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Optimization of Robot Plasma Coating Efficiency using Genetic Algorithm and Neural Networks

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ABSTRACT

This work describes the Taguchi analysis coupled with Artificial Neural network and Genetic algorithm to optimize the robot deposition parameters used for plasma coating on titanium aluminum alloy material. L27 orthogonal array have been used for coating the work piece using robot. The Arc current (Amp), Arc voltage (volt), powder feed rate(mm/sec), substrate Surface Roughness (µm), Spray gun distance (mm) and TiO2 content in feedstock (%) have been considered as input parameters and coating efficiency is considered as output parameters. Using feed forward Artificial Neural Networks (ANNs) trained the experimental values with the Levenberg–Marquardt algorithm, the most influential of the factors were determined. Regression analysis are used to predict the robot coating efficiency and ANOVA analysis are used to contribute the individual process parameter on robot deposition coating efficiency. The developed mathematical model was further analyzed with Genetic algorithm to find out the optimum conditions leading to the maximum coating efficiency.

Keywords: *Robot Coating, Taguchi Analysis, Regression Analysis, Neural Network, Genetic Algorithm.*

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Nomenclature

ANNs	: Artificial Neural Networks
ANOVA	: Analysis of variance
EDM	: Electrical Discharge Machining
HVLP	: High Volume Low Pressure
DOF	: Degree of Freedom
Ra	: Surface Roughness
S/N ratio	: Signal to Noise ratio
N	: no. of measurements
y	: no. of response value
I	: Plasma spray current
V	: Plasma voltage
T	: Content in the feedstock of titanium
F	: F-Distribution
P	: t-test in ANOVA
RMSE	: Root mean square error
NN	: Neural network
GA	: Genetic Algorithm
RSM	: Response Surface Methodology

Greek Symbol

η	: Robot Efficiency

Subscripts

Wn	: Weights
R^2	: Residuals
Rj	: Actual output
tRj	: Neural network output predicted values

Introduction

Plasma spray [12] is regarded as the most versatile of all the thermal spray processes e.g. flame spraying, arc spraying and High Velocity Oxy-Fuel. The plasma spraying process involves the latent heat of ionized inert gas being used to create the heat source. The most common gas used to create the plasma is argon as the primary gas and hydrogen or helium as the secondary gas. However, the gas usage depends on the type of material to be sprayed and coating application. The use of plasma torches in processes that requires high temperatures, such as metal recovering and residues treatment. The problems related to power quality and process efficiency should satisfy these conditions. A simple and good performance controller strategy, presenting its design procedure. The controller achieves fast DC current regulation, high power factor at the AC side and compensation for AC side oscillation damping [1].

The development of an accurate simulator of robotically applied spray coatings on sculptured surfaces. The method allows parameterization of this spray distribution using a single spray test pattern applied by the robot, without symmetry assumptions. It results in less noise than the individual thickness measurements on which they are based, even when measured data points are not much more numerous [2]. The Artificial Neural Network (ANN) and regression model were developed to predict surface roughness in abrasive water jet machining process. In the development of predictive models, machining parameters of traverse speed, water jet pressure, standoff distance, abrasive grit size and abrasive flow rate were considered as model variables. For this purpose, Taguchi's design of experiments was carried out in order to collect surface roughness values [3].

The prediction and evaluation of thrust force and surface roughness in drilling of composite material using candle stick drill. The approach is based on Taguchi method and the artificial neural network. The experimental results indicate that the feed rate and the drill diameter are the most significant factors affecting the thrust force, while the feed rate and spindle speed contribute the most to the surface roughness [4]. The ANN using Taguchi method has been implemented for minimizing objective functions relevant to the forming process. The orthogonal array and the results of simulation are used as training data of ANN [5]. The neural network modeling approach is presented for the prediction of surface roughness in CNC face milling. The data used for the training and checking of the networks performance derived from experiments conducted on a CNC milling machine according to the principles of Taguchi design of experiments method. Using feed forward ANNs trained with the Levenberg–Marquardt algorithm, the most influential of the factors were determined [6]. The optimal injection molding conditions for minimum shrinkage was determined by the Taguchi, experimental design and the Analysis of variance (ANOVA) methods. After the degree of significance of the studied process parameters was determined, the ANN model was generated and was shown to be an efficient predictive tool for shrinkage [7].

The material removal rate, electrode wear ratio and work piece surface finish on process parameters during the manufacture of SKD61 by Electrical Discharge Machining (EDM) was analysed. A hybrid method including a back-propagation neural network, a Genetic Algorithm (GA), and response surface methodology were proposed to determine optimal parameter settings of the EDM process [8]. A mathematical model based on both the material behavior and the machine dynamics to determine cutting force for milling operations. The system used for optimization is based on powerful artificial intelligence called genetic algorithms (GA) The machining time is considered as the objective function and constraints are tool life, limits of feed rate, depth of cut, cutting speed, surface roughness, cutting force and amplitude of vibrations while maintaining a constant material removal rate. The result of the work shows how a complex optimization problem is handled by a genetic algorithm and converges very quickly [9].

A multi-objective optimization technique, based on genetic algorithms, to optimize the cutting parameters in turning processes: cutting depth, feed and speed. Optimization of cutting parameters is one of the most important elements in any process planning of metal parts. The proposed model uses a genetic algorithm in order to obtain the non dominated sorting genetic algorithm and build the Pareto front graph. In this paper, describes the Taguchi analysis coupled with Artificial Neural network and Genetic algorithm to optimize the robot deposition parameters used for plasma coating on titanium aluminum alloy material [10]. The Taguchi design of experiment techniques proved to be an efficient tool for the design of neural networks' surface roughness to predict in the grinding process, where CNT mixed nanofluids are used as dielectric for machining AISI D3 Tool steel material. Feed forward artificial neural networks are used to train the experimental values with the Levenberg–Marquardt algorithm; the most influencing factors are determined. The predicted surface roughness for without using CNT based cutting fluid is 11.3% and with CNT is 10.37%. Further, a fuzzy logic system is used to investigate the relationship between the machining process parameters accuracy and to determining the efficiency of each parameter design with Taguchi design of experiments [11].

Genetic Algorithm

The Genetic Algorithm (GA) is an evolutionary algorithm that uses genetic operators to obtain optimal solutions without any assumptions about the search space. GA is computerized search and optimization algorithms and work with asset or population of solutions as opposed to traditional optimization technique and evolve the set of optimum solution using the principle of natural genetics and natural selection. Genetic algorithm is very efficient stochastic search technique that tries to emulate natural evolution. An important feature of GA is that it searches several paths simultaneously starting with initial population. Each individual element in the population is called a chromosome. Each chromosome can represent a feasible solution containing a sequence/string of binary or real numbers known as genes. During an evolution process, the current population is replaced by a new generation of chromosomes.

The new population may contain both parent chromosomes and newly generated chromosomes called off springs. Operators like crossover, mutation etc. are used to generate the offspring chromosomes. The crossover operation is a process of merging two parent chromosomes and formation of one or two new chromosomes. Mutation refers to a process of modifying the structure of a selected chromosome by arbitrarily changing one or more genes. A fitness function representing the objective function is used to evaluate the chromosomes. The chromosomes with high fitness among the parents and off springs will be selected for the next generation. This process repeats until the satisfaction of the stopping criteria that can be either a limited number of generations are reached or no further improvement in solutions. The inputs to Genetic algorithm parameters are shown in Table 1.

Table 1: Input to Genetic Algorithm

GA Parameters	Values
Population type	Double vector
Population size	100
Number of generation	200
Number of stall generation	50
Fitness function	Rank scaling
Selection function	Roulette wheel
Crossover function	Two point
Crossover fraction	0.8
Mutation function	adaptive feasible
Migration	Forward
Migration fraction	0.2

Objective functions

The objective function of Robot plasma coating process is to improve the optimum coating efficiency of robot spray method.

$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_5 + a_6x_6 + a_{11}x_1^2 + a_{22}x_2^2 + a_{33}x_3^2 + a_{44}x_4^2 + a_{55}x_5^2 + a_{66}x_6^2 \quad 1$$

The coefficient ao is the free term, ai are the linear terms and aii are the quadratic terms and y is the robot coating efficiency (%) and x1, x2, x3, x4, x5 and x6 are input parameters of Arc current (Amp), Arc voltage (volt), powder feed rate (mm/sec), Substrate surface roughness (μm), Spray gun distance (mm) and TiO2 content in feedstock (%).

GAobj can be used to solve the objective function optimization problem in six different variables. Here we want to maximize the objective, and having one decision variable.

$$\text{Max F(x)} = [\text{objective1(y)}] \quad (2)$$

Where, objective1(y) = Robot coating efficiency

The goal of the robot coating efficiency objective using genetic algorithm is to find a set of solutions in that range (ideally with a good spread). The set of solutions is also known as a Pareto front. All solutions on the Pareto front are optimal.

Basic Algorithm of GA

Step 1 Choose a coding to represent problem parameters, a selection operator, and a crossover Operator and a mutation operator. Choose population size, n, crossover probability, pm. Initialize a random population of strings of size 1. Choose a maximum allowable generation number tmax. Set t = 0.
Step 2 Evaluate each string in the population.
Step 3 If t > tmax or other termination criteria is satisfied, Terminate.
Step 4 Perform reproduction on the population.
Step 5 Perform crossover on the random pairs of strings.
Step 6 Perform mutation on every string.
Step 7 Evaluate strings in the new population. Set t = t+1 and go to Step 3.

The algorithm is straightforward with repeated application of three operators (Step 4 to 7) to a population of points (strings).

Experimental Work

Performance evaluation of the industrial robots in various levels are conducting in every year according to the situational needs and benefits, but this is an analysis of the robot for the characteristic evaluation of certain parameters which have a direct influence on the application of spray coating. The experiments were carried out on ABB IRB 2400 robot with specially designed end-effectors with spray gun. This is a six-axis articulated industrial manipulator. Each axis is servo-controlled with resolver for feedback. The payload capacity of the manipulator is 10 kg, and the reach is 1.5 m. The robot is controlled through updated IRC5 controller. For this experiment a gravity feed HVLP spray gun is used which has an improved atomization capability for maximum transfer coating efficiency. For the consistency of pressure in the tip of spray gun, a specially arranged end effectors were fabricated and maintain a required pressure on the entire experiments. The robot is incorporated with the plasma spray gun, which is connected to the powder feeder and power supply. The experimental setup is shown in Figure 1.

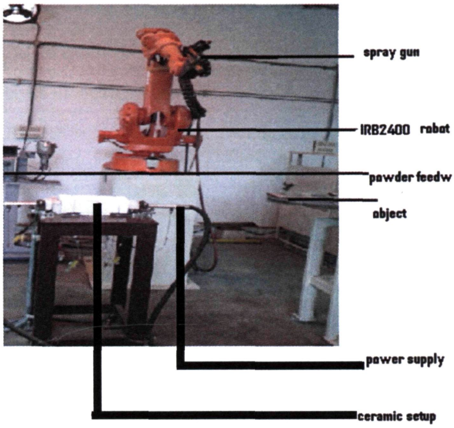

Figure 1: Experimental setup of robot plasma coating

Flow process of genetic algorithm for the robot plasma coating process is shown in Figure 2. This shows the population size, cross over and mutation probability and maximum generation of data using GA.

Specifications of robot

Plasma coating has been carried out using the following robot specifications on titanium aluminum alloy work piece materials as shown in Table 2.

Table 2: Specification of IRB2400 robot

Parameters	Values
Robot make	IRB2400 ABB robot
Reach	1.5 m
Program Memory:	3000- 12000 Instructions (1-5 MB)
Robot arm velocity	0.5 – 200 mm/sec
DOF	6
Pay load	10 kg

Robot spray coating was carried out on titanium aluminum alloy using IRB1410 industrial robot and image has shown in Figure 3. Globules of debris and craters are considerably reduced in the coated plates and the reason is to adhesion property of coating material and also hard material of Titanium alloy. The thickness variation of spray and coated surface was measured using microscopic image analyzer and shows that uniform thickness was achieved using robot coating.

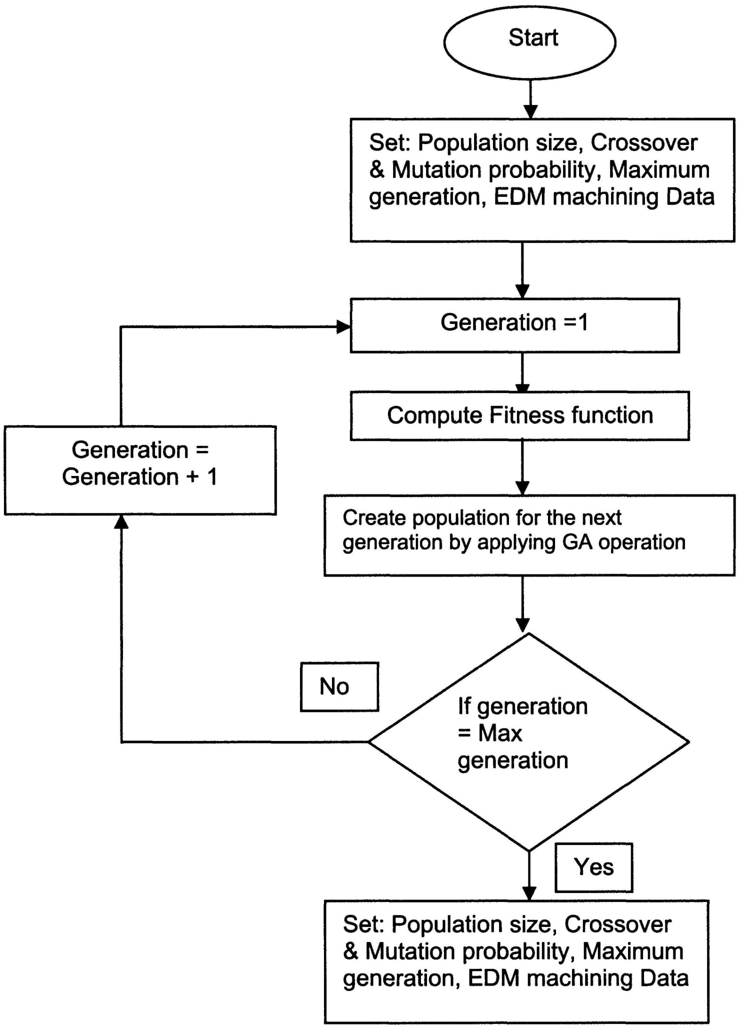

Figure 2: Flow chart of genetic algorithm for robot plasma coating process

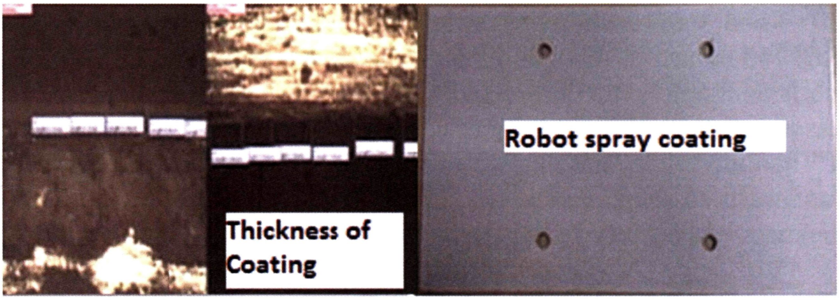

Figure 3: (a) Coating Thickness (b) Spray coating workpiece

Taguchi design of experiments technique is used to carry out the modeling and analysis of the influence of process variables (design factors) on the response variables. In the present study Arc current (Amp), Arc voltage (volt), powder feed rate (mm/sec), Substrate surface roughness (µm), Spray gun distance (mm) and TiO2 content in feedstock (%) have been selected as design factors for robot coating while other parameters have been assumed to be constant over the experimental domain. The process variables (design factors) with their values on different levels are listed in Table 3. The selection of the values of the variables is limited by the capacity of the robot used in the coating process. Three levels within the operating range of the parameters have been selected for each of the factors. In the present investigation, L27 orthogonal array design has been considered Table 4 for experimentation. Interaction effect of process parameters has been assumed negligible. The experimental values along with design matrix are shown in Table 5.

Table 3: Coating process variables and their levels

Item	Control Factor	Units	Level 1	Level 2	Level 3
A	Current	amp	200	300	400
B	Voltage	volt	40	50	60
C	Powder feed rate	mm/sec	8	12	16
D	Surface roughness	µm	4.5	5.8	7.2
E	Spray gun distance	mm	75	100	125
F	TiO_2 in feedstock	%	0	10	20

Table 4: L27 orthogonal array

Exp. no	A	B	C	D	E	F
1	1	1	1	1	1	1
2	1	1	1	1	2	2
3	1	1	1	1	3	3
4	1	2	2	2	1	1
5	1	2	2	2	2	2
6	1	2	2	2	3	3
7	1	3	3	3	1	1
8	1	3	3	3	2	2
9	1	3	3	3	3	3
10	2	1	2	3	1	2
11	2	1	2	3	2	3
12	2	1	2	3	3	1
13	2	2	3	1	1	2
14	2	2	3	1	2	3
15	2	2	3	1	3	1
16	2	3	1	2	1	2
17	2	3	1	2	2	3
18	2	3	1	2	3	1
19	3	1	3	2	1	3
20	3	1	3	2	2	1
21	3	1	3	2	3	2
22	3	2	1	3	1	3
23	3	2	1	3	2	1
24	3	2	1	3	3	2
25	3	3	2	1	1	3
26	3	3	2	1	2	1
27	3	3	2	1	3	2

Table 5: Deposition efficiency of S/N ratio value

Sl. No.	Arc Current (amp)	Arc Voltage (volt)	Powder Feed Rate (mm/sec)	Substrate surface roughness (μm)	Torch to Base Distance (mm)	TiO_2 content in feedstock (wt.%)	Deposition Efficiency (%)	S/N Ratio
1	200	40	8	4.5	75	0	17.87	24.28
2	200	40	8	4.5	100	10	13.54	25.31
3	200	40	8	4.5	125	20	21.51	27.59
4	200	50	12	5.8	75	0	16.38	25.23
5	200	50	12	5.8	100	10	18.43	26.67
6	200	50	12	5.8	125	20	23.98	28.18
7	200	60	16	7.2	75	0	18.27	28.83
8	200	60	16	7.2	100	10	21.56	29.94
9	200	60	16	7.2	125	20	25.67	27.40
10	300	40	12	7.2	75	10	27.65	28.93
11	300	40	12	7.2	100	20	31.43	30.28
12	300	40	12	7.2	125	0	23.45	29.47
13	300	50	16	4.5	75	10	27.98	30.28
14	300	50	16	4.5	100	20	32.66	30.99
15	300	50	16	4.5	125	0	29.78	28.90
16	300	60	8	5.8	75	10	32.67	31.57
17	300	60	8	5.8	100	20	35.45	29.47
18	300	60	8	5.8	125	0	27.88	30.26
19	400	40	16	5.8	75	20	37.91	31.35
20	400	40	16	5.8	100	0	29.77	29.56
21	400	40	16	5.8	125	10	32.59	30.54
22	400	50	8	7.2	75	20	36.95	31.55
23	400	50	8	7.2	100	0	30.08	30.22
24	400	50	8	7.2	125	10	33.66	30.82
25	400	60	12	4.5	75	20	37.84	24.28
26	400	60	12	4.5	100	0	32.44	25.31
27	400	60	12	4.5	125	10	34.76	27.5970
				Mean(μ)				**28.70**

Results and Discussion

S/N Ratio have been calculated based on quality of the characteristics. The objective function of this method is to improve the deposition efficiency of robot in Titanium aluminum alloy material. So, the larger the best S/N Ratio is calculated. The formula used for calculating the S/N ratio is given below:

Larger the best

$$\frac{S}{N} Ratio(\eta) = -10 \log 10 \frac{1}{n} \sum_{i=1}^{n} 1/y^2 \quad (3)$$

N = no. of measurements
y = no. of response value

Deposition coating efficiency has been calculated using the following formula:

$$\eta = K0 + K1 \times I + K2 \times V + K3 \times T \quad (4)$$

η = Deposition coating efficiency
Ki (i = 0, 1, 2, 3)
I = Plasma spray current
V = Plasma voltage
T = Content in the feedstock of titanium (wt.%)

Using the results presented in the Table 5, the full form of the derived mathematical models for robot coating efficiency of robot has been shown in Equation (5).

$$Robot\ efficiency(\eta) = -6.45 + 0.0715\,x_1 + 0.171x_2 + 0.091x_3 + 0.007x_4 - 0.0005x_5 + 0.319x_6 \quad (5)$$

ANOVA analysis

The adequacies of the models are checked by using the Analysis of Variance (ANOVA) technique. The ANOVA tables for Robot deposition efficiency are presented in Table 6. The p-values of models less than 0.4, indicates that the models are significant. In the same manner, the main effect of each linear factor and square effect of arc current is significant. The p-values of 0.559 and 0.420 for substrate surface roughness and torch distance are more than 0.4 which is non significant parameters affecting the robot coating thickness efficiency. These insignificant model terms can be removed and may result in an improved model. By reducing Equation (5), the following Equation (6) are final empirical model for robot coating efficiency. A large F (188.06) value indicates that particular parameter and interaction terms are significant that affect the process output.

$$Robotefficiency(\eta) = -6.46 + 0.0715\,x_1 + 0.171x_2 + 0.091x_3 + 0.319x_6 \tag{6}$$

Table 6: ANOVA for response surface quadratic model (response: Robot coating efficiency)

Predictor	Coeff.	SE Coef.	F	P	
X_1	976.88	488.44	188.06	0.000*	
X_2	52.88	26.44	10.18	0.002*	
X_3	5.57	2.79	1.07	0.369*	
X_4	3.15	1.57	0.61	0.559	Non Significant
X_5	4.79	2.40	0.92	0.420	Non Significant
X_6	193.90	96.95	37.33	0.000*	
R-Sq = 97.14%					
R-Sq(adj) = 94.70					
Residual Error		36.36			
Total	1273.54	*Significant			

Additionally, the developed response surface models for robot deposition coating efficiency have been checked by using residual analysis. The residual plots for the response parameters of deposition efficiency are shown in Figure 4 (a–d). In normal probability plots, the data are spread approximately in a straight line, which indicates that a good correlation between experimental and predicted values. Both responses as shown in Figure 4(a). Figure 4(b) indicates the residual versus predicted values, which shows only a minimal variation between observed and fitted values. The statistics about the residuals are shown in histogram plots in Figure

4(c). Figure 4(d) shows the residuals calculated against the order of experimentation. It is asserted that a tendency to have runs of positive and negative residuals indicate the existence of certain correlation. As a whole analysis of residual plots for both responses, the models do not reveal inadequacy.

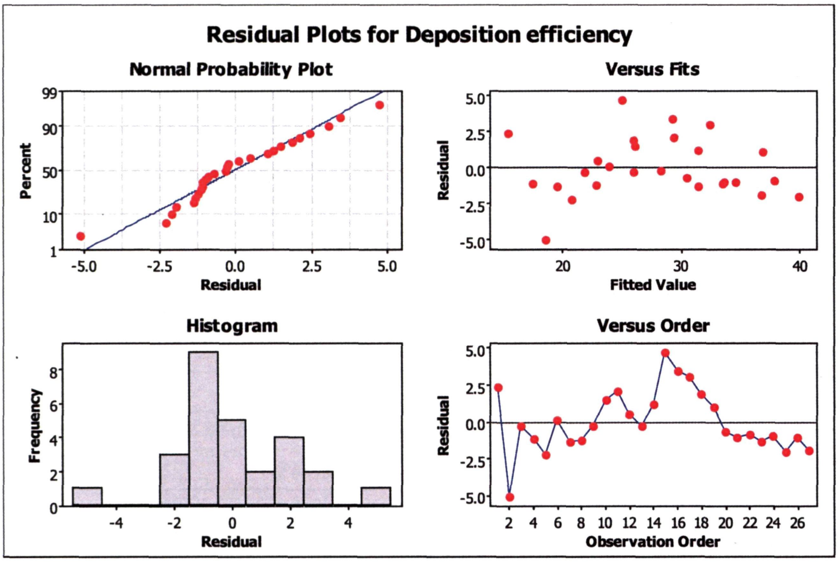

Figure 4: Plot of residuals for response deposition coating efficiency; (a) Normal probability plot of the residuals, (b) Residuals versus the fitted values, (c) Histogram of the residuals, (d) Residuals versus the order of the data

Table 7: Comparison of response surface model with experimental measurements for robot coating efficiency

Exp. No.	Robot Deposition efficiency (%)					
	Experimental Measurements	**Predicted response surface model**	**Error (%)**	**Experimental Measurements**	**Predicted response surface model**	**Error (%)**
1	17.87	15.40	13.7	17.87	17.45	2.35
2	13.54	18.59	17.3	14.54	16.62	12.7
3	21.51	21.78	1.29	21.51	20.1	6.56
4	16.38	17.48	6.72	16.38	16.62	1.47
5	18.43	20.67	12.1	18.43	17.45	5.32
6	23.98	23.86	0.49	23.98	23.62	1.50
7	18.27	19.55	7.03	18.27	19.71	7.88
8	21.56	22.74	5.50	21.56	20.1	6.77
9	25.67	25.93	1.03	25.67	24.23	5.61
10	27.65	26.11	5.56	27.65	28.28	2.28
11	31.43	29.30	6.77	31.43	31.96	1.69
12	23.45	22.92	2.25	23.45	23.62	0.72
13	27.98	28.18	0.73	27.98	28.28	1.07
14	32.66	31.37	3.93	32.66	33.06	1.22
15	29.78	24.99	16.0	29.78	31.17	4.67
16	32.67	29.16	10.7	32.67	33.06	1.19
17	35.45	32.35	8.72	35.45	37.62	6.12
18	27.88	25.97	6.82	27.88	28.28	1.43
19	37.91	36.81	2.88	37.91	37.7	0.55
20	29.77	30.43	2.23	29.77	31.17	4.70
21	32.59	33.62	3.17	32.59	33.06	1.44
22	36.95	37.79	2.29	36.95	37.7	2.03
23	30.08	31.41	4.44	30.08	31.96	6.25
24	33.66	34.60	2.81	33.66	33.06	1.78
25	37.84	39.87	5.36	37.84	37.7	0.37
26	32.44	33.49	3.24	32.44	33.06	1.91
27	34.76	36.68	5.52	34.76	33.06	4.89
	Mean		0.85			1.22

From the Table 7 maximum test errors for robot coating efficiency using response surface model is 17.35%. From the results, error of measurements occurred in robot coating efficient is well controlled using optimum experimental values.

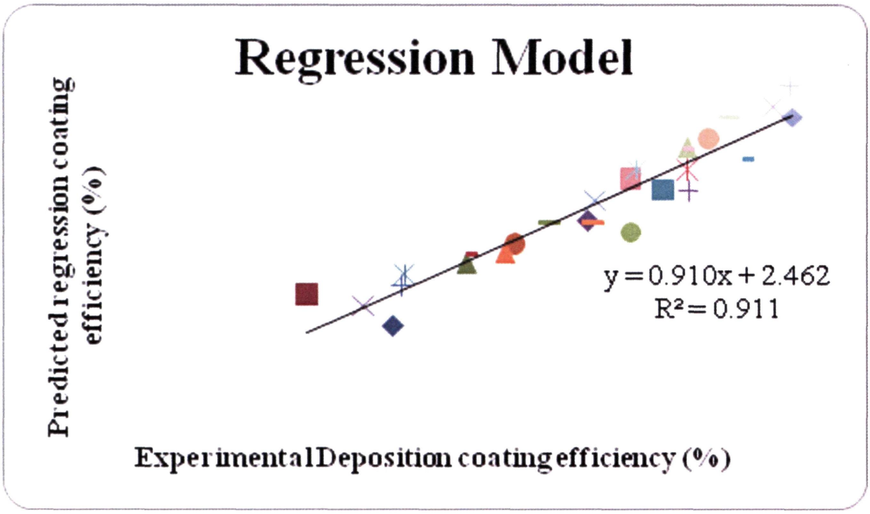

Figure 5: Error analysis of regression model with experimental values

Regression model Figure 5 shows that the error analysis of regression model coating efficiency with experimental values. The R2 value of robot coating efficiency is 0.911. The high R2 indicate that better model fit the data very well using robot coating applications.

Neural networks

For modeling the robot plasma coating efficiency processes the Neural Network (NN) is attempt to predict the deposition efficiency. NNs are well suited for problems whose solutions require knowledge that is difficult to specify but for which there are enough data or observations. A feed forward and back propagation multilayer ANN was used for solving the problem, and the network training and testing were carried out using the MATLAB software package.

Neural networks are basically connectionist systems in which various nodes are interconnected shown in Figure 6. A typical neuron receives more than one input signal. Here arc current, arc voltage, powder feed rate, surface roughness and torch to base distance and TiO2 content in feed stock s are given as an input signals and the robot deposition efficiency is given as an output signal from experimental data. After choosing the network architecture the network is trained. The network performs the adjustment of its parameters so that error between the actual experimental values and desired output is minimized. The feed forward back propagation neural network is most widely used as a neural network is shown in Figure 7. The back propagation algorithm iteratively adjusts the network weights to minimize the squares objective function, the sum of the squared residuals (Difference between the desired and estimated output). The weights Wn are adjusted by a multiple linear regression procedure, so that, sum of the squared residuals is minimal.

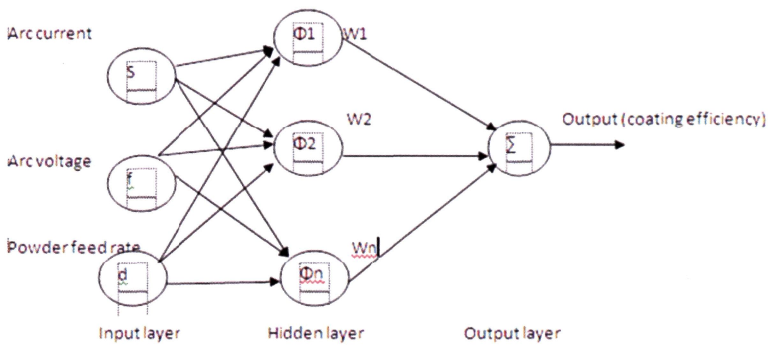

Figure 6: Neural network architecture selected as predicted model for robot coating efficiency

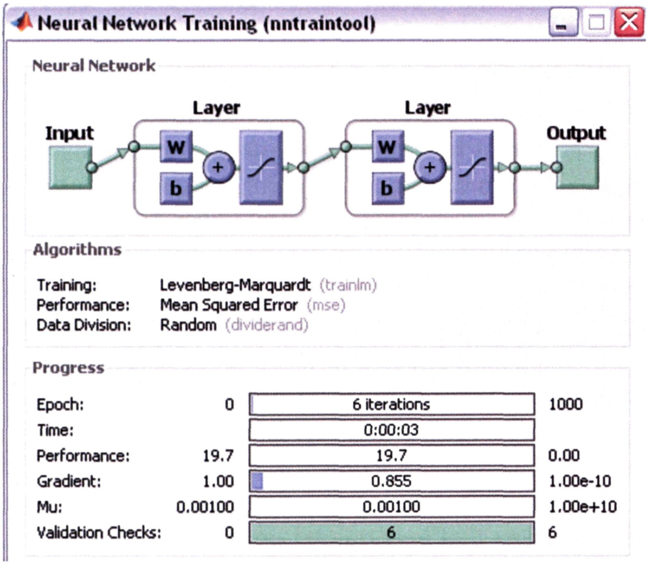

Figure 7: Neural network progress for robot coating efficiency

Levenberg-Marquardt (trainlm) training method has been used as shown in Figure 7 with the mean square error performance function with random data division. The magnitude of the gradient 0.855 and the number of validation checks 6 are used to terminate the training for robot coating. The gradient will become very small as the training reaches a minimum of the performance. Here, the magnitude of the gradient is 1e-10 is less than 2e-10 then the training will stop. The number of validation checks represents the number of successive iterations that the validation performance fails to decrease. If this number reaches default value of 6 then the training will stop. In almost 95% of the training cases, early stopping would occur while not more than 10 or 20 epochs were required in the majority of the training cases.

From the training window can access three plots like performance, training state and regression. The performance plot shows the value of the performance function versus the iteration number.

The training state plot shows the progress of other training variables, such as the gradient magnitude, the number of validation checks, etc. From the Figure 8 with robot coating the gradient values of 0.855 and Mu value of 0.001 and validation checks 6 at epochs of 6. The next step in validating the network is to create a regression plot, which shows in Figure 9, the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice. Use the regression plots to validate network performance as called in Post-Training Analysis. The four axes represent the training, validation, testing data and over all data. The dashed line in each axis represents the perfect result – outputs = targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R=1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. In the regression analysis the training data is fit with output and R values shows that 1.

The high R value near to 1 is indicated that better training model fit well with output data and the validation and testing the R values are 1. The overall performance of training, testing and validation the R value is 0.90634 which means that less trained error with good output values fit very well with model. The scatter plot is helpful in showing that certain data points have poor fits. The next step would be to investigate this data point to determine if it represents extrapolation (i.e., is it outside of the training data set). If so, then it should be included in the training set, and additional data should be collected to be used in the test set. If the network is not sufficiently accurate try initializing the network and the training again. Each time initialize a feed forward network, the network parameters are different and might produce different solutions.

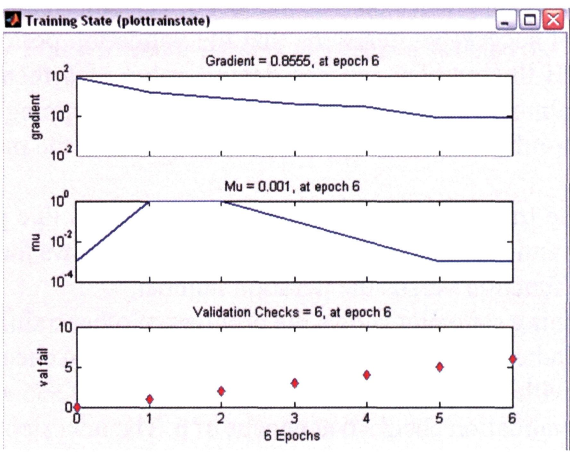

Figure 8: Training state plot for robot coating

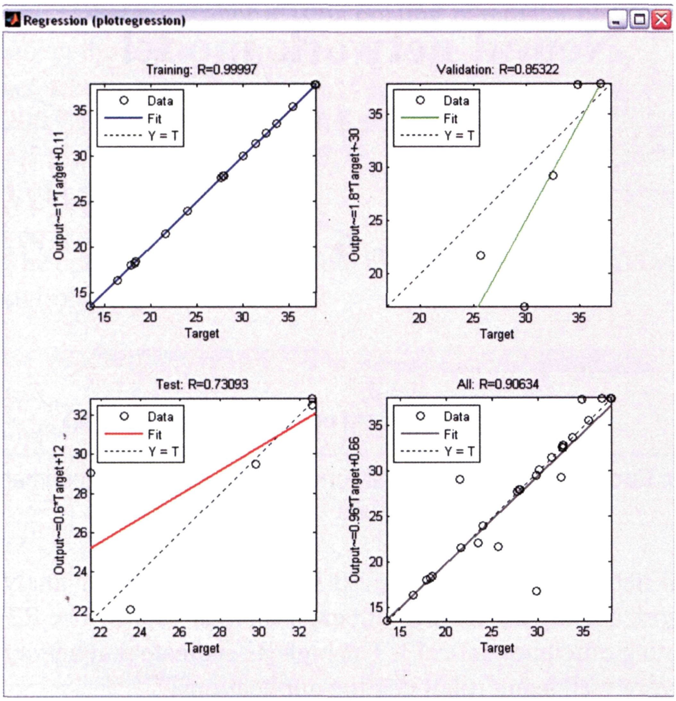

Figure 9: Regression plot between network output and target for robot coating efficiency

The experimental robot coating efficiency values are compared with predicted NN values obtained as a result of the testing process. The NN model providing the best prediction values with respect to the root mean square error (RSME) calculated using the Equation (7).

$$RMSE = \sqrt{\frac{1}{N}\sum_{J=1}^{N}(R_j - tR_j)^2} \tag{7}$$

Where Rj is the actual output and tRj is the Neural network output predicted values and N is the total number of measurements. The calculated error percentage between neural networks based predicted and experimental output values are shown in Table 6, at each robot coating experimental condition are calculated. The range of maximum deviation in predicted error for robot coating efficiency is from 0.37% to 12.7%.

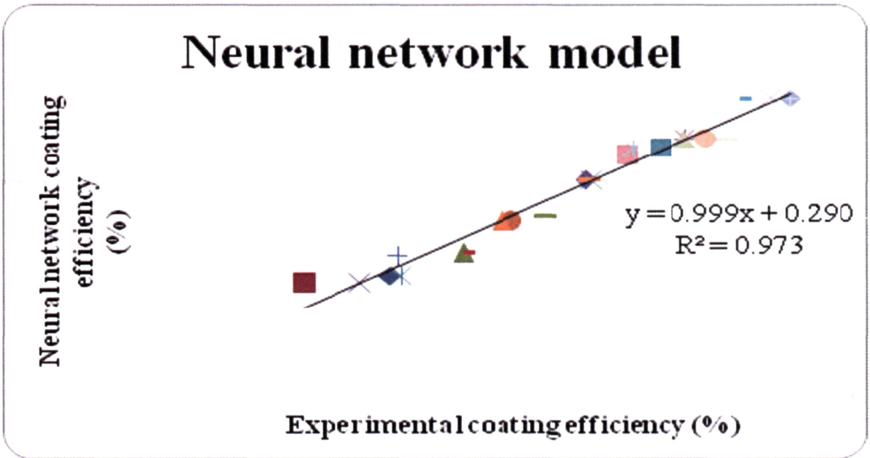

Figure 10: Error analysis of neural network with robot coating experimental values

Neural network model, Figure 10 shows that the error analysis of neural network coating efficiency with experimental values. The R2 value of robot coating efficiency is 0.973. The high R2 indicate that better model fit the data very well using robot coating applications.

Genetic Algorithm analysis of robot coating efficiency

A Genetic Algorithm (GA) operates on a population of potential solutions by applying the principle of the survival of the fittest to produce successively better approximations to a solution. At each generation of the GA, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain, and reproducing them, using operators from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals from which they were created, just as in natural adaptation. So, the objective function is to maximize the robot plasma coating efficiency. The objective function is derived from RSM methods in the following equations:

$$Robot\ efficiency(\eta) = -6.45 + 0.0715\,x_1 + 0.171x_2 + 0.091x_3 + 0.007x_4 - 0.0005x_5 + 0.319x_6 \quad (8)$$

The following Robot plasma coating parameter conditions are used to optimize the objective functions of coating efficiency is:

$200 \leq I \leq 400$; $40 \leq V \leq 60$; $8 \leq Pf \leq 16$;
$4.5 \leq Ra \leq 7.2$; $75 \leq d \leq 125$; $0 \leq fs \leq 20$;
$13.54 \leq \eta \leq 37.4$;

The optimization is carried out in GA Tool box of MATLAB (Version: 7.6) environment.

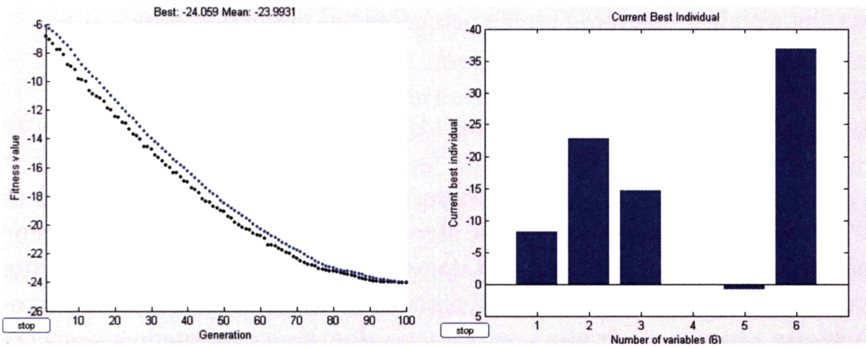

Figure 11: Fitness value of GA output robot coating (left)
Best individual parameter (right)

The GA predicted value of maximum robot coating efficiency and the corresponding control parameter values are shown in Figure 11. It is observed from the figure that the best maximum robot coating efficiency predicted using GA is 24.09% with the corresponding control parameter values of arc current 102 Amp, arc voltage 42 volt, powder feed rate 14.69 mm/sec, substrate surface roughness 8.4 μm, Spray gun distance 87.8 mm and TiO2 content in feedstock 16.98%.The best (optimum) cutting condition leading to the maximum surface coating efficiency and an experiment was carried out at the optimal parametric settings for deposition coating surface so that targeted value of response parameter can be obtained. Table 8 shows the predicted value of deposition coating efficiency obtained from the GA and experimental result with the parametric optimal setting as obtained from GA. Prediction are in good agreement with the experimental results because the percentage error of the predicted value with respect to the experimentally observed value for coating efficiency is not high.

Table 8: Optimized results of genetic algorithm analysis with initial design

	Initial Design	Genetic algorithm optimum design
Parameter Setting levels	A1B3C3D3E3F3	A1B1C3D3E2F3
Robot Deposition coating Efficiency (%)	27.40	24.09

Validation of the simulation results with the experimental results is done in order to confirm the simulation results to the actual working conditions and to know how much is it varying with the actual experimental results which is measured by the percentage of prediction error.

Error % =
((Experimental output - GA output) / Experimental output) * 100 (9)

The optimum robot deposition coating efficiency is obtained as 27.40% and compared with genetic algorithm model is 24.09%. The genetic algorithm model based approach improves the predicted model of better coating parameters accurately and precisely as shown in Table 8. The error between experimental values and genetic algorithm predicted values were calculated based on the Equation (9) for coating efficiency is 12.08%.

Conclusion

To improve the process quality and reliability of plasma spray, an integrated reactive plasma spray system has been developed, which provides users with the high quality of spray forming and coatings. This system can meet the requirement of advanced materials processing, and also has satisfying operation and fine control effects.

1. A control approach is presented to eliminate the influence of suspension injection on the plasma jet. It is helpful for users to achieve the optimal process parameters and develop process control in spraying process. The powerful Levenberg–Marquardt training algorithm dramatically improved the ability to generalize and the required training time respectively. In almost 95% of the training cases, early stopping would occur while not more than 6 or 7 epochs were required in the neural network training for with robot coating process.

2. The adequacies of the regression model were checked by using the Analysis of Variance (ANOVA) technique. The insignificant model terms can be removed and may result in an improved model. Large F values indicate that particular parameter and interaction terms are significant to affect the robot deposition coating efficiency output.
3. The maximum test errors for robot coating efficiency using response surface model is 17.35%. From the results, error of measurements occurred in robot coating efficient is well controlled using optimum experimental values.
4. The predicted coating efficiency of robot using ANN model the maximum error occurs is 12.7%. ANN can produce an accurate relationship between input coating parameters and deposition efficiency. Therefore, ANN can be used for modeling the robot coating so that it can be estimated close to real values of experiments. It was shown that the artificial neural network prediction model obtained is a useful, reliable and quite effective tool for modeling robot spray coating.
5. The predicted optimum cutting condition was validated with an experimental measurement. The maximum percentage of absolute error between the experimental value and GA predicted value is 12.08%. This result validates the prediction accuracy of GA, because the maximum percentage absolute error for the predicted value with respect to the experimentally observed value for coating efficiency is not high. The results of the present study based on RSM and GA models can be used for effective and economical coating using robot.

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