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MULTI-OBJECTIVE OPTIMIZATION OF EDM PARAMETERS USING GREY RELATION ANALYSIS

N. RADHIKA*, G. KISHORE CHANDRAN, P. SHIVARAM, K. T. VIJAY KARTHIK

Department of Mechanical Engineering, Amrita School of Engineering
Amrita Vishwa Vidyapeetham, Coimbatore, India
*Corresponding Author: n_radhika1@cb.amrita.edu

Abstract

This paper involves the multi-objective optimization of process parameters of AlSi10Mg/9 wt% alumina/3 wt% graphite in Electrical Discharge Machining for obtaining minimum surface roughness, minimum tool wear rate and maximum material removal rate. The important machining parameters were selected as peak current, flushing pressure and pulse-on time. Experiments were conducted by selecting different operating levels for the three parameters according to Taguchi's Design of Experiments. The multi-objective optimization was performed using Grey Relation Analysis to determine the optimal solution. The Grey Relation Grade values were then analysed using Analysis of Variance to determine the most contributing input parameter. On analysis it was found that peak current, flushing pressure and pulse-on time had an influence of 61.36%, 17.81% and 8.09% respectively on the optimal solution.

Keywords: Grey relation analysis, Electrical discharge machining, Multi-objective optimization, Analysis of variance.

1. Introduction

Industrial age new materials are being developed depending on the field of application. Initially all components are made from monolithic metals without any inclusion of alloying materials. But as time progressed, the need for alternate materials with better properties arises to meet the ever growing demands of engineering applications. So improving upon the base metals, composites are manufactured with properties much superior to their predecessors.

Nomenclatures

I	Peak current, A
MRR	Material removal rate, g/hr
p	Flushing pressure, kPa
Ra	Surface roughness, µm
T_{off}	Pulse off time, µs
T_{on}	Pulse on time, µs
TWR	Tool wear rate, g/hr

Abbreviations

Al	Aluminium
AMMCs	Aluminium metal matrix composites
ANOVA	Analysis of variance
DOE	Design of experiments
EDM	Electrical discharge machining
GRA	Grey relation analysis
GRC	Grey relation coefficient
GRG	Grey relation grade
MMCs	Metal matrix composites

Metal Matrix Composites (MMCs) are made from metals in combination with alloying elements that individually possess desired properties to bolster the base metal properties [1]. Out of all the MMCs, Aluminum Metal Matrix Composites (AMMCs) are most diverse and popular due to the abundance of aluminium and its use in various engineering applications. Aluminium is a light metal known for its good strength, thermal conductivity and a high strength to weight ratio. The aluminium matrix is such that it allows for a wide variety of materials to be alloyed with it [2]. One such material is graphite and it is a well-known solid lubricant. When graphite is added to the aluminium matrix, it reduces the friction during sliding and increases dry sliding wear resistance. Also, alumina, being a hard and brittle material, gets accommodated easily in the softer aluminium matrix [3]. Thus it increases the strength and stiffness of the composite.

The alloy AlSi10Mg containing 9 wt % of alumina and 3 wt % of graphite is chosen as it shows great dry sliding wear resistance properties. Although the reinforcements in aluminium improve the properties, they also increase the hardness of the composite and this poses a great deal of difficulty in machining. Thus, there arises a need for effective machining that produces a good surface finish while maintaining precise dimensional accuracy [4].

A non-conventional machining such as Electrical Discharge Machining (EDM) would serve the purpose as it uses intermittent sparking of electricity to cause removal of atoms from the surface of the material. Since there is no physical contact between tool and workpiece, the tool does not wear out as quickly as opposed to conventional techniques that use abrasion for removal of materials [5]. The tool and the workpiece act as electrodes that aid in removal of material. The tool is generally a material harder than the workpiece as it is required that more material be removed from the workpiece. Since EDM removes material by surface erosion, it takes a longer time for machining and this in turn increases operation costs. Machining in EDM depends on several input parameters, among them peak current (I), pulse-on time (T_{on}) and flushing pressure (p) have the major influence. Pulse-off time (T_{off}), though being a less prominent parameter, controls the duration between two successive sparks during EDM [6]. So it is important to set the T_{off} properly to avoid improper flushing and unwanted increase of machining time. These critical input parameters thus have to be optimized such that a low Surface Roughness (Ra) and Tool Wear rate (TWR) with a high Material Removal Rate (MRR) is achieved. The low Ra is important when the material is used in applications where there is extensive metal to metal contact. Also, when the MRR is high and TWR is low, the machining time and the tooling cost reduces.

This calls for multi-objective optimization of the parameters, which can be done with various techniques such as Genetic Algorithm, Ant colony optimization, etc. Grey Relation Analysis (GRA) is one such technique that helps in obtaining the best set of input parameters that result in achieving all the objectives. As the name suggests, GRA finds the optimized result in the grey region between white region, which contains complete information, and black region that contains no information. Thus for an extensive set of input conditions, GRA provides the optimized operating levels that can be set to achieve all objectives equally.

To find out the optimum parametric condition which mostly affects the performance measures, optimization technique based on Design of Experiments (DOE) can also be applied [7, 8]. Optimization of the parameters using DOE is one of the techniques used in manufacturing sectors to arrive for the best manufacturing conditions, which is an essential need for industries towards manufacturing of quality products at lower cost [9]. Taguchi method is applied for the optimization to study the influence of EDM parameters on the machining characteristic such as MRR, TWR and Ra. It is reported that peak current of EDM is the dominating factor that mainly influences on the TWR and Ra [10]. To find the contribution of each input parameter and errors towards the variation of responses, Analysis of Variance (ANOVA) method is used [11, 12]. Thus by determining the contribution of the parameters towards the responses, the influence of individual parameters on the response change can be determined, thereby enabling the user to concentrate on the important factor that is most likely to cause a change in the responses.

2. Experimental Setup

The machinability test in this work is carried out by machining holes of size 8 mm diameter in the AMMCs specimen of length 22 mm and diameter 12 mm. The chemical composition of Al-Si10Mg alloy is given in Table 1.

Table 1. Composition of Al-Si10Mg alloy.

Chemical Composition	Cu	Mg	Si	Others (Mn, Ni, Zn, Fe, Pb, Sn, Ti)	Al
wt.%	0.1 max	0.3 max	10 max	1.50 max	Balance

Figure 1 shows Electronica ZNC small die sinker machine (500×300 mm), which is used to drill holes in the composite specimen. A 415 Volt Alternating Current supply is used for machining. The electrode that machines the specimen must have high wear resistance characteristics so as to reduce the tool wear and improve the reusability of the electrode tool. So the electrode material is chosen based on the specimen material to be machined. Based on the material being aluminium, copper is chosen as the electrode in EDM. So in this machining, hole is to be drilled in the specimen using copper electrode. There are various conditions and parameters that are crucial for machining other than the considered input parameters. Of these, the dielectric fluid chosen is kerosene for its good dielectric properties and better combination with aluminium. Figure 2 shows the machined composite specimen.

Fig. 1. Electronica ZNC die sinker machine.

Fig. 2. Machined test specimen.

The power supplied to EDM generates an electric potential between the workpiece (anode) and tool (cathode), which leads to the generation of sparks. These sparks produced are a result of bombardment of electrons and ions on the workpiece and the tool. The kinetic energy of these electrons and ions gets converted into heat, which melts and vaporizes the material from the workpiece and the tool. The intensity and duration of these sparks are controlled by peak current and pulse-on time respectively. As discussed earlier a proper pulse-off time is to be ensured for effective flushing to occur, so this pause period is maintained at a constant value of 30 μs. During the pause period, the dielectric fluid flushes away the eroded material and also dissipates the heat from the spark gap.

The experiment is planned by considering three levels for each of the three input process parameters as shown in Table 2. The levels are chosen such that a wide range of peak current, flushing pressure and pulse-on time are considered. The range is selected by taking into consideration the capacity of the machine on which the experiment is being conducted on. In EDM machine, the maximum limit for peak current is 40 A, thus in order to avoid effect of machine errors, peak current is limited between 10 A and 30 A. Similarly flushing pressure is limited between 100 and 200 kPa as 300 kPa is the maximum available pressure. In case of pulse-on time, three levels were considered from the three predefined categories-super finish, good finish and rough finish. This wide range helps determine a better optimal level for obtaining maximum MRR and minimum TWR and Ra.

Table 2. Parameters and their levels.

Level	Peak current (I, A)	Flushing Pressure (p, kPa)	Pulse-on time (Ton, μs)
1	10	100	120
2	20	150	190
3	30	200	420

The experimental conditions are determined based on the L_9 orthogonal array (Table 3). The L_9 orthogonal array is chosen as it covers entire machining parameter space with just 9 experiments. The parameters were set for the first three columns of the L_9 orthogonal array.

Table 3. L9 Orthogonal array and its responses.

Exp. No.	Levels of parameters			Surface Roughness	Material Removal Rate	Tool Wear Rate
	Peak Current (I, A)	Flushing Pressure (p, kPa)	Pulse-on Time (T_{on}, μs)	Ra (μm)	MRR (g/hr)	TWR (g/hr)
1	10	100	120	3.085	19.0884	0.2299
2	10	150	190	3.414	16.1068	0.1051
3	10	200	420	2.632	13.5612	0.4096
4	20	100	190	3.376	25.2340	0.0976
5	20	150	420	2.823	19.0237	0.3613
6	20	200	120	2.712	16.0324	0.2126
7	30	100	420	5.509	24.9279	0.3774
8	30	150	120	6.491	23.1250	0.1603
9	30	200	190	4.680	19.8409	0.3554

On completing the experiments, MRR and TWR response values are calculated by weight loss method.

$$\mathrm{MRR} = \frac{\text{initial mass of workpiece} - \text{final mass of workpiece}}{\text{machining time}}$$

$$\mathrm{TWR} = \frac{\text{initial mass of electrode} - \text{final mass of electrode}}{\text{machining time}}$$

Ra of the machined workpiece was measured using a stylus type surface roughness tester (TESA RUGOSURF 10G).

3. Results and Discussion

Multi-objective optimisation is performed using GRA to arrive at the best operating level and the results are discussed briefly in the following sections.

3.1. Grey relation analysis

GRA is carried out to obtain the optimal set of process parameters based on the output responses.

3.1.1. Data pre-processing

Since the experimental data responses lie in different domains, GRA of the responses is carried out by transferring the original sequence to a comparable sequence. Such a transfer is made by normalizing the responses in the range between zero and one. This data pre-processing depends on the characteristics of the responses [13]. For larger-the-better type responses such as MRR, the original sequence is normalized based on Eq. (1).

$$x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \tag{1}$$

So that maximum MRR fits into the reference sequence. Whereas for smaller-the-better type responses such as TWR and Ra, minimum values of each is fit into the reference sequence by normalizing their original sequence using Eq. (2).

$$x_i^*(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)} \tag{2}$$

In Eqs. (1) and (2), $x_i(k)$ and $x_i^*(k)$ are responses before and after normalizing respectively and k=2 for MRR in equation (1) and k = 1, 3 for Ra and TWR in Eq. (2); i = 1, 2, 3,…, 9 for experiments from 1 to 9. The sequence after normalizing is given in Table 4.

Table 4. Sequence of each response after normalizing.

Exp. No.	Surface Roughness (Ra)	Material Removal Rate (MRR)	Tool Wear Rate (TWR)
Reference Sequence	1.0000	1.0000	1.0000
1	0.8826	0.4735	0.5759
2	0.7973	0.2180	0.9759
3	1.0000	0.0000	0.0000
4	0.8072	1.0000	1.0000
5	0.9505	0.4679	0.1548
6	0.9792	0.2117	0.6314
7	0.2544	0.9737	0.1032
8	0.0000	0.8193	0.7990
9	0.4692	0.5379	0.1737

On normalizing, the deviation sequence for each parameter is obtained by calculating the amount of each response which deviates from the reference sequence using Eq. (3).

$$\Delta_{0i}(k) = \left| x_0^*(k) - x_i^*(k) \right| \tag{3}$$

where, $x_0^*(k) = 1$; is the reference sequence and $\Delta_{0i}(k)$ is the deviation sequence as shown in Table 5 for each of the response parameters.

Table 5. Deviation sequences.

Exp. No.	ΔRa(1)	ΔMRR(2)	ΔTWR(3)
1	0.1173	0.5264	0.4240
2	0.2026	0.7819	0.0240
3	0.0000	1.0000	1.0000
4	0.1927	0.0000	0.0000
5	0.0494	0.5320	0.8451
6	0.0207	0.7882	0.3685
7	0.7455	0.0262	0.8967
8	1.0000	0.1806	0.2009
9	0.5307	0.4620	0.8262

3.1.2. Computing grey relation coefficient and grades

Grey Relation Coefficient (GRC) gives the degree of closeness of each of the actual normalized response parameters results to their ideal values in the reference sequence. It is calculated using Eq. (4) [14],

$$\xi_i(k) = \frac{\Delta_{\min}(k) + \zeta\Delta_{\max}(k)}{\Delta_{oi}(k) + \zeta\Delta_{\max}(k)} \tag{4}$$

where, k = 1, 2 and 3 for Ra, MRR and TWR respectively and ζ is the distinguishing coefficient, which is taken as 0.5 to give equal importance to all the responses. GRC for each of the 9 experiments and 3 parameters are given in Table 6.

GRC is concerned with each individual performance characteristic, so for the evaluation of multi-performance characteristic, Grey Relation Grade (GRG), γ, is calculated by averaging individual GRC's for each experiment using Eq. (5).

$$\gamma_i(k) = \frac{1}{3}\sum_{k=1}^{3} \xi_i(k) \tag{5}$$

where, i = 1 to 9 for each experiment. Similar to GRC, GRG gives the degree of closeness of the experimental results to the ideal result, in which MRR is maximum and Ra, TWR are minimum. From Table 6, it can be seen that Experiment no. 4 has the best multi-performance characteristic as it has the high

GRG value. This level 20 A for peak current, 100 kPa for flushing pressure and 190 µs for pulse-on time from experiment 4 is a near optimal solution.

Table 6. Calculated grey relation coefficient and grades.

Exp. No.	Grey Relation Coefficients			Grey Relation Grade	Rank
	Ra $\xi(1)$	MRR $\xi(2)$	TWR $\xi(3)$	γ	
1	0.8098	0.6551	0.7796	0.7481	4
2	0.7115	0.5611	0.9842	0.7522	3
3	1.0000	0.5000	0.6000	0.7000	6
4	0.7217	1.0000	1.0000	0.9072	1
5	0.9099	0.6527	0.6396	0.7340	5
6	0.9601	0.5592	0.8027	0.7740	2
7	0.4014	0.9744	0.6258	0.6672	8
8	0.3333	0.8470	0.8818	0.6873	7
9	0.4851	0.6839	0.6448	0.6046	9

Since the motive of this work is to find a level of machining parameters with maximum MRR and minimum TWR and Ra, the optimization of EDM parameters for the AMMCs is converted to optimization of GRG. So mean GRG for each level of the input parameters and their total mean are calculated (Table 7). From this table, the optimal level of input parameters is found to be 20 A for peak current, 100 kPa for flushing pressure and 190 µs for pulse-on time. The ranking of the process parameter reveals that peak current is the most dominant parameter on the output response and a similar behavior is observed in the case of optimization of EDM parameters using Taguchi method and GRA for mild steel [15]. So in this work, since the optimal level exists in the L_9 orthogonal array both the solutions, near optimal and optimal are same.

Table 7. Mean GRG for each level.

Machining Parameters	GRG			Main Effect	Rank
	Level 1	Level 2	Level 3	(max-min)	
Peak Current (I)	0.7334	0.8050*	0.6530	0.152	1
Flushing Pressure (p)	0.7741*	0.7245	0.6928	0.0813	2
Pulse-on Time (T_{on})	0.7364	0.7546*	0.7004	0.0542	3
Total Mean Value of GRG = 0.7304					

*Optimal level of GRG for each parameter

3.2. Analysis of variance

ANOVA assists in extensive understanding of the obtained data. In statistics, it is generally used to test for the hypothesis that the confidence interval for the data is 95%. But in this case, ANOVA is mainly used to determine the percentage contribution of each of the input parameters for the variation caused in the output.

During experimentation, the variation caused in the output can be caused by chance causes or assignable causes [16]. Assignable causes are the ones that are caused by the intentional variation in the input parameters and chance causes are the errors that occur during measurement or due to the randomness of nature that cause variation in responses during machining. In an ideal case, the variations due to chance causes is regarded as zero but this case is not possible in real life conditions. Hence it is necessary to find the contribution of each input parameter and the error towards the variation of the responses (Table 8). For a proper data set, the contribution of the error has to be lesser than that of all other parameters. The Fisher's ratio (F ratio) determines the significance of a particular parameter [17]. For a particular input parameter, the F-ratio has to be more than one to be considered as a significant parameter.

Table 8. Analysis of variance of GRG.

Source	Degree of freedom	Sum of squares	Adjusted Mean squares	F ratio	P	Percentage contribution
Peak Current (I)	2	0.034710	0.017355	4.82	0.172	61.36
Flushing Pressure (p)	2	0.010077	0.005039	1.40	0.417	17.81
Pulse-on Time (T_{on})	2	0.004577	0.002288	0.64	0.611	8.09
Residual Error	2	0.007199	0.003599			12.72
Total	8	0.056562				

From Fig. 3, it can be seen that peak current (61.36%) is the most dominant parameter followed by flushing pressure (17.81%) and pulse on time (8.09%) and this can also be concluded from the F-ratio in Table 8 and a similar trend is observed in machining of aluminium/silicon carbide/graphite hybrid metal matrix composites using EDM [18]. Also, since the cause due to error is less in percentage, this data set is a reliable one. The error percentage of 12.72 could be probably due to pulse off time, spark gap and also noise factor such as temperature of dielectric fluid.

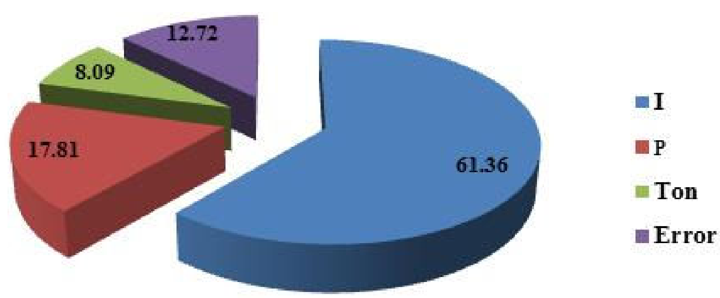

Fig. 3. Percentage contribution of source.

4. Conclusions

In this work, the EDM of aluminium hybrid MMC was extensively discussed and the optimization of input parameters for a better MRR, Ra and TWR was carried out. GRA used in optimization lead to a single best optimal level of input parameters with 20 A for peak current, 100 kPa for flushing pressure and 190 µs for pulse-on time. Based on ANOVA, it was shown that peak current followed by flushing pressure and pulse-on time has significant influence on the response parameters. Peak current was found to be the most dominant parameter with contribution of 61.36%. Thus, the obtained optimal level of process parameters was found to lead to good surface finish, reduced TWR and better MRR in the EDM of aluminium hybrid composites.

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