



# STUDY OF INFLUENCE OF PROCESS PARAMETERS ON SURFACE ROUGHNESS OF AMMCs IN WIRE ELECTRICAL DISCHARGE MACHINE

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## ABSTRACT

The usage of composite materials has been increasing globally in all manufacturing industries. Non-Traditional machining methods like Wire Electrical Discharge Machining (WEDM) plays important role in precision manufacturing. In this study, an attempt is made to study the influence of process parameters like pulse-on time, pulse-off time and peak current on surface roughness of Aluminum Metal Matrix Composites (AMMCs). The composite material containing aluminum alloy as matrix, 5 wt % silicon carbide as reinforcement is produced by stir casting technique. Experiments are conducted based on design of experiments. The results show that the machined Surface quality improves with increase in pulse-off time, while the pulse-on time produces poor surface quality. Higher peak current leads an inferior surface finish. The pulse duration has also an important and overbearing effect on surface roughness. Finally, Prediction of Surface Roughness (Ra) in terms of the process parameters using Artificial Neural Networks (ANN) is performed and the predicted values were compared with experimental data by varying the number of neurons in the intermediate hidden layers (i.e 5, 6, 7 neurons). Based on the analysis carried out, it was observed that the neural network structure with 3 layers and 7 neurons was best in predicting the surface roughness.

**Keywords:** AMMCs, WEDM, surface roughness, Artificial Neural Networks (ANN).

## 1. INTRODUCTION

In the past few years, research work in materials has shifted towards composite materials to meet the requirements of modern industry like higher strength, low weight, high hardness, low density and less wear. Aluminum Metal Matrix Composites (AMMCs) are appropriate material for any industry, which satisfies these requirements. They are preferred to have high thermal requirements, higher strength, good damping properties and lower density and are used in several applications such as cylinder block liners, vehicle drive shafts, automobile pistons and bicycle frames [1, 2]. In several such kinds of applications, nontraditional machining process, like Electric Discharge Machining(EDM), is being employed for easy machining of aluminum based metal matrix composite [3,4]. In EDM process, machining parameters such as pulse current, pulse duration and gap voltage have influences more on the output responses like Material Removal Rate (MRR), Electrode Wear Rate (EWR) and Surface Roughness (SR) [5]. Obtaining maximum material removal with good surface finish is demand of manufacturing industry. Karthikeyan *et al.* [6] investigated the effect of pulse current and pulse duration on electrode wear rate, MRR and SR and also framed a mathematical model and concluded that the current affects the MRR and EWR proportionally, where as an increase in the pulse duration reduces both MRR and EWR. The surface texture of the machined surface has to be measured in order to improve the quality. Few researchers have worked with the composite materials with an objective to reduce the

surface roughness. Mohan *et al.* [7] investigated the machinability study of the Al-SiC composite particle and electrode material on the surface roughness. The results show that the roughness value decreases with an increase in the current and with less SiC particles in the composite. Suresh Kumar *et al.*[8] carried the experimental investigation to identify the optimal combination of input parameters of electron discharge machining of Al(6351) matrix reinforced with 5wt% silicon carbide(SiC) and 10 wt% boron carbide(B<sub>4</sub>C) particles using grey relation analysis. The major input parameters selected to evaluate the process are electrode wear ratio, surface roughness and power consumption, and the corresponding machining parameters are pulse current, pulse on time, pulse duty factor and voltage. Further, ANOVA analysis was carried out to find the contribution of each parameter.

Ramesh *et al.* [9] carried the experimental investigation of Al6061/SiC<sub>p</sub>/B<sub>4</sub>C<sub>p</sub> hybrid MMCs in wire electrical discharge machine. In this study, an attempt is made to study the effect of wire electric discharge machining parameters like voltage, pulse-on time, pulse-off time and current on material removal rate and surface roughness in hybrid metal matrix composites. The results show that increase in silicon carbide leads to decrease in material removal rate and surface finish and addition of boron carbide results decrease in machining performance. It is found that higher pulse on time results in poor the surface finish. It is also found that higher pulse off time resulted in lower surface roughness. Rajesh *et al.* [10] carried out a comparative study on mechanical properties



of SiC and Graphite reinforced Aluminum MMC's. it was found that increasing the SiC content within the aluminum matrix results in significant increase in the UTS, hardness and Young's modulus, but a decrease in the ductility. The percentage of reinforcing particulates in the MMC is varied from 0% to 5% by weight and it was found that the reinforcing particulates beyond 7% and above lead to rejection from the melt.

Kathiresan and Sornakumar [11] conducted EDM studies on Aluminum Alloy Silicon Carbide Composites developed by Vortex Technique and Pressure Die Casting. They studied the effect of variation of SiC on the machinability characteristics like Surface roughness and MRR of AMMC. The MRR decreases with increase in the percent weight of silicon carbide. The surface finish of the machined work piece improves with percent weight of silicon carbide. The Material Removal Rate (MRR) and Surface roughness of the work piece increases with increase in the current. They did not include in their study the effect of pulse duration, pulse on and pulse off times on machinability characteristics. Surface roughness is an important measure of the technological quality of a product and a factor that greatly influences manufacturing cost. Quality of the surface plays a very important role in manufacturing the components. A good quality surface significantly improves fatigue strength, corrosion resistance, creep life and wear resistance [12-15]. In addition, surface roughness also affects surface friction, light reflection, ability of holding a lubricant, electrical and thermal contact resistance [16]. The setting of machining parameters in wire EDM relies strongly on the experience of operators and machining parameter tables provided by machine tool builders. Dragan rodic *et al.* [17] investigated about the comparison of Fuzzy and Neural Network for Modelling surface Roughness in EDM. The Fuzzy logic and neural network techniques were used to predict the effect of machining variables (discharge current and pulse duration) on the surface roughness of manganese alloyed cold work tool steel in order to improve and increase its range of application.

From the literature survey, it is understood by this author that there is a lot of scope for studying the machinability of AMMCs by non-traditional machining techniques like WEDM. Taking this into consideration, the author has embarked on studying the influence of process parameters like pulse-on time, pulse-off time and peak current on Wire cut EDM of Aluminum metal matrix with 5wt% SiC as reinforcement. This work also includes the prediction of surface roughness with respect to input parameters of WEDM of AMMCs using ANN technique.

## 2. EXPERIMENTAL PROCEDURE

### 2.1 Manufacturing of composites using stir casting technique

In the present work, aluminum alloy and 5% wt SiC were die casted, using LM 24 aluminum alloy as matrix material and silicon carbide particles of average size 50 microns as a reinforcement material. The aluminum was

melted in a graphite crucible at a controlled temperature. The graphite stirrer was introduced into the crucible to perform mixing process when the molten temperature reached 850°C. The stirring was carried out for 45 minutes at the rate of 200 rpm. Silicon carbide particles were preheated to 200°C and introduced into the vortex created in the molten alloy. Here, the crucial thing is to create good wetting between the particulate reinforcement and the liquid aluminum alloy melt. The simplest and most commercially used technique is known as vortex technique or stir-casting technique. The vortex technique involves the introduction of pre-treated SiC particles into the vortex of molten alloy created by the rotating impeller. The molten slurry is poured into the mould and is allowed to cool in air. The AMMC of size 200x70x7mm<sup>3</sup> was prepared for conducting experiments on WEDM as shown in Figure-1.



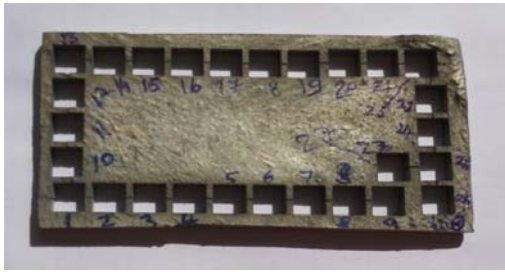
Figure-1. Aluminum with 5% SiC prepared MMC.

### 2.2 WEDM experiments

All the experiments were conducted on ULTRACUT 843 CNC Wire cut EDM. In this machine, all the axes are servo controlled and can be programmed to follow a CNC code which is fed through the control panel. Though an NC code, machining can be programmed. Each an experiment was performed, with a particular set of input parameters were chosen and work piece (Al with 5% SiC Metal Matrix Composite) was cut with a dimension of 10mmx10mm, whose thickness is 7mm. the cutting operation performed on wire EDM is shown in Figure-2 and machined specimen and pieces removed from specimen shown in Figure-3 and Figure-4.



Figure-2. Cutting operation.



**Figure-3.** Aluminum metal matrix after machining 10mm slots.



**Figure-4.** Pieces removed from specimen.



**Figure-5.** Surface roughness tester.

A 0.25 mm diameter uncoated brass wire with vertical configuration was chosen and discarded once used. Surface roughness is calculated using a surface roughness tester as shown in Figure-5. Surface Roughness (Ra) is measured in a direction perpendicular to the cutting direction. An average of three measurements at three different places was recorded as response value. The input parameter values are tabulated in Table-1 and the Table-2 gives the Experiments designed by using Design of Experiments.

**Table-1.** Input parameter levels.

S. No.	Parameters	Symbol	Levels		
			1	2	3
1	Pulse-on time (micro secs)	$T_{on}$	100	105	108
2	Pulse-off time (micro secs)	$T_{off}$	45	50	55
3	Peak current (amp)	$I_p$	10	11	12

**Table-2.** Experiments designed by using design of experiments.

Exp No.	Pulse-on time ( $\mu$ s)	Pulse-off time ( $\mu$ s)	Peak current (amp)
1	100	45	10
2	100	45	11
3	100	45	12
4	100	50	10
5	100	50	11
6	100	50	12
7	100	55	10
8	100	55	11
9	100	55	12
10	105	45	10
11	105	45	11
12	105	45	12
13	105	50	10
14	105	50	11
15	105	50	12
16	105	55	10
17	105	55	11
18	105	55	12
19	108	45	10
20	108	45	11
21	108	45	12
22	108	50	10
23	108	50	11
24	108	50	12
25	108	55	10
26	108	55	11
27	108	55	12

### 3. RESULTS AND DISCUSSIONS

A total of 27 experiments were conducted by varying the input control variables within the feasible ranges. All the 27 experiments are used for predicting of surface roughness (Ra) in machining of aluminum metal matrix composites. The analysis was made using popular software specially used for design of experiment applications known as MINITAB 14. Before any attempt is made to use this simple model for predicting the performance, the possible interactions between the factors must be considered. The factorial design incorporates a simple means of testing for the presence of interaction effects. The same readings are used to validate the efficiency of 3 neural network configurations considered in prediction of surface roughness (Ra). Neural network analysis is carried out using MATLAB.

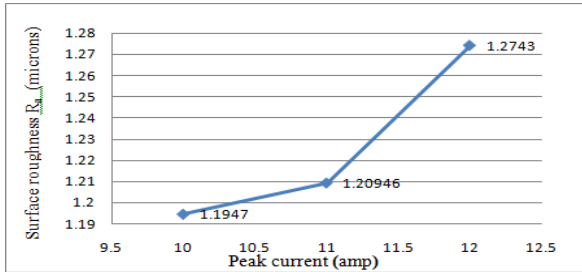
#### 3.1 Effect of peak current on surface roughness

For a given constant pulse duration (pulse-on time + pulse-off time), it is found that the increase in peak current increases surface roughness. This is due to higher peak current results in higher energy pulses which produces a greater depth crater and over cut. It leads to poor surface finish. The Tables-3 and 4 show the results for the pulse duration of 145  $\mu$ s (100 + 45) and 158  $\mu$ s (108 + 50) respectively. The same is also depicted through the plots 6 and 7.



**Table-3.** Experimental values of Ra at different peak currents for a constant pulse duration of 145 μs(100 + 45).

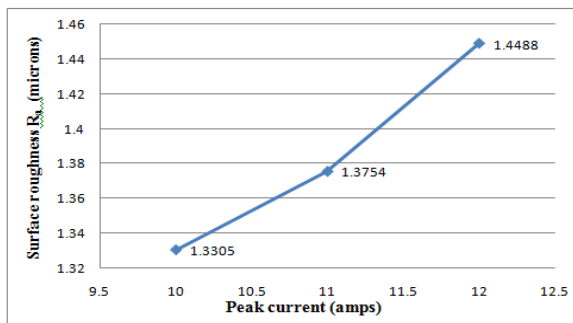
S. No.	Peak current (amp)	Ra(microns)
1	10	1.1947
2	11	1.2094
3	12	1.2743



**Figure-6.** Variation of surface roughness with peak current at constant pulse duration of 145 μs.

**Table-4.** Experimental values of Ra at different peak currents for a constant pulse duration of 158 μs (108 + 50).

S. No	Peak current(amp)	Ra(microns)
1	10	1.3305
2	11	1.3754
3	12	1.4488



**Figure-7.** Variation of surface roughness with peak current at constant pulse duration of 158 μs.

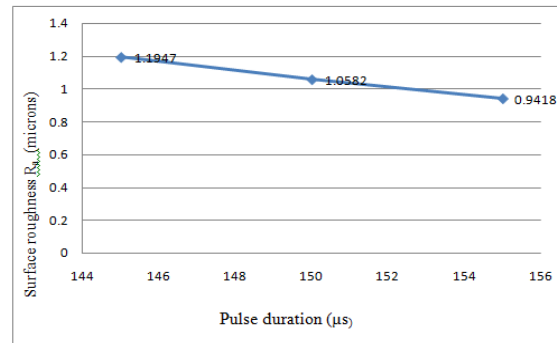
**3.2. Effect of pulse-off time on surface roughness for a constant peak current and pulse-on time**

For a given constant peak current and pulse-on time, it was found that the increase in pulse-off time decreases surface roughness values i.e a better surface finish is obtained. This is due to the fact that the eroded material from the work piece will be flushed away if the pulse-off time is enhanced. It also avoids resolidification of the eroded material on the surface of the work piece. Hence, for a given pulse-on time, increase in pulse-off time will yield good surface finish. This trend can be

understood from the plots.8 and 9.The corresponding values are tabulated in the Table-5 and 6.

**Table-5.** Experimental values of Ra at different pulse-off time (μs) for a constant peak current (10 amp) and pulse-on time (100 μs).

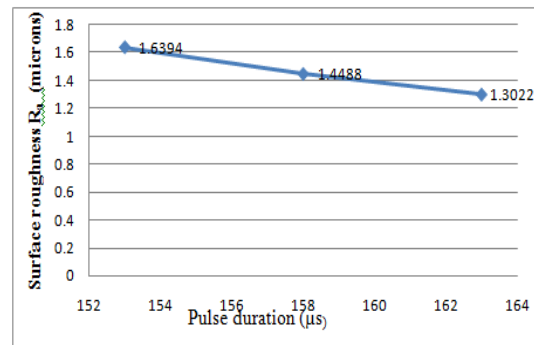
S. No.	Pulse duration (μs)	Pulse off	Ra
1	145	45	1.1947
2	150	50	1.0582
3	155	55	0.9418



**Figure-8.** Variation of surface roughness with pulse duration at constant peak current (10 amp) and pulse-on time (100 μs).

**Table-6.** Experimental values of Ra at different pulse-off time (μs) for a constant peak current (12 amp) and pulse-on time (108 μs).

S. No.	Pulse duration (μs)	Pulse-off time (μs)	Ra (microns)
1	153	45	1.6394
2	158	50	1.4488
3	163	55	1.3022



**Figure-9.** Variation of surface roughness with pulse duration at constant peak current (12 amp) and pulse-on time (108 μs).

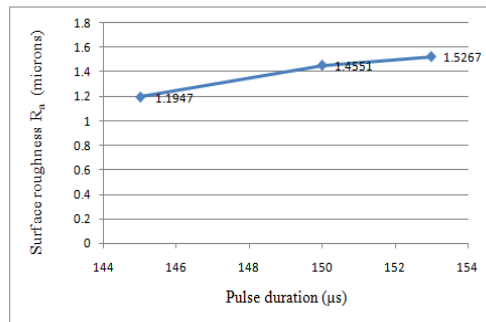


### 3.3 Effect of pulse-on time on surface roughness for a constant peak current and pulse-off time

For a given constant peak current and pulse-off time, it was found that the increase in pulse-on time decreases both surface finish quality. Therefore, the increase in pulse duration by increasing the pulse-on time will deteriorate the surface roughness. This trend can be observed from the results tabulated in the Table-7 and also understood from plot 10.

**Table-7.** Experimental values of  $R_a$  at different pulse-on time ( $\mu\text{s}$ ) for a constant peak current (10 amp) and pulse-off time ( $45 \mu\text{s}$ ).

S. No.	Pulse duration ( $\mu\text{s}$ )	Pulse-on time ( $\mu\text{s}$ )	$R_a$ (microns)
1	145	100	1.1947
2	150	105	1.4551
3	153	108	1.5267



**Figure-10.** Variation of surface roughness with pulse duration at constant peak current (10 amp) and pulse off time ( $45 \mu\text{s}$ ).

### 3.4 Effect of both pulse-on time and pulse-off time on surface roughness for a constant peak current.

The relative dominance of pulse-on time and pulse-off time on surface for a constant peak current of 10 amp is also studied and observations are reported in Table 8.

**Table-8.** Experimental values of  $R_a$  at different pulse-on time ( $\mu\text{s}$ ) and pulse-off time ( $\mu\text{s}$ ) for a constant peak current (10 amp).

S. No.	Pulse-on time ( $\mu\text{s}$ )	Pulse-off time ( $\mu\text{s}$ )	$R_a$ (microns)
1	100	45	1.1947
2	105	50	1.2501
3	105	55	1.0769

The results show that if both pulse-on and pulse-off times are increased by  $5 \mu\text{s}$ , it was observed that there is degradation of surface finish. It means that pulse-on time has higher influence on the parameters when compared to pulse-off time. It can also be observed that if pulse-on time increases by  $5 \mu\text{s}$  and pulse-off time through  $10 \mu\text{s}$ , there is decrease in values of surface roughness from 1.1947 to 1.0769, which means good surface finish is obtained. Hence it can be inferred that the increase in pulse-on time will produce higher pulse energies. The effective utilization of this pulse energy is possible by enhancing the pulse-off time through higher magnitudes than pulse-on time.

### 3.5 Artificial neural network modeling for WEDM

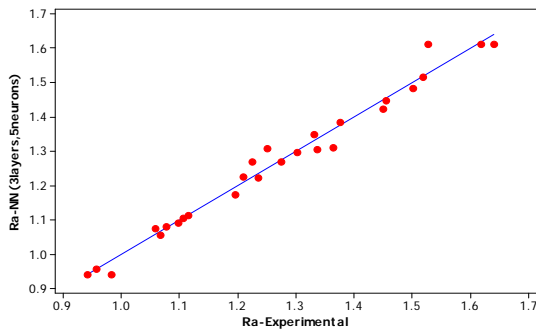
Neural networks are highly flexible modeling tool with the ability to learn the mapping between the input parameters and output parameters. A neural network is logical structure in which multiple processing elements communicate with each other through the interaction between the processors. The knowledge is presented by the interconnection weight, which is adjusted during the learning stage. In this study, MATLAB 7.7.0.471(R2008b) version is used to create, train and test the ANNs. H. Demuth and M. Beale [18] explained the usage of neural network tool box.

#### 3.5.1 Training process and determination of best model

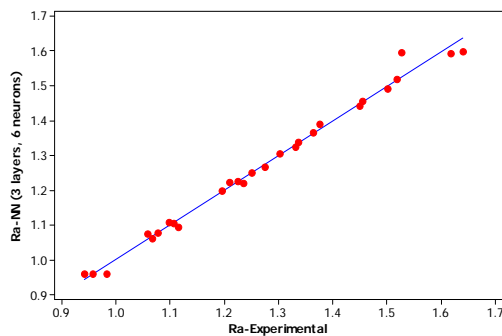
The experimental data is used for training the network. Before applying the neural network for modeling, the architecture of the network has been decided, means the number of hidden layers and number of neurons in each layer. As there are 3 inputs and 1 outputs in the present research work, the number of neurons in the input and output layer has to be set as 3 and 1 respectively.

The general architecture of a 3-layered Multi Layer Perceptron (MLP) consists of input layer, hidden layer and output layer. MLP uses Back Propagation Algorithm (BPA) for training the network in supervised manner and forms the basis for majority of practical applications. The number of hidden layers is to be considered as 5, 6, 7 in each network for predicting the output response. It is found that the average error for 3-5-1 technique is noted as 1.47%, whereas for 3-6-1 technique is noted as 0.93% and finally for 3-7-1 technique, it is noted as 0.93%. It concludes that the average error decreases from 1.47% to 0.93% with increase in hidden layers.

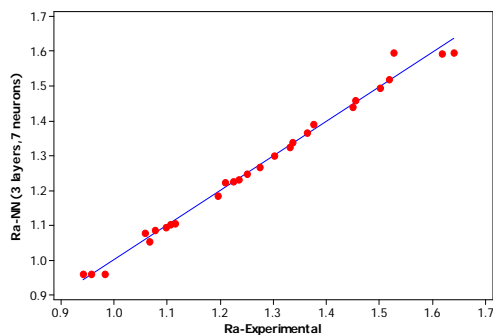
A scatter points plot using the experimental values of  $R_a$  on x-axis and predicted values of 3 different neural networks on y-axis are drawn as shown in Figures 11 to 13 and it is observed that the scattered points are in close agreement with the Regression line which indicates that the neural network developed is efficient for predicting the surface roughness values.



**Figure-11.** Scatter point plot for Ra-Experimental and Ra-NN (3layers, 5neurons).



**Figure-12.** Scatter point plot for Ra-Experimental and Ra-NN (3layers,6 neurons).



**Figure-13.** Scatter point plot for Ra-Experimental and Ra-NN (3layers, 7neurons).

### 3.6 ANN predicted output

The generated ANN model which was trained is now used for the prediction of the surface roughness. In this, the different input parameters were given as input to the ANN model and output parameters for these are predicted and compared with the experimental output as reported in the Table-9. The well trained ANN model i.e 3-7-1 is quite effective for prediction of surface roughness without going for experimentation and thus can save time and money.

**Table-9.** Predicted data table for surface roughness using ANN.

S. No	Pulse on time (μs)	Pulse off time (μs)	Peak current (amps)	Predicted Ra using ANN (microns)	Experimental value $R_a$ (microns)	% error
1	102	47	11	1.1902	1.1816	0.7226
2	102	47	12	1.2027	1.1952	0.6236
3	102	47	13	1.2780	1.2608	1.3459
4	102	52	11	1.0618	1.0479	1.3091
5	102	52	12	1.077	1.0594	1.6342
6	102	52	13	1.1169	1.1047	1.0923
7	102	55	11	0.9430	0.9343	0.9226
8	102	55	12	0.9518	0.9481	0.3887
9	102	55	13	0.9791	0.9739	0.5311

### 4. CONCLUSIONS

- The machining was carried on Wire Electrical Discharge Machine (WEDM) for Aluminum Metal Matrix composite with 27 combinations of the basic process parameters like Pulse-on time, Pulse-off time and Peak current. The Surface roughness is taken as output parameter and influence of pulse-on, pulse-off times and peak current on the Surface roughness is studied. The following conclusions are drawn from this analysis.
- Higher peak current results in higher energy pulses which produces a greater depth crater and over cut. It leads to poor surface finish.
- The increment in pulse off time is found to be producing favorable results, means it produces superior surface quality. This phenomenon can be explained by the fact that the eroded material from the workpiece will be flushed away if the pulse-off time is enhanced. It also avoids resolidification of the eroded material on the surface of the workpiece.
- The increase in pulse-on time decreases surface finish quality. Higher pulse-on time with fixed pulse duration results in higher energy discharge there by producing craters on the surface which leads to poor surface quality.
- The pulse duration has an important and overbearing effect on output parameters. It is observed through this work that increase in pulse duration by increasing pulse off time will produce superior results while the increase in pulse on time will produce unfavorable results.

Neural networks technique was also successfully applied for the prediction of surface roughness in WEDM process. The results obtained were in conformance with



experimental values and the following conclusions can be drawn from the study.

- Based on the results obtained for three ANN techniques, the best one was found to be 3 layer 7 neurons i.e (3-7-1).
- The well trained ANN model i.e 3-7-1 is quite effective for prediction of surface roughness for other process parameters without going for experimentation and thus can save time and money.

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