Optimization of Electrical Discharge Machining of Al-Mg-TiO2 Metal Matrix Nanocomposites

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Abstract:

Pure Al-Mg metal is toughened with TiO_2 nano particle fabricated by a stir - casting process. Electrical discharge machining (EDM) is one of the nontraditional machining processes used to cut the harder and intricate components. Voltage (V), current (Ip), pulse on time (T_{on}) and pulse off time (T_{off}) are considered as input parameters. The objective of this study was to achieve a higher material removal rate (MRR), lesser tool wear rate (TWR) and surface roughness (Ra) of Al-Mg-TiO_2 nano composite. The Minitab-14 Software is used to design the L_{27} orthogonal array. The optimal suitable values of input parameters are found, and the most influencing parameters are identified by ANOVA. Grey relational analysis is applied to obtain the optimal value of input parameters for the response levels.

Keywords: Stir casting; electrical discharge machining; metal matrix nano composite; material removal rate; tool wear rate; surface roughness.

1. Introduction

Aluminium-based MMCs are widely used in the field of automotive, space vehicle and defence sectors because of the high impact strength and rigidity at high-temperature working condition. Metal matrix composites are toughened with boron carbide (B_4C), silicon carbide (SiC), titanium carbide (TiC), titanium dioxide (TiO_2), titanium diboride (TiB_2), aluminium nitride (AlN), silicon nitride ($Si_3 N_4$) and aluminium dioxide (Al_2O_3), which have trivial advantages over traditional materials. The element-toughened MMCs have previously been established to be economically utilized on the usual processing techniques. Aveek Mohanty *et al.* (2014) have concluded that the cutting of Inconel 825 in EDM, the peak current (I_p) and the pulse on time (T_{on}) are the major influencing parameters for higher MRR. Lowering the level of I_P and T_{on} gives a better surface finish in EDM for the same material.

P.M George *et al.* (2004) have concluded that the pulse on time and pulse current are the most essential parameters for TWR and MRR at three parameters and for the two levels of carbon–carbon composites machining. The results of the proportion of SiC and the other machining characteristics are considered. S. Gopalakannan *et al.* (2013) have optimized the SiC MMC on EDM, in which the composites possess machinability and high specimen quality. The MRR influences the pulse current with the pulse on time to the best possible value. R. Karunanithi *et al.* (2014) have discussed the electrochemical behaviour of TiO_2 reinforced with Al 7075 composite and have stated that the optical scanning microscope has exhibited the even distribution of the particle in different volume fraction of TiO_2 in the Al 7075 matrix. Due to the increase in TiO_2 content, the tendency of clustering and porosity increases. The Taguchi and RSM methods are widely used for the assessment of machining performance, particularly the machining of MMNC in EDM. J.Lan *et al.* (2004) have analysed the microstructure and microhardness of SiC nanoparticles toughened with the composite of magnesium and prepared by the ultrasonic method. The experimental results show that the even sharing and excellent scattering of the SiC particles in nanosize that are present in the magnesium matrix, even though a few particles (less than 300 nm) are in the matrix. The microhardness of nanocomposites has enhanced drastically, when evaluated to that of pure AZ91D. P. Narendar Singh *et al.* (2004) have recommended that in the EDM process, the hard materials such as cemented carbide, tungsten carbide and other composites are machined easily. The machining investigations of MMCs with particle reinforcement are acknowledged and completed, during the machining of Al–SiC, the increasing SiC particle reduces the MRR and amplifies TWR and SR. Jong Hyuk Jung *et al.* (2010) have investigated and optimized the high aspect ratio (h/d) EDM-drilled hole using both the Taguchi method and grey relational analysis. They found that 60V voltage, 680 pf capacitance, 500 ohm resistance, 1.5 μm/s feed rate, 1500 rpm spindle speed as optimum machining conditions for producing microhole of 40 μm. P. S. Kao *et al.* (2003) have applied the grey relational analysis to optimize the electrochemical polishing of 316L SS with different performance characteristics. They have justified that the improvement of grey relational grade is 0.338. Some researchers have used entropy-based GRA technique for optimization. S. Sivasankar *et al.* (2012) have applied the grey entropy with regression analysis for tool material performance and conducted the EDM machining on hot-pressed ZrB_2 disc in two different cycles. Ahilan.C *et al.* (2009) have investigated the optimum level of CNC turning process parameter by the grey-based fuzzy logic approach. They have identified by ANOVA that the cutting velocity and the feed rate are the most influencing parameters. B. P. Mishra *et al.* (2017) have investigated the optimum level of performance of EDM of EN-24 steel using both Taguchi and GRA. They have used four input parameters and two response parameters as MRR and TWR. They have concluded that the optimum parameters at the maximum level of MRR, minimum level of the tool wear and lead-time. They suggested that the reinforcement could be particles, long fibres, short fibres or pre-forms. Stir casting is found to be predominating as it could be readily mixed and monitored economically in various processing parameters. Specimens from stir casting have high hardness and finer grains in the microstructure and enhance the ductility than the powder metallurgy. In order to create MMNCs, it is very tough for the normal mechanical magnificent route to dispense and dissolve nanoparticles evenly in metals, as of the higher specific surface areas of nanoparticles. The MMNC properties will improve drastically with lesser volume fraction (up to 8%) of nanoparticles. The MMNCs could offer a considerably improved performance on eminent temperature, and also in the view of the microstructure, Al alloy/TiO_2 shows the formation of the Al_3Ti and the MgO particles. The deformation reactions are performed partially on the content of TiO_2 particles. The indentation hardness and yield strength are better than the ultimate tensile strength and elongation due to increase in the amount of TiO_2 nanoparticles in the matrix. The controlled annealing of MMNC at 400°C for 3 hours gives improved strength and elongation. In this connection, the solid-state chemical reactions occurred without anomalous grain growth of the matrix.

2. Materials and methods

2.1 Preparation of Al-Mg-TiO_2 nano composites

Ultra-pure TiO_2 (rutile) nano powder 99.97% of purity with 250nm Size was purchased from Sisco Research Laboratories Pvt. Ltd., Mumbai. Pure aluminium (99%) was used as the matrix material. TiO_2 was added as the reinforcement material. One of the best casting processes named as the stir casting process was decided to fabricate the metal matrix nano composites for its convenience.

During the stir casting process, 90 % of Al Ingots was initially melted in the heating chamber at 750°C. 7% of magnesium was added to avoid the wet ability. Then the 3% of preheated TiO_2 nano particles was mixed with the melted Al-Mg pool to improve the viscosity. The argon gas was employed to prevent the melt pool from being oxidized. When the melting temperature attains 800°C, the ceramic-coated stirrer with constant speed was used to stir the melt at six minutes for the uniform distribution of TiO_2 nano particle. The MMNC pool was poured into a mould size of 110 X ϕ22 mm that is previously heated up to 500°C at a separate electric furnace. After the casting process, the mould gets cooled by the room temperature. During the annealing process, the phase transfer occurs between Al_3Ti and MgO in the mould. The chemical composition of Al-Mg-TiO_2 nano composite is given in Table 1.

$$Al+Mg+TiO_2 \longrightarrow Al_3Ti + MgO$$

Table 1 Chemical composition of Al-Mg-TiO_2

Constituent	Al	Si	Fe	Mn	Mg	Ni	Zn	Sn	Ti	Bi	Ga
Content (%)	Balance	0.709	1.250	0.327	4.780	0.486	0.155	0.854	1.5	0.599	0.459

Table 2 Machining level of contribution parameters

Parameters	**Labels**	**Levels**		
		-1	**0**	**1**
Voltage, V (Volt)	A	55	60	65
Pulse current, I_p (A)	B	6	10	14
Pulse on time, T_{on} (μs)	C	4	6	8
Pulse off time, T_{off} (μs)	D	5	7	9

3. Experimental Procedure

The Minitab-14 software was used to prepare the experimental design. The four input parameters and levels were mentioned in Table 2, the constant flushing pressure was set at 0.5 kg/cm^2 considered based on the previous literature. The trials were designed on the basis of Taguchi design as shown in Table 3.

3.1 Work Material and Tool Material

The work material is cut into diameter of 22 mm and 5 mm thickness in size by wire EDM. A 10-mm-diameter copper electrode is used to make a hole using Sparkonix MOS 15A die-sinking EDM. The work piece acts as a positive electric polarity, and the tool as a negative polarity. The circular type of electrode is selected when compared to the other shape of the tool to provide better performance. Business ranking kerosene is preferred for the dielectric fluid, and the worn out material from the sparking region is flushed away by impulse jet flushing system.

The material removal rate and tool wear rate were calculated by weight difference before and after the machining of the material by means of 0.001g accuracy digital weighing machine. The machined surface of the specimen was examined using the scanning electron microscope as shown in Fig. 1.

Table 3 Design of Experiments and Observed values

S.No	Factor 1 A: Voltage	Factor 2 B: Current	Factor 3 C: T_{on}	Factor 4 D: T_{Off}	Response 1 MRR (g/min)	Response 2 EWR (g/min)	Response 3 SR(µm)
1	60	6	4	5	0.084	0.004	12.425
2	55	6	6	7	0.136	0.006	18.095
3	60	6	8	9	0.116	0.004	21.955
4	55	10	4	7	0.125	0.007	11.897
5	60	10	6	9	0.069	0.009	21.5
6	65	10	8	5	0.211	0.016	25.705
7	55	14	4	9	0.033	0.004	14.35
8	60	14	6	5	0.435	0.012	25.393
9	60	14	8	7	0.381	0.015	38.65
10	55	6	4	5	0.136	0.006	12.005
11	60	6	6	7	0.093	0.006	17.56
12	65	6	8	9	0.098	0.005	28.81
13	55	10	4	7	0.102	0.007	12.61
14	55	10	6	9	0.099	0.008	22.26
15	65	10	8	5	0.206	0.016	32.02
16	55	14	4	9	0.04	0.004	14.09
17	60	14	6	5	0.633	0.013	24.8
18	65	14	8	7	0.628	0.011	39.04
19	55	6	4	5	0.085	0.005	13.163
20	60	6	6	7	0.136	0.006	21.28
21	65	6	8	9	0.089	0.004	21.38
22	65	10	4	7	0.131	0.006	14.543
23	60	10	6	9	0.102	0.009	27.95
24	65	10	8	5	0.502	0.016	26.07
25	55	14	4	9	0.035	0.004	12.92
26	65	14	6	5	0.643	0.011	25.231
27	55	14	8	7	0.589	0.012	38.012

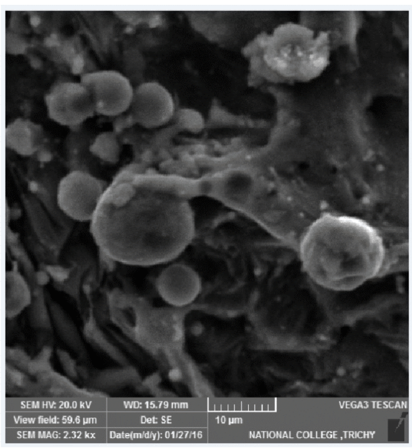

Fig.1 SEM picture of the drilled hole

Fig. 2 Specimen of Al-Mg-TiO_2 nano composite and EDM

4. Results and discussion

The various responses studied are MRR, TWR, and SR for the selection of machining performance.

$$MRR = (W_{sb} - W_{sa}) / t \qquad \text{---------} (1)$$

Where,

W_{sb} - Specimen weight before machining in grams,

W_{sa} - Specimen weight after machining in grams, and

t - Machining time in minutes.

Tool wear rate, which means the weight difference between earlier than and later than machining of the tool (Wtb-Wta) to the time of machining (t).

$$TWR = (W_{tb} - W_{ta}) / t \qquad \text{---------} (2)$$

Where,

W_{tb} - Tool weight before machining in grams,

W_{ta} - Tool weight after machining in grams, and

t - Machining time in minutes.

$$\text{Percentage of Tool wear} = \frac{\text{The weight of the eliminated material from the tool/time}}{\text{The weight of the eliminated material of the specimen/time}} \times 100 \qquad \text{---------} (3)$$

Totally 27 trial runs are agreed by Taguchi method. The MRR and TWR are calculated by each trial and tabulated in table 3. Further, the surface roughness machine (MITUTOYO SA 411) calculated the irregularity of the machined surface. The common roughness value Ra (μm) was preferred from the three values of a machined surface at different positions on a single specimen.

The effect of the nano particle in the metal matrix composite and various input parameters, fixed some ranges to find the optimal value. It increases with an increase range of the discharge current. The increase rate of the metal elimination and the tool is attributed to the elevated loading of thermal due to the elevated discharge current.

4.1. Grey Relational Analysis (multi objective method)

Grey analysis, initially developed by Deng in the year of 1982 to fulfil the essential mathematical decision for dealing with unpredictable system, can efficiently suggest a way of optimizing the intricate relationships among the multi objective performance characteristics. The GRA is an efficient tool for multiple input parameters and for one additional response. On the other hand, the GRA gives the necessary details of the interaction between the parameters. The steps to be followed for performing optimization by GRA are as follows:

(1) Estimate the grey relational generation (GRG) from the response.
(2) Estimate the grey relational coefficient (GRC).
(3) Estimate the grey relational grade.
(4) Analyze the investigation results using grey relational grade.
(5) Observe the optimum level of contribution parameters.
(6) Verify the most favourable parameter level by conformation test.

4.2 Grey relational generation (GRG)

In the view of GRA, when the level is very high or the number of values is too big, the purpose of the factors is abandoned. If the objectives and the direction of the factor are dissimilar, the grey relational analysis may give inaccurate results. Therefore, the initial processing of data, that is, grey relational generation, is necessary to set the progressions. The data preprocessing methods are functional to the response like MRR, TWR and SR. Therefore, the experiment results lie in between zero and one. The GRG "higher is better" for MRR is expressed as,

$$X_i(k) = \frac{Y_i(k) - Min\ Y_i(k)}{Max\ Y_i(k) - Min\ Y_i(k)} \qquad \text{--------} \quad (1)$$

When the "lesser is better" characteristics is used for the surface roughness and the tool wear rate of the sequence of investigation results, it is expressed as,

$$X_i(k) = \frac{Max\ Y_i(k) - Y_i(k)}{Max\ Y_i(k) - Min\ Y_i(k)} \qquad \text{--------} \quad (2)$$

where

X_i (k) is the assessment of grey relational generation (GRG) for the i_{th} experiment.

Y_i (k) is the value of i_{th} experiment in the sequence of particular responses.

Min Y_i (k) is the minimum value in the sequence.

Max Y_i (k) is the maximum value in the sequence.

GRG for corresponding sequence gives equal to 1.

Table 4 Data preprocessing of the experimental result

Exp.No.	Grey relational generation			Exp.No.	Grey relational generation		
	MRR (g/min)	EWR (g/min)	SR(µm)		MRR (g/min)	EWR (g/min)	SR(µm)
1	0.0836	1.0000	0.9805	15	0.2836	0.0000	0.2586
2	0.1689	0.8333	0.7717	16	0.0115	1.0000	0.9192
3	0.1361	1.0000	0.6294	17	0.9836	0.2500	0.5246
4	0.1508	0.7500	1.0000	18	0.9754	0.4167	0.0000
5	0.0590	0.5833	0.6462	19	0.0852	0.9167	0.9534
6	0.2918	0.0000	0.4913	20	0.1689	0.8333	0.6543
7	0.0000	1.0000	0.9096	21	0.0918	1.0000	0.6506
8	0.6590	0.3333	0.5028	22	0.1607	0.8333	0.9025
9	0.5705	0.0833	0.0144	23	0.1131	0.5833	0.4086
10	0.1689	0.8333	0.9960	24	0.7689	0.0000	0.4778
11	0.0984	0.8333	0.7914	25	0.0033	1.0000	0.9623
12	0.1066	0.9167	0.3769	26	1.0000	0.4167	0.5087
13	0.1131	0.7500	0.9737	27	0.9115	0.3333	0.0379
14	0.1082	0.6667	0.6182				

4.3 Computing Grey Relational Coefficient.

After the completion of data preprocessing, the GR coefficient is calculated to execute the relationship between the experimental results. Based on the literature appraisal, the value (ε) of the individual response can be fixed. Thus, the grey relational coefficient can be calculated by

$$\gamma_{i\ (k)} = \frac{\Delta min + \varepsilon \Delta max}{\Delta_i(k) + \varepsilon \Delta max} \qquad \text{-------} \quad (3)$$

Where

$\gamma_{i\ (k)}$ = Grey relational coefficient

ε = Value of responses (distinguishing coefficient)

$\Delta_i(k) = |\, x_0 (k) - x_i (k)|$

Δmax = max Δ_i (k)

Δmin = min Δ_i (k)

4.4 Calculating the grey relational grade

This following expression can be used for calculating the grey relational grade

$$\alpha_i = \frac{1}{m} \sum_{k=1}^{m} \gamma_{i\ (k)} \quad \text{------} \quad (4)$$

Where α_i is the calculated grey relational grade for the corresponding response values to the 'm' number of performance characteristics. The average grade value is calculated from different multiple response values. The elevated value of the grey relational grade shows that the investigation results are very near to the ideal normalized value. Ultimately, the first experiment gives the highest degree grade value among all the experiments as shown in Table 5. In other words, the optimization of the various performance characteristics can be converted into a single grey relational grade. Table 5 indicates the rank of the grey relational grade of the 27 experiments. The MRR is considered as the elevated better characteristics while the TWR and SR are considered as the lower better characteristics; that is, the priority value (ε) is given more to the MRR when compared to the tool wear rate and surface roughness.

Table 5 Grey Relational Grade for each experiment and its Rank

S.No	G.R grade	GR Grade Rank	S.No	G.R grade	GR Grade Rank	S.No	G.R grade	GR Grade Rank
1	0.764	1	10	0.636	6	19	0.6416	5
2	0.4963	15	11	0.4973	14	20	0.4619	18
3	0.6047	9	12	0.4632	17	21	0.6057	7
4	0.605	8	13	0.5748	10	22	0.5578	11
5	0.3767	23	14	0.3914	22	23	0.3405	24
6	0.3172	25	15	0.2886	27	24	0.4051	20
7	0.7006	4	16	0.7079	3	25	0.7408	2
8	0.4005	21	17	0.5219	13	26	0.5448	12
9	0.3168	26	18	0.4797	16	27	0.4393	19

However, the importance of the multiobjective machining parameters needs to predict the optimal response level, which can be determined clearly. Therefore, the ANOVA table is discussed detail in the next section.

4.5 ANOVA used for statistical result analysis

The necessity of analysis of variance (ANOVA) is to find out the important parameter that disturbs the performance characteristics. The entire variation of grey relational grade is calculated by the sum of the squared deviation between the mean of the grey relational grade and the error. Table 6 illustrates the GR grade ANOVA, which gives the most influencing parameter, the pulse on time and current for highest MRR, lowest TWR and SR. Only when the MRR is considered, the current (I_P) and the pulse off time (T_{off}) are the very essential parameters to affect the machining process. Only when the tool wear rate is considered, the current (I_p), pulse on time (T_{on}) and the pulse off time (T_{off}) are important parameters. Current and pulse on time are the most preferred parameters for obtaining better surface finish.

Voltage always shows the insignificant parameter for all the individual optimum responses. In multiobjective optimization, the pulse on time and current are always the parameters that influence the performance characteristics. The optimum values of input machining parameters are obtained based upon the uppermost mean value of GR grade using the response table and response graph, which is also discussed in the next section in detail.

Table 6 ANOVA for Grey Relational Grade

Machining parameters	D.O.F	Sum of square	Mean square	F-Value	Contribution %
Pulse on Time (μm)	2	0.1943	0.0972	25.14	48.95
Current (A)	2	0.1092	0.0546	14.13	27.51
Pulse off Time (μm)	2	0.0180	0.0090	2.33	4.54
Voltage (V)	2	0.0059	0.0029	0.76	1.48
Error	18	0.0696	0.0039		17.52
Total	26	0.3970			100.00

4.6 GRA Response table and graph

The table 7 indicates the average GR grade of every stage of machining parameters. For example, the voltage level like 50, 55 and 60V are separately grouped together, and the average GR grades are calculated.

Table 7 Response table for the average GR Grade

Parameter/level	Symbol	GR Grade			Max-min
		Level1	Level2	Level3	
Voltage	A	0.5934	0.4760	0.4578	0.1356
Current	B	0.5745	0.4286	0.4700	0.1459
Pulse on	C	0.6587	0.4479	0.4356	0.2231
Pulse off	D	0.5022	0.4921	0.5479	0.0558

As shown in Figure 3, if the voltage is at the lower level, the grey relational grade increases, and when the voltage level increases, it reduces gradually. In the case of lower level current, the GR grade is higher, which then decreases gradually. The grey relational grade increases at lower levels of pulse on time when considered with the pulse off time. Further, the grade decreases at higher levels. The grade value is very nearer to the average value at the first two levels of the pulse off time parameter, which then increases in the last level. Therefore, the final multiobjective optimized parameter in the grey relational analysis is $A_1B_1C_1D_3$.

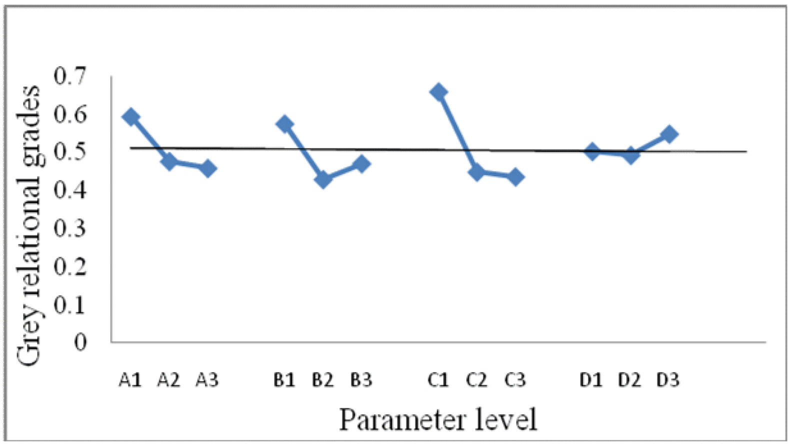

Fig.3 Grey Relational Grade graph

4.7. Prediction of optimum result

The anticipated mean at the optimum level (μ) is found by applying the following method for getting the optimal prediction value.

$$\mu = \overline{A}_1 + \overline{B}_1 + \overline{C}_1 + \overline{D}_3 - 3 * \overline{T}_{gg}$$

Where $\overline{A}_1$,$\overline{B}_1$,$\overline{C}_1$ and $\overline{D}_3$ are the average values of the grey relational grade of optimum parameter level. $\overline{T}_{gg}$ is the mean value of the overall grey relational grade resulting in the expected mean at the optimum level, 0.8323.

5 % of confidence intervals (CI) can be obtained by

$$CI = \sqrt{F_r(1,f_e)M_e[\frac{1}{T_{eff}} + \frac{1}{T_c}]}$$

$$= \pm 0.1508$$

Where

$F_r(1, f_e)$ – 5% confidence level of F-ratio,

f_e – Degree of freedom of error,

M_e – Mean square error value,

T_{eff} – Total number of efficient experiments and

T_c – Number of verification tests.

$$T_{eff} = \frac{\text{Total number of experiment conducted}}{1 + \text{No. of degrees of freedom related with items used to calculate the } \mu_c}$$

Hence, CI calculates 95% of the expected optimum condition range. μ_c is the grey relational grade assessment by carrying out the verification test with optimum surrounding levels, that is A_1, B_1, C_1 and D_3.

$$(0.8323 – 0.1508) < \mu_c < (0.8323 + 0.1508)$$

$$0.6815 < \mu_c < 0.9831$$

4.8 Confirmation test

After calculating the optimum level of input parameters, the subsequent process is to expect and conduct the confirmation test to ensure the improvement in the performance characteristics. Table 8 indicates the difference between the initial and optimal parameter levels. The initial value is taken as of the overall grey relational grade. In Table 8, $A_3B_3C_3D_2$ are the initial parameter levels, which are mentioned in the experiment number 18 in Table 3. In the prediction of optimum parameter level setting, the MRR varies from 0.628 g/min to 0.138 g/min, TWR is changed from 0.011g/min to 0.005 g/min, and SR improves from 39.04µm to 24.8µm, respectively. Thus, the grey relational grade increases from 0.4797 to 0.8323. The development in grey relational grade is 0.3527. It clearly shows that the multiobjective optimization parameter level is $A_1B_1C_1D_3$ machining of Al-Mg-TiO_2 nano composite by die sinking EDM.

Table 8 The difference between the initial and optimal EDM parameters

Output parameters	Initial machining parameter	Optimal machining parameter	
		Prediction	Experimental
Setting level	$A_3B_3C_3D_2$	$A_1B_1C_1D_3$	$A_1B_1C_1D_3$
MRR, g/min	0.628	-	0.438
TWR, g/min	0.011	-	0.004
SR, µm	39.04	-	12.8
Grey relational Grade	0.4797	0.8323	0.8324

Improvement of grey relational grade is 0.3527.

5. Conclusions

The optimization of EDM of Al-Mg-TiO_2 nanocomposite by grey relational analysis is obtained as follows:

ANOVA results indicate that the pulse on time and the current are the significant parameters that impinge on the drilling of Al-Mg-TiO_2. The contribution percentage of pulse on time is 48.95 µs, and the current is 27.51Ams.

The best suitable performance characteristics are found with the optimum setting of $A_1B_1C_1D_3$.

The predicted optimal machining parameter of EDM process is verified by the confirmation test.

Therefore, the outcome of this research work can be very useful in space vehicle and automobile with sensor industries to obtain better machining performance at optimum level of parameters in EDM of Al-Mg-TiO_2 MMNC. The major influencing parameters found out to be current and pulse on time.

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