Artificial Neural Networks based prediction and Multi Response Optimization on EDM of Aluminium/Fly ash composites

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Abstract: Aluminium Metal matrix composites reinforced with fly ash particles of three different particle size ranges ((53–75) µm, (75–103) µm and (103–125) µm) were fabricated using stir casting technique. Electrical discharge machining (EDM) was employed to machine the composite materials with copper electrode. The influence of EDM process parameters namely peak current, pulse-on-time, pulse-off-time, particle size and the percentage fly ash on Material Removal Rate (MRR), Tool Wear Rate (TWR) and Surface Roughness(SR) were investigated. Artificial Neural Network (ANN) model was employed to predict the material removal rate, tool wear rate and surface roughness of the composites. The experimental values coincide with the predicted values of the proposed networks. The process parameters are then optimized using desirability based multi response optimization technique to maximize the MRR and minimize both TWR and SR. Increase in peak current and pulse-on time increased the MRR while increase in pulse-off time, percentage fly ash and fly ash particle size decreased the MRR.

Key-Words: - Composites, EDM, ANN, Multi response optimization.

1 Introduction

Metal matrix composites (MMC) are gaining increasing attention in aerospace, defense, and automobile industries that require lightweight and greater wear resistance than the conventional materials [1]. Among all the non-conventional machining methods, electric discharge machining (EDM) is one of the most popular machining methods for machining of any material, which is electrical conductive - irrespective of its hardness, shape and strength. Electrical discharge machining process is based on removing material by means of a series of repeated electrical discharges between tool called the electrode and the work piece in the presence of a dielectric fluid. The material is removed with the erosive effect of the electrical discharges from tool and work piece. Even highly fragile sections and weak materials can be machined by EDM because there is no direct contact between the tool and the work piece. Components such as dies, moulds, parts of aerospace, automotive industry and surgical components can be machined by EDM [2, 3, 4]. The EDM process is independent of the hardness of the work piece, but depends on its electrical and thermal conductivities and its melting point. EDM has become one of the most important methods for machining micron and submicron components [5]. Machining of Metal Matrix Composite (MMC) by traditional methods is difficult due to the highly abrasive nature of ceramic reinforcements. EDM is an effective alternative method for machining MMC with high level of accuracy [6]. Gurgui et al.[7] used conventional EDM process to manufacture products used in medical field such us biological cells, mono fluidics systems for dosing drug, tissue engineering. Deionised water, kerosene and water-in-oil emulsion, water-based dielectrics and gaseous dielectrics such as air and oxygen can be used as alternative to the commonly used hydrocarbon oil based dielectrics. There was a huge difference in the geometrical shape of the craters formed while using different dielectrics

[8,9]. The current, pulse-on time, flushing pressure, gap voltage, pulse-off time, dielectric fliud are the parameters influencing the metal removal rate (MRR), tool wear rate (TWR), radial overcut (ROC), and surface roughness (SR) of Al-MMC composites [10, 11]. Chattopadhyay et al [12] reported that peak current and pulse-on time are the most significant parameters for MRR and TWR, while the peak current and electrode rotation are the most significant parameters for SR. Diver et al. [13] employed EDM process to produce tapered micro-holes in diesel fuel injection nozzles with high level of accuracy. In addition to machining, EDM can also be considered viable alternative for surface treatment [14,15]. The size of the reinforcement particles present in aluminium composites is one the major factors influencing the hardness, tensile strength, impact strength, dry sliding wear and friction of the composites[16,17].

Artificial neural networks (ANNs) is an alternative to the statistical analysis methods, offering the potential to resolve a number of the problems encountered in different applied engineering fields. The main advantage of the neural network approach over conventional method is that the neural network gives a solution without specifying the relationships or the form of relationships between the input and output variables [18]. The neural networks are composed of elements (neurons) operating in between the layers. The nonlinear transfer function between the elements plays a vital role in the quality of prediction. A definite function of the ANN can be trained through adjusting the values of weights [19]. Sathyabalan et al.[20] employed a feed forward, multi layer perception neural network with a single hidden layer to predict the sliding wear loss and hardness of fly ash and SiC reinforced aluminium alloy. Joshi and Pande [21] reported that the radial basis function neural network is fast and easy to configure, but the feed forward back propagation neural network provided more accurate process model. Fadare at al.[22] used a three layered feed-forward, back-propagation artificial neural networks to study the influence of cutting speed, feed rate, depth of cut, coolant pressure, and tool type on the process parameters namely the cutting force, feed force, machined surface roughness, and circularity. ANN was successfully employed to predict the wear rate and coefficient of friction for different composites [23, 24]. Lin et al. [25] established the machining forces-tool wear relationship of an aluminium metal matrix composite using multiple regression analysis and generalised radial basis function neural network. ANN was integrated with genetic algorithms (GAs) by Chang et al.[26] to optimize the material selection for sustainable products.

Multi-objective optimization has been applied in many fields of science, including engineering, economics. Multi objective optimization is concerned with the minimization of a vector of objectives that can be the subject of a number of constraints. Multi-objective optimization involves the simultaneous optimization of two or more conflicting objectives. Debaprasanna Puhan at al. [27] proposed a hybrid optimization technique using fuzzy logic along with Taguchi's design to find the optimal solution for machinability of aluminum silicon carbide composite. Emel Kuram and Babur Ozcelik [28] conducted experiments on micro-milling of Al7075 using Taguchi method and multi objective optimization. Amirhossein Amiri at al. [29] presented a multivariate process capability index and NORTA inverse transformation for multi response optimization problem with mixed continuous-discrete responses. Ibrahim et al [30] developed a genetic algorithm based optimization with the help of neural network system using to represent complex systems.

In summary the parameters influencing the metal removal rate, tool wear rate, radial overcut and surface roughness while electric discharge machining are the current, pulse-on time, flushing pressure, gap voltage and pulse-off-time. Studies reveal that the particle size and the percentage of reinforcement present in the aluminium fly ash composite also influence the performance of the composites. Even though sufficient literature is available on EDM, no study has been reported so far on the influence of reinforcement particle size on EDM. So the main aim of the present study was to study the influence of particle size and the percentage fly ash on EDM. An ANN model was developed to predict the MRR, SR and TWR of aluminium fly ash composites. EDM parameters were than optimized using desirability based multiple response optimization method.

2. Material Preparation

Fly ash particles procured from thermal power plant (Table.1) was sieved into three different particle size ranges of (53–75) µm, (75–103) µm and (103–125) µm [16]. These particles were reinforced into the A380 aluminium alloy (Table.2) by means of stir casting technique. Aluminium ingots melted in a graphite crucible at a controllable temperature of $800^{o}C$ was degassed using solid dry hexachloroethane and the fly ash particulates were preheated for 15 min at 650ºC to remove the moisture content. Fly ash particles (3%, 6% and 9% weight) and 1wt % magnesium are then added to the molten metal and stirred continuously for 8 min at an impeller speed of 600 rpm. The composite melt was then poured into the cylindrical permanent metallic mould of 12 mm diameter and 20 mm length.

Table 1 Chemical composition of fly ash in weight percentage

Constituent	SiO_2	Al_2O_3	Fe_2O_3	CaO	MgO	SO_3	K_2O	TiO_2	Loss on Ignition
Percentage	53.44	22.72	4.48	7.25	3.33	1.34	3.93	1.82	1.58

Table 2 Chemical composition of aluminium (A380) alloy in weight percentage

Constituent	Cu	Si	Mg	Fe	Mn	Zn	Ni	Pb	Sn	Ti	Al
Percentage	3.25	8.35	0.18	0.9	0.15	1.65	0.32	0.12	0.09	0.06	balance

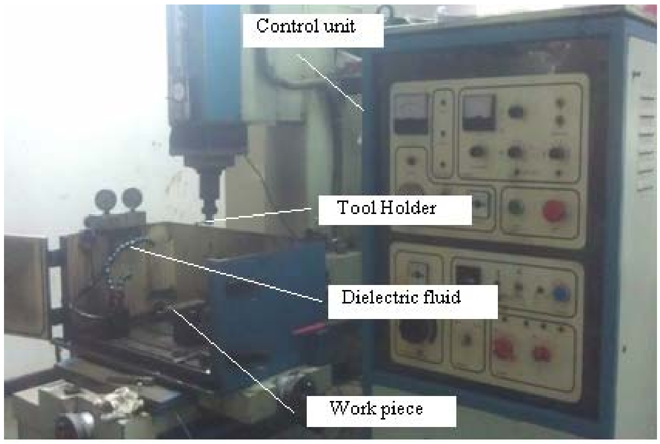
3. Experimental Work

The cast specimens were machined to a uniform diameter of 10 mm and height 15 mm. Electronica sinking electric discharge machine (Fig. 1) was used to drill holes of 5 mm diameter in the work piece. Copper electrode tool of 5 mm in diameter was used and commercial grade kerosene was used as dielectric media at a constant jet flushing pressure. The work piece and the tool were weighed before and after machining by means of an electronic weighing machine having accuracy of 0.001g. An electronic timer was used to record the machining operation time. MRR is defined as the ratio of the difference in mass of work piece before and after machining to the machining time. TWR is defined as the ratio of the difference in mass of tool before and after machining to the machining time. TESA RUGOSURF 10G make surface roughness tester was used to measure the surface roughness (Ra) of the machined work piece. After each experiment, the SR of the machined work piece surface was measured using a stylus type surface roughness tester placed over the surface table [Fig. 1(b)] with a diamond indenter.

MRR and TWR were calculated using Equations [1, 2]:

MRR = (initial mass of work piece - final mass of work piece) / machining time--------[1]

TWR = (initial mass of electrode - final mass of electrode) / machining time --------[2]



(a) Die sinking electric discharge machine

(b) Surface Roughness Tester
Fig.1 Experimental setup

4. Microstructure Studies

A homogeneous distribution of secondary particles in aluminium matrix is critical to achieve high strength. Microstructure was obtained using an inverted optical microscope having a magnification range of 100X- 1000X. An optical microphotograph of aluminium composite containing 6 wt % fly ash composites and (103-125) μm in size range is shown in Fig. 2. The microstructure shows that the fly ash particles are distributed uniformly in aluminium alloy.

5. Design of Neural Network

An artificial neural network (ANN) is a system that is based on biological operations of neural networks. ANN offer the potential to resolve a number of the problems encountered in various engineering fields. ANNs have been proposed as alternatives to the various statistical analysis methods. The basic processing elements of ANN are called artificial neurons are highly interconnected which transforms a set of inputs to a set of desired outputs. Once a network has been structured for a particular application, that network is ready to be trained. At the start of the process the initial weights are chosen randomly. During supervised training, both the inputs and the outputs are provided. The network processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually tweaked. The same set of data is processed many times as the connection weights are ever refined. The response of the neural network is reviewed and the configuration of the system is refined until the neural network's analysis of the training data reaches a satisfactory level [31].

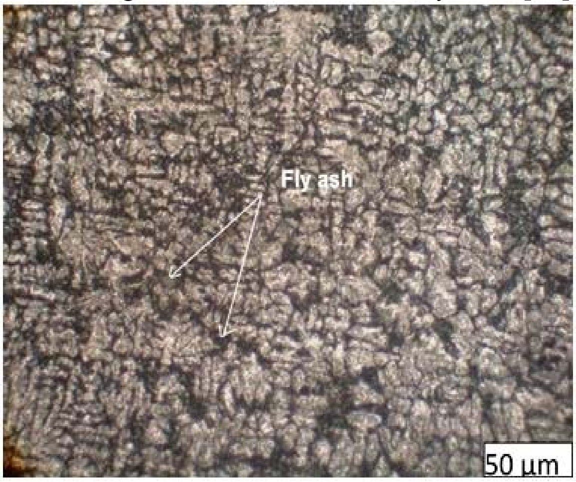


Fig.2 Optical microstructure of composite [6% fly ash and (103-125) µm size]

The basic ANN architecture consists of three types of neuron layers namely the input layer, hidden layer, and output layers. In feed-forward networks, the signal flows from input to output, in a forward direction. The feed forward back propagation neural network (BPNN) is a more accurate process model and is suitable for modeling of complex manufacturing processes such as EDM [21]. The basic steps adopted in the design process of ANN are (a) experimentation and collection of data (b) analysis and pre-processing of data (c) design of the neural network (d) training and testing of the neural networks (e) simulation and prediction with the neural networks and (f) analysis and post-processing of predicted result. The network was trained automatically with the MATLAB® function 'train' with the 'weights' and 'biases' initialized to random values. During training the weights and the biases are adjusted so as to minimize the Mean Square Error (MSE). The training can be terminated when the MSE = 0.001 or when the number of iterations is equal 1000 [22,37]. The performance of the networks is tested with the correlation coefficient between the predicted and the experimental values for training, test and whole dataset.

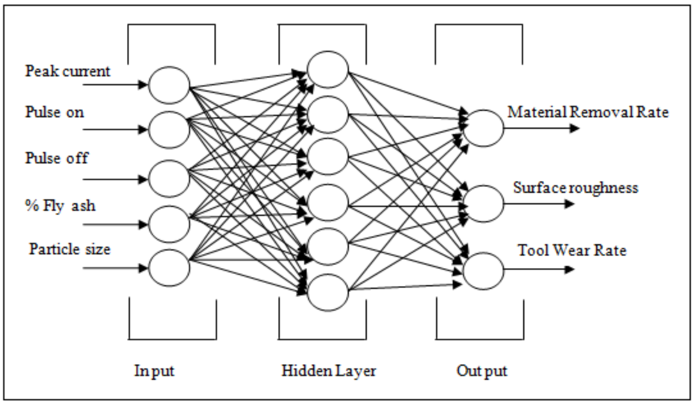


Fig. 3 Network structure (5–6–3) used for prediction

The process parameters considered in this study are the peak current, pulse-on time, pulse-off time, percentage fly ash, and fly ash particle size. The mid value (64 µm, 89 µm, 114 µm) of fly ash particle size ranges was used for training.

Table 3 Machining parameters and their levels

Sl.No	Factors	Units	Variable Levels Used		
1	Peak current (A)	I	5	10	15
2	Pulse-on Time (sec)	T	4	6	8
3	Pulse-off Time (sec)	O	1	2	3
4	Percentage fly ash (wt %)	P	3	6	9
5	Fly ash particle size range (µm)	R	53–75	75–103	103–125

A standard back-propagation feed-forward network was designed using the Neural Network Toolbox of MATLAB (R2008a). Levenberg–Marquard algorithm, substantially faster for many medium networks [19] was used to determine the optimum network generalization. Commonly used linear transfer function was used in the output layer, while the sigmoid transfer function [18] was used in the hidden layer. The neural network consists of three layers namely the input layer; hidden layer and output layer [Fig.3]. 80–90% of the data in each dataset can be used for training; the remaining 10–20% of the dataset can be utilized for testing the ANN prediction quality [18]. Randomly from the available data, 180 sets were used as training, 35 sets for testing and 10 sets were used for validating the network. The number of neurons in the input and output layers are determined generally by the number of input and output variables. In this study there are five input neurons and three output neurons as shown in Fig.3. Since there is no method to arrive at the number of neurons in the hidden layer, six neurons were used in this study [37].

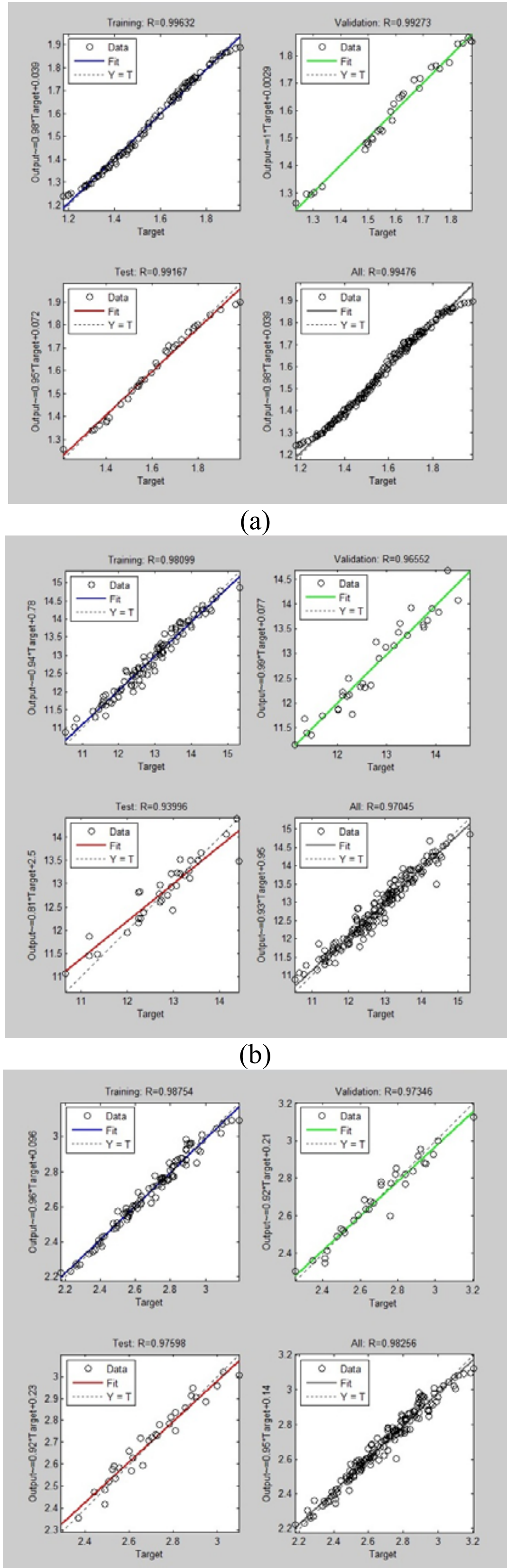
6. Results and Discussion

6.1 Validation of Neural Networks

The objective of the trained network system is to give the output with minimum percentage of error. Regression coefficient (R) value calculates the correlation between the output values and the target values. If the value of R is equal to 1, then there exists a very close relationship exists between them, zero means a random relationship and greater than 0.9 means the quality is better [32]. Fig.4 shows the training, validation; testing and combined set of all having the R value closer to one, which means that the error is less in the selected network structure (5-6-3). The correlation coefficient between the predicted and experimental values using the entire data set for MRR, TWR and SR are 0.9927, 0.9704 and 0.9825 respectively which is a good sign for the model to be accurate. A prediction is said to be perfect when all the plotted points are sitting closer to the central line (the solid line). The accuracy of the model can be easily compared by the closeness of the data clusters to this line. The best linear fit is indicated by a dashed line. It can be inferred from Fig.4 that most of the values fall closer to the central line indicating the model to be accurate. A plot of the training errors, validation errors, and test errors for MRR, TWR and SR is shown in Fig. 4. The results observed was reasonable because of the fact that the final mean square error was small (Fig.5). The test set error and the validations set error had similar characteristics indicating least significant over fitting.

In order to evaluate the accuracy of the model, the percentage error between the predicted MRR, TWR, SR and their corresponding actual values was calculated using Eqn. [3]:

Error% = {(Actual value − Predicted value)/Predicted value} × 100 ------------Eqn. [3]

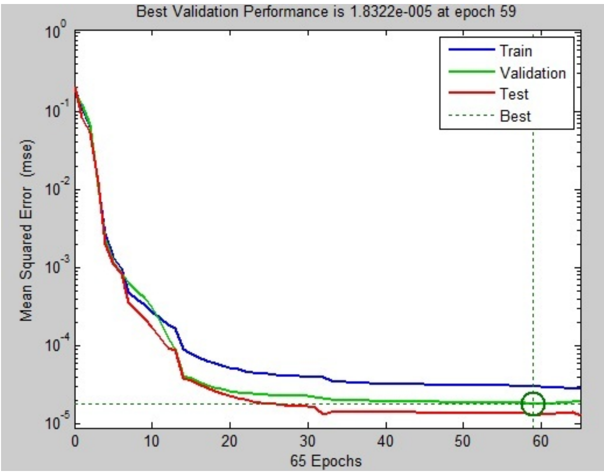


(a)

(b)

(c)

Fig.4 Regression plot for (a) Material Removal rate (b) Tool Wear rate (c) Surface Roughness



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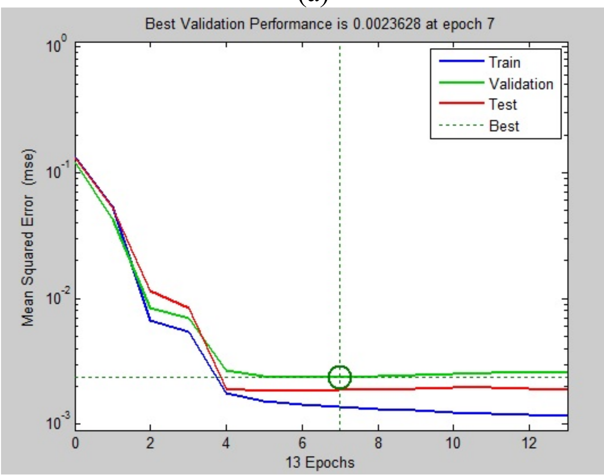

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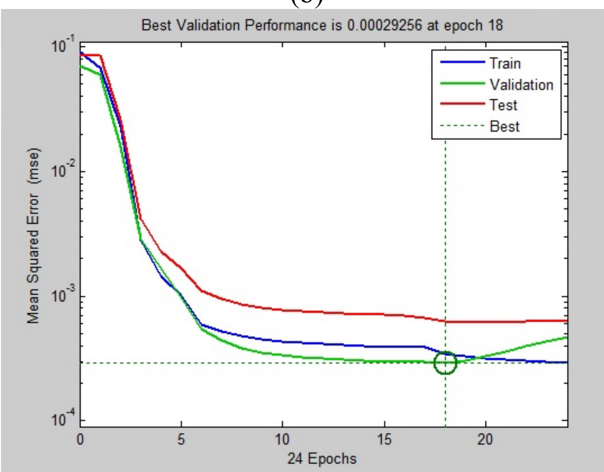


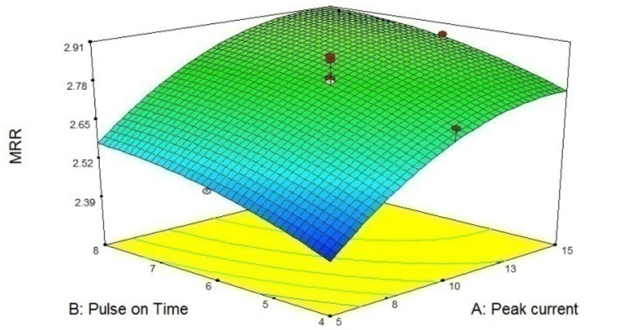
(c)

Fig .5 Mean square error plot for (a) Material Removal rate (b) Tool Wear rate (c) Surface Roughness

The predicted ANNs MRR, TWR and SR were compared with the actual values and a good agreement was observed (Table.3). The maximum deviation of the predicted MRR, TWR and SR were 6.70%, 7.62% and 5.87% respectively (Table.4). Since the predicted values are closer to the experimental values, it can be considered that the ANN model is accurate.

6.2 Influence of parameters on Material Removal Rate

MRR is the weight of the material removed per unit time during EDM process. Increase in peak current and pulse-on time increased the MRR while increase in pulse-off time, percentage fly ash and fly ash particle size decreased the MRR. The MRR is directly proportional to the product of energy transferred per pulse frequency and hence an increase in peak current increases the MRR of the composites as shown in Fig. 6(a). It can be observed from Fig. 6(a) that an increase in pulse-on time increases the MRR. An increase in pulse-on time increases the energy density between the tool and the work piece, thereby increasing the MRR [1]. An increase in pulse-off time a decreases the heat energy and temperature of the work piece and decreases the MRR (Fig. 6(b)). Decrease in MRR with increase in percentage fly ash and size of fly ash particles MRR (Fig. 6(c)) may be due to the increase in resistance for the erosion of the fly ash particles. Composites with fine fly ash particles exhibited higher MRR than those of the composites with coarse fly ash particles.



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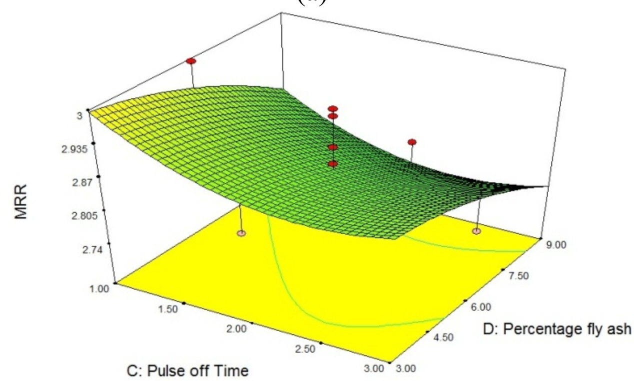

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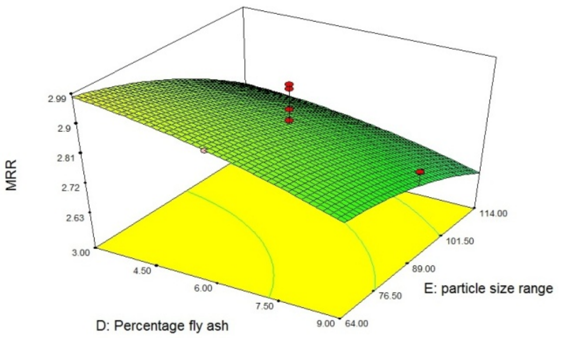
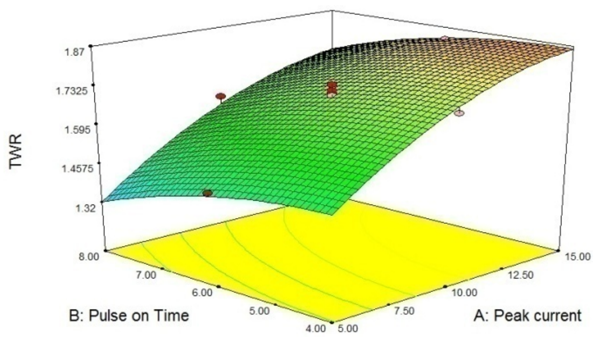


(c)

Fig. 6 Response of parameters on MRR

.3 Influence of parameters on Tool Wear Rate

Fig. 6(a) shows that an increase in peak current increased the TWR. An increase in peak current increases the discharge energy and increases the presence of debris at the gap between the work piece and the electrode causing a high electrode wear. Increase in pulse-on time decreased the TWR (Fig. 7(a)). It can be observed from Fig. 7(a) that an increase in pulse-on time decreased the TWR. This may be due to the fact that longer pulse-on time improves the heat removal around the surface of electrode, thereby decreases the temperature on the surface of the electrode and causes less tool wear [1]. Increase in pulse-off time increased the TWR (Fig. 7(b)). At shorter pulse-off time sparking efficiency increases due to the stability in temperature. On the contrary at longer pulse-off time the fluctuation in temperature and energy increases, thereby increasing the TWR. Fig. 7(c) shows that an increase in fly ash percentage and particle size decreased the TWR of the composites. An increase in fly ash particles increases the presence of fly ash particles in dielectric medium and along the surface of the tool, hence reduces the momentum of striking ions leading to a decrease in the tool wear.



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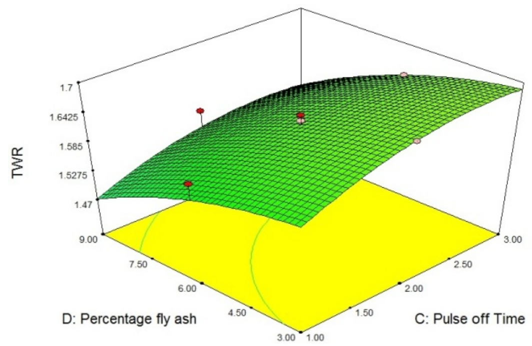

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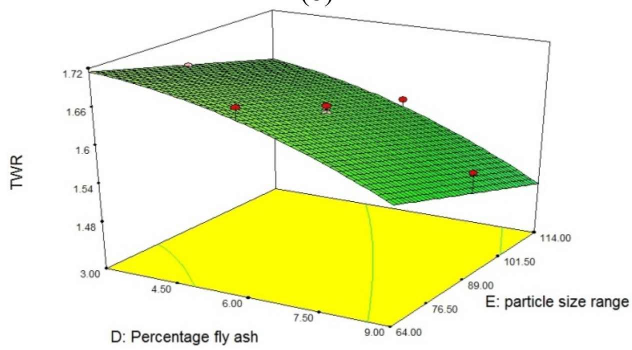


(c)

Fig.7 Response of parameters on TWR

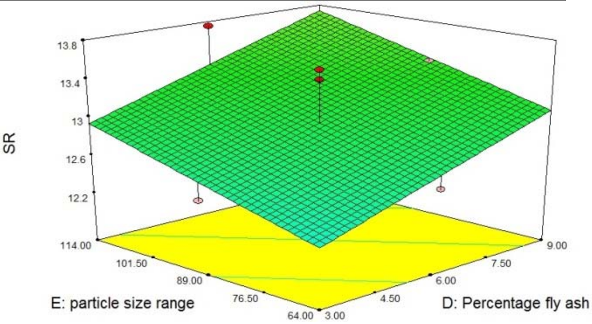
6.4 Influence of parameters on Surface Roughness

It can be observed from Fig. 8 that SR of the machined areas of composites increases with increase in peak current, pulse-on time, percentage fly ash and grain size of the fly ash particles, and decreased with increase in pulse-off time. It is evident from Fig. 8 (a) that the SR of the composites increased with increase in peak current and pulse-on time. Increase in peak current and pulse-on time increases the thermal energy and penetrates deeper into the material and produces deeper crater along the surface of the work piece. This may be reason for increase in the SR of the composites at higher peak current and pulse-on time. Also higher current and pulse-on time results in increased thermal loading on both the tool and work piece resulting in high crater size and hence rougher the surface [6]. In can be observed from Fig. 8(b), that increase in pulse-off time decreased the SR of the composites. An increase in pulse-off time reduces the temperature and provides enough time to remove the debris in the discharge gap leading to uniform erosion of work piece material, decreasing the SR. It can be observed from Fig. 8(c) that an increase in percentage fly ash and particle sizes increased the SR.

Table 4 Comparison of predicted and actual values of EDM parameters

Process parameters						Actual			Predicted			% Error		
Sl. No.	P (% wt)	R (μm)	T (sec)	O (sec)	I (A)	MRR (×10-3) (g/s)	TWR (×10-5) (g/s)	SR (μm)	MRR (×10-3) (g/s)	TWR (×10-5) (g/s)	SR (μm)	MRR (×10-3) (g/s)	TWR (×10-5) (g/s)	SR (μm)
1	3	(53–75)	6	2	5	2.699	1.503	11.520	2.587	1.591	11.537	4.32	5.57	0.15
2	3	(53–75)	8	2	15	3.150	1.813	13.466	2.952	1.877	13.629	6.70	3.41	1.20
3	3	(103–125)	4	2	10	2.581	1.676	11.926	2.635	1.613	12.670	2.06	3.91	5.87
4	6	(75–103)	8	1	15	3.014	1.648	14.439	3.213	1.694	14.136	6.20	2.69	2.14
5	6	(103–125)	6	3	15	2.712	1.749	13.667	2.789	1.893	13.312	2.75	7.62	2.67
6	6	(103–125)	8	3	10	2.620	1.468	13.981	2.491	1.568	13.527	5.19	6.36	3.36
7	9	(53–75)	4	2	15	2.802	1.828	12.702	2.897	1.786	12.917	3.28	2.37	1.66
8	9	(103–125)	6	3	10	2.447	1.476	13.599	2.458	1.453	13.129	0.45	1.58	3.58
9	9	(103–125)	8	3	5	2.355	1.195	13.913	2.389	1.147	13.453	1.44	4.18	3.42
10	9	(103–125)	6	3	5	2.266	1.279	13.055	2.399	1.269	13.874	5.56	0.79	5.90

Increase in fly ash particles and particles sizes influences the non-uniform dispersion of discharge energy, thereby increasing the SR. This is also may be due to leaving of larger size fly ash particles produce larger depression in the matrix. Leaving of larger number of fly ash particles also increase the SR.



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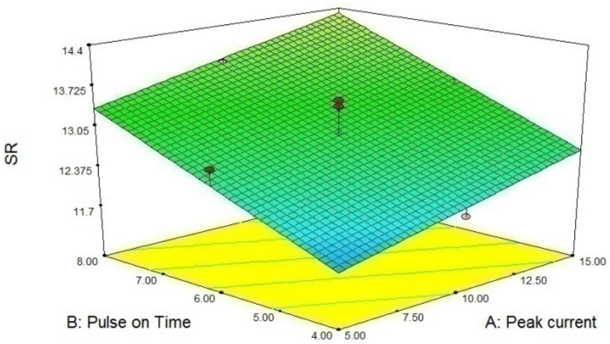

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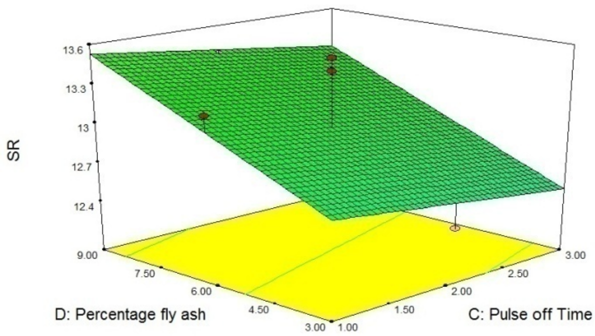

(c)

Fig.8 Response of parameters on SR

7. Multi Objective Optimization

The presence of a number of process variables in EDM operation, it is a challenging task in selecting the optimal machining parameter combination. Lobato et al.[33] studied the treatment of multi-response surface using the desirability function approach and multi-objective optimization associated with the bee colony algorithm, firefly colony algorithm and fish swarm algorithm to optimize the machinability of stainless steel. Derringer and Suich [34] described a multiple response method called desirability for optimizing the multiple quality characteristics problems. The method makes use of an objective function D(X), called the desirability function which transforms an estimated response into a scale-free value (di) called desirability. The desirability value normally ranges from 0 to 1. The weighted geometric mean of the individual desirability for the responses is termed as composite desirability. The factor settings with maximum desirability are considered to be the optimal parameter conditions [35,36].

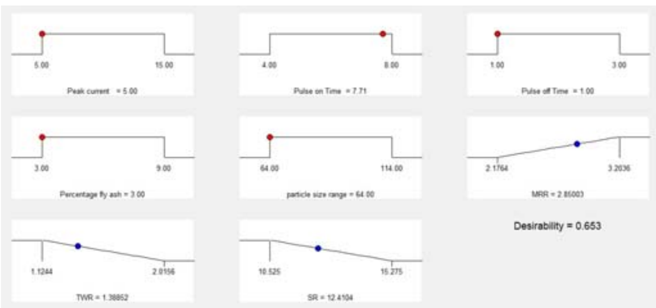

Fig.9 Ramp function graph of Desirability

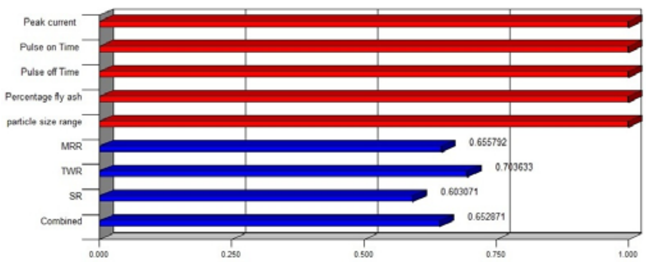

Fig.10. Bar graph of Desirability

The desirability value was evaluated with the help of Design Expert Software. Three responses namely the MRR, TWR, and SR, have been optimized simultaneously using a set of 50 input values derived from Response Surface Method (RSM). The optimality solution is to evaluate the input process parameters in maximizing the MRR and minimizing the TWR and SR respectively. The range and goals and optimum values of input parameters namely peak current, pulse-on time, pulse-off time, percentage fly ash, particle size range and the output characteristics viz. MRR, TWR and SR are given in Table 5. The constraints used for multi objective optimization of process parameters during EDM of composites plays an important role. Equal importance and weights were assigned to all the process parameters and responses [Table.5]. The values of process parameters were allowed to vary from lower limit to higher limit. The set of conditions with highest desirability value is selected as optimum condition for the responses. The optimal set of conditions with higher desirability function is given in Table 5. The ramp function graph and bar graph of desirability are shown in Fig.9 and Fig.10. The dot on each ramp indicates the factor setting or response prediction for that particular characteristic. The height of the dot shows the desirability of the response. The bar graph shows the overall desirability function of the responses. Desirability varies from 0 to 1 depending upon the closeness of the response towards the output. The near optimal region had an overall desirability value of 0.653 which indicates the closeness of the target [36]. The optimum parameter set for the current study is Peak current- 5 Amps, Pulse-on Time-7.71 sec, Pulse-off Time-1sec, Percentage fly ash-3% and Particle size-64 µm for maximizing the MRR, minimizing TWR and the SR.

Table 5 Range of parameters and responses for desirability

Sl.No.	Process parameter	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance	Optimum Values
1	Peak current (A)	In range	5	15	1	1	3	5
2	Pulse-on Time (sec)	In range	4	8	1	1	3	7.71
3	Pulse-off Time (sec)	In range	1	3	1	1	3	1
4	Percentage fly ash (wt %)	In range	3	9	1	1	3	3
5	Particle size range (µm)	In range	64	114	1	1	3	64
6	MRR x 10^{-3} (g/s)	Maximize	2.346	3.203	1	1	3	2.850
7	TWR x10^{-3} (g/s)	Minimize	1.124	2.015	1	1	3	1.388
8	SR (µm)	Minimize	10.52	19.85	1	1	3	12.4104

8. Conclusions

The effect of process parameters namely the peak current, pulse-on-time, pulse-off-time, particle size and the percentage fly ash on the material removal rate, tool wear rate and surface roughness of aluminum–fly ash composites was investigated.

- Artificial Neural Network was employed to predict the material removal rate, tool wear rate and surface roughness of the composites.
- The correlation coefficient (R^2) between the predicted and experimental values for MRR, TWR and SR are 0.9927, 0.9704 and 0.9825 respectively which is a good sign for the model to be within an acceptable limit.
- Increase in peak current and pulse-on time increased the MRR while increase in pulse-off time, percentage fly ash and fly ash particle size decreased the MRR.
- Increase in pulse-on time, fly ash percentage and particle size are decreased the TWR. On the contrary increase in peak current and pulse-off time increased the TWR.
- The SR of machined surface of the composites are increased with increase in peak current, percentage fly ash and grain size of the fly ash particles, and decreased with increase in pulse-off time and pulse-off time.
- The parameters are then optimized using desirability based multi response optimization technique to maximize the MRR and minimize both TWR and SR.
- The optimum parameter set for the current study is Peak current- 5 Amps, Pulse-on Time-7.71 sec, Pulse-off Time-1sec, Percentage fly ash-3% and Particle size-64 µm for maximizing the MRR, minimizing TWR and the SR.

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