ISSN: 0974-5823 Vol. 6 No. 3 December, 2021

International Journal of Mechanical Engineering

STUDY THE IMPACT OF ELECTRICAL DISCHARGE MACHINING PARAMETERS ON Al-Mg-TiO_2 NANO COMPOSITE

S. Senthilkumar[1], Dr.J. Jerald[2]

[1]Research scholar, Department of Production Engineering, NIT, Tiruchirappalli, India.

[2]Associate Professor, Department of Production Engineering, NIT, Tiruchirappalli, India.

. ***Abstract*:** This effort aims to study the impact of the selected EDM drilling input parameters such as current, voltage, pulse on time and pulse off time at their three levels of material removal rate (MRR), tool wear rate (TWR) and surface irregularity (Ra) of Al-Mg-TiO_2 Nano Composite material. The electrode is made of copper. Metal metrics are fabricated by adding nano TiO_2 and Magnesium powders to the pure Aluminium by stir casting method. Scanning Electron Microscope (SEM) is used to confirm the excellent dispersion of TiO_2 nano particles in the aluminium matrix. The hardness of the nanocomposite is 89.75 BHN. L27 orthogonal experimental design is implemented for analysing the impact of selected parameters on the output response parameters. The results revealed that voltage 65 V, pulse current 14 A, pulse on time 8 µs along with pulse off time 5 µs are the optimised values of Taguchi based single objective method. The best suitable performance characteristics are found with the optimum setting of voltage 60 V, pulse current 6 A, pulse on time 4 µs along with pulse off time 9 µs for multi objective method (grey relational analysis). The pulse on time and current are the most dominating parameter for both the methods.

Keywords: Electrical discharge machining; Metal matrix nano composite; Taguchi method; Grey relational analysis; Material removal rate; Tool wear rate; Surface roughness.

1. INTRODUCTION

Aluminium composites are extensively used in the production of automobile, space vehicle and electronic industries for the reason of its high specific strength and stiffness at eminent working condition. Aluminium metals are toughened with silicon nitride (Si_3N_4) silicon carbide (SiC), titanium carbide (TiC), titanium di boride (TiB_2), titanium dioxide (TiO_2), boron carbide (B_4C), and aluminium dioxide (Al_2O_3), which are all used in high strength required production component. S. Gopalakannan *et al.* [1] fabricated the Al7075 metal reinforced with nano SiC particles. RSM was used to design the experiment of composite to be machined by EDM. The optimum assessment of current and pulse on time greatly influenced the MRR values. R. Karunanithi *et al.* [2] discussed the electrochemical behaviour of Al7075-TiO_2 MMN composite. The value of clustering and porosity increases with increased in the volume % of TiO_2. Taguchi and RSM methods are discussed in the EDM machining of MMNC. Mehdi Hourmand *et al* [3] reviewed the EDM process on Al-Mg2Si MMC and concluded the voltage, current and pulse on time are important parameters. After the confirmation test the error was found to be less than 7% when compared to the predicted value. J.Lan *et al.* [4] analysed the microstructure of magnesium reinforced SiC nano composite prepared by the ultrasonic cavitations method. The SEM image showed even circulation of the nano sized SiC elements in the magnesium matrix. P. Narendar Singh *et al.* [5] recommended that an enhance in the wt% of SiC in the aluminium matrix reduces the MRR and increases the TWR and SR. Jong Hyuk Jung *et al.* [6] optimized the process parameter for making a high aspect ratio hole (40 µm diameter) using electro discharge machining. It was found that 60V voltage, 680 pf capacitance, 500 ohm resistance, 1.5 µm/s feed rate and 1500 rpm spindle speed are optimum machining conditions. P. S. Kao *et al.* [7] applied electrochemical cleaning of 316L SS with altered performance characteristics. The improvement in the grey relational grade was set to be 0.338. Ahilan. C *et al* [8] have examined the CNC turning route parameter by grey-support fuzzy logic approach. The cutting velocity and the rate of feed were found to be the most influencing parameters. S. Siva sankar *et al.* [9] conducted EDM process on hot-pressed ZrB_2 disc in two different cycles. The grey entropy with regression analysis for tool material was performed M. Ravichandran *et al* [10] concluded that the addition of TiO_2 increases the density and strength value and also decreases the strain-hardening indicator of the MMC.Density and buckling property were improved in 2.5 wt% of TiO_2 in addition to 2 wt% of graphite composite. The hoop, true effective and hydrostatic static stresses are better for the Aluminium with 5 % of TiO_2 and 4 % of Gr hybrid composites, when compared to previous composition. B. P. Mishra *et al.* [11] have examined the optimum level of presentation of EDM of EN-24 steel in both Taguchi and GRA. 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. Mohammad reza Shabgard *et al* [12] conducted the experiment on FW4 Welding Metal and compared it with the usual EDM process and US-EDM process. Pulse on time and current are the higher performance in US-EDM process and lower in the EDM process. S.Roseline *et al* [13] prepared the Aluminium 6061 matrix reinforced with ZrO_2 by stir casting process. The reinforcements were seen to be consistently circulated in the matrix and the grains were also refined in an excellent manner. Zirconia was seen to be completely penetrated into molten Aluminium eliminating the breakage and shrinkage of the composites. **S**tir casting route is used to enhance the ductility, hardness and yield strength property. The gradual annealing of MMNC gives improved strength and elongation. Y. Yang *et al.* [14] have prepared an ultrasonic cavitations technique of collective solidification processes based on the even sharing of SiC nano particles in molten Aluminium alloy. The regular manufacturing methods for the nano composites cannot be followed for the bunch of production and other manufacture of intricate structural workings. These composites are extensively used for separate work in space vehicle, automotive and other applications. Yan-Cherng lin *et al.* [15] have explained that the type of polarity and peak current are the major influencing parameters which have an outcome on the MRR and TWR. The only parameter that affects the SR is the peak current. They have concluded the process by using ANOVA and F-Test data taken from the cutting of SKH 57 HSS material in EDM. It is estimated that MMCs toughened by ceramic nano particles, named as metal matrix nano composites, can overcome the limitations connected with the usual MMCs. MMnCs prepared by conventional casting procedure results in an inconsistent sharing of particles contained in the matrix due to less wettability of nano-particles. The important problem is low wettability of ceramic nano-particles formed in large scale of production of metal matrix nano composites. So the conventional casting processes are not suitable for MMC, Because of the irregular distribution of particles within the matrix. Due to high surface energy of the nano particles, which are effective in hindering the movement of dislocations and can generate a physical-chemical bond to the matrix, thus reducing significantly the strengthening capability of nano particles [16-18].The current work is visualized to study about the mechanical properties of Al-Mg-TiO_2 nano composite and parametric optimization of EDM by developing numerical model and evaluate the outcomes of responses on casted nano composite using Taguchi method. Hence, the numerical models have been carried out to study the influence of input parameters over the response values by using both Taguchi method and Grey relational analysis.

2. MATERIALS AND METHODS

2.1 Preparation of Al-Mg-Tio$_2$ Nano Composites

Ultra pure Aluminium ingot was used as a matrix material. Pure TiO_2 nano powder 250nm size was acquired from Sisco Research Laboratories Pvt. Ltd., Mumbai for reinforcement material. The Al-Mg-TiO_2 nano composite was produced through stir casting process**.** During the casting process, 3 weight percentages of preheated TiO_2 nano particles was mixed with the melted pure aluminium metal. 7 weight % Magnesium was added to avoid wettability. To avoid oxidizing of the melt, argon gas was supplied to the melted pool. When the furnace temperature attains more than 650ºC, the aluminium ingots has started to melt. The temperature reach more than 850ºC all the aluminium ingots gets melt and the ceramic-coated stirrer was used to stir the melt pool continuously for the uniform sharing of TiO_2 particle. Finally the melted MMnC pool was poured into a 110 X Ø 22 mm size preheated mould. Then the mould was cooled by annealing process. During the annealing process, the phase transfer occurs between Al_3Ti and MgO in the mould. The high-resolution SEM micrograph (Fig 1) showed even distribution of nanoparticles in the Al-Mg-TiO_2 mould. The size of TiO_2 nano particle was found to be less than 1 micron scale in the entire SEM image.

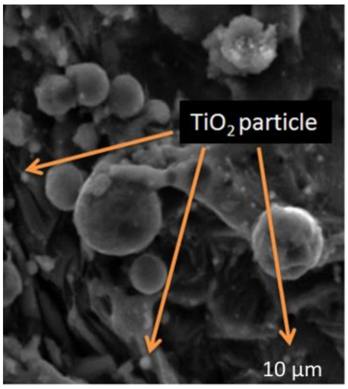

Figure.1 SEM image of Al-Mg-TiO_2 sample

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

TABLE 1 Chemical Composition of Al -Mg-TiO_2

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

2.2. Mechanical Properties and Analysis of Nano Composites

The test specimen diameter Ø22 x 5mm thickness was cut by using wire EDM machine. The hardness of the sample was calculated by the Brinell hardness testing machine, while applying a load of 250kg yielded 89.75BHN. At least five hardness readings were taken from the different samples to reduce the error. The XRD pattern of Al-Mg-TiO_2 nanocomposite shows the Al, Mg and TiO_2 peaks that are indexed using JCPDS software as shown in Fig. 2.

TABLE 2 Level of Machining Parameters

Parameter	Labels	Levels		
		1	2	3
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

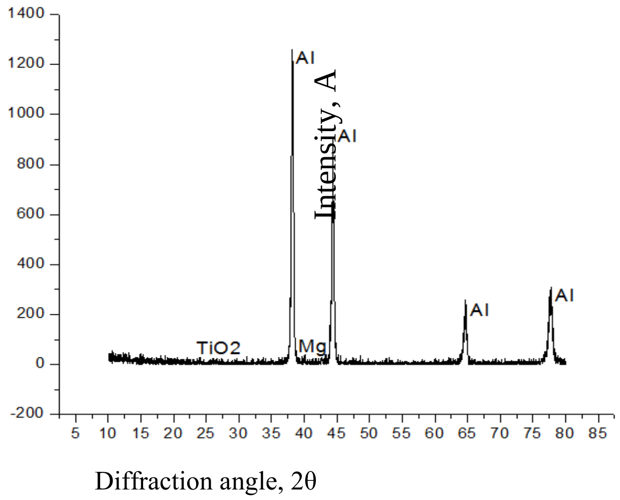

Figure.2 XRD pattern of Al-Mg-TiO_2

3. EXPERIMENTAL PROCEDURE

Table 2 indicates the level of input parameters for a spartronix EDM machine shown in fig.3. Based on the literature survey the constant dielectric fluid pressure was set at 0.5 kg/cm^2. The Minitab-16 software was utilized to plan the L_{27} Orthogonal array as shown in Table 3.

TABLE 3 L27 Orthogonal Array and Responses

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 Ra (µm)
1	55	6	4	5	0.136	0.006	12.005
2	55	6	6	7	0.138	0.006	18.095
3	55	6	8	9	0.098	0.005	28.81
4	55	10	4	7	0.125	0.007	11.897
5	55	10	6	9	0.099	0.008	22.26
6	55	10	8	5	0.208	0.014	24.616
7	55	14	4	9	0.04	0.004	14.09
8	55	14	6	5	0.435	0.012	25.393
9	55	14	8	7	0.589	0.012	38.012
10	60	6	4	5	0.084	0.004	12.425
11	60	6	6	7	0.093	0.006	17.56
12	60	6	8	9	0.116	0.004	21.955
13	60	10	4	7	0.123	0.005	14.887
14	60	10	6	9	0.102	0.009	27.95
15	60	10	8	5	0.211	0.016	25.705
16	60	14	4	9	0.033	0.004	14.35
17	60	14	6	5	0.633	0.013	24.8
18	60	14	8	7	0.381	0.015	38.65
19	65	6	4	5	0.136	0.006	12.005
20	65	6	6	7	0.093	0.006	17.56
21	65	6	8	9	0.098	0.005	28.81
22	65	10	4	7	0.131	0.006	14.543
23	65	10	6	9	0.102	0.009	27.95
24	65	10	8	5	0.211	0.016	25.705
25	65	14	4	9	0.033	0.004	14.35
26	65	14	6	5	0.643	0.011	25.231
27	65	14	8	7	0.628	0.011	39.14

3.1Preparation of Process Materials

The cast specimen for EDM machining was cut into 22 mm diameter and 5 mm thick by wire EDM. A 25 X ϕ10mm copper electrode was used as a tool to make a hole using Sparkonix die-sinking EDM. Based on the literature survey, the casted piece was fixed at positive electric polarity the electrode has a negative polarity for optimum result [2]. The circular shape of electrode was preferred for better machining performance [1]. Impulsive type of jet flushing system was employed to remove the worn out parts using business ranking kerosene as a dielectric fluid.

The weight of the specimen and tool was found before and after machining and the difference in the weight was used to calculate the MRR and TWR. Digital balance with an accuracy of 1x10^{-3}grams was used for this purpose.

Figure 3 Sample of Al-Mg-TiO_2 nano composite and EDM

4. RESULTS AND DISCUSSION

4.1Calculation of MRR, TWR and SR

Material removal rate can be defined as the weight variation of the specimen earlier than and later than machining (W_{sb} - W_{sa}) to the time taken for drilling (t) [11].

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

Where,

W_{sb} - Weight of the specimen earlier than machining in grams,

W_{sa} - Weight of the specimen later than machining ingrams,

t - Time taken for drilling in minutes.

Tool wear rate is the amount of material detached from the tool for the period of machining (W_{tb}-W_{ta}) to the time of machining (t).

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

Where,

W_{tb} - Weight of the tool earlier than machining in grams,

W_{ta} - Weight of the tool weight later than machining in grams, and

t - Time taken for drilling in minutes.

$$\% \text{ of Tool wear} = \frac{\text{The mass of the removed material from the tool/time}}{\text{The mass of the removed material of the specimen/time}} \times 100 \quad (3)$$

Table 3 shows the MRR and TWR are measured for every drilling operation. Then, the surface roughness of the machined holes is calculated by MITUTOYO SA 411 surface roughness tester. The average value taken from the three different positions of a specimen was considered as the roughness value of the hole. The multi objective optimum input parameter value can be calculated by different optimization techniques. One of the more reliable techniques to be used to find the optimum value is Grey Relational Analysis. The increase rate of the metal removal in cast sample and the tool wear is attributed to the elevated thermal condition and discharge current.

4.2 Analysis of MRR, TWR and SR

Table 4 ANOVA for MRR

Source	DF	Seq SS	Adj SS	Adj MS	F	
Voltage	2	0.0052	0.0052	0.0026	0.2600	0.
Current	2	0.3850	0.3850	0.1925	19.0900	0.
Pulse on	2	0.1914	0.1914	0.0957	9.4900	0.
Pulse off	2	0.2429	0.2429	0.1214	12.0400	0.
Error	18	0.1816	0.1816	0.0101		
Total	26	1.0061				
S = 0.100436		R-Sq = 81.95%		R-Sq(adj) = 73.93%		

Table 5 ANOVA for TWR

Source	DF	Seq SS	Adj SS	Adj MS	F
Voltage	2	0.000000	0.000000	0.0000001	0.1000
Current	2	0.000119	0.000119	0.0000597	39.3200
Pulse on	2	0.000155	0.000155	0.0000775	51.0200
Pulse off	2	0.000118	0.000118	0.0000588	38.7300
Error	18	0.000027	0.000027	0.0000015	
Total	26	0.000420			
S = 0.00123228		R-Sq = 93.49%		R-Sq(adj) = 90.59%	

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Voltage	2	5.97	5.97	2.98	0.22	0.8050
Current	2	235.98	235.98	117.99	8.66	0.0020
Pulse on	2	1272.90	1272.90	636.45	46.70	0.0000
Pulse off	2	28.17	28.17	14.08	1.03	0.3760
Error	18	245.29	245.29	13.63		
Total	26	1788.31				
S = 3.69153		R-Sq = 86.28%		R-Sq(adj) = 80.19%		

Table 6 ANOVA for SR

The obtained values are R^2 = 81.95% and R^2 (Adj) = 73.93% for MRR, R^2 = 93.49 % and R^2 (Adj) = 90.59 % for TWR, R^2 = 86.28% and R^2 (Adj) = 80.19% for SR. From Table 4, it can be observed material removal rate amplifies with increase in current, pulse off time and pulse on time. When comparing it with the p-values, these parameters are more significant to voltage. Similarly in Table 5, the tool wear rate decreases with boost in current, pulse off time and pulse on time and the p-values also show more significance to voltage. As the surface roughness improved an increase in current and pulse on time is observed in Table 6. When comparing the p-values of this table, these parameters are more significant to voltage and pulse off time. When the wt% of nano particles is increasing in the matrix, the MRR decreases drastically because of the protecting effect of the particle [10]. Also the flushing system improves the machining performance by means of clearing the unwanted materials from the cast specimen.

4.3 S/N Ratio Plot Discussion for MRR, TWR and SR

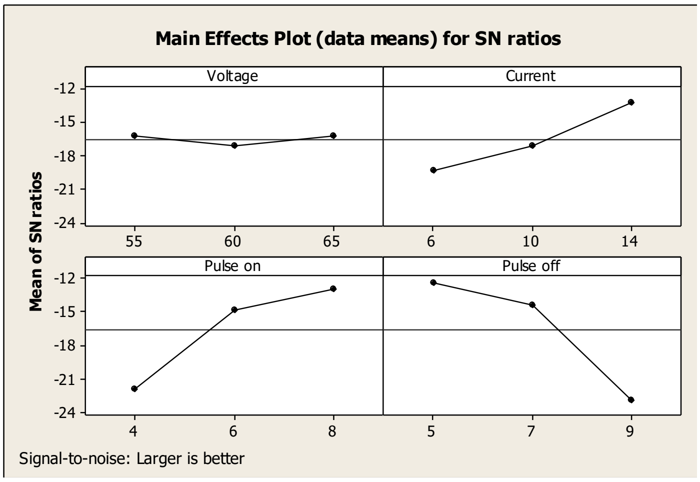

Figure 4 S/N ratio plot for MRR

Figure 4 shows that by rising current and pulse on time, the MRR value is improved. The increase in these two parameters increases the electrical power and hence thermal energy is created in electrical discharge path. This energy is shifted to the work piece resulting in enhance the MRR. No significant changes can be observed in the three levels of voltage. But the MRR value drastically reduced when pulse off time increased. In figure 5 the pulse current, as well as the pulse on time comes close to the most favourable value thereby decreasing the tool wear rate and it can be monitored in the TWR plot for S/N ratio.The current and the pulse on time are the insignificant parameter for TWR. No significant change in three voltage levels was observed. The TWR value enhances as the level of pulse off time also increases.

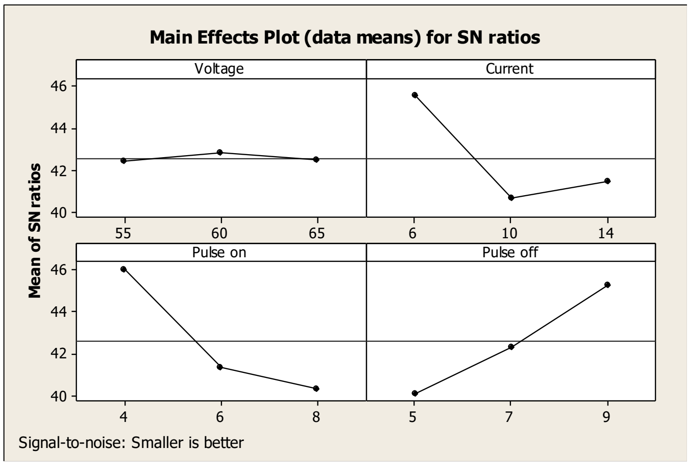

Figure 5 S/N ratio plot for TWR

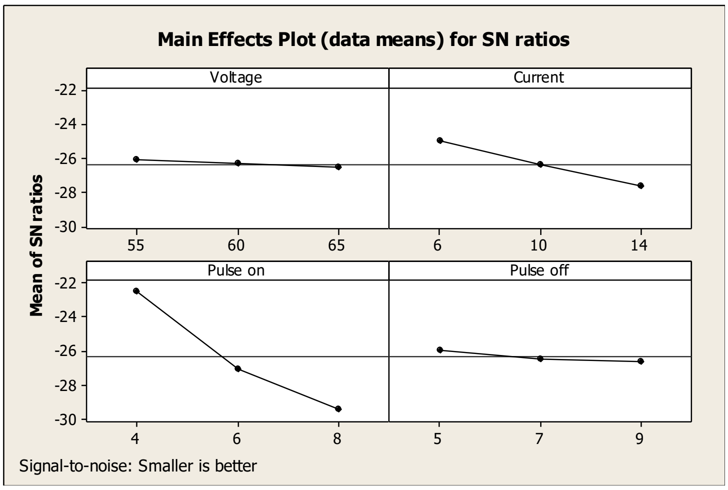

Figure 6 S/N ratio plot for SR

In figure 6, the raise in pulse current and pulse on time, improves the surface irregularity thereby increasing the electrical energy. This guides to enhance in machining duration, flickering energy and radius of plasma path. There is no significant change in increases of voltage and pulse off time in all the levels.

The quadratic equations are discussed for various response variables in MRR, TWR and SR. The curve fit summary exposes the optimized representation, which is considered to evaluate the response variables. The superior reaction optimization model fixes the genuine data, when R^2 approaches unity. It shows the variation between the predicted and the genuine data. It is used when it gives a relatively perfect calculation of all reaction variable averages associated with quantities calculated for the period of the trial. It is performed on the balanced data for the wide variety of experimental designs. It determines the F-ratio, which is related to the mean square of regression mean value and the error. It refers to the result of a factor and the discrepancy due to the mistaken terms.

The calculated F-ratio is greater than the tabulated value, the representation is sufficient at a designed stage. This is the evaluation of machining response as well as in the parameters. These results are used for the progress of an empirical model.

It adapts to both the arithmetic and numerical method that are supported in the modeling as well as the investigation of the problems. The importance is occupied by many variables, and the reason is taken from the best value of the output. The final response equation facilitates to investigate the power of self-governing variables on an exact dependent variable by enumerating the relationship to analyze the calculated values and the contributing factors. The arithmetical optimization model thus improves the linking of the machining responses and their parameters to assist the machining process.

As a result, the obtained arithmetical models are used to correct and to predict the investigation result, and in the intervening time, the trial of lack-of-fit exhibits to be unimportant. The removal processes eradicate the unimportant conditions to regulate the fixed quadratic models as well. During the rearward removal process, the obtained equation gives the ultimate quadratic models of response equations. The predicted and observed values are mentioned in Table 7.

TABLE 7 the Predicted and Observed Values and Its Error of Responses

Parameter	Goal	Predicted Value	Observed Value	% of Error
MRR (g)	Maximum	0.5776	0.611	5.78
EWR (g)	Minimum	0.0104	0.011	5.77
SR(μm)	Minimum	24.88	26.572	6.8

The regression equations for predicting the optimal value is

Material removal rate,

$$MRR = - 0.312 + 0.00292*A + 0.0396*B + 0.0473*C - 0.0466*D \quad (4)$$

Tool wear rate,

$$TWR = 0.00334 + 0.000008*A + 0.000520*B + 0.00136*C - 0.00126*D \quad (5)$$

Surface roughness,

$$SR = - 28.0 + 0.120*A + 4.15*B + 4.33*C + 0.812*D \quad (6)$$

5 GREY RELATIONAL ANALYSIS

Grey Relational Analysis was developed by Deng (1982) to accomplish the necessary mathematical conclusion for unexpected system, also suggest a way of optimizing approach to the multi objective performance characteristics. The GRA gives the required details of the communication among the parameters.

The step by step procedures for conducting GRA are as follows:

a) Estimation of the grey relational generation (GRG) from the response value.
b) Estimation of the grey relational coefficient (GRC).
c) Estimation of the grey relational grade.
d) Evaluation of response table and ANOVA table of the grey relational grade.
e) Examine the optimum level of contribution parameters.
f) Conducting conformation test with optimal parameter level.

5.1 Grey Relational Generation (GRG)

The selected factor and their levels in this experiment are different from each other as shown in the table 2. If the factor levels are dissimilar, the grey relational analysis may give inaccurate results. Therefore, the initial processing of the data is changed to a single value grey relational generation. The data pre-processing procedures are applied to all the response variables and lie in between zero and one.

TABLE 8 Grey Relational Generation 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	0.1632	0.8182	0.9944	15	0.2843	0.0909	0.4923
2	0.1664	0.8182	0.7712	16	0.0000	1.0000	0.9085
3	0.1018	0.9091	0.3786	17	0.9661	0.1818	0.5255
4	0.1454	0.7273	1.0000	18	0.5590	0.0000	0.0180
5	0.1034	0.6364	0.6186	19	0.1632	0.8182	0.9944
6	0.2795	0.0909	0.5322	20	0.0937	0.8182	0.7908
7	0.0081	1.0000	0.9180	21	0.1018	0.9091	0.3786
8	0.6462	0.2727	0.5038	22	0.1551	0.8182	0.9014
9	0.8950	0.2727	0.0413	23	0.1082	0.5455	0.4101
10	0.0792	1.0000	0.9790	24	0.2843	0.0909	0.4923
11	0.0937	0.8182	0.7908	25	0.0000	1.0000	0.9085
12	0.1309	1.0000	0.6298	26	1.0000	0.3636	0.5097
13	0.1422	0.9091	0.8888	27	0.9580	0.3636	0.0000
14	0.1082	0.5455	0.4101				

In GRG "higher is better" for MRR and is expressed as,

$$Xi(\mathrm{k}) = \frac{Yi(\mathrm{k}) - \mathrm{Min}\, Yi\ (\mathrm{k})}{\mathrm{Max}\, Yi\ (\mathrm{k}) - \mathrm{Min}\, Yi\ (\mathrm{k})} \quad (1)$$

"Smaller is better" for surface roughness and TWR is expressed as,

$$Xi(\mathrm{k}) = \frac{\mathrm{Max}\, Yi\ (\mathrm{k}) - Yi(\mathrm{k})}{\mathrm{Max}\, Yi\ (\mathrm{k}) - \mathrm{Min}\, Yi\ (\mathrm{k})} \qquad (2)$$

Where

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

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

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

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

GRG for corresponding sequence gives the value equal to 1.

5.2 *Calculating Grey Relational Coefficient.*

After the completion of data pre-processing, the GR coefficient is calculated to execute the correlation between the experimental results. The MRR is considered as the “higher is better” characteristics while the TWR and SR are considered as the “lower is better” characteristics. So, based on the arithmetic hierarchy process the priority value (ς) is given more to the MRR when compared to the tool wear rate and surface roughness.Thus, the grey relational coefficient can be calculated by

$$\gamma_i(\mathrm{k}) = \frac{\Delta min + \varsigma \Delta max}{\Delta \mathrm{i}(\mathrm{k}) + \varsigma \Delta max} \qquad (3)$$

Where

γ_i(k) = Grey relational coefficient

ς = distinguishing coefficient

Δmax = max Δ_i(k)

Δmin = min Δ_i (k)

$\Delta i(k)$ = | x_0 (k)-x_i (k)|

5.3 *Calculating the Grey Relational Grade*

TABLE 9 Grey Relational Grades for Each Trial 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	0.6265	5	10	0.7622	1	19	0.6265	6
2	0.4887	15	11	0.4895	13	20	0.4895	14
3	0.4569	17	12	0.6043	7	21	0.4569	18
4	0.5974	8	13	0.5951	9	22	0.5494	10
5	0.3844	21	14	0.3340	22	23	0.3340	23
6	0.3269	24	15	0.3210	25	24	0.3210	26
7	0.7068	2	16	0.6998	3	25	0.6998	4
8	0.3927	20	17	0.5067	12	26	0.5396	11
9	0.4268	19	18	0.3107	27	27	0.4641	16

To calculate the grey relational grade by using the following expression

$$\alpha_i = \frac{1}{m} \sum_{k=1}^{m} \gamma_i(\mathrm{k}) \qquad (4)$$

$\alpha_i$is the average grey relational grade for the all the three response values of the individual experiment. ‘m’ is the quantity of response value considered.

The grey relational grade rank given for individual experiments based on the sequences of decremented value of the grey relational grade in OA. Ultimately, the 10^{th} experimentation gives the highest degree grade value among all the experiments conducted and the 18^{th}experiment gives the minimum value as shown in Table 9. Then the different response grade value is converted into a single grade value and ranked by higher value is the best. However, the important part of the multi objective machining parameter is predicted from the optimal response level, which can be concluded clearly.

5.4 *ANOVA Used for Statistical Result Analysis*

The stipulation of analysis of variance (ANOVA) is to find out the significant parameter that excites the output performance characteristics. The entire variation of grey relational grade is calculated by means of the sum of the squared deviation between the mean of the grey relational grade and the grey relational grade of a particular trial. ANOVA of the grey relational grade as shown in table 10 gives the most significant parameter pulse on time with current for highest MRR, lowest TWR and SR. 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. 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.

TABLE 10 ANOVA for Grey Relational Grade

Machining parameters	DF	Sum of squares	Mean Squares	F - Ratio	Contribution %
Pulse on time	2	0.3122	0.156113	44.96	65.40
Current	2	0.0950	0.04749	13.68	19.90

			1		
Pulse off time	2	0.0050	0.002503	0.72	1.05
Voltage	2	0.0027	0.001342	0.39	0.56
Error	18	0.0625	0.003472		13.09
Total	26	0.4774			100.00

For all the individual responses, voltage always behaves as an insignificant parameter. In multi objective optimization, the pulse on time along with current is always the parameters that influence the performance characteristics. The optimum values of input machining parameters are obtained based on the uppermost mean value of GR grade by means of the response table and its graph, which is also discussed in the subsequently section in detail.

5.5 GRA Response Table and Graph

The table 7 indicates the average GR Grade for input parameter levels. The difference between maximum and minimum grade for the individual parameter is calculated and rank is given to the higher value to the lower value.

TABLE 11 the Average GR Grade for Input Parameter Levels

Parameter/ level	Symbol	GR Grade			Max-min	Rank
		Level1	Level2	Level3		
Pulse on	C	0.6515	0.4399	0.4098	0.2417	1
Current	B	0.5557	0.4181	0.5275	0.1376	2
Pulse off	D	0.4915	0.4901	0.5197	0.0296	3
Voltage	A	0.4897	0.5137	0.4979	0.024	4

From the Table 11, the voltage and pulse off time is in the lower level, the grey relational grade is in normal value. When the both parameter levels are increased, no further changes in the grade value takes place. In case of current, the GR grade is higher at lower input level than the grade value decreases and again increases gradually at higher input level. The grey relational grade increases at lower levels of pulse on time than the grade value which decreases gradually in further level of input value. Therefore, the final multi objective optimized parameter in the grey relational analysis is indentified by $A_2B_1C_1D_3$ from the graphical representation of the fig.7.

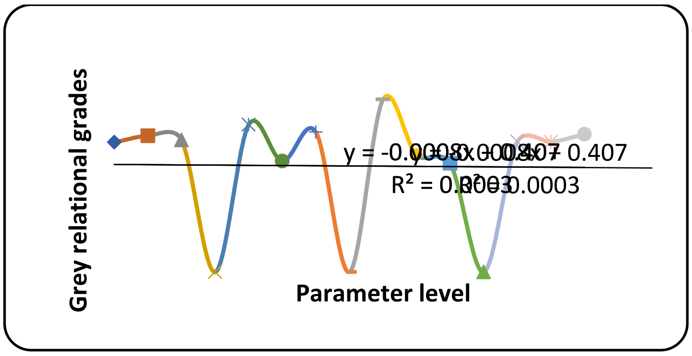

Figure 7 Grey Relational Grade vs. Parameter level graph

5.6 Prediction of Optimum Result

The optimal prediction mean value at the optimum level (μ) is found by the following equation [8].

$$\mu = \overline{A_2} + \overline{B_1} + \overline{C_1} + \overline{D_3} - 3 \cdot \overline{T_{gg}}$$

Where

$\overline{A_2}, \overline{B_1}, \overline{C_1}$ *and* $\overline{D_3}$ are the average grey relational grade values 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, 0.7394.

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

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

$$= \pm 0.1429$$

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.

$$T_{eff} = \frac{\text{Total number of experiments conducted}}{\text{1+No.of degrees of freedom related with items used to caculate the } \mu^{c}}$$

Hence, CI calculates 95% of the expected optimum condition range. μ is the grey relational grade assessment by carrying out the verification test with optimum surrounding levels, which are A_2, B_1, C_1 and D_3.

$$(0.7394 - 0.1429) < \mu_c < (0.7394 + 0.1429)$$

$$0.5965 < \mu_c < 0.8823$$

5.7 Confirmation Test

After manipulating the optimum input parameter level, the confirmation test is used to ensure the improvement in the performance characteristics by comparing the prediction GRG value. Table 12 indicates the difference between the initial and optimal parameter levels. The input parameter level $A_1B_1C_1D_1$ is considered as initial parameter levels, which are mentioned in the experiment number 1 in Table 3. The GRG value for this trial is 0.6265. In the prediction of optimum parameter level setting, the MRR varies from 0.136 g/min to 0.116 g/min, TWR is changed from 0.006g/min to 0.004g/min, and SR changes from 12.005µm to 12.724µm. Thus, the grey relational grade increases from 0.6265 to 0.7563. The progress in grey relational grade in confirmation test is 0.1298. It clearly shows that the multi objective optimization parameter level is $A_2B_1C_1D_3$ machining of Al-Mg-TiO_2 nano composite by die sinking EDM.

Table 12 The difference between the initial and optimal EDM parameters

Output parameters	Initial machining parameter	Optimal machining parameter	
		Prediction	Experimental
Setting level	$A_1B_1C_1D_1$	$A_2B_1C_1D_3$	$A_2B_1C_1D_3$
MRR, g/min	0.136	-	0.116
TWR, g/min	0.006	-	0.004
SR, µm	12.005	-	12.724
Grey relational Grade	0.6265	0.7394	0.7563

Improvement of grey relational grade is 0.1298.

6 CONCLUSIONS

a) The EDM of Al-Mg-TiO_2 metal matrix nanocomposite is successfully carried out, and the single objective optimization of their parameter from regression equation is obtained as follows:

- The difference among the expected values and the investigational values of MRR, TWR and SR is less than 7 % reasonably.
- The best possible parameter of grouping situation for Al-Mg-TiO_2 are voltage 65 V, current 14 A, pulse on time 8 µs along with pulse off time 5 µs for optimum MRR, lower TWR and SR.

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

- Even distribution of TiO_2 nano particles in aluminium matrix is confirmed by SEM image.
- Pulse on time as well as current are the most significant parameters that influence the machining of Al-Mg-TiO_2 nanocomposite material.
- The contribution percentage of pulse on time is 65.40 µm and the current is 19.90 Amps.
- The best suitable performance characteristics are found with the optimum setting of $A_2B_1C_1D_3$.
- 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 to fix the optimum parameter level for better machining performance in EDM of Al-Mg-TiO_2 MMNC.

REFERENCES

[1] S. Gopalakannan, T. Senthilvelan, Application of response surface on machining of Al- SiC nano-composites, Journal of Measurement,2013, https://doi.org/10.1016/2013.04.036.

[2] R. Karunanithi, Supriya Beera, K.S.Ghose, Electrochemical behaviour of TiO_2 reinforced Al 7075 composite, Material Science and Engineering B, 2014, 190, 133-143, https://doi.org/10.1016/j.mseb.2014.06.013.

[3] Mehdi Hourmand, Saeed Farahany, Ahmed A. D. Sarhan, Mohd Yusof Noordin, Investigating the electrical discharge machining (EDM)parameter effects on Al-Mg2Si metal matrix composite (MMC) for high material removal rate (MRR) and less EWR–RSM approach,2014, DOI 10.1007/s00170-014-6491-2.

[4] J.Lan, Y. Yang, X. Li,Microstructure and Microhardness of SiC nanoparticles reinforced Magnesium composites fabricated by ultrasonic method, Journal of Material Science Engineering, 2004, A 386, 284–290, DOI:10.1016/j.msea.2004.07.024.

[5] P. Narendar Singh, K. Raghukandan, M. Rathinasabapathi, B.C. Pai, Electric discharge machining of Al–10% SiCp as-cast metal matrix composites, Journal of Material Processing Technology, 2004, 156–157, 1653–1657,doi.org/10.1016/j.jmatprotec. 2004.04.321.

[6] Jong nyuk jung and won tae kwon, Optimization of EDM Process for multiple performance characteristics using Taguchi method and grey relation analysis, journal of mechanical science and technology, 2010,DOI: 10.1007/s 12206-010-0305-8.

[7] P .S .Kao and H. Hocheng , Optimization of electrochemical polishing of stainless steel by grey relational analysis, journal of material processing technology, 2003, 255-259 DOI : 10.1016 80924 -0136(03) 00747-7.

[8] Ahilan. C, Kumanan. S and Sivakumaran. N, Multi objective optimization of CNC turning process parameter using grey based fuzzy logic, International journal of machining and machinability of materials, 2009, vol. 5No. 4 pp. 434-45.

[9] S Sivakumar and R. Jeyapaul, Application of grey entropy and regression analysis for modelling and prediction on tool materials performance during EDM of hot pressed ZrB_2 at different duty cycles, Procedia Engineering, 2012, 38,3977-3991, DOI : 10.1016 /J.proeng:/2012 .06.455.

[10] M Ravichandran, A Naveen Sait and V Anandakrishnan, Synthesis and forming characteristics of Al–TiO_2 powder

metallurgy composites during cold upsetting under plane stress state conditions, Journal of Sandwich Structures and Materials 1–17 2015 DOI: 10.1177/1099636214565762.

[11] B.P Mishra and B C Routara, An experimental investigation and optimization of performance characteristics in EDM of EN -24 alloy steel using Taguchi method and Grey Relational analysis materials today proceedings, 2017, volume 4, issue 8 pages 7438-7447.

[12] Mohammadreza Shabgard, Hamed Kakolvand, Mirsadegh Seyedzavvar, Ramin Mohammadpour Shotorbani, Ultrasonic assisted EDM: Effect of the work piece vibration in the machining characteristics of FW4 Welded Metal. Frontiers of Mechanical Engineering, 2011, 6: 419. https://doi.org/10.1007/s11465-011-0246-7.

[13] S.Roseline, V.Paramasivam, S.Jayabal, Evaluation of Structure and Mechanical Properties of Zirconia Reinforced Aluminium Matrix Composites, Journal of Computational and Theoretical Nano science,2018,Vol. 15, 1–9, doi:10.1166/jctn.2018.7162.

[14] Yang Y, Lan J, Li X, Study of bulk aluminium matrix nano-composite fabricated by ultrasonic dispersion of nano-sized SiC particles in molten aluminium alloy, Material Science and Engineering, 2004, A 380 , 378–383, DOI:10.1016/j.msea.2004.03.073.

[15] Yan-cherng Lin, chao-hsu cheng, Bo-lin su and Lih-ren hwang**,** Machining characterstics and Optimization of machining Parameters of SKH 57 high speed steel using electrical discharge machining based on Taguchi method, Materials and Manufacturing Processes, 2006, 21:922-929, DOI: 10.1080/03602550600728133.

[16] K.K. Alaneme, B.O. Ademilua, M.O. Bodunrin. Mechanical properties and corrosion behaviour of aluminium hybrid composites reinforced with silicon carbide and bamboo leaf ash. Tribol Ind, 35 (1) (2013), pp. 25-35.

[17] D.S. Prasad, C. Shoba, N. Ramanaiah, Investigations on mechanical properties of aluminum hybrid composites, J Mater Res Technol, 3 (1) (2014), pp. 79-85.

[18] K.K. Alaneme, T.M. Adewale. Influence of rice husk ash – silicon carbide weight ratios on the mechanical behavior of Al-MgSi alloy matrix hybrid composites. Tribol Ind, 35(2) (2013), pp. 163-172.