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MULTI-ATTRIBUTE OPTIMIZATION OF EDM PROCESS PARAMETERS OF AL-2050 ALLOY USING TAGUCHI BASED TOPSIS AND GRA WITH DIFFERENT ROTATING TOOLS

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Abstract: The present work investigates the optimization of process parameters of EDM for Al-2050 with different rotating tool electrodes (Cu, W & Cu-W alloy). Taguchi design of experiments linked with TOPSIS and GRA for prediction of optimizing output parameters has been developed. Five independent input parameters namely tool type, tool rotational speed, discharge current, pulse on time and pulse off time have been chosen as input variables to establish their influence on the output parameters such as MRR, TWR and Depth. Using MINITAB software, ANOVA has been determined to find the most significant parameters at a 95% confidence level. Estimated results are validated by the confirmatory test and it is found that improvement in the preference values are 0.880068 and 0.262154 using TOPSIS and GRA respectively with tool rotation. But the improvements in the preference values are 0.439190 and 0.115099 using TOPSIS and GRA respectively without tool rotation.

Key words: Al-2050 alloy, Taguchi method, Multi-attribute optimization, TOPSIS, GRA

1. INTRODUCTION

For machining newly developed high strength alloys with high degree of dimensional accuracy and lower cost of production, EDM (electrical discharge machining) is a very successful, practical and profitable non-conventional machining process as compared to conventional machining. These materials are generally useful for many commercial and industrial applications like aircraft, automotive, aerospace, tool and die making, medical & surgical equipment etc. where high strength, hardness, high wear resistance and thermal stability are essential. We have selected the third generation Al-alloy (Al-2050) for machining, which finds wide applications in aerospace industry. EDM is broadly used in producing complex dies, tools and other components of hard and electrically conductive materials. EDM is very useful for Al-2050 alloy because it is Li-based complex hard alloy, which is electrically conductive. A considerable study has been carried out in the context of EDM of advanced materials and optimization of the process parameters of EDM by various optimization techniques. But relatively less investigation has been conducted in the area of EDM machining and drilling of Al-2050 alloys. Soni [1] studied on formation of debris during rotary EDM of Ti-alloy and high carbon high chromium die steel with tool rotational speed of 0, 500, 700 & 1000 rpm. It is found out that EDM can be effectively used for production of debris powder of various composition, sizes and desired properties. Yan and Wang [2] analysed the machining characteristics of Al2O3/6061Al composite using rotary EDM with a tube electrode. From this analysis, it is found out that the constant cutting feed rate is independent of the depth of the workpiece and the rotating speed & flushing pressure of the electrode have minor effects on the material removal rate (MRR), electrode wear rate (EWR), and surface roughness (SR). Mohan et al. [3] investigated the effect of EDM parameters (polarity, current, electrode material, pulse duration & rotation of electrode (270 & 750 rpm)) on MRR, tool wear rate (TWR), and surface roughness of metal matrix composite Al-SiC with 20 and 25 vol. % SiC. Chattopadhyay et al. [4] analysed the machining characteristics of EN-8 steel with copper as a tool electrode and rotational speed of 18, 32 & 48 rpm during rotary EDM process. Experimental results further revealed that maximizing the MRR while minimizing EWR and improving the surface roughness, cannot be achieved simultaneously at a particular combination of control parameters setting. Dwivedi & Choudhury [5] investigated the effect of tool rotation (0 & 1000 rpm) on AISI D3 steel during EDM. It shows that tool rotation significantly improves the MRR and surface finish by 41% & 12% respectively. Gohil & Puri [6] presented an experimental investigation of Electric Discharge Turning on Titanium alloy (Ti-6Al-4V) using Taguchi-Grey Relational Approach. In this analysis, surface roughness is improved by 2.23 times due to rotation of tool (40 to 60 rpm and 60 to 120 rpm). Kachhap et al. [7] found that MRR is improved with hollow brass tool electrode & TWR is reduced with solid copper electrode during electric discharge drilling with tool rotation 600 rpm. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Grey relational analysis (GRA) are generally used for optimization of tools for dispute, multi input and discrete data problems. TOPSIS has been adopted by many researchers for optimization of process parameters of different manufacturing processes like laser drilling [8], computer integrated manufacturing technology [9], robust design [10], forging [11], EDM [12-14, 40, 41, 43, 46] etc. Kumar & Mondal [11] used Fuzzy-TOPSIS to select the forging problems and estimate all influencing parameters by considering various criteria. These criteria are extremely responsible for different types of forging problems. Dewangan et al. [12] used fuzzy-TOPSIS based multi-criteria decision making (MCDM) to study surface integrity and dimensional accuracy. Satpathy et al. [13] and Bhuyan et al. [14] utilized the TOPSIS to optimize the process parameters. GRA has been used by many researchers for optimization of different manufacturing processes like drilling [15], end milling [16], turning [17], MIG welding [18], TIG welding [19], forging [20] and EDM [21-28, 38, 41, 44, 45]. Purohit et al. [21] reported the optimization of process parameters like MRR, EWR and over cut during EDM of M2 tool steel using GRA based on an L9 orthogonal array based Taguchi method. Selvarajan et al. [22] investigated the optimization of process parameters like MRR, TWR, wear ratio (WR), SR etc. of EDM for Si3N4-TiN conducting ceramic composite with Cu-electrode using GRA based on Taguchi L25 orthogonal array to improve form and orientation tolerance. Different advanced materials have been chosen for machining and optimization of machining parameters but no such work on EDM and optimization using GRA and TOPSIS for Al-2050 alloys is reported in the literature.

In this paper, we have optimized the process parameters of EDM for Al-2050 alloy using two decision making techniques, TOPSIS & GRA with different rotating tools. We have attempted to determine the best likely group of process variables using decision making optimization techniques such as TOPSIS & GRA. Through these, we have tried to obtain material removal rate (MRR) & Depth as maximum and tool wear rate (TWR) as minimum. In machining, MMR and TWR are the two important parameters commonly considered in optimization study but in case of drilling, depth is also become very important as it shows how much hole is cut in the fixed machining time. So depth is also considered as output parameter taking drilling as a possible application area along with machining. Five parameters namely tool type, tool rotational speed, discharge current, pulse on time and pulse off time are chosen as input variables. GRA and TOPSIS have been chosen as optimization tools as these are capable of solving any complex and multi-criteria decision making problem in a very simple way by converting it into a single objective problem. Most of the studies on EDM are done for the tool rotation less than 1000 rpm in the literature [1, 3-7]. In this paper, we have used the higher tool rotation that is up to 1600 rpm starting with 900 rpm. This will increase the production rate as less time will be required to complete the process. No work has been reported on the combined effect of tool rotation and optimization which is very important to enhance the efficiency of the process. By the application of ANOVA (Analysis of variance), the most affecting output feedback input parameters are identified, which are statistically significant. In addition, improvement in their preference values by comparison between two optimization techniques (TOPSIS & GRA) has also been done. The result is compared with the result of EDM process without tool rotation and found that the output parameters are improving significantly.

The remainder of this paper is organized as follows. In section 2, experimentation and methodology, factors and levels are outlined. The techniques used in the present paper are also discussed. In section 3, results based on different optimization techniques are presented. Concluding remarks are made in section 4.

2. EXPERIMENTATION AND METHODOLOGY

2.1 Experimentation

Experiments have been carried out on EDM (die-sinking type) machine, Model expert 1, equipped with servo head and electrode having positive polarity. A rotary set up was designed & fabricated to provide the rotation to the tool at different speed. Experimental set up is shown in Figure 1. Following important parts of this experimental set-up like supporting Al-plate (270x270x6 mm^3), motor [0.5 KW, 8500 rpm (AC/DC 0.5 A)], shaft (allow motion), belt (V-type), tool holder (self-centering, three jaw chuck, holding 1 to 13 mm drill bit), auto regulator or Varic (speed of tool controlled) are used. Some of the components of the experimental set up are shown in Figure 2.

In this experiment, EDM oil (commercial grade) has been used as dielectric fluid. Its freezing point is 940°C and specific gravity is 0.763. Its working pressure is 0.3 kg/cm^2. Machining parameters used in the experiments with dielectric fluid & fluid flushing are as following: sparking voltage - 50V; servo system – electrohydraulic; polarity - reverse polarity; electrode tool polarity - positive; workpiece polarity - negative.

2.1.1 Workpiece Material

In the present work, we have selected the third generation Al-alloy (Al-2050) for machining purpose because this alloy has not been considered for optimization of EDM process parameters so far in the literature with best of our knowledge. Al-2050 alloy is very useful in aerospace industry. This alloy is specially designed for structural components subjected to high fatigue stress and risk of corrosion. Processing Al-2050 are generally done by milling and drilling. But these techniques have limitations on design specifications.

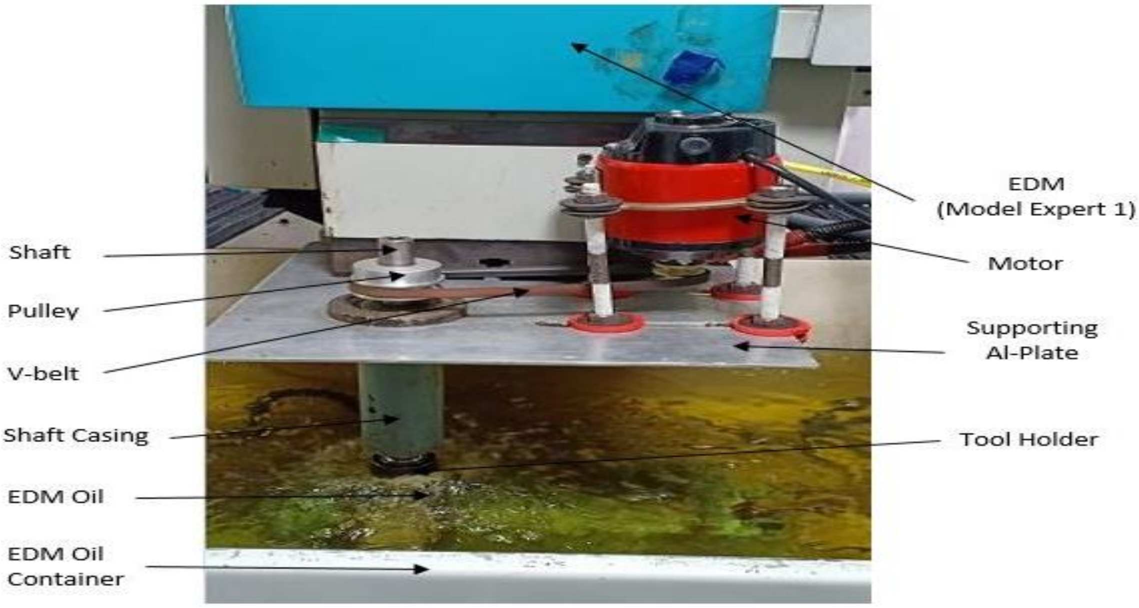

Fig. 1. Experimental Set up

(a) (b) (c) (d)

Fig. 2. Components of experimental set up (a) Drill chuck (b) Bearing fixed with Al-plate (c) Motor fixed with Al-plate attached with pulley system (d) Complete experimental set up

For very small size operation, these techniques can't be used. EDM is very useful for such purpose. Optimization of EDM process parameters for Al-2050 is essential to reduce the cost of machining. Al-2050 alloys chemical composition is presented in Table 1. Workpiece specimen of surface (90×45 mm^2) and thickness (15 mm) used in experiments (before and after) is shown in Figure 3.

Table 1. Workpiece material % by mass chemical composition

Element	Al	Si	Mn	Mg	Cu
Mass %	95.9045	0.1079	0.3788	0.5278	2.3436
Element	V	Zr	Ti	Fe	Li
Mass %	0.0457	0.0733	0.0915	0.4693	0.0576

2.1.2 Electrode (Tool) Material

In EDM, tool materials are selected on the basis of discharge erosion, electrode loss, machining speed, machining accuracy and machining stability. Also we have selected the tool material on the basis of tool rotational speed. In this work, we have chosen copper (Cu), tungsten (W) & Copper-Tungsten (Cu-W) alloy as the tool material. Copper has high corrosion resistance due to its high heat conductivity and heat transfer coefficient. Therefore, the electrode of red copper is often used as the electrode material for the processing of small and medium cavity die parts, and it has less tool wear. Copper-Tungsten provides high strength and hardness, good electrical conductivity and thermal conductivity, low thermal expansion coefficient, good arc resistance, high-temperature oxidation resistance and resistance to fusion welding. Tungsten has very high strength, density, hardness and high melting point nearly 3400°C. It is also good wear resistance and relatively low tool wear rate. Tool (Cu, W & Cu-W) is cylindrical shape having diameter 10 mm & Brinell hardness is 134 (Cu), 294 (W) & 223 (Cu-W). Tools used in experiments (before and after) are shown in Figure 4.

(a) (b)

Fig. 3. Workpiece: (a) Before machining; (b) After machining

(a) (b)

Fig. 4. Tool: (a) Before machining; (b) After machining

2.1.3 Design of experiment

Taguchi Technique [29-37, 39, 42, 45] has been applied to find the optimal setting of parameters on the EDM performance. Taguchi method is generally used to reduce the number of experiments to reach the optimum state. The five input parameters selected are tool (T), tool rotational speed (TRS), discharge current (DC), pulse on time (T_{on}) and pulse off time (T_{off}) varying at three levels. Factors (process parameters) and corresponding levels are shown in Table 2. The influence of process parameters (eg. –T, TRS, DC, T_{on} and T_{off}) on machining characteristics has been examined. Taguchi's orthogonal array L27 is used in performing the experiments using a number of factors & their levels which is shown in Table 3. Taguchi's technique normalizes the functions by using means. Dependent parameters (MRR & TWR) are measured with the help of following equations and Depth is measured by depth gauge in mm.

MRR equation:

$$MRR\left(mm^3/\min\right) = \frac{W_i - W_f}{T * \delta} * 1000 \qquad (1)$$

Where: W_i = Initial volume of the Material
W_f = Final volume of the Material
T = Machining Time
δ = Density of the Material

TWR equation:

$$TWR\left(mm^3/\min\right) = \frac{T_i - T_f}{T * \delta} * 1000 \qquad (2)$$

Where: T_i = Initial volume of the Material
T_f = Final volume of the Material
T = Machining Time
δ = Density of the Material

Table 2. Process factors and corresponding levels

Factors	Unit	Symbol	Level 1	Level 2	Level 3
Tool	-	T	Cu	W	Cu-W
Tool Rotational Speed	rpm	TRS	900	1200	1600
Discharge Current	A	DC	10	15	20
Pulse on Time	µs	T_{on}	150	300	500
Pulse off Time	µs	T_{off}	8	16	24

Table 3. Orthogonal L27 experimental procedure design with output variable

Run	T	TRS	DC	T_{on}	T_{off}	MRR	TWR	Depth
1	Cu	900	10	150	8	0.058	0.004	1.284
2	Cu	900	10	150	16	0.104	0.004	2.068
3	Cu	900	10	150	24	0.122	0.006	2.324
4	Cu	1200	15	300	8	0.118	0.006	2.585
5	Cu	1200	15	300	16	0.174	0.008	3.480
6	Cu	1200	15	300	24	0.228	0.010	4.458
7	Cu	1600	20	500	8	0.184	0.012	3.333
8	Cu	1600	20	500	16	0.284	0.014	5.339
9	Cu	1600	20	500	24	0.293	0.018	5.401
10	W	900	15	500	8	0.124	0.004	2.009
11	W	900	15	500	16	0.192	0.002	3.668
12	W	900	15	500	24	0.194	0.004	3.767
13	W	1200	20	150	8	0.148	0.004	3.011
14	W	1200	20	150	16	0.170	0.006	3.149
15	W	1200	20	150	24	0.200	0.006	3.503
16	W	1600	10	300	8	0.032	0.004	0.653
17	W	1600	10	300	16	0.052	0.004	1.097
18	W	1600	10	300	24	0.068	0.008	1.267
19	Cu-W	900	20	300	8	0.204	0.008	4.137
20	Cu-W	900	20	300	16	0.196	0.008	4.028
21	Cu-W	900	20	300	24	0.160	0.014	3.938
22	Cu-W	1200	10	500	8	0.078	0.002	1.695
23	Cu-W	1200	10	500	16	0.120	0.002	2.013
24	Cu-W	1200	10	500	24	0.138	0.004	2.764
25	Cu-W	1600	15	150	8	0.144	0.008	4.026
26	Cu-W	1600	15	150	16	0.158	0.006	4.679
27	Cu-W	1600	15	150	24	0.172	0.012	5.013

2.2 Multi-objective optimization techniques

2.2.1. TOPSIS

The most useful alternative is determined from a fixed set of data by the utilization of TOPSIS. The principle of the technique is that the selected criteria should be nearest from positive best solution and farthest from negative best solution, the finest solution being the one having the most relative closeness to the ideal solution [41]. There are following steps involved in TOPSIS as stated below:

1) The first step of TOPSIS is to create decision matrix ('n' attributes and 'm' alternatives), expressed as:

$$D_m = \begin{bmatrix} X_{11} & X_{12} & X_{13} & \dots & \dots & X_{1n} \\ X_{21} & X_{22} & X_{23} & \dots & \dots & X_{2n} \\ X_{31} & X_{32} & X_{33} & \dots & \dots & X_{3n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ X_{m1} & X_{m2} & X_{m3} & \dots & \dots & X_{mn} \end{bmatrix} \quad (3)$$

where, X_{ij} = accomplishment of i^{th} alternative w.r.t j^{th} attribute.

2) Utilizing the following relation, normalized matrix is determined as

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (4)$$

3) Let W_j (j=1, 2…, n) be the weight per attribute. The decision matrix of weighted normalized V= [V_{ij}] is calculated as

$$V = W_j \, r_{ij} \quad (5)$$

where,

$$\sum_{j=1}^{n} W_j = 1.$$

4) Positive ideal & negative ideal solutions are determined as

$$V^+ = \left\{ \sum_i^{\max} \left(V_{ij} \middle| j \in J \right), \left(\sum_i^{min} \middle| j \in J \middle| i = 1,2,\dots,\dots,m \right) \right\} = \left\{ V_1^+, V_2^+, V_3^+, \dots, V_n^+ \right\} \quad (6)$$

$$V^- = \left\{ \sum_i^{\min} \left(V_{ij} \middle| j \in J \right), \left(\sum_i^{max} \middle| j \in J \middle| i = 1,2,\dots,\dots,m \right) \right\} = \left\{ V_1^-, V_2^-, V_3^-, \dots, V_n^- \right\} \quad (7)$$

5) The separations among alternatives from the ideal positive & ideal negative solutions are calculated as

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{\ +})^2} \quad \text{i=1, 2 … m} \quad (8)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^{\ -})^2} \quad \text{i=1, 2 … m} \quad (9)$$

6) The distinct alternative relative nearness to the ideal solution is evaluated as

$$P_i = S_i^- / (S_i^+ + S_i^-) \quad i = 1, 2\dots m \quad (10)$$

7) The most preferred & the least preferred solution of set of alternatives are arranged in decreasing order of P_i values.

2.2.2 Grey relational technique

It is important to follow optimal combination of process parameters utilizing minimum resources to obtain the required output. For a particular response, the optimal parameter setting can have adverse effect on other responses. Hence, developing a multi-objective optimization technique to acquire an optimal parameter setting is very much important. In GRA, the measured quality characteristic experimental values are assigned within zero to one. These assigned values within a range can be recognized as "grey relational generation", followed by computation of grey relational coefficient (GRC). The estimation of the grey relational grade (GRG) decides overall performance characteristic and transformation of multi-objective optimization to single objective problem [41]. The highest GRG is assigned as optimal parametric setting. For grey relational generation, the Material removal rate (MRR) results to "higher the better" principle that is specified as:

$$X_i(k) = (y_i(k) - \min y_i(k)) / (\max y_i(k) - \min y_i(k)) \quad (11)$$

EWR and SR consequent to "lower the better" condition that is specified as:

$$X_i(k) = (\max y_i(k) - y_i(k)) / (\max y_i(k) - \min y_i(k)) \quad (12)$$

where: $X_i(k)$ =grey relational generation
max $y_i(k)$ = highest value for the k^{th} response
min $y_i(k)$ = least value for the k^{th} response
with k = 1,2,3,4 (various output response)

GRGs after normalization are shown in Table 8. GRC is evaluated to provide a relationship between the finest data and the fixed assigned data. The GRC is formulated as:

$$\xi_i(k) = (\Delta_{\min} + \psi\,\Delta_{\max}) / (\Delta_{0i}(k) + \psi\,\Delta_{\max}) \quad (13)$$

where $\Delta_{0i}(k) = |X_0(k) - X_i(k)|$, ψ is the distinctive coefficient ranging between $0 \le \psi \le 1$, Δ_{min} is the minimum value for Δ_{0i} and Δ_{max} is the maximum value for Δ_{0i}.

The GRG is expressed as:

$$\alpha_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \quad (14)$$

where n = number of output responses.

Arrangement of parameters closer to the optimum solution depends on the higher value of GRG.

3. RESULTS AND DISCUSSION

3.1 Material removal rate

The focus behind machining was to get higher material removal and minimum tool wear. The material of tool in machining have been picked on the basis of low electrical resistance & high melting point. Improvement in MRR for initial set level with rotary tool in comparison to stationary tool is nearly 2.23 times for both the techniques (TOPSIS & GRA). Also improvement in MRR for optimal set level with rotary tool in comparison to stationary tool is nearly 2.4 times & 1.775 times using TOPSIS & GRA respectively. MRR for initial & optimal set level with rotary and stationary tool are shown in Table 4. Figure 5 represents the effect of MRR with T, TRS, DC, T_{on} and T_{off}.

Table 4. MRR for initial & optimal set level with rotary and stationary tool

Techniques	Initial set level		Optimal set level	
	MRR with rotary tool	MRR with stationary tool	MRR with rotary tool	MRR with stationary tool
TOPSIS	0.058	0.026	0.293	0.122
GRA	0.058	0.026	0.284	0.160

Fig. 5. MRR variation with T, TRS, DC, T_{on} and T_{off}

From Figure 5, the highest MRR is for Cu tool in comparison to other tools (like W & Cu-W). It also shows that MRR slightly increases with the increase the TRS from 900 to 1600 rpm. MRR increases with increase in discharge current (DC) from 10 to 20 A due to increment in DC results in increased heat density within the spark gap. It also shows that MRR first decreases with the increase of T_{on} from 150 µs to 300 µs and then increases from 300 µs to 500 µs because T_{on} enables dielectric fluid to expel particles that are eroded in light of the fact that the work surface is cooled by the pressurized dielectric and disintegrated particles are flushed out once the sparking procedure is culminated. While MRR increases as T_{off} changes from 8µs to 24µs because of bigger crater formation that is resultant of the converted maximum spark energy into heat energy.

3.2 Tool wear rate

The ideal tool should have maximum MRR and minimum self-erosion. The tool electrode wear depends on both melting point and thermal conductivity of the tool electrode material. The tool electrode wear can be minimized if the temperature at the inter-electrode gap is controlled. For initial set level, TWR with rotary & stationary tool is equal for both TOPSIS & GRA. For optimal set level, TWR with rotary tool in comparison to stationary tool is increased by 2.25 times & 1.75 times using TOPSIS & GRA respectively. TWR for initial & optimal set level with rotary and stationary tool are shown in Table 5. Figure 6 shows the main effect for tool wear rate (TWR) with T, TRS, DC, T_{on} and T_{off}.

From Figure 6, TWR first decreases as the tool changes from Cu to W and then increases from W to Cu-W. It also shows that TWR first decreases with the increase the TRS from 900 to 1200 rpm then increases from 1200 to 1600 rpm. TWR increases with increase in discharge current (DC) from 10 to 20 A. It also shows that TWR first increases with the increase of T_{on} from 150 µs to 300 µs and then decreases from 300 µs to 500 µs. While TWR increases as T_{off} changes from 8 µs to 24 µs because of bigger crater formation that is resultant of the converted maximum spark energy into heat energy.

Table 5. TWR for initial & optimal set level with rotary and stationary tool

Techniques	Initial set level		Optimal set level	
	TWR with rotary tool	TWR with stationary tool	TWR with rotary tool	TWR with stationary tool
TOPSIS	0.004	0.004	0.018	0.008
GRA	0.004	0.004	0.014	0.008

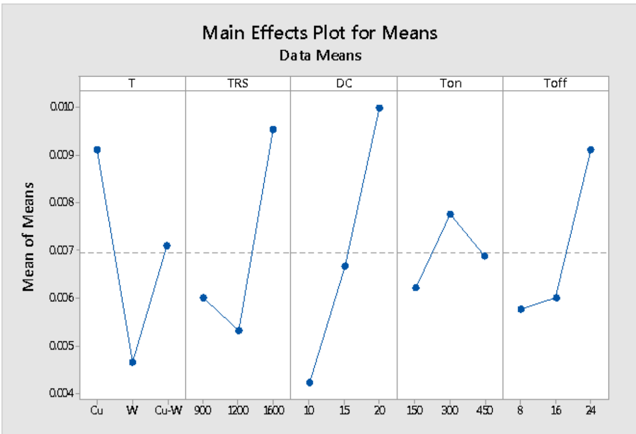

Fig. 6. TWR variation with T, TRS, DC, T_{on} and T_{off}

3.3 Depth

In EDM, the material removal rate directly affects the depth. For drilling, it becomes more important as it is the main purpose of the process. Improvement in depth for initial set level with rotary tool in comparison to stationary tool is nearly 2.04 times for both the techniques (TOPSIS & GRA). Also improvement in depth for optimal set level with rotary tool in comparison to stationary tool is nearly 2.08 times & 1.656 times for TOPSIS & GRA respectively. Depth for initial & optimal set level with rotary and stationary tool are shown in Table 6. Figure 7 shows the variation of depth with respect to T, TRS, DC, T_{on} & T_{off}.

Table 6. Depth for initial & optimal set level with rotary and stationary tool

Techniques	Initial set level		Optimal set level	
	Depth with rotary tool	Depth with stationary tool	Depth with rotary tool	Depth with stationary tool
TOPSIS	1.284	0.628	5.401	2.587
GRA	1.284	0.628	5.339	3.224

From Figure 7, Depth first decreases as the tool changes from Cu to W and then increases from W to Cu-W. It also shows that depth first slightly decreases with the increase of TRS from 900 to 1200 rpm then increases from 1200 to1600 rpm. Depth increases with increase in discharge current (DC) from 10 to 20 A. It also shows that Depth first decreases with the increase of T_{on} from 150 µs to 300 µs and then increases from 300 µs to 500 µs. While Depth increases as T_{off} changes from 8 µs to 24 µs because of bigger crater formation that is resultant of the converted maximum spark energy into heat energy.

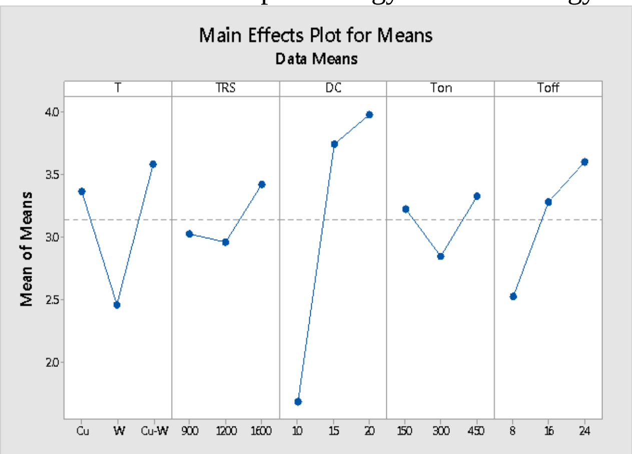

Fig. 7. Depth variation with T, TRS, DC, T_{on} and T_{off}

3.4 TOPSIS

Using TOPSIS, optimization of machining characteristics (MRR, TWR & Depth) in EDM was performed. Using equations (3)-(9), preference value for each experimental set was calculated. Using equation (10), each alternative preference value is calculated observing the relative nearness to the optimum solution that is evaluated. Under ideal conditions, consideration of all performance parameters is equally important when machining is done so equal weightage is appointed to all output reactions. Utilizing Taguchi's design combined with TOPSIS, multi-objective optimization is thus transformed into single objective optimization. The preference values of each experimental run are determined by TOPSIS method and their corresponding rank orders are presented in Table 7. The ideal solution of the optimal performance is identified by the maximum preference value as it represents relative nearness to ideal solution. In this manner, the performance is measured based on highest rank that is assigned the best value.

Table 7. Estimated preference values with corresponding rank orders

Experiment no.	Preference value	Rank order
1	0.119912	25
2	0.220704	22
3	0.304058	18
4	0.313500	17
5	0.477252	9
6	0.633569	5
7	0.598006	6
8	0.835388	2
9	0.999998	1
10	0.244506	21
11	0.380044	15
12	0.417731	13
13	0.329407	16
14	0.404440	14
15	0.454711	12
16	0.083349	27
17	0.105240	26
18	0.265326	20
19	0.538651	7
20	0.525953	8
21	0.650950	4
22	0.136705	24
23	0.213191	23
24	0.303824	19
25	0.471020	10
26	0.465635	11
27	0.652739	3

It can be found that experimental run #9 (highest preference order) is the most suitable set followed by runs #8 and #27. But in orthogonal experimental design, separation effect of different parameters at distinct levels gets feasible. With the higher values of reaction of preference solution, best parametric combination is decided. The response preference solutions at every level of input parameters are evaluated after estimating the mean of preference solution for the specific set of levels from the result experimentally attained. For all the levels, responses for preference solution are obtained in the same way as presented in Table 8. By considering the higher values of reaction of preference order, optimal parametric combination is decided. The parameter set

T_1, TRS_3, DC_3, T_{on3} & T_{off3} is the optimal combination.

Table 8. Response for preference solution

Level	Tool	TRS	DC	T_{on}	T_{off}
1	0.5003	0.3781	0.1947	0.3803	0.3150
2	0.2983	0.3630	0.4507	0.3993	0.4031
3	0.4399	0.4974	0.5931	0.4588	0.5203
Delta	0.2020	0.1345	0.3984	0.0785	0.2053
Rank	3	4	1	5	2

3.4.1 ANOVA for TOPSIS

Using ANOVA, the performance attribute can be evaluated by the considerable effect of process variables. Preference solution obtained from ANOVA is represented in Table 9 at 95% confidence level. Utilizing MINITAB, the results of factor reactions are recognized by applying 'higher-the-better' assumption. From Table 10, it can be observed that T, TRS, DC, T_{on} & T_{off} are important parameters having role in the development of preference solution of T, TRS, DC, T_{on} & T_{off} as presented in Table 8.

Table 9. ANOVA for preference solution

Source	DF	Adj SS	Adj MS	F-value	P- value
T	2	0.19342	0.096709	31.33	0.000
TRS	2	0.09766	0.048828	15.82	0.000
DC	2	0.73344	0.366719	118.80	< 0.001
T_{on}	2	0.03021	0.015105	4.90	0.022
T_{off}	2	0.19097	0.095485	30.93	0.000
Error	16	0.04939	0.003087		
Total	26	1.29508			

Table 10. Confirmatory experiment findings

Initial factor setting		Optimal set (Experimental)
Level	$T_1TRS_1DC_1T_{on1}T_{off1}$	$T_1TRS_3DC_3T_{on3}T_{off3}$
T	Cu	Cu
TRS (rpm)	900	1600
DC (A)	10	20
T_{on} (μs)	150	500
T_{off} (μs)	8	24
MRR (mm^3/min)	0.058	0.293
TWR (mm^3/min)	0.004	0.018
Depth (mm)	1.284	5.401
Value for preferred solution	0.119912	0.999998
Enhancement in preference value for ideal solution = 0.880068		

3.4.2 TOPSIS confirmatory experiment

Once the optimal parameter setting is assessed then forecast and validation for the development of quality characteristic using the most appropriate set of process variables is performed. In table 10, TOPSIS signifies that increase in MRR, Depth and TWR in optimal setting are obtained. In this way, productivity & quality characteristic are improved. For ideal solution, the enhancement in preference value by TOPSIS is 0.880068.

3.5 Grey relational analysis

For the different output parameters, the experimental results obtained as shown in Table 3 were first normalized using equations (11) and (12). Using equation (13), Grey relational coefficient (GRC) for each output response was calculated, and used to estimate the grey relational grade (GRG) with the help of equation (14). In ideal conditions, considering equal weightage for all performance characteristics, the GRG is used to represent the overall performance of machining process characteristics. By using GRC, the value of GRG was evaluated for each run and presented in Table 11. A multi-criteria optimization problem becomes a single objective optimization problem combining Taguchi design and GRA. Optimum or relative result to the optimum sequence of input parameters depends upon the higher value of GRG.

Table 11. GRC estimation for performance features (ψ=0.5) and GRG with rank order

Run	MRR	TWR	Depth	GRG	Order
1	0.357045	0.800000	0.365737	0.507087	23
2	0.408451	0.800000	0.415980	0.540936	19
3	0.432836	0.666667	0.435516	0.511161	21
4	0.427169	0.666667	0.457418	0.516567	20
5	0.523046	0.571429	0.552736	0.548521	18
6	0.667519	0.500000	0.715707	0.627114	6
7	0.544885	0.444444	0.534444	0.507417	22
8	0.935484	0.400000	0.974548	0.769241	2
9	1.000000	0.333333	1.00000	0.777000	1
10	0.435726	0.800000	0.411724	0.548601	17
11	0.563715	1.000000	0.578037	0.713204	3
12	0.568627	0.800000	0.592315	0.652994	4
13	0.473684	0.800000	0.498321	0.590078	12
14	0.514793	0.666667	0.513186	0.564317	15
15	0.583893	0.666667	0.555712	0.601488	10
16	0.333333	0.800000	0.333333	0.488400	26
17	0.351279	0.800000	0.355496	0.501756	25
18	0.367089	0.571429	0.364782	0.433999	27
19	0.594533	0.571429	0.652556	0.605566	9
20	0.573626	0.571429	0.633574	0.592283	11
21	0.495256	0.400000	0.618713	0.504152	24
22	0.377713	1.000000	0.390461	0.588802	13
23	0.429984	1.000000	0.412010	0.613384	7
24	0.457093	0.800000	0.473758	0.576373	14
25	0.466905	0.571429	0.633236	0.556633	16
26	0.491525	0.666667	0.766796	0.641021	5
27	0.518887	0.444444	0.859522	0.607010	8

It is found that experimental run #9 is having the highest GRG that is the most appropriate set of performance attribute, followed by runs #8 and #11. With orthogonal L27 experimental procedure design, it is convenient to distinguish the effect of different parameter at different level. On the basis of higher value of GRG, optimal parametric set is decided. With the acquired experimental results, the mean GRG is driven from estimation of the mean of GRG at the specific setting of levels at each level of input parameters. Mean GRG can be obtained in identical way as presented in Table 12 at all the levels. Total mean GRG is obtained from the mean of all the GRG (shown in Table 11) whose value is 0.5809.

Table 12. Estimation of mean GRG

Factor	Grey Relational Grade			
	Level 1	Level 2	Level 3	Delta
T	0.5894	0.5661	0.5872	0.0234
TRS	0.5751	0.5807	0.5869	0.0118
DC	0.5291	0.6013	0.6124	0.0833
T_{on}	0.5689	0.5354	0.6386	0.1032
T_{off}	0.5455	0.6094	0.5879	0.0639
Total mean GRG = 0.5809				

3.5.1 ANOVA for GRA

ANOVA is a statistical tool being used to differentiate the average performance of the set of parameters or items under test consideration. At a 95% confidence interval, ANOVA specified the process variables or parameters, which affect the response parameter most significantly. Utilizing MINITAB 17, the results of factor reactions are determined by adopting higher-the-better prospect. Means of GRG, ANOVA results are presented in Table 13. The parameters which contribute the most in the improvement in GRG of T, TRS, DC, T_{on} & T_{off} are presented in Table 14.

Table 13. GRG ANOVA results

Source	DF	Adj SS	Adj MS	F-value	P -value
T	2	0.002994	0.001497	0.38	0.689
TRS	2	0.000631	0.000315	0.08	0.923
DC	2	0.036820	0.018410	4.69	0.025
T_{on}	2	0.049878	0.024939	6.36	0.009
T_{off}	2	0.019061	0.009530	2.43	0.120
Error	16	0.062756	0.003922		
Total	26	0.172139			

Table 14. Response for GRG

Level	T	TRS	DC	T_{on}	T_{off}
1	0.5894	0.5751	0.5291	0.5689	0.5455
2	0.5661	0.5807	0.6013	0.5354	0.6094
3	0.5872	0.5869	0.6124	0.6386	0.5879
Delta	0.0234	0.0118	0.0833	0.1032	0.0639
Rank	4	5	2	1	3

3.5.2 GRA confirmatory experiment

By optimal setting of estimated parameter, the forecast & verification of quality growth characteristics is carried out. The estimated GRG (α̃) is evaluated from the optimal parameter level as:

$$\tilde{\alpha} = \alpha_m + \sum_{i=1}^{p} \overline{\alpha} - \alpha_m \qquad (13)$$

Where,

α_m = Total mean GRG

α_i = Mean GRG

p = Number of major variables.

Table 15. Confirmatory results

Initial factor setting		Optimal set	
		Predicted	Experimental
Level	$T_1TRS_1DC_1$ $T_{on1}T_{off1}$	$T_1TRS_3DC_3$ $T_{on3}T_{off2}$	$T_1TRS_3DC_3$ $T_{on3}T_{off2}$
T	Cu		Cu
TRS	900		1600
DC (amp)	10		20
T_{on} (μs)	150		500
T_{off} (μs)	8		16
MRR (mm^3/min)	0.058		0.284
TWR (mm^3/min)	0.004		0.014
Depth (mm)	1.284		5.339
GRG	0.507087	0.713100	0.769241

From Table 15, it is found that MRR, Depth and TWR are increased as processed from initial set to experimental set through predicted set value.

Table 16. Relative error estimation with optimum level of significant process parameters

Response	Optimal combination		Advancement in approved grade	
	With tool rotation	Without tool rotation	With tool rotation	Without tool rotation
TOPSIS	$T_1TRS_3DC_3T_{on3}T_{off3}$	$T_3DC_3T_{on2}T_{off2}$	0.880068	0.439190
GRA	$T_1TRS_3DC_3T_{on3}T_{off2}$	$T_3DC_3T_{on2}T_{off3}$	0.262154	0.115099

Table 16 presents the result of confirmatory tests and improvement obtained using TOPSIS and GRA techniques.

4. CONCLUSIONS

An attempt has successfully been made to improve the productivity of manufacturing products by increasing the MRR & Depth and decreasing the TWR of third generation aluminium alloy, Al-2050 alloy using different electrodes (Cu, W & Cu-W alloy). Taguchi’s technique is used to carry out the experiments by changing the different process parameters (e.g. –T, TRS, DC, T_{on} & T_{off}). Multi-attribute optimization using TOPSIS & GRA is performed to obtain most significant optimal setting of process variables. Important observations from the present work are following:

The optimal combination of process parameters are T = Cu, TRS = 1600 rpm, DC = 20 A, T_{on} = 500 μs and T_{off} = 24 μs (from TOPSIS) and T = Cu, TRS = 1600 rpm, DC = 20 A, T_{on} = 500 μs and T_{off} =16 μs (from GRA).

Using TOPSIS and GRA, improvement in preference values for the experimental and initial setting are 0.880068 and 0.262154 respectively from confirmatory tests that are acceptable.

The average improvement in MRR by using tool rotation is 2.4 times and 1.775 times, TWR is increased by 2.25 times and 1.75 times and Depth is also improved by 2.08 times and 1.656 times using TOPSIS & GRA respectively in optimal combination set. It also shows that for each of the twenty seven set of experiments, the rotary tool EDM yields better MRR, TWR & Depth in comparison to the stationary one.

At 95% confidence level, process characteristics are affected by ANOVA, which is implemented to get the better significant machining parameters. T, TRS, DC, T_{on} & T_{off} are the most significant parameters in improvement of preference solution.

Depending upon the required performance characteristics, it is observed that both the techniques are convenient to set up the best achievable result for the input parameters combination. Using different electrode (Cu, W & Cu-W alloy) in EDM machining/drilling of Al-2050 alloy, the findings of this research work would be helpful in improving the machining quality for industrial processes.

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