Multi-response Optimization and Analysis of Al/B_4Cp EDM using Grey Relational Analysis

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ABSTRACT

Development of material, especially metal matrix composite (aluminum-based MMC), attracts worldwide researchers due to its enhancement in wear and abrasive resistance, lightweight and high strength, low coefficient of thermal expansion. This work investigates the electrical discharge machining (EDM) of Aluminum/Boron Carbide (Al/B_4C) MMC. The optimization will help the researchers or metal processing industries use the investigated optimized process parameters for efficient and effective machining parameters. Pulse on time (PON), pulse off time (POFF), a variation of boron carbide(CP), and input current (IP) were varied to measure material removal rate (MRR), wear rate of the tool (TWR), and the surface roughness (Ra). The Taguchi method is used for the analysis of the machining parameters. Grey relational grade (GRA) is employed for the optimization of machining responses and the input parameters. The influence of various EDM parameters is investigated by analysis of variance (ANOVA). The multi-response optimization was carried out by GRA (CP: 4% of B_4C, PON"

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25 micro-sec, POFF: 9 micro-sec, and input current of 8 amp). The optimum responses were MRR: 17.58 mm^3/sec, TWR: 0.064 mm^3/sec, and Ra: 1.20 microns. The Aluminum-based alloys or composites are widely used in aerospace applications, automobile sectors, construction, aircraft industries, etc.

Keywords: *Al/B_4C MMC; Grey Relational Analysis; Multi-Response Optimization; Taguchi Method*

Nomenclature

- PON Pulse_on_time
- POFF Pulse_off_time
- IP Input current
- B_4C Boron Carbide
- MRR Material removal rate
- TWR Tool wear rate
- Ra Surface roughness
- GRA Grey relational analysis
- GRG Grey relational grade
- CP % Composition
- Al/B_4Cp Aluminum Boron Carbide Composite
- ANN Artificial neural network

Introduction

Nowadays, with the technological changes, advanced machining proves its effectiveness in the manufacturing industries. The use of lightweight materials in the machining industries improves drastically. The importance is due to the essential properties such as lightweight and higher strength to weight ratio. Al/B_4C is used because of some crucial properties such as high hardness, good chemical resistance, low density, and good nuclear properties, which helps to absorb neutrons without forming long-lived radio-nuclides and make the material attractive as an absorbent for neutron radiation. Mohal and Kumar [1] have examined the performance of multi-walled carbon nanotube (MWCNT) during the EDM of Al/SiC MMC. The experiments were carried out with the nano-powder mixed dielectric fluid during the machining. The impact of various wire electric discharge machining (WEDM) process parameters on the novel Al/SiC material has been examined during the investigation. Buckingham's pi theorem (DA) and ANN were chosen for the analysis. Authors have studied the impact of individual process parameters of the MMR [2]. Mohanty et al. [3] has conducted the experiments with the help of an L_9 orthogonal array. Vikor index method (VIM) was used for the multi-parametric response optimization of the process. ANOVA was done to examine machining parameters with their best levels, which intensify the performance. Roy et al. [4] have analyzed the impact of process variables on CNC milling performance for Al/Cu/TiC composite with 4.5% Cu. June et al. [5] has investigated the dimple formation on a titanium alloy (Ti-6Al-4V). Phate et al. [6] has carried out multi-response optimization of surface roughness (Ra) during different machining cut types using fuzzy-based GRA. Joshi et al. [7] has investigated the characterization failure during the WEDM process using ultra-thin wafers. The RSM-based experimental plan was adopted for experimenting. Phate et al. [8] have examined the performance of WEDM during the machining of oil harden non-shrinkage die steel (OHNS) using dimensional analysis and desirability function. Kumar et al. [9] has examined the machining performance of unidirectional glass fiber reinforced plastics using fuzzy-grey relational analysis techniques. Debnath et al. [10] have optimized EDM of composite material using a very effective decision-making technique.

The impact of various WEDM parameters was investigated to optimize the response MRR, and the quality of the workpiece finish measure in Ra. The multi-objective technique like grey relational analysis was employed to determine the best process parameters [11]. Multi response techniques like general regression neural network and ratio analysis (MOPORA) were used to get the best surface quality and microhardness [12]. The authors examined the machining of Al/SiC metal matrix composite. Soft computing techniques such as ANN integrated with the RSM are effectively implemented by the authors [13]. The Taguchi approach coupled with the utility concept was effectively implemented to optimize the WEDM process parameters of Nimonic-80 materials. The Taguchi approach was used for the analysis and examined the process for the response variable MRR and Ra [14]. Phate et al. [15] have tried various MMC fabrication and analysis compositions to determine the impact of different process parameters of WEDM on the responses. Various techniques like ANN, RSM, and DA represent the system with reliable models [16]. In the present work, the aim is to examine the influence of various EDM process parameters and determine the optimum process conditions during the EDM of Al/B_4C MMC [17]. The Al/Cu/Ni alloy was prepared, and experiments were carried out to know the ease of the EDM process [18]. The researcher examined the WEDM of Al/SiC MMC to determine the optimized machining parameters [19]. The machining process parameters were investigated to machine hypereutectic Al-Si alloys and optimize the finishing process [20]. The effect of machining process parameters was investigated to minimize the Ra of Al6061 alloy and the AISI steel material [21, 22].

The literature shows, it is observed that the lightweight material is very effectively used for making automotive parts, military items such as armor plates and bulletproof jackets, etc. It is also helpful in the aerospace and electricity industries. Hence, the presented work will provide the optimized machining environment for easy and effective utilization of the suggested material. The material's effective machining is the most critical concern in the machining industries from the above discussion.

Material and Method

Preparation of Al/B_4Cp MMC

In the present work, the filler material for MMC preparation consists of B_4C (Boron Carbide) with the variation of B_4C composition 2, 4, and 6 % of the fraction in the Aluminium matrix. The workpiece (Al/B_4Cp) is developed using the sand casting technique. The shape of the workpiece (100 mm x 50 mm x 10 mm) is shown in Figure 1. The electrode used for the EDM is a copper electrode of a triangular shape, as shown in Figure 1. The list, along with the level (test points), is as appear in Table 1.

Experimentation

The filler material used for MMC preparation consists of B_4C (Boron Carbide) with the variation of B_4C composition 2, 4, and 6 % of the fraction in the aluminum matrix. The workpiece is prepared by using the sand casting technique. The EDM machine setup is as appears in Fig. 1. The Cu tool with a rectangular shape was used during the machining. The tool and workpiece shape are also highlighted in Figure 1. The experiments were carried out using Taguchi’s L_9 plan. The responses measured during the experimentation were tabulated in Table 2. There are various responses in the EDM process, such as MRR, TWR, surface roughness, and power consumption. All the responses are essential, but the present work is restricted to only MRR, TWR, and Ra responses. The power consumption can be analyzed as future work. The MRR and TWR are measured by measuring the workpiece/ tool material removed w.r.t the machining time while the surface roughness is measured using a surface roughness tester.

Grey Relational Analysis (GRA)

GRA is a beneficial and efficient technique used for multi-response optimization. Following steps are involved in the GRA technique:

i. Step 1: Normalization of the actual measure responses:- The actual data can not be used for the analysis because the objectives of the responses are different. i.e., maximization or minimization. Normalization is the first step in the GRA. The real data is tabulated in Table1. The responses are calculated by using Equation (1). The realistic responses are converted into the range of 0.00 to 1.00. The objectives of responses are of two types i.e., for MRR response, the aim is maximization while for, TWR and Ra the objective is minimization. The maximization type of response 'Higher-the-better' criterion is used while minimizing the kind of response 'Lower-the-better' criterion is used. The normalized values for both the criterion are given by Equation (1) and Equation (2). The objectives of responses are of two types i.e., for MRR response, the aim is maximization, while for the TWR and Ra, the objective is minimization.

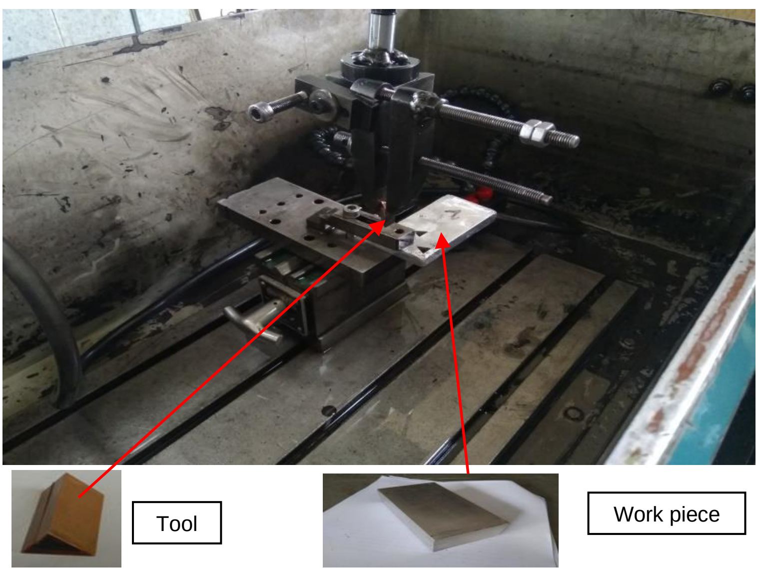

Figure 1: Experimental setup for EDM of Al/B_4C alloy.

The levels of various process parameters are selected based on the available machine, its range, and the experience of the machine operator corresponding to the material processing, and the ease of machining for a similar kind of material processing. The selected l; levels of various process parameters are tabulated in the following Table 1.

Table 1: List of EDM parameters along with their selected test points

Process Parameters	Test points (Levels)		
	Low	Medium	High
B_4C % (CP)	2	4	6
Pulse_on_time (PON)	20	25	30
Pulse_off_time (POFF)	3	6	9
Input Current (IP)	8	12	16

Table 2: Experimental Data as per Taguchi's L_9 plan of experimentation

Exp. no.	Process Parameters (Input)				Responses Parameters (Output)		
	CP	PON	POFF	IP	MRR (mm^3/min)	TWR (mm^3/min)	Ra (Micro-meter)
01	2	20	3	8	11.31	0.109	4.42
02	2	25	6	12	38.87	0.219	1.05
03	2	30	9	16	44.61	0.231	2.51
04	4	20	6	16	19.97	0.188	1.85
05	4	25	9	8	17.58	0.064	1.20
06	4	30	3	12	40.47	0.157	1.36
07	6	20	9	12	18.48	0.061	2.84
08	6	25	3	16	54.72	0.219	5.97
09	6	30	6	8	30.20	0.163	3.46

$$x_i^*(j) = \frac{Maxx_i^k(j) - x_i^k(j)}{Maxx_i^k(j) - Minx_i^k(j)} \tag{1}$$

$$x_i^*(j) = \frac{x_i^k(j) - Minx_i^k(j)}{Maxx_i^k(j) - Minx_i^k(j)} \tag{2}$$

where $x_i^k(j)$ is the realistic or actual response measure during the experimentation, $x_i^*(j)$ is the normalized value of the responses. $Minx_i^k(j)$ and $Maxx_i^k(j)$ is the minimum surface roughness and tool wear rate and maximum value of material removal rate**.** The normalized data is tabulated in Table 3.

ii. Step 2: Calculation of maximum sequence: After normalizing the realistic responses as per the appropriate criterion. In this step, grey relational grade (GRG) is calculated. Let M be the reference value. The maximum value is given by Equation (3).

$$M(j) = Max[x_i^*(j)] \tag{3}$$

Table 3: Calculation for Normalized matrix

Exp. no.	Responses Parameters (Output)			Normalized responses		
	MRR	TWR	Ra	MRR (Max)	TWR (Min)	Ra (Min)
01	11.31	0.109	4.42	1.000	0.721	0.315
02	38.87	0.219	1.05	0.365	0.070	1.000
03	44.61	0.231	2.51	0.233	0.000	0.703
04	19.97	0.188	1.85	0.800	0.254	0.837
05	17.58	0.064	1.20	0.856	0.983	0.970
06	40.47	0.157	1.36	0.328	0.437	0.937
07	18.48	0.061	2.84	0.835	1.000	0.636
08	54.72	0.219	5.97	0.000	0.074	0.000
09	30.20	0.163	3.46	0.565	0.400	0.510

iii. Step 3: The deviational sequence is the difference between the normalized value and the corresponding maximum value. This is calculated by using Equation (4). The deviational sequence is tabulated in Table 4.

$$\partial(ijk) = x(ijk) - M(j) \tag{4}$$

iv. Step 4: Calculation for grey relational coefficient and grade (GRG):
Grey relational coefficient calculated using Equation (5).

$$\varepsilon_i(k) = \frac{\partial \min + \alpha(\partial \max)}{\partial oi(k) + \alpha(\partial \max} \tag{5}$$

Here, $\partial oi(k)$ is the deviational sequence. It is calculated by Equation (6).

$$\partial oi(k) = \left\| X_o^*(k) - X_i^{*o}(k) \right\| \tag{6}$$

$$\partial \max = \max \max \left\| X_o^*(k) - X_i^{*o}(k) \right\| \tag{7}$$

$$\partial \max = \min \min \left\| X_o^*(k) - X_i^{*o}(k) \right\| \tag{8}$$

Here, 'α' is the distinguishing coefficient. It is taken as 0.5 i.e.α ϵ [0, 1]. Grey relational grade is calculated by taking the mean of grey relational coefficient of all responses. The grey relational grade is given by the following Equation (9). The GRG is tabulated in Table 5.

$$r_i = \frac{1}{n} \sum_{k=1}^{n} i\partial i(k) \tag{9}$$

Table 4: Calculation for deviation matrix

Exp. No.	Deviation Matrix			Grey relational coefficient		
	MRR	TWR	Ra	MRR (Max)	TWR (Min)	Ra (Min)
01	0.000	0.279	0.685	1.000	0.642	0.422
02	0.635	0.930	0.000	0.441	0.350	1.000
03	0.767	1.000	0.297	0.395	0.333	0.628
04	0.200	0.746	0.163	0.715	0.401	0.755
05	0.144	0.017	0.030	0.776	0.967	0.943
06	0.672	0.563	0.063	0.427	0.470	0.888
07	0.165	0.000	0.364	0.752	1.000	0.579
08	1.000	0.926	1.000	0.333	0.351	0.333
09	0.435	0.600	0.490	0.535	0.454	0.505

In GRA, the higher value of GRG indicates the stronger closeness. The highest value of GRG indicates the optimum process parameters.

Table 5: Calculation for Grey Relational Grade(GRG)

Exp. no.	Process Parameters (Input)				GRG Calculation and Decision		
	CP	PON	POFF	IP	GRG	Rank	Remark
01	2	20	3	8	0.688	3	
02	2	25	6	12	0.597	5	
03	2	30	9	16	0.452	8	
04	4	20	6	16	0.624	4	
05	4	25	9	8	0.895	1	Optimum condition
06	4	30	3	12	0.595	6	
07	6	20	9	12	0.777	2	
08	6	25	3	16	0.339	9	
09	6	30	6	8	0.498	7	

Results and Discussion

The presented work investigates the performance evaluation of EDM of Al/B_4C_P MC and its optimization for efficient and efficient utilization of the novel fabricated MMC for various industrial applications. The experimental findings indicate that the parameters PON significantly impact the MRR, followed by the parameters IP and B_4C. The parameters IP has a significant impact on response TWR followed by the POFF and B_4C. Similarly, the parameter B_4C has a considerable impact on the response Ra followed by the IP and POFF [19]. The impact of different machining parameters on the various responses has appeared in Table 6.

The influence of the different process parameters is plotted using interaction plots, as shown in Figures 2, 3 and 4. An interaction plot displays the levels of one variable (process parameter) on the horizontal (X) axis. It has a separate line for the means of each level of the other variable. The vertical (Y) axis is the dependent variable (response variable). A look at this graph shows that the effect of process parameters is varies depending on the process responses.

Regression analysis is applied for developing the model in the form of regression equations. The novel regression models for the various responses are generated for determining MRR, TWR, and Ra and given by Equation (10) to Equation (12), respectively [2]. These equations correlate the performance responses with the process parameters.

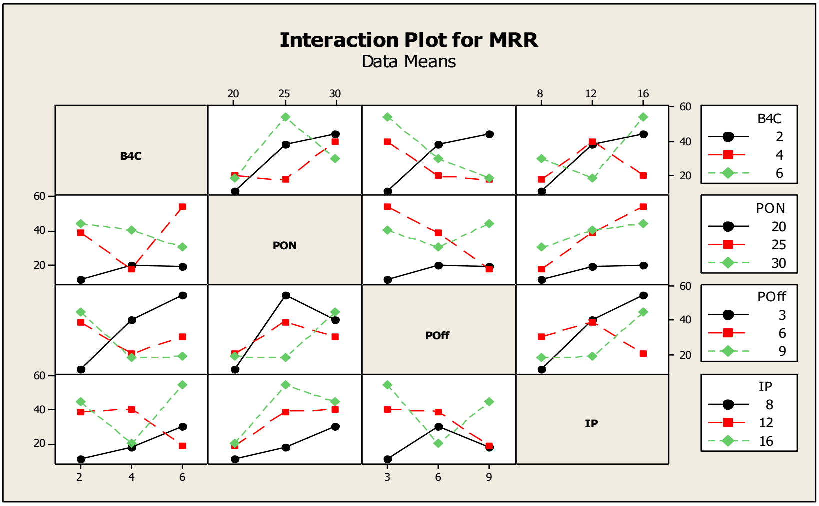

Figure 2: Interaction plot for MRR response during the EDM of Al/B_4C.

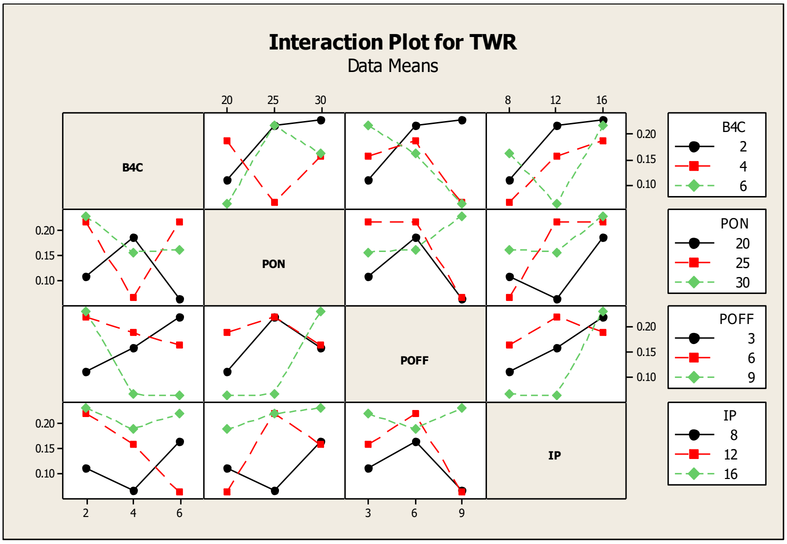

Figure 3 Interaction plot for TWR response during the EDM of Al/B_4C.

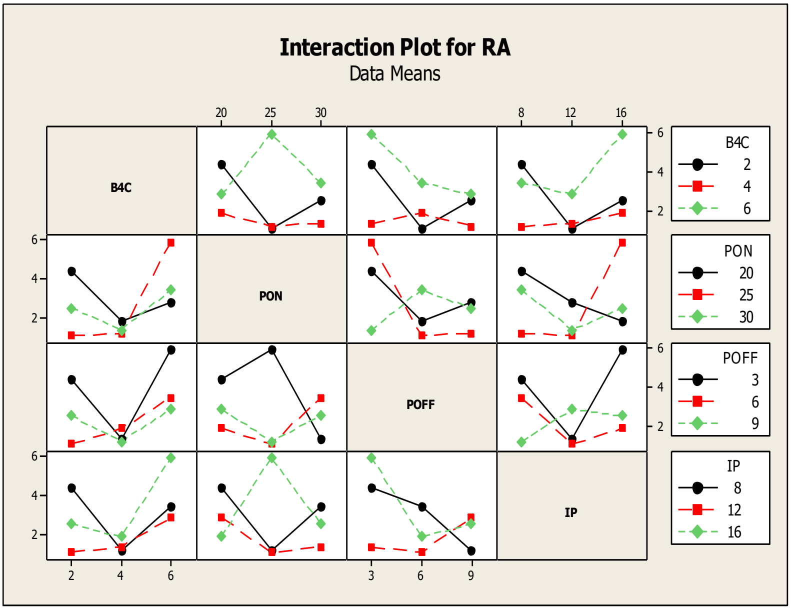

Figure 4: Interaction plot for Ra response during the EDM of Al/B_4C.

The mean of the response for the various input process parameters at levels 1, 2, and 3 can be estimated by taking the average response value at that level. The signal-noise ratio for the mean of various responses is tabulated in Table 6. To find out the optimum process parameter. The highest value of GRG (Table 5) is considered to find out the optimum process parameter. From Table 5, it is seen that the optimum machining condition for the multi-response optimization is CP (4% of B_4C), PON (25 micro-sec), POFF (9 micro-sec), and IP (8 Amp) corresponding to experiment number 5 GRD of 0.895.

$$\begin{aligned} MRR &= -48.2702 + 0.717505 * B4C + 2.184.3 * PON \\ &- 1.43516 * POFF + 2.50883 * IP \end{aligned} \tag{10}$$

$$\begin{aligned} TWR &= -0.073712 - 0.0096824 * B4C + 0.006450 * PON \\ &- 0.00709114 * POFF + 0.012584 * IP \end{aligned} \tag{11}$$

$$\begin{aligned} Ra &= 3.90167 + 0.3575 * B4C - 0.059333 * PON \\ &- 0.28889 * POFF + 0.0520833 * IP \end{aligned} \tag{12}$$

The various multiple linear regressions are developed using MINITAB 18 software for the responses MRR (Equation 12), TWR (Equation 13), and the response Ra (Equation 13). These are the statistical models which determine the relationship between the multiple inputs and output variables. These models allow predicting the response with a minimal amount of error. The sign of various input variables tells us whether the output process parameter increases or decreases. The positive sign indicates that the response parameter increases with the input process parameter. The negative sign indicates that the response variable decreases with a decrease in the input process parameter.

Table 6: Calculation of Signal/noise(S/N) ratio for all respose varaibles

Level	Process Parameters (Input)				Response
	CP	PON	POFF	IP	
01	28.62	24.14	29.33	25.19	MRR
02	27.69	30.49	29.14	29.76	
03	29.90	21.58	27.74	31.25	
Rank	3	1	4	2	
01	15.03	19.31	16.16	19.59	TWR
02	18.12	16.72	14.45	17.81	
03	17.70	17.83	20.24	16.46	
Rank	4	3	2	1	
01	-7.109	-9.106	-10.366	-8.425	Ra
02	-3.199	-5.842	-5.516	-4.054	
03	-11.789	-7.149	-6.214	-9.619	
Rank	1	4	3	2	

Based on the regression Equations (10) – (12) developed using MINITAB 18 software. The response MRR increases with an increase in the B4C, PON, and IP while it decreases with an increase in POFF. The response TWR is increased with an increase in PON and IP while decreasing with B4C and POFF. Ra's response is increased with an increase in the B4C and IP, while it decreases with POFF and PON.

Table 7: ANOVA for the GRG response (before pooling)

ANOVA						
Source	DOF	Seq. SS	Adj. SS	Adj. MS	F	P
CP	2	0.04525	0.04525	0.02262	*	*
PON	2	0.04936	0.04936	0.02468	*	*
POFF	2	0.04727	0.04727	0.02363	*	*
IP	2	0.08478	0.08478	0.04239	*	*
Error	0	*	*	*	*	*
Total	8	0.226668				

In the MRR model (Equation 10), the coefficients of PON, IP, and B_4C are positive, whereas the term POFF is negative. It shows that the parameters i.e., PON, IP, and B_4C, directly affect the repose MRR while POFF is inversely propositional to the MMR. ANOVA is performed for the response GRG (Overall grade) to know the impact of various process parameters on the overall performance of the machining. ANOVA before pooling (Table 7) does not show significant results since the degrees of freedom (DOF) is associated with the term 'error' is 'zero' [19]. The error is due to the mismatching of various process parameters and their levels. In such a situation, a pooling principle is applicable where the factor which has the least influence on the response process parameter is neglected. From Table 8, it is seen that the process parameter POFF has the least impact on the GRG hence neglected.

Table 8: Calculation of Signal/noise(S/N) ratio for GRG

Level	Process Parameters (Input)				Response
	CP	PON	POFF	IP	
01	0.5790	0.6963	0.5407	0.6937	GRG
02	0.7047	0.6103	0.5730	0.6563	
03	0.5380	0.5150	0.7080	0.4717	
Rank	0.5790	0.6963	0.5407	0.6937	

Table 9: ANOVA for the GRG response (after pooling)

ANOVA						
Source	DOF	Seq. SS	Adj. SS	Adj. MS	F	Contribution
Regression	3	0.125770	0.1257770	0.0419234	2.07753	
CP	1	0.002521	0.002522	0.0025215	0.12495	1.1121%
PON	1	0.049323	0.049323	0.0493227	2.44420	21.7588%
IP	1	0.073926	0.073926	0.073926	3.66342	32.6142%
Error	5	0.100897	0.100897	0.0201795		remaining
Total	8	0.226668				

ANOVA (After pooling) is carried out for further analysis. The obtained results are tabulated in Table 9. It is interpreted that the parameter IP is the major significant parameter followed by the PON, which contributes 32.6142% and 21.7588% towards the impact on GRG or overall performance[18].

Conclusion

In this study, Electric discharge machining of Al/B_4C_p MMC was investigated, and the multi-response optimization was carried out using Grey relational analysis.

i. Taguchi's L_9 plan of experimentation coupled with grey relational analysis is used for the investigation. A novel composition of Aluminum and Boron Carbide is tried and its ease of machining parameters during the EDM was found out for better use in the machining industries. A 'Cu' electrode is used for machining purposes.

ii. The multi-response optimization obtained were CP: 4%of B_4C, PON: 25 micro-sec, POFF: 9 micro-sec, and input current of 8 amp. The optimum responses were MRR: 17.58 mm^3/sec, TWR: 0.064 mm^3/sec, and Ra: 1.20 microns.

iii. Regression models were developed for all the responses, and the effect of machining parameters are examined during the analysis. The contribution of process parameters on the overall performance of the EDM responses measured in terms of GRG is found out using ANOVA.

iv. From the outcome of the presented work, it can be stated that the parameters PON have a significant impact on the MRR followed by the parameters IP and B_4C. The parameters IP has a substantial effect on response TWR followed by the POFF and B_4C. Similarly, the parameter B4C substantially impacts the response Ra followed by the IP and POFF.

v. From the GRG, it can be stated that the machining parameters such as input current and pulse on time are the most influencing process parameters followed by the B_4C composition, while the impact of pulse off time is least amongst all other processes parameters on the overall performance.

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