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ORIGINAL ARTICLE

Investigating the effects of electric discharge machining parameters on material removal rate and surface roughness on AISI D2 steel using RSM-GRA integrated approach

Muhammad Hanif [1] · Wasim Ahmad [1] · Salman Hussain [1] · Mirza Jahanzaib [1] · Abdul Hakim Shah [2]

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Abstract

The present research focuses on optimizing the process parameters of die-sinking electric discharge machining on tool steel. The basic objective of this research is to investigate the influence of two categorical factors including dielectric type and electrode polarity, and two numeric factors including discharge current, and Spark/Discharge Gap on material removal rate (MRR) and surface roughness (R_a) for machining of AISI D2 steel. Box-Bhenken design based on response surface methodology (RSM) was applied for experimental design. For estimation and evaluation, the effects of the process parameters on response variables, RSM has been integrated with grey relational analysis (GRA). Ranking of factors has been done with respect to the grey relational grade. (ANOVA) was further performed for determining the significance of grey relational grade. ANOVA results reveal that that polarity having 50% of percentage contribution was the most significant factor affecting the performance measures followed by the spark gap, discharge current, and dielectric type. The grey relational grades were further optimized through desirability function and the optimal condition for input parameters was obtained. The optimum levels were discharge current at 15 A, dielectric type of kerosene oil, spark gap at 6 mm, and polarity of positive has been determined. The confirmatory tests were run for verifying and validating the results and improvement in productivity (MRR) up to 17.23 mm^3/min and quality (R_a) up to 3.86 μm at an optimum have been observed.

Keywords Die-sinking EDM · AISI D2 steel · RSM · GRA · Material removal rate · Surface roughness

1 Introduction

AISI D2 steel is very hard material containing high carbon and chromium percentage. It is preferred over other steels for the applications requiring high compressive strength, high wear resistance, and high stability. It is widely used in metal stamping dies, drawing and stainless steel sheet blanking dies, coining, and general purposes. In non-conventional manufacturing processes, electric discharge machining is extensively adopted in manufacturing of complicated shaped molds, tools, dies, and parts having intricate contours employed in surgical automobile and aerospace industries [1]. EDM process used thermoelectric energy between tool and workpiece interface which helps in the removal of material. In this process, electrical sparks in between tool-work part interface remove the material. Thermal energy in the spark induces the intense heat on workpiece surface triggered melting and vaporizing the material [2]. The process can be conveniently used for the machining of electrically conductive parts regardless of their shape, hardness, and toughness [3, 4], also utilized for construction of polycrystalline diamond tools and 3-D microcavities [5]. The main advantage of EDM is that no contact between tool and work part eliminates the mechanical stresses and hence capable of forming complex shapes.

✉ Abdul Hakim Shah
dr.abdulhakim@kkkuk.edu.pk

[1] Department of Industrial Engineering, University of Engineering and Technology Taxila, Taxila, Pakistan

[2] Department of Physics, Khushal Khan Khattak University Karak, Karak, Pakistan

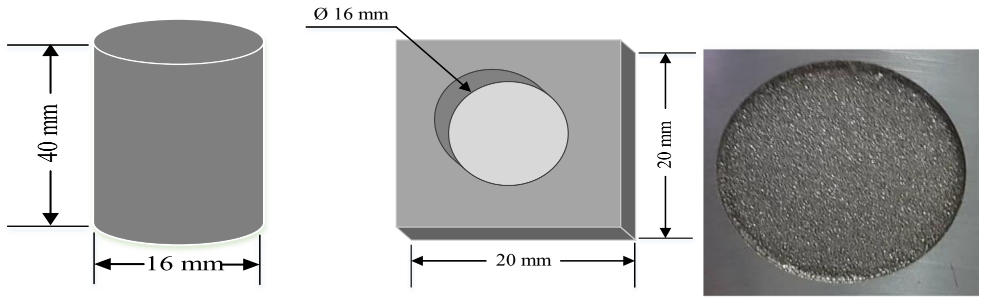
Table 1 Chemical composition of AISI D2 steel [25]

Element	C	Mn	Si	Cr	Mo	V	Fe
Wt (%)	1.58	0.7	0.8	11.65	0.68	1.12	Balanced

In last decades, in electric discharge machining, focus of researchers was to attain better productivity (MRR) and surface quality (R_a) [6, 7]. Certainly, the various electrical factors such as discharge current, pulse on time, pulse off time, and gap voltage affects the material removal rate [8–10], but the non-electrical parameter such as dielectric, tool electrode, and workpiece material also need much attention for the EDM process. Polarity has also a significant factor in EDM process, as when polarity changes, surface roughness and material removal rate are highly influenced [11]. Dielectric provides a medium between the tool and work part for discharging and it has also been used as a coolant after the materials is removed. Hence, it plays an important role for the quality of products. Mostly kerosene oil is used as a dielectric in EDM due to its properties, but some new coolant should by analyzed having same properties to minimize the cost and enhancing the quality of products. In this research, three different dielectrics that are distilled water, transformer oil, and kerosene oil are taken as input parameter including the discharge current, sparking gap, and polarity. Discharge current has already been employed as most significant factor reported by many researchers [12–14]. Both MRR and R_a are increasing with increase in discharge current [15]. Mandaloi et al. [16] have studied the effects of parameters such as pulse on time, spark gap, and discharge current on material removal rate, electrode wear rate, and surface finish for crystalline structure of AISI M2 steel. Beside electrical parameters, dielectrics also play a dynamic role in the removal of material in EDM. Misbah et al. [17] have studied different dielectrics such as distilled water and kerosene oil for aluminum alloy 6061 T6 alloy. Their results revealed that kerosene oil performed well for wear rate and rate of removal. Surface quality and cost of machining highly depends upon dielectric used [18, 19]. Electrode polarity also influence performance measures such as material removal rate, tool wear rate, and white layer [20, 21]. The results of Mohan et al. [22] revealed that surface roughness and material removal rate is high for negative polarity as compared to positive. Kansal et al. [23] have studied the effects of parameters on AISI D2 steel using machining rate as a performance measure. Peak discharge current and powder concentration were identified as most significant process parameter using the Taguchi method. Pradhan and Biswas [24] presented the neural network and neuro-fuzzy models for the prediction of MRR, tool wear and radial overcut of AISI D2 steel, and full factorial design was employed for conducting experiments. It was perceived that the discharge current is critical factor for material removal rate and radial overcut while pulse duration is for tool wear rate. The rarely reported work on the transformer oil and spark gap as well as the use of several

Fig. 1 Electric discharge machine

Fig. 2 Dimensions of workpiece and electrode



dielectrics describes various effects on EDM performance which needs to be analyzed for better quality and productivity. Until no work has been done on comparison of transformer oil with other dielectrics in terms of productivity and quality.

In the present research, the influence of dielectric type, discharge current, discharge gap and electrode polarity on material removal rate (MRR), and surface roughness (R_a) were studied for AISI D2 steel in die-sinking EDM. The response surface methodology by Box-Bhenken design, a powerful technique for designing the experiments, has been used for conducting the experiments. Further analysis has been carried out by grey relational analysis to optimize the two performance measures, i.e., material removal rate and surface roughness simultaneously to achieve the optimum condition.

2 Materials and methods

2.1 Experimental setup

AISI D2 steel was used for machining purpose in the discharge current research having chemical composition as shown in Table 1. The chemical composition was examined using optical emission spectrometer.

The experiments were conducted using electric discharge machine shown in Fig. 1. A 16-mm diameter and 45-mm length copper electrode was employed during machining.

Face of electrode and workpiece surface was ground just using manual grinding of the surfaces as shown in Fig. 2.

Table 2 Constant parameters and its values

S. No.	Parameter	Values
1	Working time	3 s
2	Servo speed	75%
3	Dielectric pressure	1.5 kg/cm^2, 21 Psi
4	Jump time distance	1.3 mm
6	High-voltage setting	2 A, 240 V
7	Depth of cut	0.5 mm

For assessing the performance of EDM, input parameters such as discharge current, dielectric type, spark gap, and polarity with selected ranges have been used. Dielectric type includes kerosene oil, transformer oil, and distilled water. Parameters, which were kept constant during the entire experimentation, are stated in Table 2.

The performance measures, material removal rate (MRR), and surface roughness (R_α) were measured in this study. MRR is actually the productivity of the machining and determines the economics of machining. MRR is defined as the bulk of the material removed over machining time. The expression for the material removal rate is given in Eq. (1).

$$MRR = (w_1 - w_2)/t.\rho \tag{1}$$

$\mathrm{MRR} = \frac{w_1 - w_2}{t \times \rho}$ where w_1 and w_2 are the initial and final weight of workpiece respectively, t denotes the total time for experiment, and ρ denotes the density of the material.

Surface roughness (R_α) measures the texture of a surface which was measured for the specimens using roughness tester meter SJ-410 as shown in Fig. 3.

2.2 Experimental design using RSM

Discharge current, spark gap, dielectric fluid, and electrode polarity were selected as input variables in the present study due to their significant impact on surface quality and material removal rate [22, 26–28]. Upper and lower ranges of the continuous variables are selected after the trial experimentation so that machining of parts gives better surface finish and material removal rate. The selected input variables along with their specified ranges and categories are presented in Table 3.

The effects of input variables on material removal rate and surface roughness were analyzed using Box-Bhenken design (response surface methodology) [29]. Using two continuous variables (discharge current and spark gap) and two categorical variables (dielectric fluid and electrode polarity). In categorical variables, electrode polarity has two levels. Hence, overall 34 experiments were performed using five center

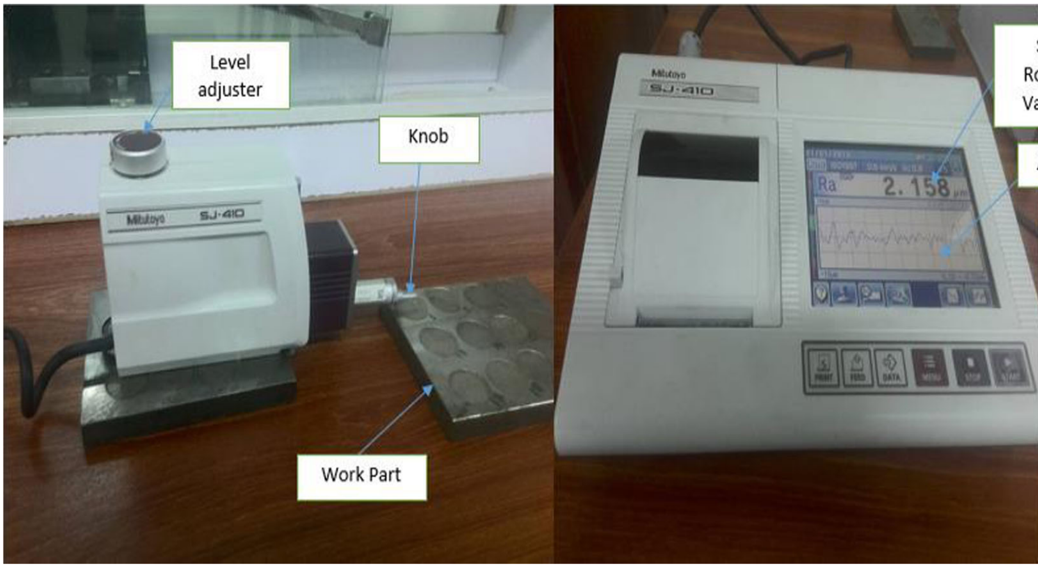


Fig. 3 Roughness tester meter

points with one replication for each positive and negative polarity.

The experimental design included standard order of experimentation, input variables, and response variable are given in Table 4. Here, material removal rate (MRR) was measured using Eq. (1) as discussed earlier. Surface roughness (R_a) was measured five times using surface roughness tester at different locations (one at center and other four locations were randomly selected) for each experiment and their average value was taken.

2.3 Analysis method (grey relational analysis)

Establishing a standardized data, coefficient of grey relational analysis has been determined in order examine the correspondence between theoretical and actual statistics. Averaging the grey relational coefficients that corresponds to responses measured, we obtain overall grey relational grade. In GRA, there are two criteria that correspond to the response variables, i.e., Lower-the-better (LB) and Higher-the-better (HB) criteria [30]. In the present study, surface roughness (R_a) corresponds to the minimum-the-better case and original sequence is normalized by Eq. (2):

$$\alpha_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{2}$$

Where $\alpha_i(k)$ is the grey relation generated value for smaller-the-best case; $\min y_i(k)$ and $\max y_i(k)$ show the minimum and maximum values for all k^{th} responses. Where $\alpha_0(k)$ shows the ideal sequence for the two responses for $k = 1$ to 6.

Similarly, the response variable, material removal rate (MRR) corresponds to maximum-the-better case, shows the productivity of electric discharge machining and original sequence is normalized by Eq. (3):

$$\beta_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{3}$$

In the above expression, $\beta_i(k)$ is the grey relation generated value. $\min y_i(k)$ and $\max y_i(k)$ show the minimum and

Table 3 Levels of machining parameters

Variables	Symbol	Levels		
		Low	Middle	High
Discharge current (A)	A	9	12	15
Dielectric type	B	Distilled water	Kerosene oil	Transformer oil
Spark Gap (mm)	C	2	4	6
Electrode polarity	D	Positive	–	Negative

Table 4 Experimental design with measured MRR–R_a values

Run order	Process parameters				Performance measures	
	Numeric factors		Categorical Factors			
	A: discharge current	B: dielectric type	C: spark gap	D: polarity	MRR (mm^3/min)	R_a (μm)
1	12	Transformer oil	6	+ ve	5.58	2.45
2	12	Kerosene oil	4	+ ve	11	3.05
3	12	Transformer oil	2	+ ve	5.91	3.23
4	12	Kerosene oil	4	+ ve	9	3.89
5	15	Distilled water	4	+ ve	5.91	5.35
6	15	Distilled water	4	− ve	2.58	4.44
7	12	Kerosene oil	4	− ve	1.57	5.03
8	12	Kerosene oil	4	− ve	1.83	4.38
9	9	Distilled water	4	+ ve	2.87	2.98
10	12	Distilled water	2	− ve	1.34	3.45
11	15	Kerosene oil	6	+ ve	15.46	5.37
12	9	Transformer oil	4	+ ve	4.57	2.06
13	9	Kerosene oil	2	− ve	2.09	4.99
14	9	Distilled water	4	− ve	1.17	5.81
15	12	Distilled water	2	+ ve	2.34	2.9
16	15	Kerosene oil	2	+ ve	14.35	6.38
17	15	Kerosene oil	6	− ve	5.58	3.33
18	12	Distilled water	6	+ ve	2.51	1.87
19	12	Transformer oil	6	− ve	2.23	3.68
20	12	Transformer oil	2	− ve	2.39	4.74
21	9	Kerosene oil	6	+ ve	9.13	3.47
22	12	Kerosene oil	4	+ ve	10.04	3.80
23	15	Kerosene oil	2	− ve	4.95	4.48
24	9	Kerosene oil	2	+ ve	8.37	3.87
25	9	Kerosene oil	6	− ve	3.46	4.78
26	12	Kerosene oil	4	− ve	1.52	4.12
27	9	Transformer oil	4	− ve	1.93	6.84
28	12	Kerosene oil	4	− ve	1.66	5.04
29	15	Transformer oil	4	+ ve	12.56	5.36
30	12	Distilled water	6	− ve	1.48	3.34
31	15	Transformer oil	4	− ve	5.43	6.39
32	12	Kerosene oil	4	− ve	2.64	4.25
33	12	Kerosene oil	4	+ ve	11.16	3.55
34	12	Kerosene oil	4	+ ve	11.16	4.74

maximum values for all k^{th}responses. Where $\beta_0(k)$ shows the ideal sequence for the two responses for $k = 1$ to 6. Then, finally, the grey generated relational values $\alpha_i(k)$ and $\beta_i(k)$ are commonly taken as $x_i(k)$ for determining the sequence of deviation. Deviation sequence $\Delta_{0i}(k)$ is determined using Eq. (4):

$$\Delta_{0i}(k) = \left|x_o^*(k) - x_i^*(k)\right| \tag{4}$$

Grey relational grade reveals the degree of freedom between ideal sequences $x_0(k)$ and $x_i(k)$. The coefficient of grey relational analysis $\delta_i(k)$ is determined using Eq. (5):

$$\delta_i(k) = \frac{\Delta_{\min} + \psi\Delta_{\max}}{\Delta_{0i}(k) + \psi\Delta_{\max}} \tag{5}$$

In Eq. (5), $\Delta_{0i}(k)$ shows the sequence of deviation reference taken from ideal sequence $x^*_{0(k)}$ and the comparability sequence $x^*_{i(k)}$, and ψ represents coefficient of identification or distinguishing coefficient. The value of identification coefficient ranges between 0 and 1. If equal importance is given to each parameters; then, its value is 0.5. The grey grade (y_i) for the i^{th} experiments is given by Eq. (6):

$$y_i = \frac{1}{n}\sum_{k=1}^{n}\delta_i(k) \tag{6}$$

where n is the number of responses. As the value of grey relational grade is higher and higher, this means strong relationship between references and given sequences, i.e., $\alpha_0(k)$ and $\alpha_i(k)$ for smaller-the-better case, $\beta_0(k)$ and $\beta_i(k)$ for larger-

Table 5 Grey coefficient and grey grades for response variables

Exp. no.	Parameters				Responses		Grey relational coefficient		Grey relational grade (y_i)	Rank
	A	B	C	D	MRR	R_a	MRR $\delta_i(1)$	R_a $\delta_i(2)$		
1	12	Transformer oil	6	+ ve	5.58	2.45	0.4198	0.8106	0.6152	5
2	12	Kerosene oil	4	+ ve	11	3.05	0.6158	0.6779	0.6468	4
3	12	Transformer oil	2	+ ve	5.91	3.23	0.4280	0.6459	0.5370	13
4	12	Kerosene oil	4	+ ve	9	3.89	0.5252	0.5514	0.5383	12
5	15	Distilled water	4	+ ve	5.91	5.35	0.4280	0.4169	0.4225	25
6	15	Distilled water	4	− ve	2.58	4.44	0.3568	0.4920	0.4244	24
7	12	Kerosene oil	4	− ve	1.57	5.03	0.3397	0.4398	0.3898	31
8	12	Kerosene oil	4	− ve	1.83	4.38	0.3439	0.4973	0.4206	26
9	9	Distilled water	4	+ ve	2.87	2.98	0.3621	0.6910	0.5265	16
10	12	Distilled water	2	− ve	1.34	3.45	0.3360	0.6112	0.4736	19
11	15	Kerosene oil	6	+ ve	15.46	5.37	1.0000	0.4149	0.7075	1
12	9	Transformer oil	4	+ ve	4.57	2.06	0.3961	0.9286	0.6624	3
13	9	Kerosene oil	2	− ve	2.09	4.99	0.3484	0.4436	0.3960	29
14	9	Distilled water	4	− ve	1.17	5.81	0.3333	0.3867	0.3600	33
15	12	Distilled water	2	+ ve	2.34	2.9	0.3525	0.7074	0.5300	14
16	15	Kerosene oil	2	+ ve	14.35	6.38	0.8661	0.3550	0.6106	6
17	15	Kerosene oil	6	− ve	5.58	3.33	0.4198	0.6298	0.5248	17
18	12	Distilled water	6	+ ve	2.51	1.87	0.3556	1.0000	0.6778	2
19	12	Transformer oil	6	− ve	2.23	3.68	0.3508	0.5783	0.4645	20
20	12	Transformer oil	2	− ve	2.39	4.74	0.3535	0.4645	0.4090	28
21	9	Kerosene oil	6	+ ve	9.13	3.47	0.5305	0.6079	0.5692	8
22	12	Kerosene oil	4	+ ve	10.04	3.80	0.5691	0.5632	0.5661	9
23	15	Kerosene oil	2	− ve	4.95	4.48	0.4047	0.4876	0.4462	21
24	9	Kerosene oil	2	+ ve	8.37	3.87	0.5021	0.5548	0.5285	15
25	9	Kerosene oil	6	− ve	3.46	4.78	0.3733	0.4606	0.4170	27
26	12	Kerosene oil	4	− ve	1.52	4.12	0.3389	0.5245	0.4317	23
27	9	Transformer oil	4	− ve	1.93	6.84	0.3457	0.3333	0.3395	34
28	12	Kerosene oil	4	− ve	1.66	5.04	0.3412	0.4391	0.3901	30
29	15	Transformer oil	4	+ ve	12.56	5.36	0.7114	0.4161	0.5638	10
30	12	Distilled water	6	− ve	1.48	3.34	0.3382	0.6282	0.4832	18
31	15	Transformer oil	4	− ve	5.43	6.39	0.4161	0.3545	0.3853	32
32	12	Kerosene oil	4	− ve	2.64	4.25	0.3580	0.5109	0.4344	22
33	12	Kerosene oil	4	+ ve	11.16	3.55	0.6246	0.5966	0.6106	7
34	12	Kerosene oil	4	+ ve	11.16	4.74	0.6246	0.4644	0.5445	11

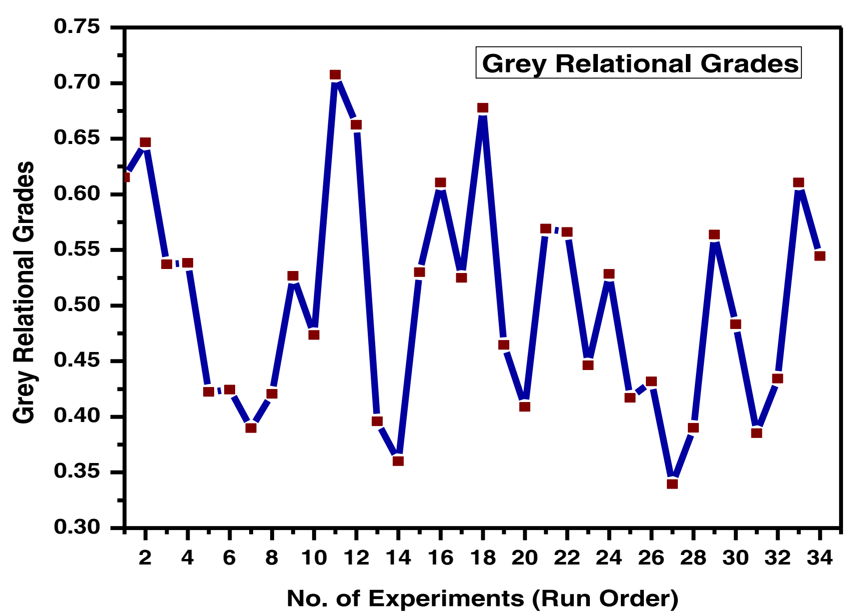


Fig. 4 Variations of grey relational grades (GRG)

Table 6 Mean response table for GRD

Symbol	Parameters	Grey relational grade (GRG)			Optimum levels	Main effect (max-min)	Rank
		Level 1	Level 2	Level 3			
A	current	0.474879	0.482275	0.510603	3 (High)	0.035724	3
B	lubrication type	0.487248	0.509583	0.497074	2 (Medium)	0.022335	4
C	spark gap	0.491337	0.480960	0.557389	3 (High)	0.076429	1
D	polarity	0.419772	0	0.579832	3 (High)	0.579832	2

Total mean value of the grey relational grade y_m=0.5014

Table 7 ANOVA for grey relational grade (GRG)

Parameters	Sum of square	Degree of freedom	Mean square	F value	Percentage contribution (ρ)
A: discharge current	0.012	2	0.006	1.64	4.62
B: dielectric type	0.010	2	0.005	0.47	3.85
C: spark gap	0.017	2	0.0075	2.40	6.54
D: polarity	0.13	1	0.13	43	50
Residual	0.087	28	3.12E-03		33.46
Total	0.26	33			100

the-better case $x_0(k)$ and $x_i(k)$ $x_0(k)$ and $x_i(k)$. As a result, this shows that current parameter setting is nearer to the optimum solution. The overall calculations have been presented in Table 5.

In Table 5, the results for grey relational coefficient and grey relational grades for the corresponding response variables (MRR & R_a) has been explained. Normalization of the response variables has been done using Eqs. (2), (3), and (4).

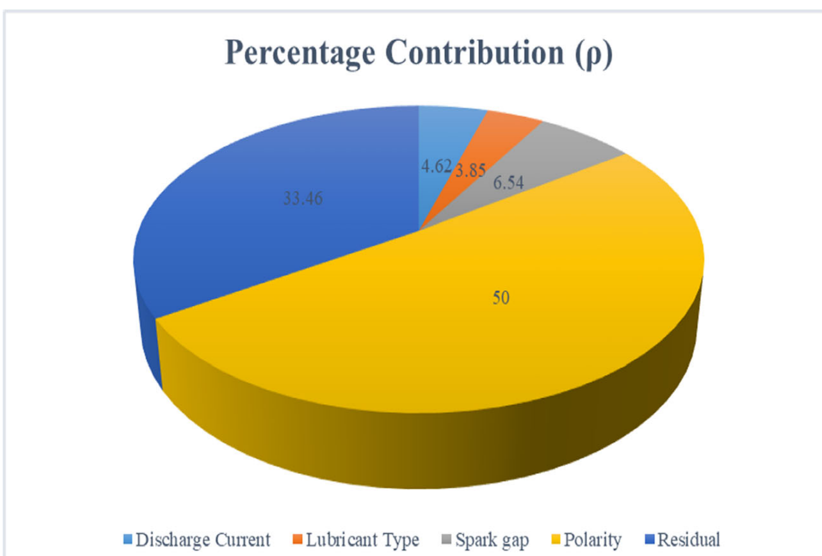


Fig. 5 Percentage contribution of process parameters

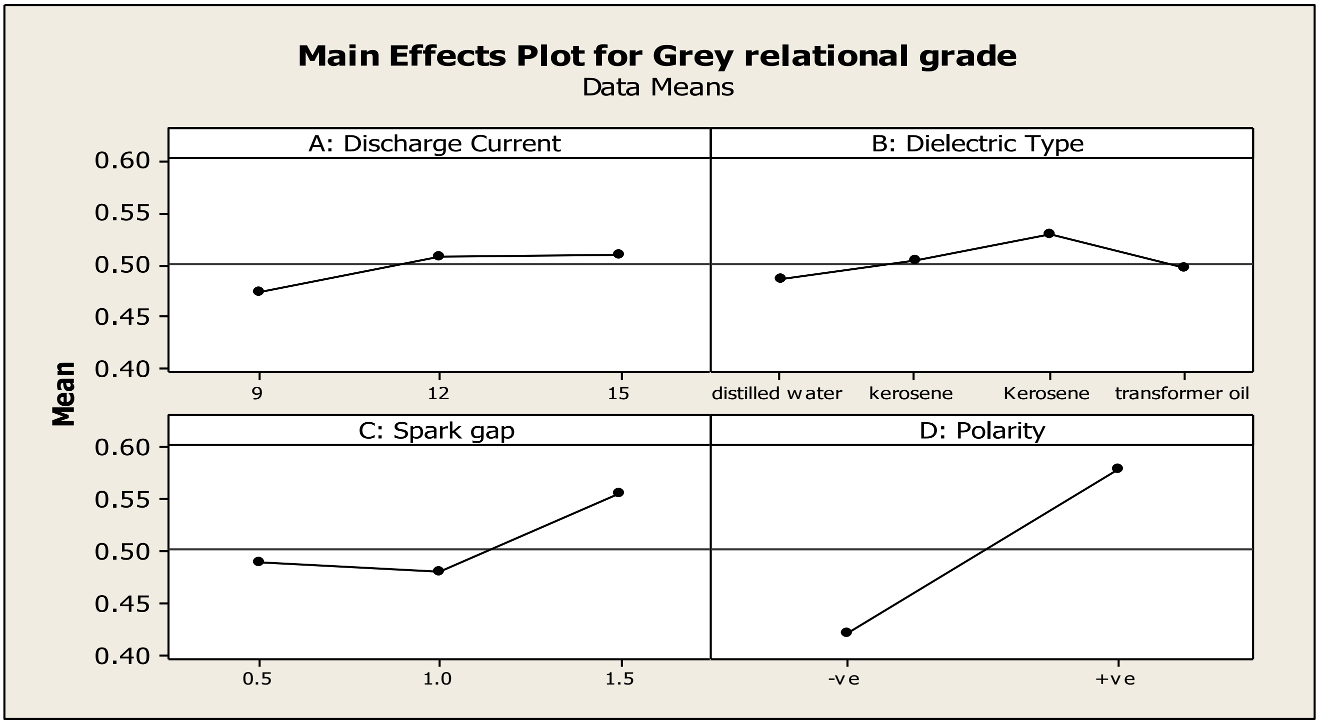


Fig. 6 Main effect plots for GRD

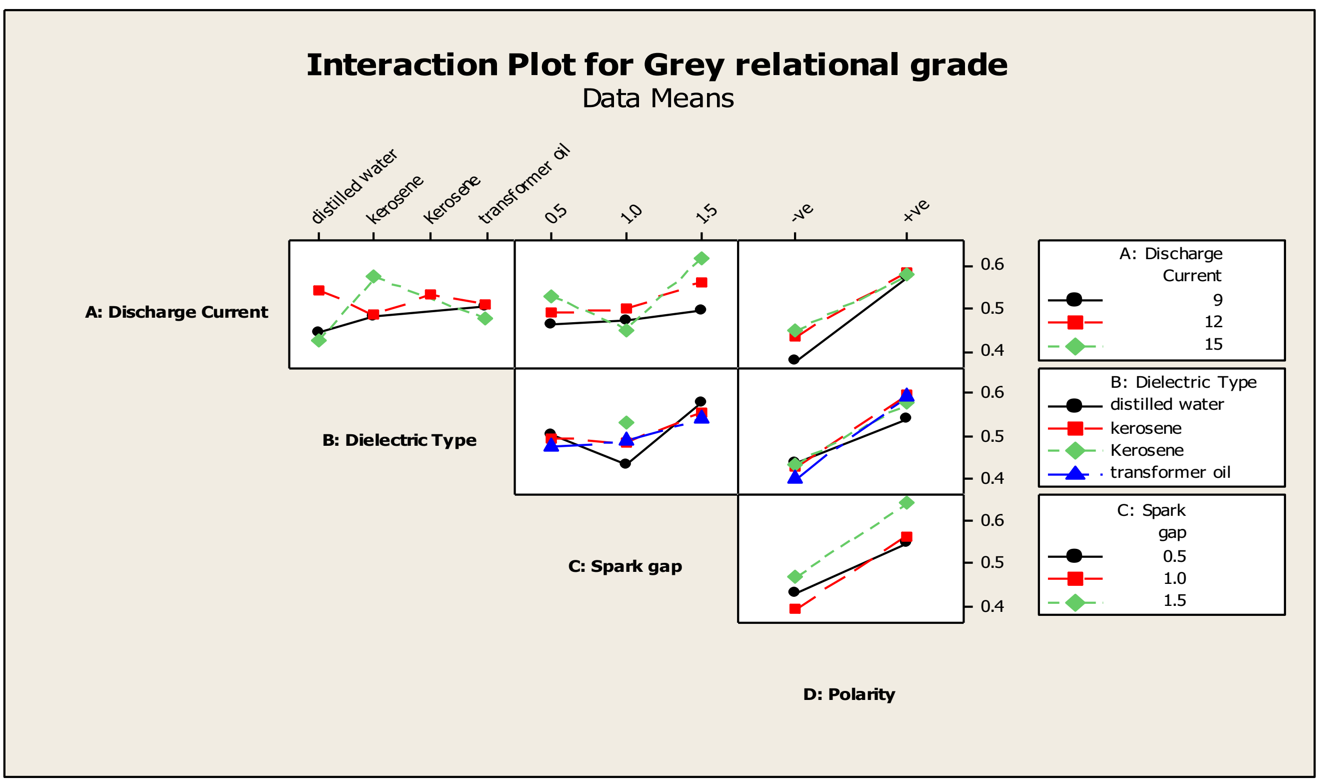


Fig. 7 Interaction effect plots for GRD

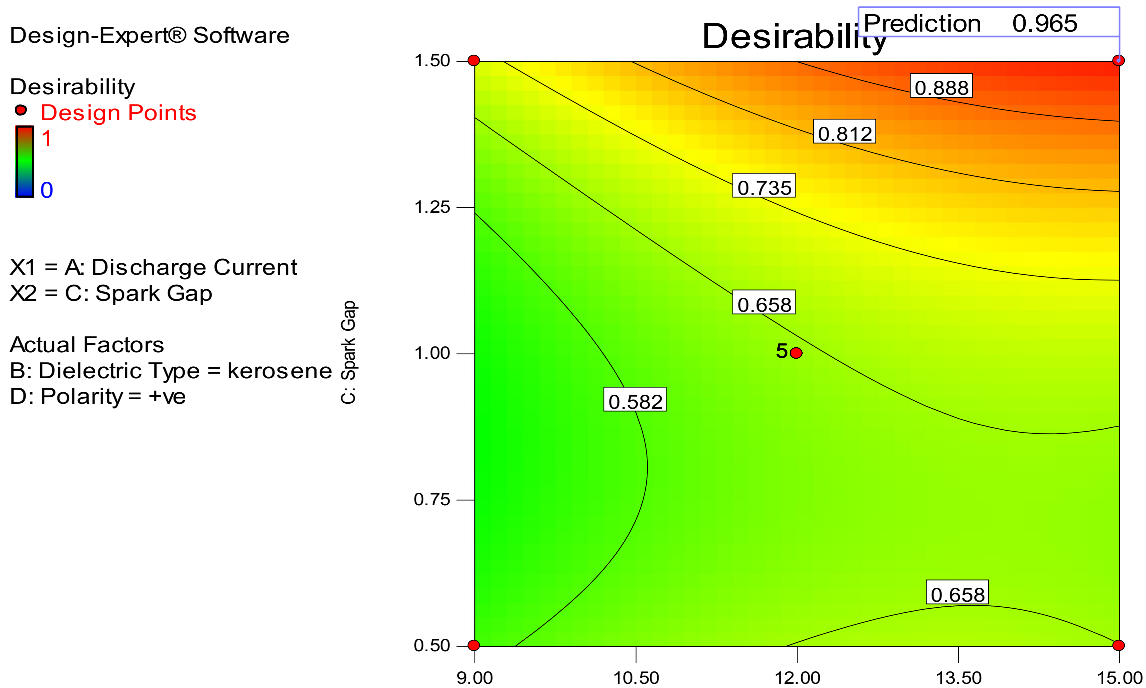


Fig. 8 Predicted and desirability values for grade response

Grey coefficients for the two response variables $\delta_i(1)$ and $\delta_i(2)$ have been calculated using Eq. (5).

The distinguishing constant coefficient is used to expand or compress the grey relational coefficient ranges. Its value may be selected by expert knowledge, and its different values provide different results in grey relational analysis. This led to the similar optimum conditions. In present case, the value of distinguishing coefficient (ψ) is taken as 0.5.

Finally, the two responses are then converted into a single response variable, named grey relational grade (GRG). GRGs have been calculated w.r.t. the process parameters: discharge current, dielectric type, spark gap, and polarity using Eq. (6). The optimal setting of parameters has been determined using grey grade. Variations of grey relational grade with the number of experiments have been shown in Fig. 5. The values of grey relation grade should found nearly to 0.7.

Figure 4 shows the variations among grey grades of all the experiments. The experiment having large grey grade should be selected for the comparison. It can be concluded that the maximum grey relational grade (GRG) is for 11th experiment at which discharge current and spark gap is at higher levels and dielectric type is kerosene oil while polarity of electrode taken is positive.

The mean values of grey grades of process parameters at each level have been determined as presented in Table 6. The total mean value of grey grade for all the experiments has been determined. This table shows that the optimum condition for higher MRR and lower R_a are ($A_3B_2C_3D_3$).

Furthermore, ANOVA for the grey relational analysis has been performed for identifying the significant factors for optimizing the grey grade. The main purpose is investigating the significance of process parameters affecting the performance measures (MRR and R_a).

Table 8 Constraints and optimization of parameters and responses

Variables	Goal	Limit	Limit	Weight	Weight	Importance
Discharge current	Is in range	9	15	1	1	3
Dielectric type	Is in range	distilled water	transformer oil	1	1	3
Spark gap	Is in range	0.5	1.5	1	1	3
Polarity	Is in range	+ve	-ve	1	1	3
GRD	Maximize	0.3395	0.7075	1	1	3

Table 9 Optimum condition of die-sinker EDM by grey relational grade

Variable	Value	Unit
Discharge current	15	A
Dielectric type	Kerosene oil	N/A
Spark gap	6	Mm
Polarity	+ ve	N/A

3 Results and discussion

3.1 ANOVA for grey grades

ANOVA has been applied for determining the significance of parameters, i.e., discharge current, dielectric type, spark gap, and polarity for optimizing the grey grade. ANOVA results are presented in Table 7.

ANOVA results show that electrode polarity is most significant factor that affects the MRR and R_a followed by the spark gap, discharge current, and dielectric type. This can also be observed by determining the percentage contribution as presented in Fig. 5. This figure also shows that polarity has greater contribution affecting the grey grade, and therefore contributes in optimizing the response variables. This means that when electrode polarity has reversed, then discharge energy is significantly affected, and hence consequently affects material removal rate and surface roughness.

The main effect and interaction effect plots have also been drawn as shown in Figs. 6 and 7 respectively, to clearly observe the influence of parameters on grey grade. The higher value of grade will be taken for each process parameters. It can be concluded that higher values of grade are for discharge current at 15 A, dielectric type is kerosene oil, spark gap at 6 mm, and electrode having positive polarity.

From Fig. 7, it is noticed that interaction effect of discharge current and dielectric type, dielectric type, and polarity has significant effect on the grey grades.

Table 10 Confirmation results

Conditions	Optimum parameter levels	
	11th (initial condition)	Optimal (GRA)
Level	$A_3B_2C_3D_3$	$A_3B_2C_3D_3$
MRR	15.46	17.23
R_a	5.37	3.86
Grey relational grade	0.71	0.76
Improvement in GRD = 0.05.		

3.2 Optimization of grey relational grade and optimum condition

Design Expert 7.0.0 software was employed for optimizing the grey relational grade, it has been noticed that the constraints and optimum condition for input parameters for two response variables, material removal rate, and surface roughness as shown in Table 8.

The predicted and desirability values for grey relational grade have been shown in Fig. 8.

The values of predicted and desirability grey relational grade are predicted grey relational grade responses = 0.965 and desirability = 0.888. Therefore, it has been observed from the predicted responses that the optimum condition for the process parameters obtained is shown in Table 9.

3.3 Confirmatory test

Confirmatory test has been done for verification to check improvement in the performance measures in EDM using *AISI D2* steel. The optimum levels have been selected for the confirmation test as shown in Table 10. The estimated value of grey relational grade $\overline{Y}$ using these optimum levels of process parameters can be determined using Eq. (7).

$$\overline{Y} = Y_m + \sum_{i=1}^{n}\left(\overline{Y_i} - Y_m\right) \tag{7}$$

In the above expression, Y_m is total mean value of grey relational grade, $\overline{Y_i}$ denotes the mean value of grade at optimum conditions, and n is the number of parameters influencing the performance measures.

4 Conclusions

In this research, the influence of various parameters such as discharge current, dielectric type, spark gap, and polarity on responses such as MRR and R_a, while machining AISI D2 steel, has been investigated. Copper rod was used as an electrode. Experiments were designed and performed using Box-Bhenken design (BBD) based on response surface methodology. The grey relational approach combined with response surface methodology was used for analysis. The grey relational analysis translates the multi-objective responses into single response, the grey relational grade, which has been further analyzed through ANOVA for identifying the significant factors. Grey relational analysis was used for optimizing the parameters affecting the grey relational grade and it was found that the optimum levels for process parameters were discharge current at 15 A, dielectric type is kerosene oil, spark gap at

6 mm, and electrode polarity was positive. The optimum values for MRR and R_a are 17.23 mm^3/min and 3.86 μm respectively. ANOVA results showed that polarity was the most influencing factor having 50% contribution followed by the spark gap, discharge current, and dielectric type. The proposed method can be used for optimization of input parameters in other processes.

Along with parameters considered in this research, other parameters including pulse on time, pulse off time, servo speed, addition of nanoparticles in dielectric, and comparison of different materials can be considered. For analysis, other statistical techniques such as genetic algorithm, ant colony optimization, and TOPSIS can be employed. Also, along with the responses evaluated in this research, other performance measures can be taken such as white layer; tool wear can be investigated.

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