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MULTI-RESPONSE OPTIMIZATION OF DIELECTRIC FLUID MIXTURE IN EDM USING GREY RELATIONAL ANALYSIS (GRA) IN TAGUCHI METHOD

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Abstract. *In the current study, combining the powder with dielectric fluid in electrical discharge machining (PMEDM) is a very fascinating technological approach. This approach is the most effective at increasing both productivity and the quality of a machined surface at the same time. The Taguchi–GRA approach was used to optimize the surface roughness (SR), material removal rate (MRR), and micro-hardness of a machined surface (HV) in electrical discharge machining of die steels in dielectric fluid with mixed powder. Workpiece materials (with 3 levels such as SKD61, SKD11, and SKT4), electrode materials (with 2 levels such as copper, and graphite), pulse-on time, electrode polarity, current, pulse-off time, and titanium powder concentration were all used in the study. The effect on the ideal results was also evaluated using some interaction pairings among the process parameters. Powder concentration, electrode material, electrode polarity, current, pulse-on time, pulse-off time, and Interaction between workpiece material and powder concentration were obtained to be significant in the ideal condition, where larger MRR and HV are wanted (as per the HB criterion), but lower values are desired for the remaining responses, such as surface roughness (SR). Powder concentration was also discovered to be a major component, however, it only accounts for 8.35 percent of the ideal condition. MRR = 54.36 mm3/min, SR = 5.65 m, and HV =832.66 HV were the best quality attributes based on the grey grade.*

Keywords: *Taguchi, GRA, Dielectric Fluid, EDM.*

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1. INTRODUCTION

Electrical Discharge Machining (EDM) is a metal- purification procedure that uses electric spark erosion in detaching metal. So, an electric spark is applied to erode the workpiece and generate the finished item in the desired shape. The metal- purification procedure is carried out by pulsing an electrical of a high frequency current that passes via the electrode and onto the item. This eliminates (erodes) very small particles of metal from the workpiece. The workpiece and electrode are bathed in dielectric liquid during the EDM process, which is an electrical insulator that helps control the arc discharge. The dielectric liquid is pushed through the arc gap to provide a mechanism of cleansing. This clears the work cavity of suspended particles of workpiece material and electrode.

This procedure is employed due to an efficient option in boosting company productivity and the machined quality after the process [1]–[3]. The conductive powder is frequently mixed with dielectric fluid in electrical discharge machining (EDM). Powder materials such as Al, SiC, W, WC, Cu, and MoS2 have all been employed to increase the surface roughness (SR), material removal rate (MRR), and electrode wear ratio (EWR) in EDM[4]–[6]. The number of process parameters in PMEDM (Powder Mixed EDM) is large, and many influencing elements (such as powder uniformity in the dielectric liquid, cycled movement of powder in the arc gap, powder shape, and physical features of the powder material) have yet to be clarified.

PMEDM is a complicated system [7]. Taguchi's approach has been frequently employed to solve optimization problems, but it can only solve a single-characteristic response optimization problem. So, the Taguchi method has recently been integrated with several other approaches, including gray relational analysis (GRA) and TOPSIS. MRR is enhanced, SR is lowered, and HV is increased when titanium powder is introduced into the dielectric fluid, according to Taguchi-TOPSIS [8]. In micro-EDM of CP Ti, Taguchi-GRA was employed to jointly maximize MRR, EWR, and OC expenses [9]. The study included current, frequency, and pulse width; current has the greatest impact, while pulse width has the smallest.

The study of joint maximization of the SR, MRR, and HV indicators in PMEDM utilizing Ti powder is presented in this paper. Dataset used in the study is collected from [8]. In the Taguchi–GRA (Grey Relational analysis) method, seven processes of parameters with three of them being interactions were studied.

2. RESEARCH METHODS

2.1 Material

2.1.1 Taguchi Approach

The Taguchi method was firstly introduced by Dr. Genich Taguchi, a Japanese scholar. The main idea of the Taguchi approach is the cost of quality should be measured as a function of deviation from the standard (target). Taguchi techniques are designed as:

1. Off-line Quality techniques in the manufacturing process
2. Make sure the Quality of Design of Processes and Products
3. Robust Design is the procedure using Orthogonal Arrays for the experimental design

   Several advantages of the Taguchi method are as follows:

1. The level of efficiency of experimental design is higher because it can conduct research that involves many factors and levels.
2. Obtain a process that produces a product that is consistent and sturdy against interference which is a factor that cannot be controlled.

Statistical methods have been widely developed and used in various fields, one of which is the field of optimization. The usual statistical method used for optimization is Taguchi. Taguchi's method is commonly used to solve one-response optimization problems [10]. As for the case of multi-response, there is a multi-response optimization method with a desirability function. The desirability function is a transformation of the response variable on a scale of zero to one [11].

2.1.2 S/N Ratio

To maximize the findings, the Taguchi procedures are applied to the signal-to-noise (S/N) ratio. The S/N coefficient will be estimated by the formula in the case of studies for various quality criteria. [18]:

- Smaller is better: $\mathrm{SN} = -10\log_{10}\ [\mathrm{S}]$

$$S = \frac{y_1^2 + y_2^2 + \cdots + y_n^2}{n}$$

S: Squared mean of the measured process.
y_i: Value collected by experiment $(i = 1{:}\,n)$.
n: Total experiments.

- Larger is better: $S/V = -10 \text{ Log } [L]\ s$

$$\frac{\frac{1}{y_1^2}+\frac{1}{y_2^2}+\cdots+\frac{1}{y_n^2}}{n}$$

L: Inverse squared mean of the measured process.

- Nominal values are the best: $\mathrm{S/N} = -10\log_{10}\quad [\mathrm{N}]$

$$N = \frac{(y_1 - m)^2 + (y_2 - m)^2 + \cdots + (y_\mathrm{n} - m)^2}{n}$$

m: Value targets.

2.1.3 Multi-characteristic optimization with GRA

Grey relational analysis (GRA) is employed for finding interrelationships among the multiple responses in the process. In this approach, the grey relational grade is estimated for analyzing the relational degree of the multiple-responses process. Research [12] has utilized the grey relational-based method in order to tackle the multi-response issues in the Taguchi methods.

The GRA theory adopts the grey theory which is derived from the mixing of clear and unclear information. For example, Black is denoted as vague information, which can be interpreted as rudimentary information. While white on the contrary denoted absolutely clear information. But one-day information can be somewhere between the combination of black and white known as Grey, information that has some things that are clear and unclear or less perfect [13].

2.2 Methods

2.2.1 Experimental Setup with Taguchi Method

The experiments were done using the Taguchi method and specific orthogonal array to maximize the number of parameter processes used in the empirical matrix and their levels as well as minimize experiment numbers. The number of factors and their degrees of freedom (dof) from each factor influence the design of an orthogonal array.

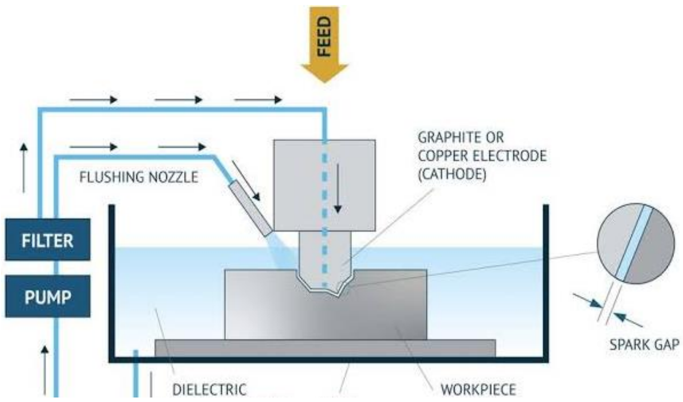

Figure 1. EDM Environment

The environment of EDM is displayed in Figure 1. Meanwhile, the factors and their levels considered in this study are shown in Table 1. The total sum of dof is 20, which includes both primary components and interaction variables. As a result of the 20 degrees of freedom, the $\boldsymbol{L_{27}}$ orthogonal array meets the current criterion because it has 26 degrees of freedom. Random error is applied to the remaining 6 degrees of freedom. The $\boldsymbol{L_{27}}$ the orthogonal array has 13 columns, each with two degrees of freedom. Table 2 shows the standard orthogonal array of $\boldsymbol{L_{27}}$ with three levels.

Table 1. Input parameters and levels

No	Factors	Symbols	Level			DoF
			Level 1	Level 2	Level 3	
1	Workpiece item	A	SKD61	SKD11	SKT4	2
2	Electrode material	B	Cu	Cu^a	Gr	1
3	Polarity	C	–	+	$-^a$	1
4	Pulse-on time(µs)	D	5	10	20	2
5	Current (A)	E	8	4	6	2
6	Pulse-off time(µs)	F	38	57	85	2
7	Powder concentration Ti(g/l)	G	0	10	20	2
8	Interaction between workpiece material and tool material	A×B	–	–	–	2
9	Interaction between workpiece material and powder concentration	A×G	–	–	–	4
10	Interaction between tool material and powder concentration	B×G	–	–	–	2

Table 2. L_{27} standard orthogonal array

	A	B	AB	AB	G	AG	AG	BG	C	D	BG	E	F
Trial no.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2	2	2	2	2	2	2
3	1	1	1	1	3	3	3	3	3	3	3	3	3
4	1	2	2	2	1	1	1	2	2	2	3	3	3
5	1	2	2	2	2	2	2	3	3	3	1	1	1
6	1	2	2	2	3	3	3	1	1	1	2	2	2
7	1	3	3	3	1	1	1	3	3	3	2	2	2
8	1	3	3	3	2	2	2	1	1	1	3	3	3
9	1	3	3	3	3	3	3	2	2	2	1	1	1
10	2	1	2	3	1	2	3	1	2	3	1	2	3
11	2	1	2	3	2	3	1	2	3	1	2	3	1
12	2	1	2	3	3	1	2	3	1	2	3	1	2
13	2	2	3	1	1	2	3	2	3	1	3	1	2
14	2	2	3	1	2	3	1	3	1	2	1	2	3
15	2	2	3	1	3	1	2	1	2	3	2	3	1
16	2	3	1	2	1	2	3	3	1	2	2	3	1
17	2	3	1	2	2	3	1	1	2	3	3	1	2
18	2	3	1	2	3	1	2	2	3	1	1	2	3
19	3	1	3	2	1	3	2	1	3	2	1	3	2
20	3	1	3	2	2	1	3	2	1	3	2	1	3
21	3	1	3	2	3	2	1	3	2	1	3	2	1
22	3	2	1	3	1	3	2	2	1	3	3	2	1
23	3	2	1	3	2	1	3	3	2	1	1	3	2
24	3	2	1	3	3	2	1	1	3	2	2	1	3

	A	B	AB	AB	G	AG	AG	BG	C	D	BG	E	F
Trial no.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
25	3	3	2	1	1	3	2	3	2	1	2	1	3
26	3	3	2	1	2	1	3	1	3	2	3	2	1
27	3	3	2	1	3	2	1	2	1	3	1	3	2

Table 3. 3-level interaction Taguchi table [14]

Column	Column											
	2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
1	3	2	2	6	5	5	9	8	8	12	11	11
1	4	4	3	7	7	6	10	10	9	13	13	12
2	-	1	1	8	9	10	5	6	7	5	6	7
2	-	4	3	11	12	13	11	12	13	8	9	10
3	-	-	1	9	10	8	7	5	6	6	7	5
3	-	-	2	13	11	12	12	13	11	10	8	9
4	-	-	-	10	8	9	6	7	5	7	5	6
4	-	-	-	12	13	11	13	11	12	9	10	8
5	-	-	-	-	1	1	2	3	4	2	4	3
5	-	-	-	-	7	6	11	13	12	8	10	9
6	-	-	-	-	-	1	4	2	3	3	2	4
6	-	-	-	-	-	5	13	12	11	10	9	8
7	-	-	-	-	-	-	3	4	2	4	3	2
7	-	-	-	-	-	-	12	11	13	9	8	10
8	-	-	-	-	-	-	-	1	1	2	3	4
8	-	-	-	-	-	-	-	10	9	5	7	6
9	-	-	-	-	-	-	-	-	1	4	2	3
9	-	-	-	-	-	-	-	-	8	7	6	5
10	-	-	-	-	-	-	-	-	-	3	4	2
10	-	-	-	-	-	-	-	-	-	6	5	7
11	-	-	-	-	-	-	-	-	-	-	1	1
11	-	-	-	-	-	-	-	-	-	-	13	12
12	-	-	-	-	-	-	-	-	-	-	-	1
12	-	-	-	-	-	-	-	-	-	-	-	11

The parameters have two levels that must be dummy treated in order to match the orthogonal array with three levels (L_{27} orthogonal array). Table 4 shows the final experimental results of three output responses: (MRR), (SR), and (HV).

Table 4. Data Experiments [8]

Experiments	A	B	C	D	E	F	G	MRR	SR	HV
1	SKD61	Cu	–	5	8	38	0	10.5	3.4	506.7
2	SKD61	Cu	+	10	4	57	10	8.2	3.2	659.0
3	SKD61	Cu	$-^a$	20	6	85	20	3.2	2.6	581.6
4	SKD61	Cu^a	+	10	6	85	0	10.2	3.6	496.7
5	SKD61	Cu^a	$-^a$	20	8	38	10	14.3	3.6	828.9
6	SKD61	Cu^a	–	5	4	57	20	0.1	1.5	629.8
7	SKD61	Gr	$-^a$	20	4	57	0	37.5	4.8	544.6
8	SKD61	Gr	–	5	6	85	10	23.6	3.2	748.4
9	SKD61	Gr	+	10	8	38	20	38.8	4.4	626.2

Experiments	A	B	C	D	E	F	G	MRR	SR	HV
10	SKD11	Cu	+	20	4	85	0	18.9	4.2	509.7
11	SKD11	Cu	$-^{a}$	5	6	38	10	3.9	2.1	679.5
12	SKD11	Cu	–	10	8	57	20	14.5	3.2	664.2
13	SKD11	Cu^{a}	$-^{a}$	5	8	57	0	10.6	3.4	546.0
14	SKD11	Cu^{a}	–	10	4	85	10	0.3	2.0	679.2
15	SKD11	Cu^{a}	+	20	6	38	20	23.6	4.6	655.2
16	SKD11	Gr	–	10	6	38	0	23.9	4.6	469.8
17	SKD11	Gr	+	20	8	57	10	59.7	4.5	907.6
18	SKD11	Gr	$-^{a}$	5	4	85	20	17.2	2.7	683.5
19	SKT4	Cu	$-^{a}$	10	6	57	0	1.3	2.6	530.7
20	SKT4	Cu	–	20	8	85	10	20.7	4.3	624.6
21	SKT4	Cu	+	5	4	38	20	4.4	2.5	631.7
22	SKT4	Cu^{a}	–	20	4	38	0	0.2	2.3	468.0
23	SKT4	Cu^{a}	+	5	6	57	10	6.8	2.9	544.4
24	SKT4	Cu^{a}	$-^{a}$	10	8	85	20	19.7	3.5	613.8
25	SKT4	Gr	+	5	8	85	0	10.6	3.2	445.4
26	SKT4	Gr	$-^{a}$	10	4	38	10	26.0	3.2	681.2
27	SKT4	Gr	–	20	6	57	20	54.4	5.7	832.7

^{a} *treated as dummy*

To maximize the findings, the Taguchi method employs the S/N ratio which is also used in the GRA to optimize the multi-response process.

2.2.1 Multi-Response Optimization with GRA

In grey relational analysis, black denotes the absence of information, whereas white denotes the presence of all information. The level of information in a grey system is somewhere between black and white. To put it another way, in a grey system, certain information is known but others are unknown. The relationships among system factors in a white system are known; in a grey system, the interactions among system factors are ambiguous [15], [16].

Higher MRR and HV are desired (as it corresponds to Higher-is-Better, HB criterion) but lower values are desirable for the remainder of the responses, like surface roughness, (as they correspond to Lower-is-Better, LB criterion). Only those two quality characteristics are used in this study.

Step 1 Calculate $\mathbf{S/N}$ ratio for the responses by using the following expression.
Larger - the – better

$$\mathbf{S/N} \text{ ratio } (\boldsymbol{\eta}) = -\mathbf{10log_{10}} \left(\frac{\mathbf{1}}{\mathbf{n}}\right) \sum_{\mathbf{i=1}}^{\boldsymbol{n}} \frac{\mathbf{1}}{\mathbf{y_{ij}^2}} \qquad (1)$$

where $\mathbf{n} =$ number of replications $\mathbf{y_{ij}} =$ observed response value where $\boldsymbol{i} = \mathbf{1}, \mathbf{2}, \dots .\boldsymbol{n}; \boldsymbol{j} = \mathbf{1}, \mathbf{2} \dots \boldsymbol{k}$

Smaller - the – better

$$\mathbf{S/N} \text{ ratio } (\boldsymbol{\eta}) = -\mathbf{10log_{10}} \left(\frac{\mathbf{1}}{\boldsymbol{n}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \boldsymbol{y_{ij}^2}\right) \qquad (2)$$

Step 2 $\boldsymbol{y_{ij}}$ is normalized as $\boldsymbol{Z_{ij}}(\mathbf{0} \le \boldsymbol{Z_{ij}} \le \mathbf{1})$ by using the following equation. Normalization is a transformation that is used for single data input. Before using the grey relation theory or any other methodology to analyze the original data, it is important to normalize it. To make the value of this array approximate to 1, a suitable value is subtracted from the values in the same array. We investigated the sensitivity of the normalization method on the sequencing outcomes since the normalization process affects the rank. As a result, while normalizing data in grey connection analysis, we propose using the S/N ratio value.

$$Z_{ij} = \frac{y_{ij} - \mathrm{m}\ (y_{ij}, i = 1, 2, \ldots n)}{\mathrm{m}\ (y_{ij}, i = 1, 2, \ldots\ldots n) - \mathrm{m}\ (y_{ij}, i = 1, 2, \ldots\ldots n)} \quad (3)$$

(To be used for Larger the better manner)

$$Z_{ij} = \frac{\mathrm{m}\ (y_{ij}, i = 1, 2, \ldots. n) - y_{ii}}{\mathrm{m}\ (y_{ij}, i = 1, 2, \ldots\ldots n) - \mathrm{m}\ (y_{ij}, i = 1, 2, \ldots\ldots n)} \quad (4)$$

(To be used for smaller the better manner)

Step 3 Calculate the grey relational coefficient for the normalized $\mathbf{S/N}$ ratio values.

$$\gamma(y_o(k), y_i(k)) = \frac{\Delta\,\mathrm{m}\ + \zeta \Delta\,\mathrm{m}}{\Delta_{vij}(k) + \zeta \Delta\,\mathrm{m}} \quad (5)$$

where

1. $j = 1, 2 \ldots n; k = 1, 2 \ldots m, n$ is the experiment number and *m* is the response number.
2. $y_d(k)$ is the reference $(y_o(k) = 1, k = 1, 2 \ldots m)$; $y_j(k)$ is the specific comparison sequence.
3. $\Delta_{cj} = \|y_0(k) - y_j(k)\|$ = The absolute value of the difference between $y_a(k)$ and $y_j(k)$
4. $\Delta\mathbf{min} = \mathbf{min}_{\forall j \in i} \mathbf{min}_{tk} \|y_\alpha(k) - y_j(k)\|$ is the smallest value of $y, (k)$
5. $\Delta\mathbf{max} = \mathbf{max}_{\nabla j \in i} \mathbf{max}_{\forall k} \|y_0(k) - y_j(k)\|$ is the largest value of $y(k)$
6. ζ is the distinguishing coefficient, which is defined in the range $0 \leq \zeta \leq 1$

Step 4 Generate the grey relational grade (GRG).

$$\bar{\gamma}_J = \frac{1}{k} \sum_{j=1}^{m} \gamma_{ij} \quad (6)$$

where $\bar{\gamma}_j$ is the grey relational grade for the j th experiment and k is the number of performance characteristics.

Step 5 Find the best component and the best level combination for it.
The higher the grey relational grade, the better the product quality; thus, the factor influence may be evaluated and the best level for each controllable component can be found using the grey relational grade (GRG). $\mathbf{E_i}$ is defined as:

$$E_i = \mathrm{m}\ (AGV_{ij}) - \mathrm{m}\ (AGV_{ij}) \quad (7)$$

If the factor i is controllable, the best level j^*, is determined by

$$\vec{j} = \max_{j}(AGV_i) \quad (8)$$

Step 6 Perform ANOVA for finding the significant factors.
The analysis of variance (ANOVA) purpose is to find the effect of specific components using a statistical method. The impact of each element on the process results can be determined very clearly using ANOVA results.

Step 7 Estimate the optimum condition.
Once the optimal level of the design parameters has been found, the final step is to predict and verify the quality characteristic. The estimated $\mathbf{S/N}$ ratio from the optimal level is estimated using the following expression:

$$\hat{\eta} = \eta_{mt} + \sum_{i=1}^{q} (\bar{\eta}_i - \eta_m) \quad (9)$$

η_{m}: Average **SN** ratio
$\bar{\eta}$: Average **SN** ratio corresponding to i^{th} significant factor on j^{th} level
q: Number of significant factors

3. RESULTS AND DISCUSSION

3.1. Taguchi Technique of Experimental Design with Dummy Treatment

As mentioned in section 2.2.1, the parameters have two levels that must be dummy treated in order to match the orthogonal array with three levels. In the final Taguchi orthogonal array in Table 4, we do not use columns 4, 7, and 11 as the other columns for interaction factors have been chosen (3,6,8) according to the 3-level interaction Taguchi table reference in Table 3 (does not apply to L_{18}). There are seven main components analyzed, two of which have two levels, each with one dof, and the interaction terms are as follows: As demonstrated in Table 3, the interaction of electrode material and workpiece material (AxB); the interaction of workpiece material and powder concentration ($A \times G$); and the interaction of electrode material and powder concentration (BxG). Signal to noise (S/N) ratio used in Taguchi analysis is also used in the GRA to optimize the multi-response results in our experiment's data.

Table 5. S/N ratio values and normalized S/N ratio values

Experiments	S/N ratios			Normalized values of S/N ratios Z_{ij}			Grey			Grey Grade
	MRR	SR	HV	MRR	SR	HV	MRR	SR	HV	
1	20.41	-10.50	54.10	0.733	0.616	0.181	0.733	0.616	0.181	0.532
2	18.24	-10.13	56.38	0.694	0.584	0.550	0.694	0.584	0.550	0.564
3	9.97	-8.16	55.29	0.548	0.418	0.375	0.548	0.418	0.375	0.477
4	20.21	-11.00	53.92	0.729	0.658	0.153	0.729	0.658	0.153	0.538
5	23.11	-11.15	58.37	0.781	0.671	0.873	0.781	0.671	0.873	0.698
6	-21.01	-3.23	55.98	0.000	0.000	0.487	0.000	0.000	0.487	0.387
7	31.47	-13.59	54.72	0.928	0.877	0.282	0.928	0.877	0.282	0.696
8	27.45	-10.21	57.48	0.857	0.591	0.729	0.857	0.591	0.729	0.659
9	31.79	-12.77	55.93	0.934	0.808	0.478	0.934	0.808	0.478	0.698
10	25.52	-12.38	54.15	0.823	0.775	0.189	0.823	0.775	0.189	0.603
11	11.72	-6.24	56.64	0.579	0.255	0.593	0.579	0.255	0.593	0.499
12	23.22	-10.10	56.45	0.783	0.582	0.561	0.783	0.582	0.561	0.591
13	20.51	-10.50	54.74	0.735	0.616	0.286	0.735	0.616	0.286	0.544
14	-9.90	-6.19	56.64	0.197	0.251	0.593	0.197	0.251	0.593	0.445
15	27.45	-13.20	56.33	0.857	0.844	0.542	0.857	0.844	0.542	0.687
16	27.56	-13.20	53.44	0.859	0.844	0.075	0.859	0.844	0.075	0.631
17	35.51	-12.97	59.16	1.000	0.824	1.000	1.000	0.824	1.000	0.913
18	24.69	-8.76	56.70	0.808	0.468	0.602	0.808	0.468	0.602	0.588
19	1.95	-8.13	54.50	0.406	0.415	0.246	0.406	0.415	0.246	0.439
20	26.34	-12.69	55.91	0.838	0.801	0.475	0.838	0.801	0.475	0.653
21	12.82	-7.82	56.01	0.598	0.389	0.491	0.598	0.389	0.491	0.500
22	-14.07	-7.08	53.41	0.123	0.326	0.070	0.123	0.326	0.070	0.380
23	16.63	-9.22	54.72	0.666	0.507	0.282	0.666	0.507	0.282	0.504
24	25.88	-10.88	55.76	0.830	0.648	0.451	0.830	0.648	0.451	0.603
25	20.55	-10.18	52.98	0.735	0.589	0.000	0.735	0.589	0.000	0.512

Experiments	S/N ratios			Normalized values of S/N ratios Z_{ij}			Grey			Grey Grade
	MRR	SR	HV	MRR	SR	HV	MRR	SR	HV	
26	28.29	-10.21	56.67	0.872	0.591	0.597	0.872	0.591	0.597	0.633
27	34.71	-15.04	58.41	0.986	1.000	0.879	0.986	1.000	0.879	0.926

3.2. Results of the GRA method

The results of the GRA Method are given in Table 5. From the value of grey relational grade in Table 5, by using Eq. (7), the initial parameter setting obtained from GRA for multi-response is A3 B3 C1 D3 E3 F2 G2. After analyzing the grade using the Taguchi method, the main effects are tabulated in Table 6 and the factor and interactions effects are plotted in Figure 2. By considering the maximization of grade values (Table 6 and Figure 2), the obtained optimal parameter conditions are A2 B3 C2 D3 E1 F2 G2.

Table 6. Main effects on grey grades

Level	Process parameters						
	A	B	C	D	E	F	G
1	0.6113	0.5358	0.5767	0.5249	0.5329	0.5843	0.5416
2	0.5833	0.6952	0.6135	0.5715	0.5956	0.6183	0.6188
3	0.5722	-	-	0.6704	0.6383	0.5642	0.6064
Delta	0.0391	0.1594	0.0368	0.1455	0.1054	0.0541	0.0772
Rank	6	1	7	2	3	5	4

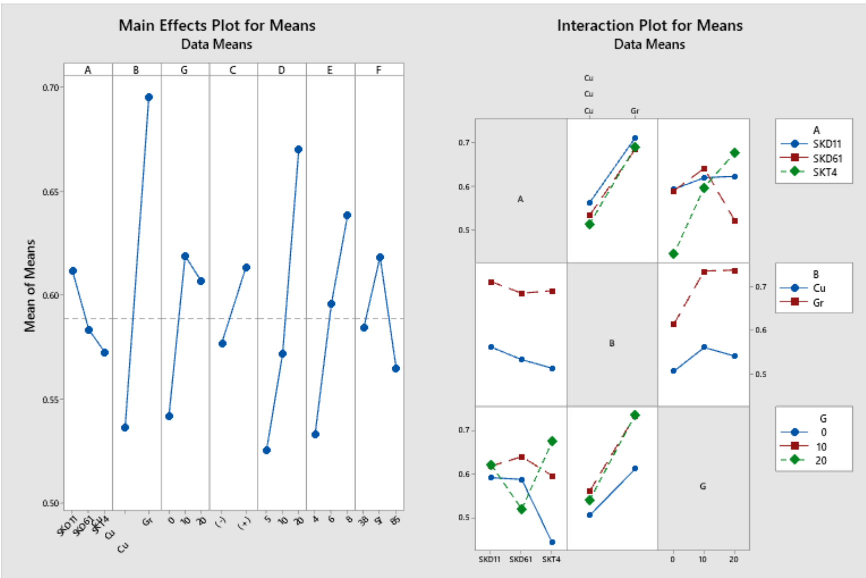

Figure 2. Factors and Its Interactions Effects on Grade Values

Table 7. Main Effects On Grey Grades

Source	DoF	Adj SS	Adj MS	F-Value	P-Value	P(%)
A	2	0.005	0.003	2.320	0.179	1.171
B	1	0.152	0.152	132.840	0.000	33.514
C	1	0.008	0.008	7.080	0.038	1.785
D	2	0.099	0.050	43.260	0.000	21.831
E	2	0.051	0.025	22.020	0.002	11.113

Source	DoF	Adj SS	Adj MS	F-Value	P-Value	P(%)
F	2	0.013	0.007	5.860	0.039	2.954
G	2	0.038	0.019	16.550	0.004	8.350
A*B	2	0.001	0.000	0.420	0.676	0.211
A*G	4	0.076	0.019	16.610	0.002	16.767
B*G	2	0.009	0.004	3.770	0.087	1.904
Error	6	0.007	0.001			1.514
Total	26	0.455				100

Furthermore, by using the grey grade value, ANOVA is formulated for finding the significant factors. The results of ANOVA are given in Table 7. From ANOVA, it is clear that B (Electrode material) (33.51%) influences more the dielectric fluid mixture effectiveness followed by D (Pulse-on time(µs)) (21.83%) and interaction between workpiece material and powder concentration $\boldsymbol{A} \times \boldsymbol{G}$ (16.76%) where the interaction can be seen in Figure 2. If we predict the grey grade by the optimal parameter conditions in step 6, we get a value of $\mathbf{0.913}$ which is a little bit lower than the initial parameter setting obtained from step 5 is $\mathbf{0.926}$. So the optimal parameter setting of dielectric fluid mixture with titanium powder is A3 B3 C1 D3 E3 F2 G2.

4. CONCLUSIONS

The Taguchi–GRA technique was used to optimize the quality characteristic of the process such as the SR, MRR, and HV. When we combine the GRA approach with the Taguchi method, we get the following results:

1. The multi-objective optimization problem is handled simply by several adjusted process parameters. The results of multi-responses optimization in PMEDM using powder Ti show that: electrode material, powder concentration, electrode polarity, pulse-on time, pulse-off time, and A G are significant for an optimal condition where higher MRR and HV are desired (as it corresponds to the HB criterion), but lower values are desirable for the remaining responses, such as surface roughness.
2. The most important factor is the electrode material, which contributes 33.51% to the optimal condition. All other variables, such as workpiece material, A B, and B x G, are irrelevant. The 27th trial yielded the best results when employing the GRA approach. However, the Grey grade values show that the optimal combination is SKD4 workpiece material, Gr electrode material, negative electrode polarity, ton =20 µs, I = 6A, tof = 57 µs, and powder concentration of 20 g/l.
3. The results show that although GRA has produced optimization results with a quite simple method. However the value for $\boldsymbol{\zeta \Delta max} = \mathbf{0.5}$ (distinguish grey coefficient) is taken as 0.5 because the author has no information about the prior knowledge of the experiment process, so it's assumed that all the process parameters are of equal weighting. Therefore, it is necessary to have a new solution to eliminate these restrictions.

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