

International Journal of Engineering Researches and Management Studies GREY FUZZY BASED OPTIMIZATION OF TOOL WEAR AND PROCESS COST IN WEDM OF AMMC

B.Haritha Bai^{*1} and G. Vijaya Kumar²

*1Acadamic consultant, 2Post Doctoral Fellow
2S.V.University, tirupathi, Andhra Pradesh, India-517502.

ABSTRACT

Wire Electrical Discharge Machining (WEDM) endorsed sensation in the production of newer materials, especially for the aerospace and medical industries. Using WEDM technology, convoluted cuts can be made through difficult-to-machine electrically conductive components with the high degree of accessible accuracy and the fine surface quality make WEDM priceless. In other hand Aluminum Metal Matrix Composites (AMMCs) are the precise materials for marine, automobile, aerospace, defense, and sports industries which are difficult to cut by conventional methods of machining. In this paper an optimal set of material and machining parameters is derived using hybrid approach called grey-fuzzy approach. For this AMMC samples are produced as per the taguchi experimental design by considering combined material and wire EDM parameters and machined using WEDM machine. The obtained responses such as tool wear and process cost are optimized using grey-fuzzy approach which is obtained by combining grey relational analysis and fuzzy logic.

Keywords- Wire EDM, AMMCs, Taguchi design, tool wear, process cost Grey-fuzzy

I. INTRODUCTION

Aluminum Metal Matrix Composites (AMMCs) are the well-defined materials for marine, automobile, aerospace, defense, and sports industries, as they have high strength to weight ratio, and possess superior physical and mechanical properties compared to non-reinforced alloys and traditional metals. However, the presence of abrasive reinforcements in the ductile matrix causes rapid tool wear and hence tool failure. This leads to an increase in machining cost, production time and poor quality of machined components. On the other hand, some techniques such as electric discharge machining (EDM) and wire electric discharge machining (WEDM) are quite successful for machining of AMMCs. EDM has limited applications as it can be used only for drilling purpose. WEDM seems to be a better choice as it conforms to easy control and can machine intricate and complex shapes. The setting for the various process parameters required in WEDM process play crucial role in achieving optimal performance. Effective and economical WEDM of AMMCs will open new areas of applications for AMMCs.

II. LITERATURE REVIEW ON WEDM OF MMCs

Very few studies have been undertaken in WEDM of MMCs. Further, most of these studies have been done by using one-parameter-at-a-time approach, which may not explain the effects of interaction among various parameters. Some of past studies on WEDM of MMCs are follows. Sahandilya.P, Jain.P.K. & Jain.N.K [1] investigated made on consider the effect of voltage, pulse-on time, pulse-off time and wire feed rate on MRR and kerf in WEDM of SiCp/6061 AlMMC. Effect of input process parameters show that maximum value of MRR and minimum value of kerf are obtained at lower level of voltage, lower level of pulse-on time. D.Satish kumar & M. Kanthababu & V.Vajjiravelu [2] investigated WEDM of Al/SiCp MMCs in various volume fractions (5%, 10% and 15% of SiC) prepared through stir casting process considering MRR and Ra as outputs. And they concluded the microstructure of stir cast composite shows discrete localized pool/agglomeration of SiC particles indicating constrain of the process for attaining uniform microstructure. Rajesh Kumar Bhuyan, B.C.Routara, Arun Kumar Parida, A.K.Sahoo [3] investigate the effect of process parameters such as pulse on time(Ton), peak current (Ip) and flushing pressure (Fp), metal removal rate (MRR), tool wear rate (TWR) and surface roughness (SR) during electrical discharge machining (EDM) of Al-SiC12% MMC. The experiment is followed by Central composite design (CCD) method under

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different combination of process parameters. K.Zakariaa, Z.Ismaila, N.Redzuana and K.W.Dalgarnob [4] investigate the effect of wire EDM cutting parameters for evaluating of Additive Manufacturing Hybrid Metal Material. Hybrid metal materials produce through Additive Manufacturing of Indirect Selective Laser Sintering. It high light those important parameters to be considered in wire cutting process of FeCuSn hybrid metal material produce by Additive Manufacturing of Indirect Selective Laser Sintering process for fabricating the near net shape metal component. Ravindranadh Bobbili, V.Madhu, A.K.Gogia [5] investigates wire-EDM process parameters of ballistic grade aluminium alloy. Experimentation has been planned as per Taguchi technique. Three performance characteristics namely material removal rate (MRR), surface roughness (SR) and gap current (GC) have been chosen for this study. Yonghua Zhao, Masanori Kunieda, Kohzoh Abe [6] were experimentally investigated the performance of EDM slicing of SiC wafers, the fundamental characteristics of EDM of SiC single crystal. Ibrahem Maher, Liew Hui Ling, Ahmed A, D.Sarha, M. Hamdi [7] experimentally investigated the WEDM for improving process parameters. They concluded that the peak current and pulse on time are the most significant parameters affecting the cutting speed, surface roughness and heat affected zone. The wire tension has minor effect on the cutting speed and heat affected zone but it has great effect on the surface roughness. Cheol-SooLee, Eun-YoungHeo, Jong-MinKim, In-HughChoi, Dong-WonKim [8] investigated this paper presents an effective model to estimate the electrode wear of EDM. The wear amount depends on discharging environment such as material type and hole shapes. The electrode wear makes it difficult to control precise electrode feeding. Therefore, this study proposes an electrode wear estimation model. V. Chengal Reddy, N. Deepthi, N.Jayakrishna [9] studied the effect of various process parameters such as pulse on time, pulse off time, wire tension, current, upper flush and lower flush for Aluminium HE30, Vukcevic and Delijic, [10] were observed an increased interest on metal matrix composite, mostly light metal based, which have found their applications in many industry branches, among others in the aircraft industry, automotive, and armaments ones, as well as in electrical engineering and electronics, etc. M. Rosso, [11] studied applications of the metal matrix and ceramic matrix composites and their process technologies. M. Dyzia, J. OEleziona, [12] have developed and studied the mechanical properties of Aluminium matrix composites reinforced with AlN particles formed in stir casting. G. Rajyalakshmi, Dr. P. Venkata Ramaiah [13] Factors like pulse on time, pulse off time, corner servo voltage, wire feed rate, wire tension, servo feed, spark gap voltage and dielectric flow rate have been found to play a significant role in rough cutting operations for maximizations of MRR, minimization of surface roughness and minimization of spark gap in WEDM. Dewan Muhammad Nuruzzaman [14] investigated aluminium-aluminium oxide MMCs of different percentages of aluminium oxide. It is observed that density of the composite specimen increases with increase in aluminium oxide volume fraction and the density of the composites are higher for 20 ton compaction load than density obtained for 10 compaction load. H. K. Shivanand, Mahagundappa M. Benal, S. C. Sharma, N. Govindraju,[15] compared Powder Metallurgy method and stir casting method for producing the AMMC through testing of mechanical properties and conclude that stir casting method is best suitable for preparation of AMMC. Mr. Anand and S. Shivade [16] attempt was made to review the different multi-optimization method used in WEDM for optimization of process parameters such as MRR, Surface roughness, kerf width, machining time, dimensional deviation. Both the performance parameters, MRR and surface roughness are optimized in one optimal input setting using Grey relational analysis method. According to the literature survey it observed that very little work has been reported on WEDM of MMCs. Past studied not clearly concluded the list of input parameters and responses. So, there is much more scope to see effects of input parameters on outputs. Kerf width, tool wear response is not focused more. Surface roughness is mostly used which essential to measure because it states the quality of machining. Compared six and seventh series of aluminium alloys, seventh series is not used more and fifth series of aluminium alloys are also less. Coming to reinforcement materials silicon carbide is mostly used and fly ash and aluminium oxide is not used more. So this research is focused on WEDM of AMMCs which are reinforced with fly ash, aluminium oxide and silicon carbide by considering kerf width, surface roughness, tool wear and process cost as machining responses and one in each series of fifth, sixth and seventh series of aluminium alloys as base material.

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International Journal of Engineering Researches and Management Studies III. DESIGN OF EXPERIMENTS AND PREPARATION OF ALUMINIUM METAL MATRIX COMPOSITES

In the present work nine AMMC samples are produced using stir casting furnace as per Taguchi L27 experimental design (Table. 2) which is obtained by considering material and WEDM parameters (Table 1). To produce AMMCs, First the stir casting furnace with graphite crucible is switched on and allow it to raise the temperature up to 500° C then the required amount of base material is poured into the crucible and the temperature is raised up to 850° C and allow it to maintain the same up to complete melting of base material. At 675° C, the wetting agent Mg of 1% is added to the base material. Then the reinforcement particles are added slowly to the molten base material while the stirrer rotating. Before adding the reinforcement particles they are heated for 2 hrs upto 1000° C to oxidise their surfaces. After mixing, the temperature of the slurry is raised upto 850° C for getting improved fluidity and stirring is continued upto 5 minuits. Then the mixed slurry was poured in different preheated steel dies to produce the samples

s.l.n.o	Influential parameters	Level 1	Level 2	Level 3						
Material Parameters										
1	Base material (BM)	A15052	A16082	A17075						
2	Type of reinforcement material (RM)	SiC	Al ₂ O ₃	Flyash						
3	Percentage of reinforcement particle (PRFM)	2.5	5	10						
WEDM Para	ameters		1	1						
4	Pulse on time(Ton)	108	110	112						
5	Pulse off time (Toff)	56	58	60						
6	Water pressure(wp)	3	7	10						
7	Wire feed (Wf)	1	2	3						
8	Servo feed (SF)	1030	1050	1070						

Table 1: Influential parameters and their levels

Table.2.1	Taguchi	design	of exp	eriments
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Exp Run	AMMC Sample	Material parameters			WEDM parameters				
No	No.	BM	RFM	PRFM	Ton	Toff	Wf	Wp	SF
1		5052	FA	2.5	108	56	1	3	1030
2	1	5052	FA	2.5	108	58	2	7	1050
3		5052	FA	2.5	108	60	3	10	1070
4	2	5052	SIC	5	110	56	1	3	1050
5	2	5052	SIC	5	110	58	2	7	1070

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6		5052	SIC	5	110	60	3	10	1030	
7		5052	Al2O3	10	112	56	1	3	1070	
8	3	5052	Al2O3	10	112	58	2	7	1030	
9		5052	Al2O3	10	112	60	3	10	1050	
10		6082	FA	5	112	56	2	10	1030	
11	4	6082	FA	5	112	58	3	3	1050	
12		6082	FA	5	112	60	1	7	1070	
13		6082	SIC	10	108	56	2	10	1050	
14	5	6082	SIC	10	108	58	3	3	1070	
15		6082	SIC	10	108	60	1	7	1030	
16		6082	Al2O3	2.5	110	56	2	10	1070	
17	6	6082	Al2O3	2.5	110	58	3	3	1030	
18		6082	Al2O3	2.5	110	60	1	7	1050	
19		7075	FA	10	110	56	3	7	1030	
20	7	7075	FA	10	110	58	1	10	1050	
21		7075	FA	10	110	60	2	3	1070	
22		7075	SIC	2.5	112	56	3	7	1050	
23	8	7075	SIC	2.5	112	58	1	10	1070	
24		7075	SIC	2.5	112	60	2	3	1030	
25		7075	Al2O3	5	108	56	3	7	1070	
26	9	7075	Al2O3	5	108	58	1	10	1030	
27		7075	Al2O3	5	108	60	2	3	1050	

IV. EXPERIMENTATION

The experiments were conducted at ultra cut WEDM Machine (supplied by Vellore Wire Cut. Pvt. ltd) as per the taguchi design of experiments and the experimental data is recorded in the Table 3. For these experiments, brass wire is used as electrode and water as dielectric fluid.

V. IDENTIFICATION OF OPTIMUM PARAMETERS COMBINATION

I. STEPS FORB IDENTIFICATION OF OPTIMUM PARAMETER COMBINATION

StepI: Pre-processing of Experimental Data

Data pre-processing is required where the range and unit in one data sequence may differ from the others. In data pre-processing, the original sequence is transformed to a comparable sequence. Depending on the quality characteristic of a data sequence, there are various methodologies of data pre-processing are available.

For quality characteristic of the "larger – the - better", the original sequence can be normalized as $x^*{}_i(k) = \frac{x^{\sigma}{}_i(k) - \min x^{\sigma}{}_i(k)}{\max x^{\sigma}{}_i(k) - \min x^{\sigma}{}_i(k)} \qquad ------1$ For quality characteristic of the "smaller – the - better" the original sequence, can be normalized as $x^*{}_i(k) = \frac{\max x^{\sigma}{}_i(k) - x^{\sigma}{}_i(k)}{\max x^{\sigma}{}_i(k) - \min x^{\sigma}{}_i(k)} \qquad ------2$



Where i = 1..., m; k = 1..., n. *m* is the number of experimental data items and *n* is the number of parameters. $x_{i}^{\circ}(k)$ Denotes the original sequence, $x_{i}^{*}(k)$ the sequence after the data pre-processing, max $x_{i}^{\circ}(k)$ the largest

value of $x^{\circ}_{i}(k)$, min $x^{\circ}_{i}(k)$ the smallest value of $x^{\circ}_{i}(k)$, and x° is the desired value. For the experimental values of, tool wear and process cost smaller-the-better is applicable. Hence, its experimental values are normalized using Eqs2 as shown in Table 4.

Expt No	Experiment	al results	Normalized values of experimental Results			
	Tool wear	Process Cost	Tool wear	Process cost		
1	0.018	633.76	0.3043	0.6652		
2	0.01	519.94	0.6521	0.7828		
3	0.014	533.65	0.4782	0.748		
4	0.018	477.10	0.3043	0.8271		
5	0.025	395.013	0	0.9119		
6	0.018	569.51	0.3043	0.7316		
7	0.015	698.01	0.4347	0.5988		
8	0.011	705.15	0.6086	0.5915		
9	0.018	1277.726	0.3043	0		
10	0.013	567.53	0.5217	0.7336		
11	0.009	394.61	0.6956	0.9123		
12	0.012	346.43	0.5652	0.962		
13	0.019	781.30	0.2608	0.5128		
14	0.013	822.94	0.5217	0.4698		
15	0.013	987.93	0.5217	0.2993		
16	0.015	408.89	0.4347	0.8975		
17	0.016	658.75	0.3913	0.6394		
18	0.009	510.02	0.6956	0.7937		
19	0.019	569.12	0.2608	0.732		
20	0.014	394.61	0.4782	0.9123		

Table3: Experimental result and Normalized values of experimental Results

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21	0.016	414.84	0.3913	0.8194
22	0.014	352.18	0.4782	0.9561
23	0.002	309.74	1	1
24	0.014	568.32	0.4782	0.7328
25	0.013	470.60	0.5217	0.8338
26	0.012	600.17	0.5652	0.9996
27	0.015	561.82	0.4347	0.7394

Step II: Determine the grey relational coefficient

After data pre-processing, the grey relation coefficient $\xi_i(k)$ for the kth performance characteristics in the ith experiment can be determined using the Eq.3

 $\xi_{i}(k) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_{\sigma i}(k) + \zeta \Delta_{\max}} \qquad -----3$

Where, Δ_{oi} is the deviation sequence of the reference sequence and the comparability sequence.

 $\Delta_{oi} = \| \mathbf{x}^*_{o}(k) - \mathbf{x}^*_{i}(k) \|$

$$\begin{split} \Delta_{\min} &= \min_{\forall j \in i} \min_{\forall k} \| x^*{}_o(k) - x^*{}_j(k) \| \\ \Delta_{\max} &= \max_{\forall j \in i} \max_{\forall k} \| x^*{}_o(k) - x^*{}_j(k) \| \end{split}$$

 $\mathbf{x}_{0}^{*}(k)$ denotes the reference sequence and $\mathbf{x}_{i}^{*}(k)$ denotes the comparability sequence. ζ is distinguishing or identification coefficient and its value is between '0' and '1'. The value may be adjusted based on the actual system requirements. A value of ζ is the smaller and the distinguished ability is the larger. $\zeta = 0.5$ is generally used. The Grey Relational coefficients of tool wear and process cost are shown in the Table.5.

Step III: Determination of Grey-Fuzzy grade

A fuzzy logic unit comprises a fuzzifier, membership functions, a fuzzy rule base, an inference engine and a defuzzifier. In the fuzzy logic analysis, the fuzzifier uses membership functions to fuzzify the grey relational coefficient first. 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 Grey-Fuzzy grade. The structure built for this study is a Two input- one-output fuzzy logic unit as shown in Fig. 1. The function of the fuzzifier is to convert outside crisp sets of input data into proper linguistic fuzzy sets of information. The input variables of the fuzzy logic system in this study are the grey relational coefficients of tool wear and process cost. They are converted into linguistic fuzzy subsets using membership functions of a triangle form, and are uniformly assigned into three fuzzy subsets—small (S), medium (M), and large (L) grade. The fuzzy rule base consists of a group of if-then control rules to express the inference relationship between input and output. A typical linguistic fuzzy rule called Mamdani is described as

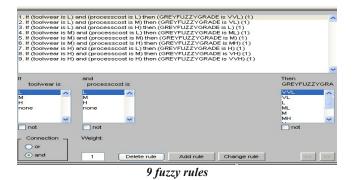
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Fig. 1 Two input- one-output fuzzy logic unit





fuzzy rule base consists of a group of if-then control rules to express the inference relationship between input and output. A typical linguistic fuzzy rule called Mamdani is described as

Rule 1: if x1 is A1, x2 is B1, then y is E1 else

Rule 2: if x1 is A2, x2 is B2, then y is E2 else

.....

Rule n: if x1 is An, x2 is Bn, then y is En else

In above Ai, Bi, are fuzzy subsets defined by the Corresponding membership functions i.e., $\alpha/4Ai$, $\alpha/4Bi$. The output variable is the Grey-Fuzzy grade yo, and also converted into linguistic fuzzy subsets using membership functions of a triangle form, as shown in Fig. 2. Unlike the input variables, the output variable is assigned into relatively nine subsets i.e., very very low (VVL), very low (VL), small(S) medium low(ML), medium (M), medium high(MH) high(H), very high (VH), very very high(VVH) grade. Then, considering the conformity of two performance characteristics for input variables, 9 fuzzy rules are defined and shown in Figure3. The fuzzy inference engine is the kernel of a fuzzy system. It can solve a problem by simulating the thinking and decision pattern of human being using approximate or fuzzy reasoning. In this paper, the max-min compositional operation of Mamdani is adopted to perform calculation of fuzzy reasoning. Suppose that x1, x2 are the input variables of the fuzzy logic system, the membership function of the output of fuzzy reasoning can be expressed as

 $\mu_{C_0}(y) = \left(\mu_{A_1}(x_1)\Lambda\mu_{B_1}(x_2)\Lambda \ \mu_{E_1}(y)\right) \vee$ $...\left(\mu_{A_n}(x_1)\Lambda\mu_{B_n}(x_2)\Lambda \mu_{E_n}(y)\right)$ Where V is the minimum operation and Λ is the maximum

operation. Grey Fuzzy Grade is shown in the Table 5

Step V Obtaining optimal combination of influential factors

After determining the GFG, the effect of each parameter is separated based on GFG at different levels. The mean values of GFG for each level of the influential factors and the effect of influential factors on multi responses in rank _____

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wise are summarized in Table 6 Basically, larger GFG means it is close to the product quality. Thus, a higher value of the GFG is desirable. From the Table 6 and fig 1, the optimal combination of influential factors is

BM3RM1PRM2TON3TOFF1WP1WF3SF1.

This means Base material at level 3 ie; Al7075 Reinforcement material at level 1 ie; SiC Percentage of Reinforcement material at level 2 ie; 5, TONat level 3 ie; 112, TOFF at level 1 ie; 56, 3, WP at level 1 ie; 3, WF at level 3 ie; 3 SF at level 1 ie; 1030.

II. CONFORMATION TEST

For the obtained optimal combination, confirmation test has been conducted and compared the results (Table 6) with initial set of parameters. These results are satisfactory as the responses for optimal combination shows better performance.

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S.No	5	nal Coefficients	Grey fuzzy
	Tool wear	Cost	Grade
1	0.6216	0.429	0.5986
2	0.4399	0.389	0.4086
3	0.5111	0.4	0.4883
4	0.6216	0.376	0.5898
5	1	0.3541	0.8339
6	0.621	0.4059	0.5942
7	0.534	0.455	0.5358
8	0.451	0.458	0.4303
9	0.6216	1	0.6869
10	0.4893	0.405	0.4587
11	0.4182	0.354	0.3875
12	0.4693	0.3419	0.4257
13	0.6572	0.4936	0.6364
14	0.4893	0.5155	0.4871
15	0.4893	0.6255	0.5187
16	0.5349	0.3585	0.5113
17	0.5609	0.4388	0.5601
18	0.4182	0.3864	0.3919
19	0.6572	0.4058	0.6125
20	0.511	0.354	0.4772
21	0.5609	0.3789	0.544
22	0.5111	0.3433	0.4749
23	0.333	0.33	0.3385
24	0.5111	0.4055	0.4896
25	0.4893	0.3748	0.4519

Table 4: Grey Relational Coefficients Grey Fuzzy Grade

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	0 0		0
26	0.4693	0.4167	0.4397
27	0.5349	0.4033	0.5221

	Table 5 GFG for each level of influential factors								
	GFG for each level of influential factors								
Level	BM	RM	PRM	Ton	Toff	Wp	Wf	sf	
1	0.574044	0.489011	0.473533	0.505711	0.541100	0.479544	0.523844	0.522489	
2	0.486378	0.551456	0.522611	0.568322	0.484767	0.537211	0.505378	0.508367	
3	0.483378	0.503333	0.547656	0.469767	0.517933	0.527044	0.514578	0.512944	
Delta	0.090667	0.062444	0.074122	0.098556	0.056333	0.057667	0.018467	0.014122	
Rank	2	4	3	1	6	5	7	8	

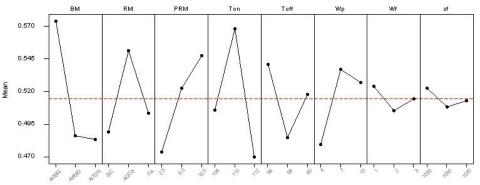


Fig 4 GFG for each level of influential factors

	Combination of Controllable Parameters	tool	process	GFG
	Combination of Controllable 1 at aneters	wear	cost	
Initial set of Combination	BM RM2PRM2TON2TOFF2WF2WP2SF2	0.018	476	0.5812
Optimal combination	BM1RM2PRFM3TON2TOFF1WP2WF1SF1	0.008	350	0.7902
Gain	N/A	0.01	126	0.2090
% of Gain	N/A	55.55	26.47	35.96

Table6 Comparison of responses between AMMC with initial combination and optimal combination

VI. CONCLUSION

After analyzing the data of obtained influential factors combination, it is concluded that Ton, BM and PRM are the most significant parameters which influence th multi responses RM and WP are the medium influenced parameters on multi responses and, Toff, WF and SF are influenced lastly the multi responses. The percentage of gain in tool wear is 55.55%, the percentage of gain in process cost is 26.47% and the percentage of gain in Grey Fuzzy Grade is 35.96



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