.100 during the training of the input-output data. The network optimization process (training and testing) is conducted for 10,000,000 cycles for which stabilization of the error is obtained. The number of cycles selected during training is high enough so that the ANN models could be rigorously trained. Neuron numbers in the hidden layer are varied and in the optimized structure of the network, this number is 8 (for mild steel) and 9 (for copper). The optimized three layer network is shown in Figure 2.

Table II: *Input Parameters Selected For Training.*

Input Parameters for Training	**Values**
Error tolerance	0. 003
Learning parameter (ß)	0.002
Momentum parameter (α)	0.002
Noise factor (NF)	0.001
Maximum cycles for simulations	10,000,000
Slope parameter (£)	0.6
Number of hidden layer neuron	8
Number of input layer neuron (I)	5
Number of output layer neuron (O)	1

4.1. Predicted Adhesion Strength Compared with Experimental Results Based on Different Feed Rate

The prediction value of neural network was tested with 12 data sets from the original process data. Each data set contained inputs such as torch input current and an output value, i.e., adhesion strength was returned by the network. Figure 3 presents the comparison of predicted output values for coating adhesion strength with those obtained experimentally for both copper and mild steel substrates, which is done at a constant 12 gm/mm powder feed rate and 100 mm torch to base distance with change in power level. The predicted results show good agreement with experimental, which assure to find out the adhesion strength by taking different parameters for future work. Here, it is clearly observed that the predicted plot goes the same

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way as that of the experimental, i.e., by increasing power level the adhesion strength increases up to a certain limit and no increase in adhesion strength with further increasing power level. Again for conformation by changing feed rate to 18 gm/min and torch to base distance 140 mm, the plot for both copper and mild steel changed (shown in Figure 4) with good agreement between predicted value and experimental value.

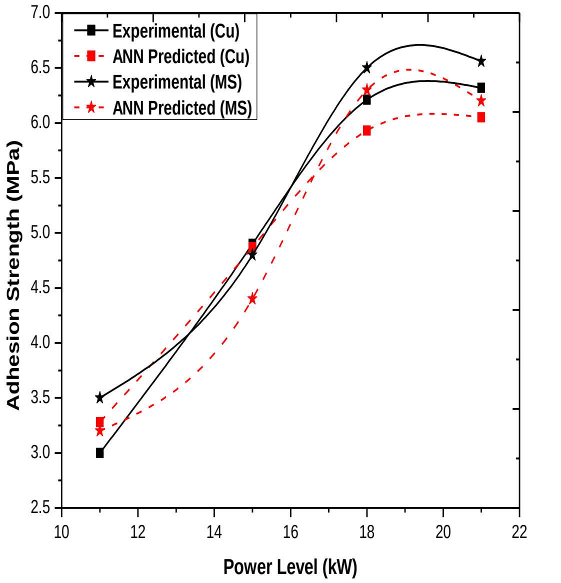


Fig 3: Comparative Plot of Experimental and ANN Predicted Values of Adhesion Strength of Fly-Ash + Quartz + Illmenite on Copper and Mild Steel Substrate (Plasma Spray at 12 gm/min Feed Rate and 100 mm Torch to Base Distance).

4.2. Comparison between Mild Steel and Copper Substrate in Account of ANN Predicted Adhesion Strength Results

In Figure 5, it is clear that the adhesion strength increases with respect to power level from 10 to 18 kW and with further increase in power level there is no change in adhesion strength. It reveals that for 12 gm/min feed rate with 40 µm powder size and 100 mm torch to base distance, one should choose ~ 18 kW power level for better spray coating. If greater than 18 kW power level is chosen, then there will be loss of process efficiency [25]. Surface morphology of powder mixture deposited on mild steel substrate at 18 kW and 21 kW power level are observed in SEM (as shown in Figure 6 (a) and (b)) for examining

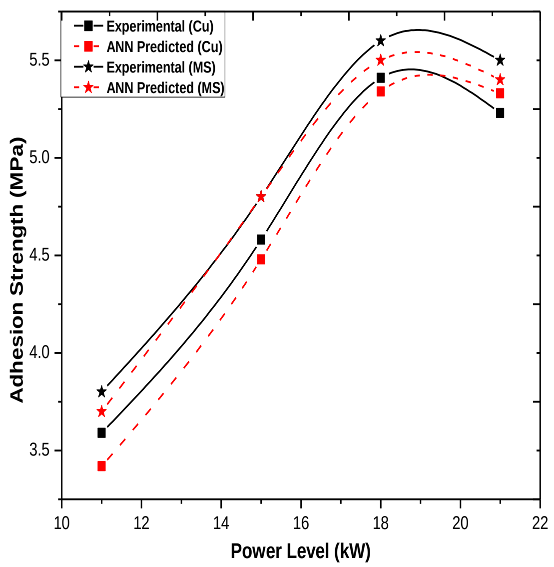


Fig. 4: Comparative Plot of Experimental and ANN Predicted Values of Adhesion Strength of Fly-Ash + Quartz + Illmenite on Copper and Mild Steel Substrate (Plasma Spray at 18 gm/min Feed Rate and 140 mm Torch to Base Distance).

the efficiency of the process. In Figure 6 (a), there are some open pores and in case of figure 6 (b), there is a large number of pores observed in inter-splat layer which hinder the substrate-coating interface bonding. Here, it is confirmed that there is decrease in adhesion strength by increasing the power level to

21 kW. The reason is that due to higher thermal energy at 21 kW, there is more vaporization of coating powder, for which splats are connected before being deposited at the surface of the substrate and there are many cavities formed at the interlayer space. But it is found that the surface roughness at 21 kW is very less in comparison to 18 kW plasma spraying because molten particles are deposited at their vaporization condition. From the prediction plot in Figure 5, the adhesion strength of mild steel is always greater than that of copper.

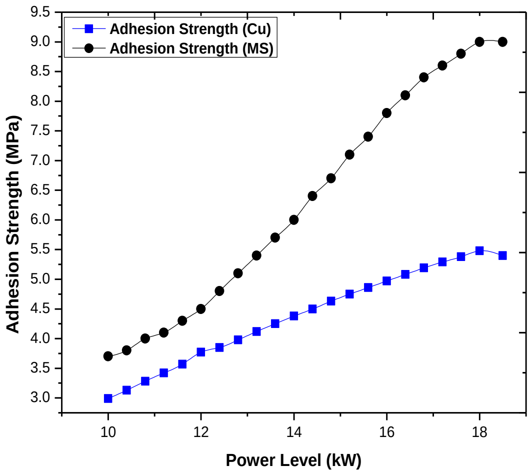
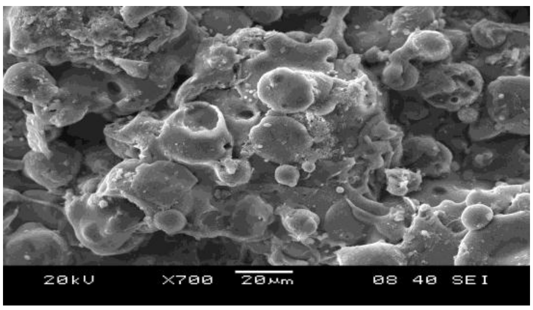
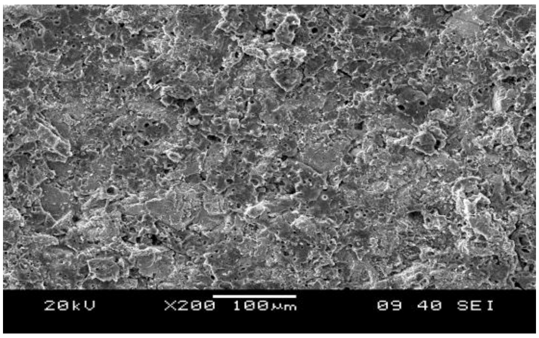


***Fig. 5**: Predicted Adhesion Strength of Copper and Mild Steel Substrate with respect to Different Power Level (Plasma Spray of Fly-Ash + Quartz + Illmenite at 12 gm/min Feed Rate and 40 µm Powder Size, 100 mm Torch to Base Distance).*



(a)



(b)

***Fig. 6**: Deposition of Fly-Ash + Quartz + Illmenite Powder Mixture on Mild Steel Substrate for Observation of Process Efficiency by Using Different Power Level (a) 18 kW and (b) at 21 kW.*

4.3. Prediction Results Based on Powder Particle Size

In case of copper, at 12 gm/min feed rate and 100 mm torch to base distance, it is observed from Figure 6 that higher the powder size, lower is the adhesion strength and there is nearly uniform increase in adhesion strength for each plot. From ANN calculation by choosing this set of parameter with 40 µm powder size, the adhesion strength for copper substrate will be 5.48 MPa at 21 kW power level. But in case of mild steel as shown in Figure 7, at 12 gm/min feed rate and 100 mm torch to base distance, the increment value of adhesion strength is very low in between 10 to13kW and then uniformly increases up to 18 kW power level. Higher adhesion strength will be 9.00 MPa for mild steel with 40 µm powder size. From Figures 6 and 7 plots, it can be seen that the plasma spray will give better result at ~ 17 kW to 18 kW power level.

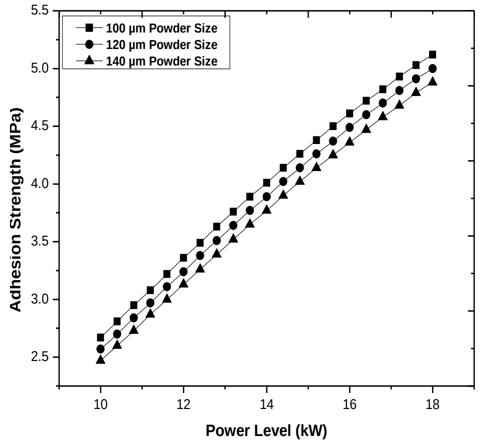


Fig. 6(c): Predicted Adhesion Strength Vs Power Level for Copper by Change in Size of Powder (Plasma Spray of Fly-Ash + Quartz + Illmenite at 12 gm/min Feed Rate and 100 mm Torch to Base Distance).

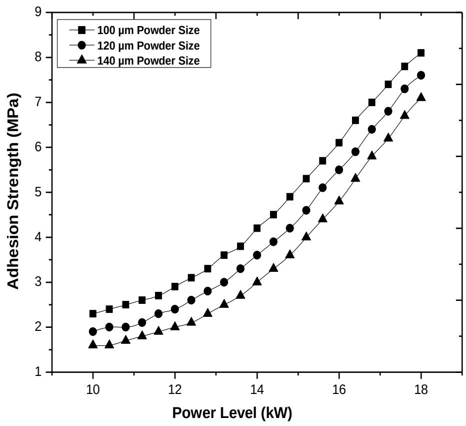


Fig. 7: Predicted Adhesion Strength Vs Power Level for Mild Steel by Change in Size of Powder (Plasma Spray of Fly-Ash + Quartz + Illmenite at 12 gm/min Feed Rate and Torch to Base Distance 100 mm).

4.4. Prediction Results Based on Torch to Base Distance

The adhesion strength decreases by increasing the torch to base distance, which is clearly observed in Figure 8. For smaller powder size (30 µm), the adhesion strength is better than that of higher powder size (70 µm, 90 µm and 120 µm), at 18 kW power level and 12 gm/min feed rate. In case of copper, for 50 µm powder size the highest adhesion strength 5.56 MPa will be achieved at 50 mm torch to base distance. Figure 9 (for mild steel) gives the same idea for coating by different particle size with respect to torch to base distance.

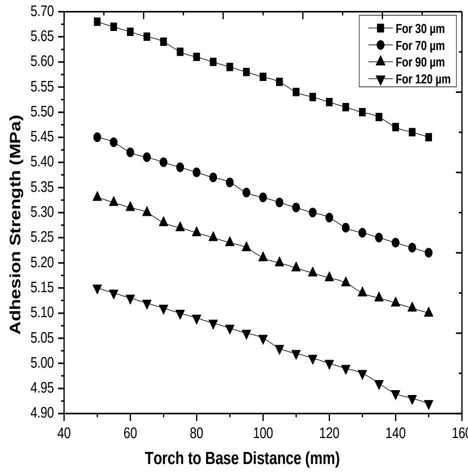


Fig. 8: Predicted Adhesion Strength Vs Torch to Base Distance for Copper by Change in Size of Powder (Plasma Spray of Fly-Ash + Quartz + Illmenite at 18 kW Power Level and 12 gm/min Feed Rate).

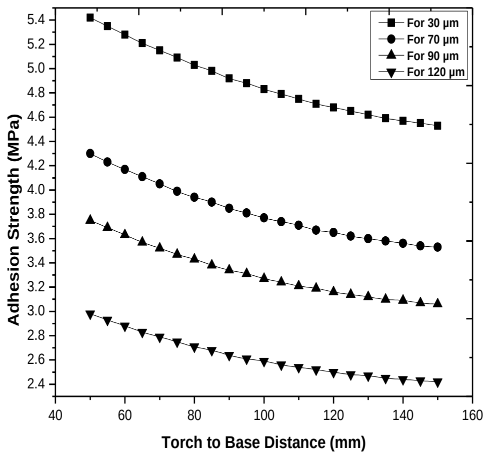


Fig. 9: Predicted Adhesion Strength Vs Torch to Base Distance for Mild Steel by Change in Size of Powder (Plasma Spray of Fly-Ash + Quartz + Illmenite at 15 kW Power Level and 12 gm/min Feed Rate).

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5. CONCLUSIONS

For plasma spraying, adhesion strength can be economically increased by tracking a particular set of parameters which are obtained from higher predicted value in ANN.

Artificial neural network system represents a demanding new generation of information processing networks. It is one of the most optimistic operations in plasma spray coating.

ANN has a major advantage that it does not need additional information about possible correlations between the input and output data of process parameter to be processed by it since it determines these and finds correlations, which are too complex for humans.

Due to these reasons, it can be concluded that neural networks have an enormous technological potential, not only regarding the plasma spraying process, but also regarding other fields of technology.

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