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Investigation on Application of Fuzzy logic Concept for Evaluation of Electric Discharge Machining Characteristics While Machining Aluminium Silicon Carbide Composite

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***Abstract*—In this work, Electrical discharge machining of Aluminium silicon carbide composite with a copper electrode and optimization of machining parameters using Fuzzy logic methodology is reported. The experiments are carried based on the L27 orthogonal array design of experiments. The parameters considered are pulse current, pulse ON time and pulse OFF time and the response variables are Material removal rate (MRR) and Surface roughness (SR) Fuzzy logic methodology is used to optimize and predict the optimal choice of each EDM parameters with considerations of multiple responses effectively. MATLAB 7.1 and MiniTab15 softwares are used in this work.**

***Index Terms*—EDM, Fuzzy Rule base, Multi-performance characteristic index (MPCI).**

I. INTRODUCTION

Electrical discharge machining (EDM) is a manufacturing method, which could be used to machine hard materials in complex shapes with high precision. EDM has been widely used in space industries and injection mould manufacturing throughout the world. The research in EDM processing has been focused on fast machining with better surface roughness. It has been classified in four groups mainly work piece related, electrode, effective EDM methods, and optimization of EDM parameters. Velmurugan et.al [1] reported that aluminium matrix composites refer to the class of light weight high performance aluminium centric material systems. Properties of aluminium matrix composites can be tailored to the demands of different industrial applications by suitable combinations of matrix, reinforcement and processing route. Thillaivanan et. Al [2] noted that a suitable selection of machining parameters for the electrical discharge machining process relies heavily on the operators' experience. Machining parameters tables provided by the machine tool builder cannot meet the operators' requirements, since for an arbitrary desired machining time for a particular job; they do not provide the optimal machining conditions. *Lin et.al., Puri et al. [3][5]* used grey relational analysis technique based on an orthogonal array and fuzzy-based Taguchi method for optimising the multi-response process without using S/N ratio to carry out experiments for solving the multiple responses in the electrical discharge machining process. Singh [4] determined the optimal combination of process parameters using grey relational grade (GRG) obtained through grey relational analysis (GRA) for multiple performance characteristics in electro-discharge machining of the standard aluminium alloy such as Al6061 and Al_2O_3 reinforced AMMC. Based on the literatures it was identified that there exists a potential in making use of fuzzy logic concept for evaluation of EDM machining characteristics.

II. EXPERIMENTAL SETUP

Aluminum Silicon carbide composite (Al6061 reinforced with 20%SiC) was the target material used in this investigation. Experiments were performed using Mitsubishi EA-8 Electrical discharge machine. *Figure.1*depicts schematically the experimental set-up.

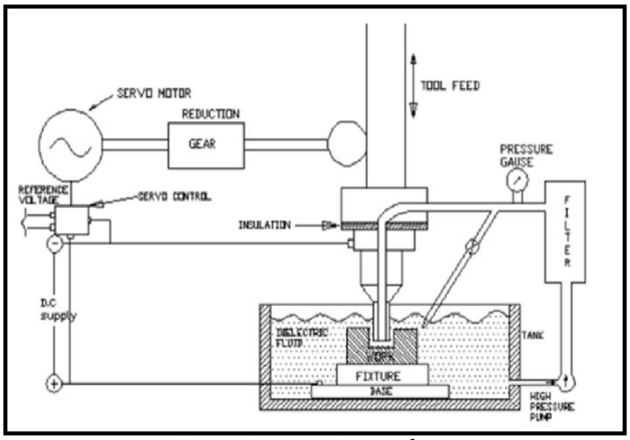

Figure 1: Experimental set up

A cylinder of pure electrolytic copper with diameter of 12mm was used as an electrode to erode a work piece of composite material. Commercial EDM oil (density =0.85, flash point=170º C) was used as a dielectric fluid and the side injection of dielectric fluid was adopted. A jet flushing system was employed to assure adequate flushing of the debris from the gap zone. The process parameters were being

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set in the EDM machine and the experiments were conducted as per the design matrix shown in Table 2. After each experiment the weights of specimen were measured with an electronic weighing machine.

III. EXPERIMENTAL PROCEDURE

The experimental procedure is shown in *Figure.2* and the important steps are briefly explained in the following sections.

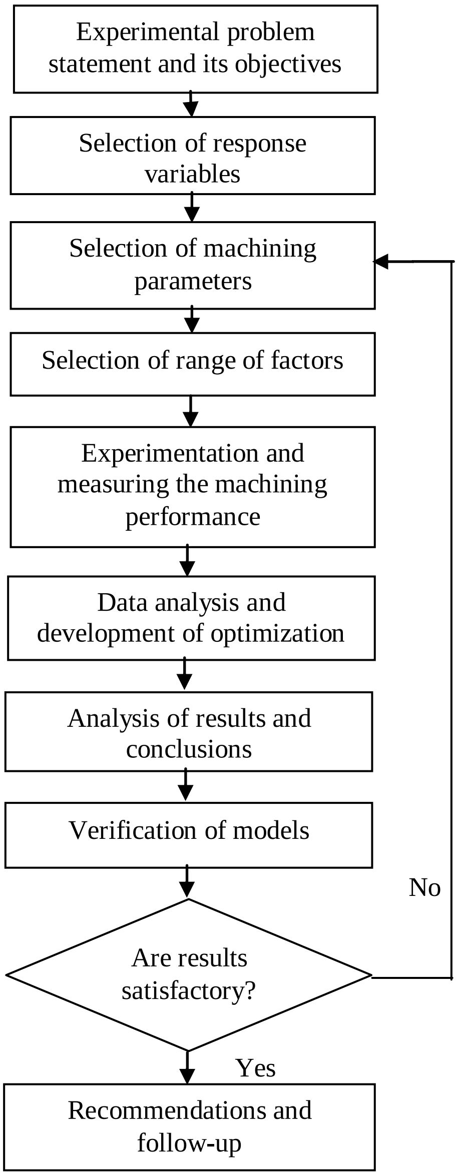

Figure 2: Experimental procedure

A. *Machining Parameters And Response Variables:*

Three controllable machining parameters were identified namely, pulse current, pulse on time and pulse off time. On the basis of preliminary experiments conducted using one variable at a time approach, the range of pulse current, pulse on time, pulse off time were selected as 10 to 25 A, pulse on time 4 to 128µs, pulse off time as 16 to 384µs. When the pulse current values are less than 10A, it was observed that metal removal rate (MRR) was not significant and for pulse current greater than 25A, the surface finish of work piece was poor necessitating the selection of the intermediate values. The range used of pulse on time and pulse off time was available in the machine specification handbook. The response variables selected for this work are metal removal rate (MRR) and surface roughness (SR).

Table 1: Machining parameters and their levels

Symbol	Experimental parameters	units	Level 1	Level 2	Level 3
A	Pulse current	A	10	15	25
B	Pulse on time	µs	4	24	128
C	Pulse off time	µs	16	96	384

B. *Machining performance evaluation:*

The Material removal rate as shown in equation 1 is defined as the work piece removal weight (WRW) over a period of machining time (T) in minutes,

$$\text{MRR} = \frac{(W_{jb} - W_{ja})}{T} \quad \text{g/min}$$

Where W_{jb} and W_{ja} are the weights of the work piece before and after machining and T is the machining time. Surface roughness is a measure of the texture of a surface. It is quantified by the vertical deviations of a real surface from its ideal form. If these deviations are large, the surface is rough; if they are small the surface is smooth. Surface roughness of the machined work piece is evaluated using a surface roughness tester. Various points are tested and average is obtained as the center line average of surface roughness (Ra in micron). *Figure 3* shows the surface roughness tester used in this work

Figure 3 Surface roughness tester

C. *Design of Experiments:*

Classical process parameter design is complex and not easy to use. A large number of experiments have to be carried out when the number of process parameters increases. To solve the problem and to analyse all possible combinations the full factorial experiment design is used in this study. Design matrix is shown in Table 2

Table 2 Design matrix and machining performances

S. No	Pulse current	Pulse ON time	Pulse OFF current	Material Removal rate (g/min)		Surface Roughness (μm)	
	(A)	(μs)	(μs)	Trial 1	Trial 2	Trial 1	Trial 2
1	10	4	16	0.07	0.08	3.14	4.03
4	10	4	96	0.06	0.07	3.15	4.91
3	10	4	384	0.05	0.06	3.21	4.34
4	10	24	16	0.06	0.08	5.42	6.98
5	10	24	96	0.13	0.12	4.50	6.60
6	10	24	384	0.07	0.06	4.48	5.55
7	10	128	16	0.39	0.42	7.82	7.36
8	10	128	96	0.28	0.28	7.09	10.55
9	10	128	384	0.09	0.09	8.34	8.57
10	15	4	16	0.24	0.24	3.51	2.58
11	15	4	96	0.07	0.08	3.08	4.83
14	15	4	384	0.05	0.05	3.79	4.96
13	15	24	16	0.63	0.62	4.81	6.90
14	15	24	96	0.31	0.29	6.38	6.79
15	15	24	384	0.06	0.05	7.06	6.11
16	15	128	16	0.94	0.96	10.97	7.57
17	15	128	96	1.00	0.99	8.72	11.60
18	15	128	384	0.26	0.26	14.17	14.16
19	25	4	16	2.31	2.42	5.66	7.05
20	25	4	96	1.95	1.97	6.04	7.12
21	25	4	384	0.52	0.50	9.71	8.71
22	25	24	16	1.71	1.70	9.29	10.16
23	25	24	96	0.62	0.62	7.79	4.82
24	25	24	384	0.09	0.08	7.44	6.92
25	25	128	16	2.89	2.91	13.87	14.51
26	25	128	96	1.60	1.61	16.08	12.81
27	25	128	384	0.73	0.71	15.45	15.11

D. Fuzzy based Taguchi Methodology:

A loss function is then defined to calculate the deviation between the experimental value and the desired value. Taguchi recommends the use of the loss function to measure the process response deviating from the desired value. The value of the loss function is further transformed into a signal-to-noise (S/N) ratio. Usually, there are three categories of the process response in the analysis of the S/N ratio, that is, the lower-the-better, the higher-the-better, and the nominal-the-better. The S/N ratio for each level of process parameters is computed based on the S/N analysis. Regardless of the category of the process response, a larger S/N ratio corresponds to a better process response. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio. This is true for the optimisation of a single process response. However, optimisation of multiple responses cannot be as straightforward as the optimisation of a single process response. A higher S/N ratio for one process response may correspond to a lower S/N ratio for another process response. As a result, an overall evaluation of the S/N ratios is required for the optimisation of a multi-response process. To solve this problem, fuzzy logic analysis is introduced into the Taguchi method for the optimisation of the multi-response process. Several fuzzy rules are derived in the fuzzy logic analysis based on the performance requirement of the process response. The loss function corresponding to each process response is fuzzified and then a single fuzzy reasoning grade is obtained by using the max–min fuzzy inference and centre of gravity defuzzification methods. Hence, optimisation of complicated multiple process responses can also be converted into optimisation of a single fuzzy reasoning grade.To obtain optimal machining performance, the minimum SR and the maximum MRR are desired. Therefore, the lower-the-better SR and the higher-the better MRR should be selected.The loss function L_{ij} of the lower-the-better performance (Surface roughness) characteristic can be expressed as

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} y_{ijk}^2$$

The loss function L_{ij} of the higher-the-better performance (Material removal rate) characteristic can be expressed as

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} \frac{1}{y_{ijk}^2}$$

The loss function is further transformed into an S/N ratio.

$$\eta_{ij} = -10 log_{10}(L_{ij})$$

a) Fuzzy Logic Unit:

A fuzzy logic unit comprises a fuzzifier, membership functions, a fuzzy rule base, an inference engine, and a defuzzifier. First, the fuzzifier uses membership functions to fuzzify the S/N ratios. Next, the inference engine performs a fuzzy reasoning on fuzzy rules to generate a fuzzy value. Finally, the defuzzifier converts the fuzzy value into a MPCI.

b) Rule Base:

In the following, the concept of fuzzy reasoning is described briefly based on the two input one-output fuzzy logic unit. The fuzzy rule consists of a group of if-then control rules with the two inputs, x1 and x2, and one output *y*, i.e.

Rule 1: if x1 is A1 and x2 is B1 then *y* is C1 else
Rule 2: if x1 is A2 and x2 is B2 then *y* is C2 else………
Rule n: if x1 is A_n and x2 is B_n then *y* is C_n.

Table 3 Fuzzy logic rule base in matrix form

Fuzzy Rule		S/N Ratio of MRR				
		VS	S	M	L	VL
S/N Ratio of SR	VS	T	VS	S	SM	M
	S	VS	S	SM	M	ML
	M	S	SM	M	ML	L
	L	SM	M	ML	L	VL
	VL	M	ML	L	VL	H

25 fuzzy rules are derived directly based on the fact that larger is the S/N ratio, the better is the performance characteristic. By taking the max-min compositional operation, the fuzzy reasoning of these rules yields a fuzzy output. Supposing that *x1* and *x2* are the two input values of the fuzzy logic unit, the membership function of the output of fuzzy reasoning can be expressed as

$$\mu_{co}(y) = (\mu_{A1}(X1)\wedge\mu_{B1}(X2)\wedge\mu_{C1}(y))\vee \dots (\mu_{An}(x1)\wedge\mu_{Bn}(x2)\wedge\mu_{Cn}(y))$$

Where ^ is the minimum operation and v is the maximum operation. Finally, a defuzzification method, called the centre-of-gravity method, is adapted here to transform the fuzzy inference output $\mu C0$ into a non-fuzzy value y_0, i.e.

$$y_o = \frac{\sum y\mu_{co}(y)}{\sum \mu_{co}(y)}$$

In this paper, the non-fuzzy value y_0 is called a fuzzy reasoning grade. Based on the above discussion, the larger the fuzzy reasoning grade, the better is the multiple process responses. *Table 4* shows the experimental results and their respective S/N ratios

Table 4 Experimental results and their S/N ratios

S. No	Material Removal rate (g/min)		Surface Roughness (µm)		S/N Ratio MRR	S/N Ratio SR
	Trial 1	Trial 2	Trial 1	Trial 2		
1	0.07	0.08	3.14	4.03	-22.50	-11.09
2	0.06	0.07	3.15	4.91	-23.68	-12.11
3	0.05	0.06	3.21	4.34	-25.51	-11.54
4	0.06	0.08	5.42	6.98	-22.91	-15.85
5	0.13	0.12	4.50	6.60	-18.17	-14.89
6	0.07	0.06	4.48	5.55	-23.54	-14.01
7	0.39	0.42	7.82	7.36	-7.90	-17.60
8	0.28	0.28	7.09	10.55	-11.09	-18.91
9	0.09	0.09	8.34	8.57	-20.92	-18.54
10	0.24	0.24	3.51	2.58	-12.41	-9.67
11	0.07	0.08	3.08	4.83	-22.85	-11.94
12	0.05	0.05	3.79	4.96	-26.02	-12.82
13	0.63	0.62	4.81	6.90	-4.10	-15.35
14	0.31	0.29	6.38	6.79	-10.43	-16.37
15	0.06	0.05	7.06	6.11	-25.19	-16.37
16	0.94	0.96	10.97	7.57	-0.46	-19.34
17	1.00	0.99	8.72	11.60	-0.07	-20.14
18	0.26	0.26	14.17	14.16	-11.75	-23.02
19	2.31	2.42	5.66	7.05	7.48	-16.06
20	1.95	1.97	6.04	7.12	5.85	-16.36
21	0.52	0.50	9.71	8.71	-5.81	-19.29
22	1.71	1.70	9.29	10.16	4.62	-19.76
23	0.62	0.62	7.79	4.82	-4.19	-15.99
24	0.09	0.08	7.44	6.92	-21.31	-17.12
25	2.89	2.91	13.87	14.51	9.34	-23.04
26	1.60	1.61	16.08	12.81	4.11	-23.19
27	0.73	0.71	15.45	15.11	-2.87	-23.68

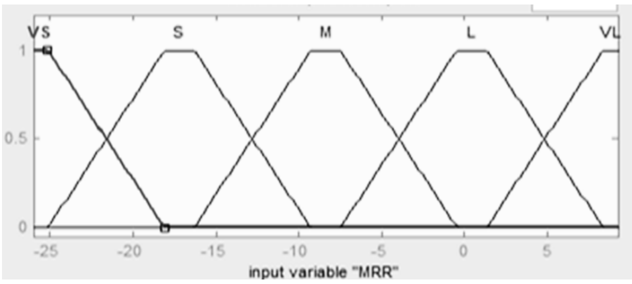

Figure 5 Membership functions for material removal rate

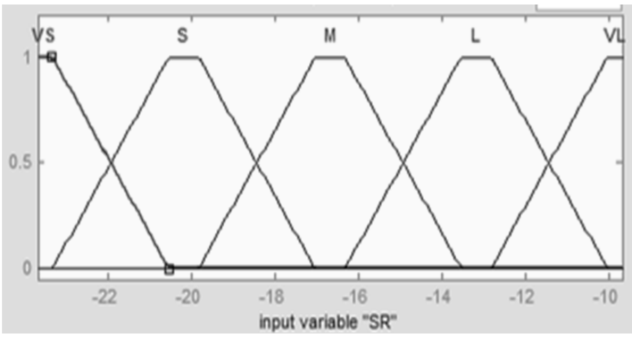

Figure 6 Membership functions for surface roughness

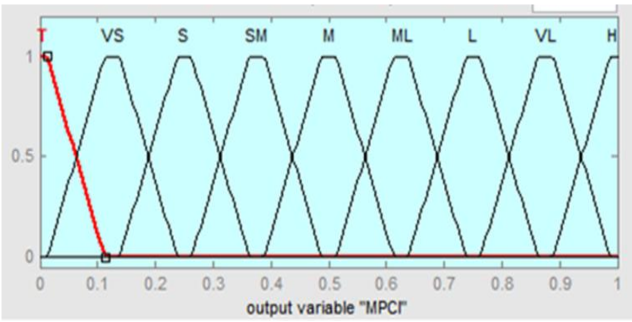

Figure 7 Membership functions for Multi-response output

c) Results of MPCI:

The results of MPCI are shown in Table 5. Based on the above discussions, the optimal machining parameters are the

Pulse current at level 3, pulse on time at level 1, and pulse off time at level 1.

Table 5 Fuzzy reasoning grade

No	MPCI
1	0.499
2	0.499
3	0.433
4	0.324
5	0.436
6	0.381
7	0.470
8	0.382
9	0.255
10	0.693
11	0.469
12	0.375
13	0.610
14	0.478
15	0.250
16	0.526
17	0.500
18	0.222
19	***0.746***
20	0.703
21	0.446
22	0.564
23	0.580
24	0.311
25	0.516
26	0.437
27	0.329

E. Analysis of experimental results:

In this work, Matlab7.6 version was successfully utilised to perform fuzzy logic analysis and analysis of variance (ANOVA) using Minitab 15.The larger the fuzzy reasoning grade, the better is the multiple process response. Based on the fuzzy reasoning grade in Table 5, the optimal machining performance for MRR, SR was obtained for pulse current (level 3), pulse on time (level 1) and pulse off time (level 1) combination. Accordingly, A3B1C1 is the optimal level of EDM parameters in the case of multiple performance characteristics because higher fuzzy reasoning grade values yield better quality. *Figure 8* shows main effect plot based on fuzzy reasoning grade, basically the larger the fuzzy reasoning grade, the better the multiple-performance characteristics. Greater values depict the high MRR and low surface roughness. However relative importance among the process parameters for the multiple performance characteristics still needs to be known, to determine the optimal combinations of the parametric levels. Thus ANOVA is also performed.

A. Analysis of variance:

The purpose of the ANOVA is to investigate which process parameters significantly affect the performance characteristics. This is accomplished by separating the total variability of the multi-performance characteristics indexes, which is measured by the sum of the squared deviations from the total mean of the MPCI, into contributions by each of the process parameter and the error. First, the total sum of the squared deviations SST from the total mean of the MPCI $\eta_m$can be calculated as

$$SS_T = \sum_{J=1}^{P}(\eta_j - \eta_m)^2$$

Where *p* is the number of experiments in the orthogonal array and η is the mean of the MPCI for the j^{th} experiment.

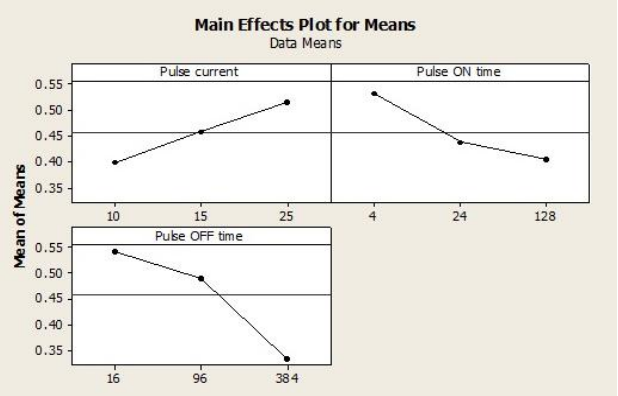

Figure 8 Effect plot of fuzzy reasoning grade graph

B. MPCI Table for mean values

The total sum of the squared deviations SST is decomposed into two sources: the sum of the squared deviations SSd_{due} to each process parameter and the sum of the squared error SS_e. The percentage contribution by each of the process parameter in the total sum of the squared deviations SST can be used to evaluate the importance of the process-parameter change on the performance characteristics. Usually, the change of the process parameter has a significant effect on the performance characteristic when the F value is large. The results of ANOVA (Table 7) indicate that Pulse off time and Pulse on time are the significant machining parameters in affecting the multiple performance characteristics.The mean values of MPCI are shown in table 6. The results of ANOVA indicate that pulse off time and pulse on time are the most significant process parameters affecting the multiple performance measures.

Table 6. Mean Value of MPCI

Machining parameter	*MPCI*		
	Level 1	*Level 2*	*Level 3*
Pulse current	*0.3988*	*0.4581*	*0.5147*
Pulse ON time	*0.5303*	*0.4371*	*0.4041*
Pulse Off time	*0.5441*	*0.4927*	*0.3347*
	Mean value of MPCI= 0.4571dB		

Table 7: Results of analysis of variance for multi-performance characteristics

Symbol	Machining parameters	Degree	Sums of squares	Mean square	F	Contribution (%)
A	Pulse current	2	0.0604	0.0302	6.51	12.73
B	Pulse ON time	2	0.0771	0.0385	8.30	16.26
C	Pulse OFF time	2	0.2146	0.1073	23.10	45.26
A*B	Pulse current * Pulse ON time	4	0.0146	0.0036	0.79	3.07
B*C	Pulse ON time * Pulse OFF time	4	0.0077	0.0019	0.41	1.62
A*C	Pulse current * Pulse OFF time	4	0.0624	0.0156	3.36	13.16
D	Error	8	0.0371	0.0046		7.82
	Total	26	0.4741			

IV. CONCLUSION

In the present study, the fuzzy based taguchi approach, based on the L27 orthogonal experimental design table is proposed as a way of studying the optimization of electrical discharge machining parameters. The fuzzy logic approach easily converts the optimization of the multiple performance characteristics into the MPCI, thus simplifying the complicated analysis of multiple performance characteristics. A fuzzy reasoning of the multiple performance characteristic has been performed by the fuzzy logic unit. As a result, the performance characteristics such as SR and MRR can be improved through this approach. From the multi-performance characteristic table the largest value of fuzzy reasoning grade for the EDM parameters was found. The following factor settings have been identified as to yield the best combination of process variables: Factor Pulse current- level 3, Pulse on time- level 1, Pulse off time- level 1.It was found that the pulse off time has the strongest effect among the other process parameters used to study the multi-performance characteristics. Experimental results have shown clearly that the material removal rate and surface roughness in the EDM process can be improved effectively through the proposed approach. This study indicated that fuzzy logic approach could be applied successfully to other operations in which performance measures are determined by many process parameters at multiple quality requests.

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