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ORIGINAL RESEARCH

Multiple performance characteristics optimization for Al 7075 on electric discharge drilling by Taguchi grey relational theory

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Abstract Electric discharge drill machine (EDDM) is a spark erosion process to produce micro-holes in conductive materials. This process is widely used in aerospace, medical, dental and automobile industries. As for the performance evaluation of the electric discharge drilling machine, it is very necessary to study the process parameters of machine tool. In this research paper, a brass rod 2 mm diameter was selected as a tool electrode. The experiments generate output responses such as tool wear rate (TWR). The best parameters such as pulse on-time, pulse off-time and water pressure were studied for best machining characteristics. This investigation presents the use of Taguchi approach for better TWR in drilling of Al-7075. A plan of experiments, based on L_{27} Taguchi design method, was selected for drilling of material. Analysis of variance (ANOVA) shows the percentage contribution of the control factor in the machining of Al-7075 in EDDM. The optimal combination levels and the significant drilling parameters on TWR were obtained. The optimization results showed that the combination of maximum pulse on-time and minimum pulse off-time gives maximum MRR.

Keywords Electric discharge drilling machining · MRR · TWR · ANOVA · Taguchi method · Grey relational analysis

Abbreviations

ANOVA	Analysis of variance
DF	Degree of freedom
EDM	Electric discharge machine
EDDM	Electric discharge drilling machine
GRA	Grey relational analysis
GRG	Grey relational grade
MRR	Metal removal rate
m	Overall mean S/N ratio
MS	Mean square
P	Percentage contribution
SEM	Scanning electron microscopy
SS	Sum of square
SS_e	Error sum of square
SS_j	Sum of square of individual process parameters
SS_T	Total sum of squares
TWR	Tool wear rate
T_{on}	Pulse on-time
T_{off}	Pulse off-time
WP	Flushing pressure
$Z_i(k)$	Comparability sequence
$Z_0^*(k)$	Reference sequence
$Z^*(k)$	Sequence after the data pre-processing
γ_i	Grey relational grade
$\xi_i(k)$	Grey relational coefficient
ζ	Identification coefficient
η	Signal to noise (S/N) ratio
$\Delta_{0i}(k)$	Deviation sequence

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Introduction

Electrical discharge machining (EDM) drilling is becoming the standard method for producing small, tight tolerance holes. It is an extremely cost-effective method for producing fast and accurate holes for hard or soft conductive materials (Bhattacharya et al. 1996). It is the process of machining electrically conductive materials using precisely controlled sparks that occur between an electrode and a workpiece in the presence of a dielectric fluid. It is based on the erosion of material through the series of spatially discrete high-frequency electrical discharges (sparks) between the tool and the workpiece. The spark removes material from both the electrode and workpiece, which increases the sparking gap (distance between the electrode and the workpiece) at that point. This causes the next spark to occur at the next-closest points between the electrode and workpiece. As EDM is a thermal process, material is removed by heat. Every discharge (or spark) melts a small amount of material from both of the electrodes. Part of this material is removed by the dielectric fluid and the remaining solidifies on the surface of the electrodes (Jain 2004).

Schematic diagram of EDM drilling is shown in Fig. 1. Micro-EDM is a machining process capable of drilling burr-free holes in a wide range of materials. In micro-hole drilling, the diameter of the electrode is selected according to the size of hole to be drilled by considering the radial overcut of process. The de-ionized water is used to flush away the burrs formed due to sparks between workpiece and electrode (McGeough 1998). There are many advantages of using fast EDM drilling versus conventional drilling.

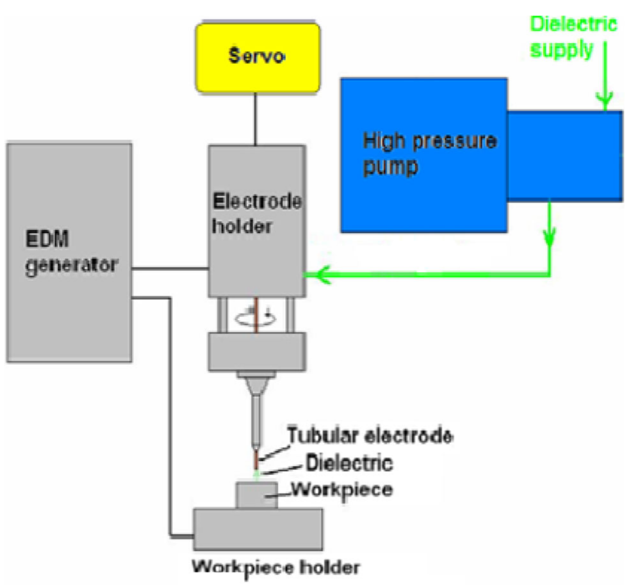


Fig. 1 Schematic diagram of electric discharge drilling machine (Yilmaz et al. 2010)

Some materials are too hard to drill using conventional methods. The EDDM drills any conductive material including carbide and hardened steel. During EDDM, there is no direct contact between tool and workpiece, so eliminating the tool pressure. This burr-free drilling saves a lot of time and labour, and is essential when difficult holes are being drilled (Simon and Grama 2011).

Literature review

The principle of EDM and EDM drilling is same except that during drilling process the electrode rotates and removes the burrs effectively with fluid pressure supplied by the channels in the electrode. Drilling micro-holes with conventional methods is often extremely difficult if not impossible. After drilling micro-holes, the geometrical accuracy was distorted and also the surface quality was not so much effective. EDM drilling is often the only practical method for producing such holes. As conventional drills enter or exit, they can break if torque is not carefully controlled. Small broken drills are often difficult to remove from the workpiece, and time is wasted replacing broken drills and parts may have to be scrapped. With EDM drilling, torque does not exist since the electrode never contacts the piece (Simon and Grama 2011). Song et al. (2009) drilled on cobalt-bonded tungsten carbide (WC–Co) with micro-electrical discharge machining. Researcher utilized bipolar pulse power source to prevent electrolytic corrosion in the machined holes.

Bursali et al. (2006) worked for the improvement of a batch saponification process using two-level factorial and face-centred central composite statistical experimental design. During their research study, the input process parameters were agitation rate, temperature, ethyl acetate and initial sodium hydroxide considering fractional conversion rate of NaOH as a response variable. Shokuhfar et al. (2008) utilized optimization technique for reduction of transverse deflection. Researchers developed and verified the model for smart composite plate deflection along with shape memory wire. This was used for the estimation of the deflection ratio, which was a mathematical function of the main process planning parameters. Ghasemi et al. (2013) optimized the process parameters for fibre metal laminates to a low velocity impact using response surface methodology and zero–one programming. It has been found that layer sequences and volume fractions of Al plies play significant role in the behaviour of fibre metal laminates.

Wang and Yan (2000) optimized the process parameters of rotary electro-discharging machining using Taguchi methodology while drilling of Al_2O_3/6061Al composite.

The input process parameters are polarity, peak current, pulse duration, powder supply voltage, rotational speed of the electrode, injection flushing pressure and response variables are metal removal rate, electrode wear rate and surface roughness. Research shows that the polarity or the peak current most prominently affects the MRR, SR or EWR amongst all of the parameters. Azad and Puri (2012) optimized the process performances such as, metal removal rate, tool wear rate and overcut based on Taguchi methodology. Thus, the optimal micro-EDM process parameter settings have been found out for a set of desired performances. The process parameters considered in the study were pulse on-time, frequency, voltage and current while tungsten carbide electrode was used as a tool. Maity and Singh (2012) fabricated micro-product on micro-electro-discharge machining (micro-EDM) operation to machine any hard conducting material of different shape and size. The micro-holes are a common feature in many micro-products. It is a challenging task to improve the surface integrity and aspect ratio of holes. The optimization of micro-EDM operation has been carried out for fabrication of micro-holes using design of experiment technique using the Taguchi method. The circularity error, the recast layer and machining time have been analysed. The workpiece is taken as copper and the tool is tungsten electrode.

Garna et al. (2011) investigated the effect of vibrations on the electrical discharges in the micro-EDM process. The electrical discharge machining of micro-bores was chosen to represent a typical application. It was found from the research that the micro-EDM boring process can be subdivided into three major parts, the start-up process, the major boring process and the workpiece breakthrough of the tool electrode. Bissacco et al. (2011) worked on the applicability of real-time wear compensation in micro-EDM milling based on discharge counting and discharge population characterization. Experiments were performed involving discharge counting and tool electrode wear measurement in a wide range of process parameters settings involving different current pulse shapes. Yu et al. (2009) said that when a micro-hole is drilled deeply by EDM, the viscous resistance in the narrow discharge gap causes difficulty in the removal of debris and bubbles from the working area, leading to frequent occurrences of abnormal discharges and resulting in extensive electrode wear. Kao et al. (2010) optimized the parameter of the electrical discharge machining process to Ti–6Al–4 V alloy considering multiple performance characteristics using the Taguchi method and grey relational analysis is reported. Performance characteristics including the electrode wear ratio, material removal rate and surface roughness are chosen to evaluate the machining effects. The process parameters selected in this study are discharge current, open voltage, pulse duration and duty factor. The validation experiments show an improved electrode wear ratio of 15 %, material removal rate of 12 % and surface roughness of 19 % when the Taguchi method and grey relational analysis were used.

Sánchez et al. (2011) developed an inversion model for Electro-discharge machining (EDM). Due to its extensive capabilities, this technique has been increasingly adapted to new industrial applications within the field of aerospace, medical, die and mould production, precision tooling, etc. The inversion model was constructed from a set of experiments and the equations formulated in the forward model described in the first part of this paper. In the forward model, the well-known ANOVA and regression models were used to predict the EDM output performance characteristics, such as MRR, EWR and SR in the EDM process for AISI 1045 steel with respect to a set of EDM input parameters.

Yilmaz and Okka (2010) drilled aerospace alloy (Inconel 718 and Ti–6Al–4 V) by electrical discharge machining to investigate the effect of electrode type and material on material removal rate, electrode wear and microhardness. Scanning electron microscopy revealed that the multi-channel electrodes produce better surfaces than single-channel electrodes for both aerospace alloys. Kumar et al. (2015) and Sharma et al. (2015) also worked on optimization of process parameters using response surface methodology and desirability function. Some of the previous works used the Taguchi method and response surface methodology as tools for the design of experiment in various areas including machining operations (Sharma et al. 2013a, b; Khanna and Singh 2013; Gupta et al. 2012; Garg et al. 2012).

An extensive research has been reported on EDM, while limited work has been reported on EDDM. So EDDM was selected to drilling micro-holes with rotating electrode. Al 7075 had applications in aerospace and transport, due to which precise holes are required to drill. A hole of 2 mm diameter is difficult to drill using conventional drill. So, in the present research, Al 7075 is processed with EDDM for precise drilling and surface integrity at drilled surface. No researcher has never processed (published) Al 7075 with EDDM till now.

Experimental procedure

Experimental setup

Experiments were performed on Electronica Make ED 300 (Fig. 2) electric discharge drilling Machine. The goal was to obtain the best machining parameters resulting in maximum MRR and minimum TWR. Holes were made in a 19-mm-thick plate of Al 7075 using a 2-mm-diameter

Fig. 2 Machine tool setup

electrode of brass. Deionised water was used as dielectric fluid. Internal flushing with linear-shaped brass tool was used to flush away the eroded materials from the sparking zone. In this experiment, voltage and air pressure was kept constant, i.e. 65 V, 3 kg/cm^2. Three process parameters were analyzed with a total number of 27 experiments performed on EDDM.

Machining parameter selection

The machine tool (ED 300) has three process parameters viz. pulse on-time, pulse off-time and flushing pressure given in Table 1. Many researchers (Kumar et al. 2013; Sharma et al. 2014) considered these parameters for optimization in spark erosion non-traditional machining methods along with other parameters. The levels of the parameters along with the units are also shown in Table 1.

Preparation of test specimen

The material used for experimentation is Al 7075. The chemical composition and mechanical properties of material is shown in Tables 2 and 3. Before experimentation, the workpiece faces were rectified to a good surface finish using a surface grinding machine. The bottom of the electrode rod is polished for best electric contact at every experiment. The aluminium plate after drilling is shown in Fig. 3.

Evaluation of response variable

The time taken for machining each hole was recorded. At completion of each hole, the workpiece was removed from the machine, washed, dried, and weighted. The material removal rate was calculated using the Eq. 1. Material MRR is expressed as the ratio of the difference of weight of the workpiece before and after machining to the machining time and density of the material.

$$\mathrm{MRR} = \frac{\text{Volume of material removed from workpiece}}{\text{Machining time}} \ \mathrm{mm}^3/\mathrm{min} \tag{1}$$

TWR is expressed as the ratio of the difference of weight of the tool before and after drilling to the drilling time. This is explained in Eq. 2.

$$\mathrm{TWR} = \frac{W_{\mathrm{tb}} - W_{\mathrm{ta}}}{t} \tag{2}$$

where W_{tb} = Weight of the tool before drilling, W_{ta} = Weight of the tool after drilling, t = drilling time

Results and discussion

The controllable variables chosen for the experimentation were peak current, pulse on-time and electrode rotation speed. Other factors such as voltage (65 V) and air pressure 3 kg/cm^2 were kept constant during the experimentation. Table 4 shows the design of experiments (Montgomery 2001) along with the response mean values and S/N ratio.

Analysis of variance (Montgomery 2001) gives the percentage contribution of significant process parameters. Table 5 gives the pooled ANOVA for mean values of MRR. The P value of all process parameters is less than 0.05 (95 % confidence level). From the Table 5, it is clear that pulse on-time has maximum effect, i.e. 94.63 % on MRR followed by pulse off-time (i.e. 4.55 %). Table 6 gives ANOVA of mean values for TWR. Pulse on-times play an important role in TWR with percentage contribution of 75.27 % followed by pulse off-time of 4.25 %. The interaction of pulse on-time and pulse off-time gives a significant contribution in both MRR and TWR.

Table 1 Machining parameters and their level

S. no.	Parameter	Unit	Level 1	Level 2	Level 3
1	Pulse on-time (A)	µs	3	6	9
2	Pulse off-time (B)	µs	3	5	7
3	Flushing pressure (C)	kg/cm^2	3	5	7

Table 2 Chemical composition of Al 7075

Elements	Si	Fe	Cu	Mn	Mg	Cr	Zn	Ti	Others	Al
Wt%	0.4	0.5	1.2–2.0	0.3	2.1–2.9	0.18–0.28	5.1–6.1	0.2	0.15	Balance

Table 3 Mechanical properties of Al 7075

Parameters	Values
Density (g/cm^3)	2.81
Hardness (HB)	60.0
Ultimate tensile strength (MPa)	228
Tensile yield strength (MPa)	103
Elongation at break (%)	16.0

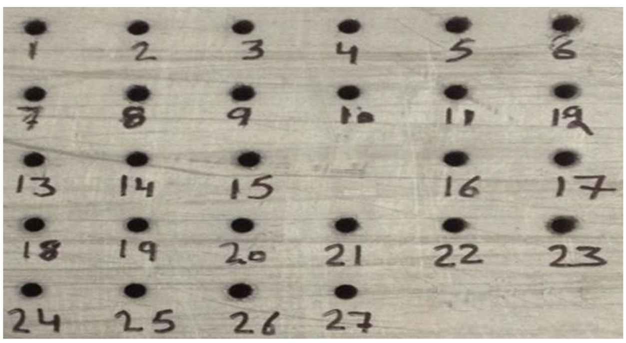


Fig. 3 Specimen after EDM drilling

Figure 4 gives the main effect plot of mean for MRR. It is clear from the figure that with the increase of pulse on-time the MRR increases. The main reason behind this is that with the increase of pulse on-time, the time for which current is on in a circuit increases. Due to which the discharge energy increases and finally MRR increases. When the pulse off-time increases the time for which current is off in a circuit increases, due to which discharge energy decreases and hence a declined curve for MRR is obtained. A slight increment in the slope of curve of MRR with flushing pressure is obtained. This is due to the fact that with increase in flushing pressure the rate at which debris are removed increases and hence MRR. The same effects of erosion take place in case of tool. As when MRR of workpiece increases same time, the erosion rate of tool also increases due to increase in discharge energy between tool and workpiece. So TWR increases with increase in pulse on-time and decreases with increase in pulse off-time (Fig. 5). Flushing pressure is a non-significant process parameter for TWR.

The optimization of process parameters for MRR and TWR can be easily evaluated by Taguchi technique. The main limitation of this approach is that only one response variable can be optimized in a time. To optimize both responses, i.e. MRR and TWR at the same time, grey relational analysis is used.

Multiple quality characteristics (grey relational analysis)

The Taguchi technique for determining the optimal setting of process parameters concentrates only on product single response. But in today scenario peoples' requirements have been changed from single response to multiple quality characteristics. According to the requirements, the industrialist is also keen to produce items and maintaining a balance between quantity and quality with minimum production cost to earn maximum profit. So the multiple quality characteristics optimizations is another task. Here, the grey relational analysis comes into play, where a mathematical technique optimizes two or more than two quality characteristics.

The theory of grey relational was proposed by Deng (1982, 1989), calculates the grey relational coefficients for all quality characteristics either they are of larger the better or smaller the best nature types. So, the grey relational coefficient can represent the relationship between the desired and actual experimental results, and the grey relational grade is simultaneously computed by averaging all the coefficients.

The multiple performance characteristics of EDDM can be optimized by producing single grey relational grade from various coefficients of performance characteristics. A higher grey relational grade corresponds to the best optimal setting of process parameters for multi responses. The Taguchi method is a systematic application of planning and analysis of experiments to improve product quality. In recent years, the Taguchi method has become a powerful tool for improving productivity during research and development also. Antony endeavoured simultaneous optimization of multiple quality characteristics in manufacturing processes using Taguchi's quality loss function. The use of Taguchi technique with the grey relational analysis can greatly simplify the parametric optimization for multiple quality characteristics (Deng 1982; Patel et al. 2010).

The procedure of GRA is illustrated in Fig. 6. Therefore, in the present work, grey relational analysis based on the Taguchi method's response table has been used to optimize EDDM of Al 7075 for multiple responses namely MRR and TWR together.

Table 4 Design matrix and corresponding experimental results

S. no.	Planning of experiments			Response characteristics of experiments			
	T_{on}	T_{off}	WP	Mean MRR (mm^3/min)	S/N ratio (dB)	Mean TWR	S/N ratio (dB)
1	3	3	3	0.0170	−35.391	0.14730	16.6359
2	3	3	5	0.0173	−35.2391	0.15490	16.1990
3	3	3	7	0.0177	−35.0405	0.14590	16.7189
4	3	5	3	0.0161	−35.8635	0.15740	16.0599
5	3	5	5	0.0165	−35.6503	0.16200	15.8097
6	3	5	7	0.0167	−35.5457	0.16500	15.6503
7	3	7	3	0.0148	−36.5948	0.16520	15.6398
8	3	7	5	0.0149	−36.5363	0.16560	15.6188
9	3	7	7	0.0153	−36.3062	0.17010	15.3859
10	6	3	3	0.0254	−31.9033	0.17270	15.2542
11	6	3	5	0.0256	−31.8352	0.17270	15.2542
12	6	3	7	0.0259	−31.734	0.17780	15.0014
13	6	5	3	0.0248	−32.111	0.19050	14.4021
14	6	5	5	0.0249	−32.076	0.20320	13.8415
15	6	5	7	0.0252	−31.972	0.20800	13.6387
16	6	7	3	0.0223	−33.0339	0.16520	15.6398
17	6	7	5	0.0227	−32.8795	0.16560	15.6188
18	6	7	7	0.0229	−32.8033	0.16500	15.6503
19	9	3	3	0.0352	−29.0691	0.24890	12.0795
20	9	3	5	0.0354	−29.0199	0.25900	11.7340
21	9	3	7	0.0359	−28.8981	0.25200	11.9720
22	9	5	3	0.0330	−29.6297	0.22350	13.0144
23	9	5	5	0.0336	−29.4732	0.22300	13.0339
24	9	5	7	0.0343	−29.2941	0.20820	13.6304
25	9	7	3	0.0297	−30.5449	0.20800	13.6387
26	9	7	5	0.0300	−30.4576	0.20320	13.8415
27	9	7	7	0.0303	−30.3711	0.20300	13.8501
Avg.	–	–	–	0.0245	−32.5657	0.18825	14.6227
Max.	–	–	–	0.0359	−28.8981	0.25900	16.7189
Min.	–	–	–	0.0148	−36.5948	0.14590	11.7340

Table 5 Analysis of variance for means (MRR)

Source	DF	SS	MS	*F*	*P*	*P*
T_{on}	2	0.001269	0.000634	32015.01	0.0001	94.63
T_{off}	2	0.000061	0.000031	1546.90	0.0002	4.55
WP	2	0.000002	0.000001	49.03	0.000	0.15
$T_{on} \times T_{off}$	4	0.000009	0.000002	111.41	0.0000	6.7
Residual error	16	0.000002	0.000001			0.15
Total	26	0.001341				

Data pre-processing

Data pre-processing is a process of transferring the original sequence to a comparable sequence. It is required since the range and unit in one data sequence may differ from the others. This is also necessary when the directions of the target in the sequence are different. For this purpose, the experimental results were normalized in the range between zero and one. Table 7 gives the normalized results for both responses after data pre-processing.

Table 6 Analysis of variance for means (TWR)

Source	DF	SS	MS	F	P	P (%)
T_{on}	2	0.020597	0.010299	376.19	0.000	75.27
T_{off}	2	0.001164	0.000582	21.27	0.000	4.25
$T_{on} \times T_{off}$	4	0.005107	0.001277	46.64	0.000	18.6
Residual error	18	0.000493	0.000027			1.80
Total	26	0.027361				

Depending on the response of data sequence, i.e. either it is of larger the better or smaller the best nature type, there are various methodologies of data pre-processing suggested by researchers for the grey relational analysis (Deng 1982, 1989). For the "larger-the-better" characteristic such as MRR, the sequence can be normalized as per Eq. 3.

$$Z_i^*(k) = \frac{Z_i(k) - \min Z_i(k)}{\max Z_i(k) - \min Z_i(k)} \tag{3}$$

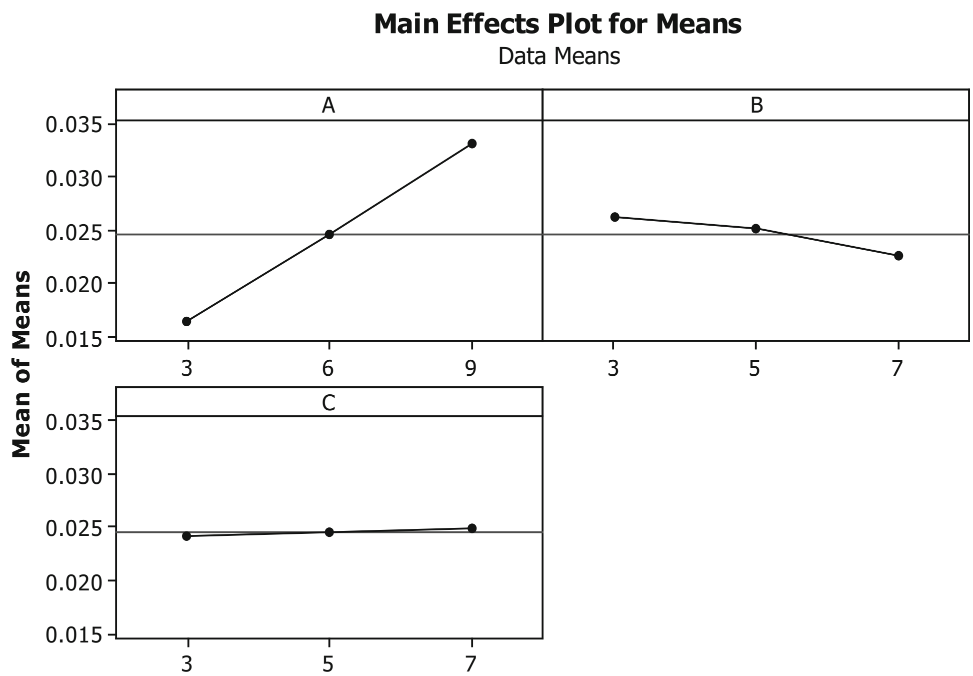


Fig. 4 Main effects plot for means (MRR)

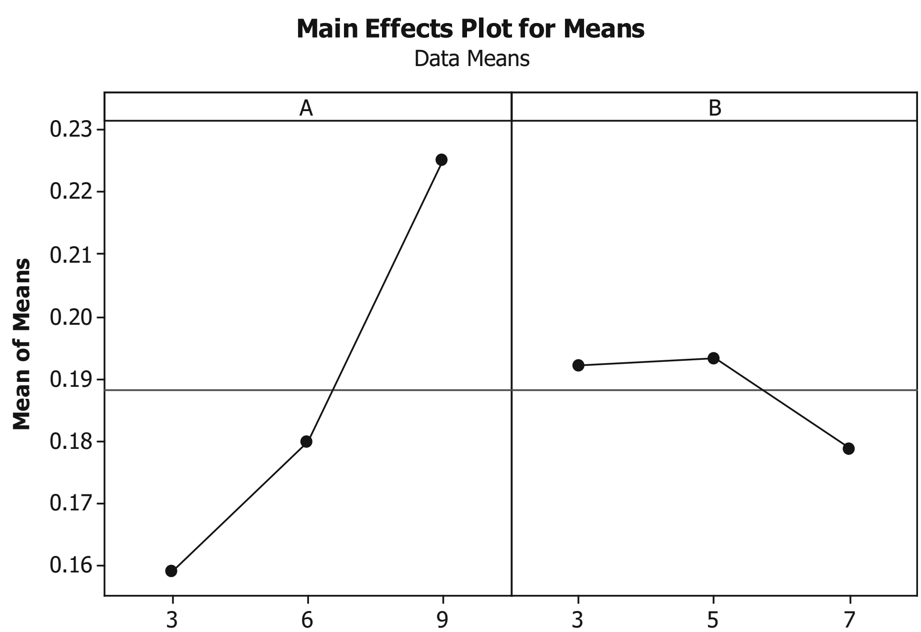


Fig. 5 Main effects plot for means (TWR)

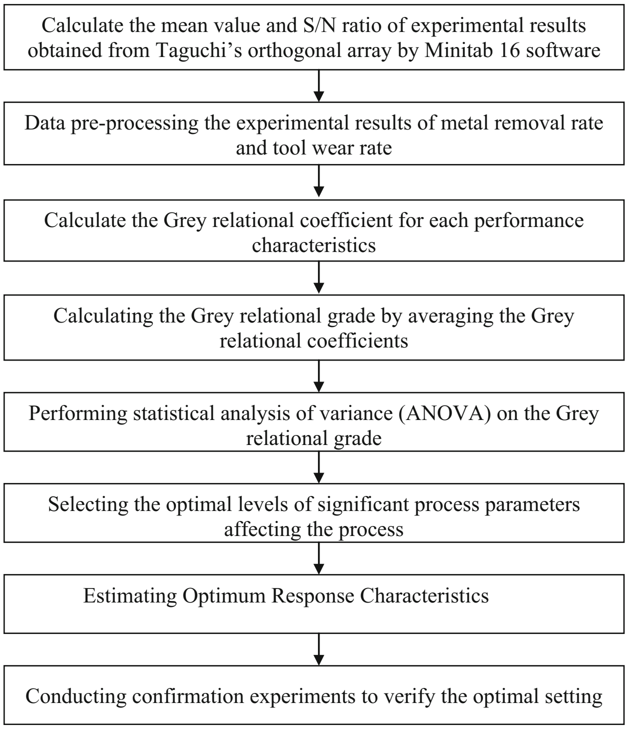


Fig. 6 Procedure for grey relational analysis

where $Z_i^*(k)$ is the sequence after data pre-processing, $Z_i(k)$ is the original sequence of mean value of MRR.

where $k = 1$ for MRR; $i = 1, 2, 3\ldots, 27$ for experiment numbers 1–27.

Table 3 reports the data after pre-processing for AA 7075. Optimal drilling performance for TWR, i.e. the "smaller-the-better" quality characteristic Eq. 4 has been used. The original sequence can be normalized by this equation:

$$Z_i^*(k) = \frac{\max Z_i(k) - Z_i(k)}{\max Z_i(k) - \min Z_i(k)} \quad (4)$$

where $Z_i^*(k)$ and $Z_i(k)$ are the sequences after the data pre-processing and original sequence of mean values, $k = 2$ for TWR; $i = 1, 2, 3\ldots, 27$ for experiment numbers 1–27. $Z_0^*(k)$ is the reference sequence whose value is equal to 1 as given in Table 7.

All the sequences after data pre-processing are listed in Table 7. After the data pre-processing, all values of the response come out in the range of 0 and 1.

Calculating the grey relational coefficient and grey relational grade

After the normalization, the deviational sequence is the next step in this grey theory. Now, $\Delta_{0i}(k)$ is the deviation sequence of the reference sequence $Z_0^*(k)$ and the comparability sequence $Z_i^*(k)$ is shown in Table 8. The deviational sequence is computed as from Eq. 5.

$$\Delta_{0i}(k) = \left|Z_0^*(k) - Z_i^*(k)\right| \quad (5)$$

For experiment number 1, i.e. $\Delta_{01}(1) = 1 - 0.104265 = 0.895735$

For experiment number 2, i.e. $\Delta_{02}(1) = 1 - 0.118483 = 0.881517$

This is the deviational sequence values of experiment 1 and 2 ($i = 1$ and 2) for MRR (i.e. $k = 1$). All the 27 values of experiment are tabulated in Table 8. Similarly, the values of TWR are computed as

For experiment number 1, i.e. $\Delta_{01}(2) = 1 - 0.987622 = 0.012378$

For experiment number 2, i.e. $\Delta_{02}(2) = 1 - 0.920424 = 0.079576$

Table 7 Data pre-processing of mean values of experimental result for each performance characteristics

Exp No	MRR	TWR	Exp No	MRR	TWR
Reference sequence	1.00	1.00	Reference sequence	1.00	1.00
1	0.104265	0.987622	15	0.492891	0.450928
2	0.118483	0.920424	16	0.35545	0.829355
3	0.137441	1	17	0.374408	0.825818
4	0.061611	0.89832	18	0.383886	0.831123
5	0.080569	0.857648	19	0.966825	0.089302
6	0.090047	0.831123	20	0.976303	0
7	0	0.829355	21	1	0.061892
8	0.004739	0.825818	22	0.862559	0.313882
9	0.023697	0.78603	23	0.890995	0.318302
10	0.50237	0.763042	24	0.924171	0.44916
11	0.511848	0.763042	25	0.706161	0.450928
12	0.526066	0.717949	26	0.720379	0.493369
13	0.473934	0.605659	27	0.734597	0.495137
14	0.478673	0.493369			

Table 8 Deviational sequence

Deviation sequence	$\Delta_{0i}(1)$	$\Delta_{0i}(2)$	Deviation sequence	$\Delta_{0i}(1)$	$\Delta_{0i}(2)$
1	0.895735	0.012378	15	0.507109	0.549072
2	0.881517	0.079576	16	0.64455	0.170645
3	0.862559	0	17	0.625592	0.174182
4	0.938389	0.10168	18	0.616114	0.168877
5	0.919431	0.142352	19	0.033175	0.910698
6	0.909953	0.168877	20	0.023697	1
7	1	0.170645	21	0	0.938108
8	0.995261	0.174182	22	0.137441	0.686118
9	0.976303	0.21397	23	0.109005	0.681698
10	0.49763	0.236958	24	0.075829	0.55084
11	0.488152	0.236958	25	0.293839	0.549072
12	0.473934	0.282051	26	0.279621	0.506631
13	0.526066	0.394341	27	0.265403	0.504863
14	0.521327	0.506631			

Other values of TWR are calculated by Eq. 5 keeping value of k equal to 2. The grey relational coefficient is calculated to display the relationship between the optimal (best) and actual normalized results. According to the data of Table 8, the absolute difference of array $\Delta_{0i}(k)$ and grey relational coefficient $\xi_i(k)$ is obtained, respectively, from the analysis model of grey theory. The average value of the grey relational coefficient $\xi_i(k)$ is the grey relational grade γ for all performance characteristics. The grey relational coefficient is calculated as from Eq. 6 (Deng 1989; Caydaş and Hasçalık 2008).

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta \cdot \Delta_{\max}}{\Delta_{0i}(k) + \zeta \cdot \Delta_{\max}} \tag{6}$$

where $\Delta_{0i}(k)$ is the deviation sequence of the reference sequence $Z_0^*(k)$ and the comparability sequence $Z_i^*(k)$, ζ is distinguishing or identification coefficient. If both the parameters are given equal preference, ζ is taken as 0.5.

After obtaining the grey relational coefficient, the grey relational grade (γ) is computed by averaging the grey relational coefficient corresponding to each performance characteristic (Eq. 7). The overall evaluation of the multiple performance characteristics is based on the grey relational grade:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \tag{7}$$

where γ_i is the grey relational grade for the ith experiment and n is the number of performance characteristics. Table 9 gives the grey relational grade for each experiment using L_{27} orthogonal array. The higher grey relational grade represents that the corresponding experimental result is closer to the ideally normalized value. The grey relational coefficients obtained from performance characteristics (i.e. MRR and TWR) are given in Table 9 and further GRG is computed according to Eq. 7. Third trial gives the largest (bold) value of grade (i.e. 0.683478), which corresponds to the optimal results of the experiments.

Analysis of variance (ANOVA) for grey relational grade

ANOVA is a statistical technique to interpret the experimental results for the analysis of experimental data. It is widely used to identify the performance of process parameters under investigation. The purpose of ANOVA is to investigate the significant process parameters along with percentage contribution of significant process parameters on the performance characteristics. Table 10 gives the ANOVA for all 27 values of grade corresponding to the DOE given in Table 4. As level of process parameters is 3 so DF for individual process parameters is computed according to Eq. 8. During the interaction of two process parameters, the DF of both parameters is multiplied. Total DF for the ANOVA is calculated as Eq. 9. The total sum of square is computed from Eq. 10.

$$\mathrm{DF} = (\text{No. of level} - 1) \tag{8}$$

$$\text{Total DF} = (\text{No. of experiments} - 1) \tag{9}$$

$$\mathrm{SS}_T = \sum_{i=1}^{n} (\eta_j - m)^2 \tag{10}$$

where m is overall mean S/N ratio. The SS_T is sum of square of individual process parameter and sum of square of error as given in Eq. 11.

Table 9 Grey relational coefficient and grey relational grade for 27 comparability sequences

S. no.	Grade relational coefficient		Grey relational grade
Comparability sequence	MRR [$\xi_i(1)$] 1.000	TWR [$\xi_i(2)$] 1.000	$\gamma = \frac{[\xi_i(1)+\xi_i(2)]}{2}$
1	0.358234	0.975841	0.667038
2	0.361921	0.8627	0.612311
3	0.366957	1	**0.683478**
4	0.347611	0.831007	0.589309
5	0.352254	0.77839	0.565322
6	0.354622	0.747521	0.551072
7	0.333333	0.74555	0.539442
8	0.33439	0.741639	0.538015
9	0.338684	0.70031	0.519497
10	0.501188	0.678464	0.589826
11	0.505995	0.678464	0.59223
12	0.513382	0.639344	0.576363
13	0.487298	0.559071	0.523184
14	0.489559	0.496706	0.493133
15	0.496471	0.476612	0.486541
16	0.436853	0.74555	0.591202
17	0.444211	0.741639	0.592925
18	0.447983	0.747521	0.597752
19	0.937778	0.354434	0.646106
20	0.954751	0.333333	0.644042
21	1	0.347679	0.67384
22	0.784387	0.421543	0.602965
23	0.821012	0.42312	0.622066
24	0.868313	0.47581	0.672061
25	0.629851	0.476612	0.553231
26	0.641337	0.496706	0.569022
27	0.653251	0.49758	0.575416

Table 10 Analysis of variance for grey relational grade

Source	DF	SS	MS	F	P (%)
T_{on}	2	0.014862	0.007431	17.99	19.76
T_{off}	2	0.026197	0.013099	31.72	34.83
WP	2	0.000664	0.000332	0.80	0.88
$T_{on} \times T_{off}$	4	0.026102	0.006525	15.80	34.70
$T_{on} \times$ WP	4	0.003246	0.000811	1.96	4.32
$T_{off} \times$ WP	4	0.000851	0.000213	0.51	1.13
Residual error	8	0.003304	0.000413		4.39
Total	26	0.075225			

$$\mathrm{SS}_T = \sum_{j=1}^{n_p} (\mathrm{SS}_j + \mathrm{SS}_e) \tag{11}$$

$$\mathrm{SS}_j = \sum_{i=1}^{l} (\eta_{ji} - m)^2 \tag{12}$$

SS_j (Eq. 12) is the sum of square of individual process parameter.

$$\mathrm{MS} = \frac{\mathrm{SS}}{\mathrm{DF}} \tag{13}$$

The mean square is simply calculated by the division of SS to the corresponding DF (Eq. 13). Error mean of square follows the same procedure. Response table for grey relation grade is given in Table 11. Higher grade will be better for a process. So from this table the grade corresponding to optimal level is bold. The predicted optimal setting given from this table is $A_3B_1C_3$. Percentage contributions for each term affecting grey relational grade are given in Fig. 7. The figure clearly shows that pulse on-time, pulse off-time and interaction of pulse on-time and off-time are the three foremost process parameters that affect grey relational grade and hence contributes in improving MRR with minimum TWR.

Table 11 Response table for grey relational grade

Machining parameters	Units	Grey relational grade			Main effect
		Level 1	Level 2	Level 3	
Pulse on-time	μs	0.5851	0.5604	**0.6177**	0.0573
Pulse off-time	μs	**0.6317**	0.5673	0.5641	0.0676
Flushing pressure	kg/cm^2	0.5891	0.5810	**0.5929**	0.0119

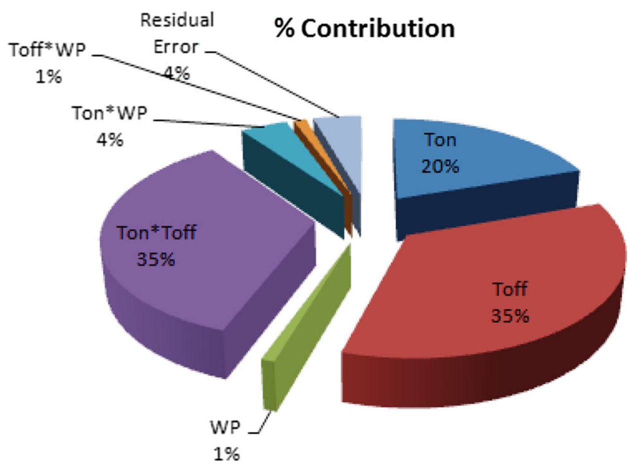


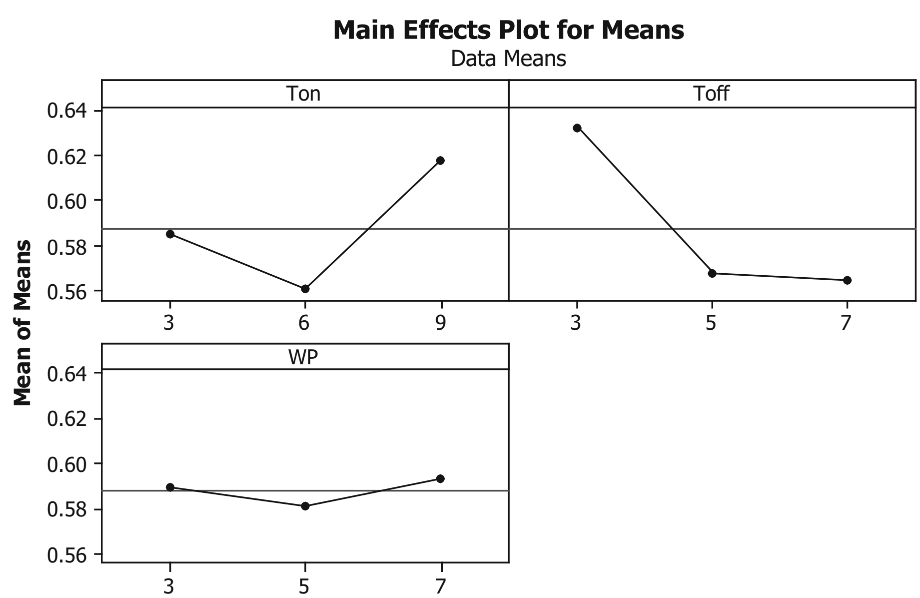
Fig. 7 Percentage contribution of each parameter in GRG

Figure 8 gives the variation of grade with the variation of process parameters. A higher GRG is obtained at a high value of pulse on-time. The probable reason for this is the higher spark between the tool and workpiece. Pulse on-time is the time for which current is on in a circuit. At larger value of T_{on}, larger current flows between the tool and workpiece, which increases the discharge energy between the spark gap and hence larger erosion rate finally increases grade value. Similarly, with increasing pulse off-time, the erosion rate decreases and GRG also decreases. This is due to the fact that the discharge energy between the tool and workpiece decreases and ultimately lowers the grade value. With the increase of flushing pressure, a little bit increase in grade value is observed.

The interaction plays an important role in this analysis. The interaction plot of mean value for GRG is shown in Fig. 8. It can easily be found from Fig. 9 that there is a strong interaction between T_{on} and T_{off}. The same can also be explained from ANOVA (Table 11) where the percentage contribution of T_{on} and T_{off} interaction is 34.7 %. While interaction between T_{on} and WP is also observed, the interaction between T_{off} and WP is not so much significant as other two.

Table 12 gives the predicted grade value at the optimal machining condition provided by response table (Table 11). At the optimal setting, the confirmation experiments are performed to get the MRR and TWR. The grade value at optimal setting is compared to first and third trial of OA. An improvement of 0.001642 in grade value has been observed, which signifies good results reproducibility. The optimal conditions suggested by GRG produce the comparable MRR and TWR in accordance with predicted results.

Fig. 8 Main effects plot for means (GRG)



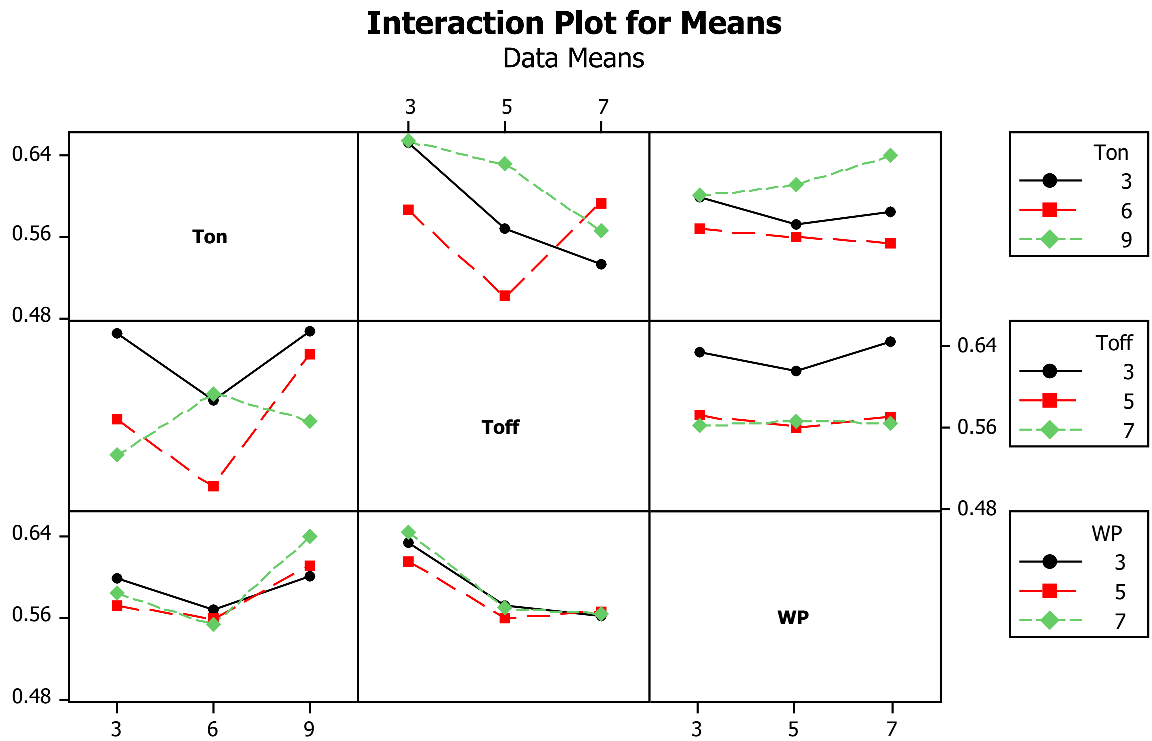


Fig. 9 Interaction plot of mean for GRG

Table 12 Predicted and confirmation experiments results of multi response optimization at optimal setting

Response	First trial of OA	Third trial of OA	Optimal machining conditions		$\% \text{ Error} = \frac{\text{Exp.}-\text{Predicted}}{\text{Exp.}} \times 100$
			Predicted	Experimental	
Setting level	$A_1B_1C_1$	$A_1B_1C_3$	$A_3B_1C_3$	$A_3B_1C_3$	
MRR (mg/min)	0.0170	0.0177	0.03511	0.0359	2.2
TWR (mg/min)	0.14730	0.14590	0.2296	0.252	8.88
GRG	0.667038	0.683478	0.685120		

Some micro-cracks along with white layer have been found with the help of scanning electron microscopy (SEM) micrograph (Fig. 10). Cracks were produce due to the development of thermal stresses beyond the fracture strength, as well as with plastic deformation. The formation of micro-cracks is not only prejudiced by the setting of process parameters but also depended on mechanical properties of materials such as tensile strength, Young's modulus, thermal conductivity and coefficient of thermal expansion. Each time the spark is generated between tool and workpiece, the material vaporizes and at the same time de-ionized water removes the debris. So the vaporized metal gets solidified when it comes in contact with water. In this way, a white layer is formed on the drilled surface. This layer is also known as recast layer and is also shown in Fig. 10a. Craters can also be seen from Fig. 10b due to the discharge produced.

Concluding points

In the present research work, the response variables (i.e. material removal rate and tool wear rate) correlate the machining parameters: pulse on-time, pulse off-time, and water pressure, in the EDM drilling process of AL-7075. An experimental plan of the L_{27} based on the Taguchi Method has been applied to perform the experimentation work. The machinability evaluation in the EDM drilling process has been analysed according to the ANOVA to obtain the following conclusions:

1. The material removal rate obtained ranged between 0.0148 and 0.0359 mm^3/min. The percentage contribution of input factors is given by pulse on-time, 94.6 %; pulse off-time, 4.6 %; water pressure, 0.14; and error, 0.67 %. The maximum material removal

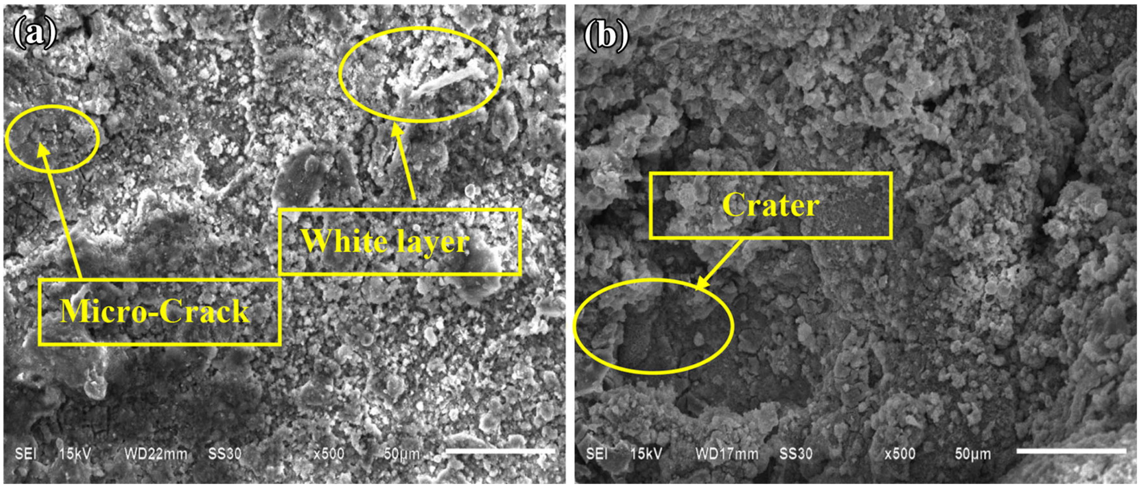


Fig. 10 **a**, **b** SEM micrograph of drilled surface

rate was obtained when the parameters were set at pulse on-time = 9 µs, pulse off-time = 3 µs and water pressure = 7 kg/cm^2. The optimal setting for metal removal rate is $A_3B_1C_3$. The predicted value for metal removal rate is 0.03501 mm^3/min. While at the optimal setting after confirmation experiments the actual value of MRR reported to be 0.0359 mm^3/min.

2. Tool wear rate obtained ranged from 0.14590 to 0.25900 g/s. Tool wear rate was most significantly affected by pulse on-time, pulse off-time. The percentage contribution of input parameters is given by pulse on-time, 75.27 %; pulse off-time, 4.54 %; and error, 0.85. The minimum tool wear rate was obtained when the parameters are set at pulse on-time = 3 µs, pulse off-time = 3 µs, water pressure = 7 kg/cm$^{2.}$ Tool wear rate of the confirmation experiment is found to be 0.1549 g/s at the optimal setting of $A_1B_3C_1$.
3. Multi-quality characteristics for the same material considering MRR and TWR are given as under by Taguchi Grey relational analysis (TGRA). The optimal setting by grey relational grade (GRG) is found to be $A_{12}B_2C_1$. The predicted value of GRG is 0.685120. The experimental value at the optimal setting is observed to be 0.0359 mm^3/min and 0.252 g/s for MRR and TWR, respectively. The percentage error between predicted and observed values of response variables exists in the range of 2.2 and 8.88 %, which represents excellent result reproducibility.
4. Micro-structure analysis shows the micro-cracks, craters and white layer produced on the drilled surface of Al 7075.

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