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Optimization of Multiple Response Characteristics on EDM Using the Taguchi Method and Grey Relational Analysis

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ABSTRACT

In this paper a new approach for the optimization of the electrical discharge machining (EDM) process with multiple performance characteristics based on the orthogonal array with the grey relational analysis has been studied on Ti–6Al–4V alloy. A grey relational grade obtained from the grey relational analysis is used to solve the EDM process with the multiple performance characteristics. Optimal machining parameters can then be determined by the grey relational grade as the performance index. In this study, the machining parameters using discharge current, gap voltage, pulse-on time and duty cycle as typical process parameters are optimized with considerations of multiple performance characteristics including material removal rate, electrode wear rate and surface roughness.The optimized process parameters simultaneously leading to a lower electrode wear ratio, higher material removal rate and better surface roughness are then verified through a confirmation experiment. Analysis of variance was used to study the significance of process variables on grey relational grade which showed discharge current, duty cycle, pulse-on time and gap voltage have been found to be the order of significant parameters. Confirmation experiment has been carried out at optimum set of parameters and predicted results have been found to be in good agreement with experimental findings. Experimental results have shown that machining performance in the EDM process can be improved effectively through this approach.

KEYWORDS:- Electrical discharge machining; Orthogonal array; Grey relational analysis

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1. INTRODUCTION

The Taguchi method [1, 2] is a systematic application of design and analysis of experiments for the purpose of designing and improving product quality. In recent years, the Taguchi method [3] as become a powerful tool for improving productivity during research and development so that high quality products can be produced quickly and at low cost However, the original Taguchi method has been designed to optimize a single performance characteristic. For the electrical discharge machining (EDM) process, material removal rate is a higher-the-better performance characteristic. However, surface roughness and electrode wear ratio are a lower-the-better performance characteristic. As a result, an improvement of one performance characteristic may require a degradation of another performance characteristic. Hence, optimization of the multiple performance characteristics is much more complicated than optimization of a single performance characteristic. In this paper, the orthogonal array with the grey relational analysis [4] is used to investigate the multiple performance characteristics in the EDM process.

Having exception properties, such as high strength–weight ratio, high temperature stability and outstanding corrosion resistance, Ti–6Al–4V alloy is widely used in the aerospace, automobile, chemical and biomedical fields. However, poor machinability using the traditional mechanical cutting process results in high tooling costs. Therefore, non traditional machining methods, such as electrical discharge machining (EDM) have been explored to machine this alloy. EDM is an energy-based technique extensively used in machining hard, high-strength and temperature-resistant materials in a contactless manner. The material is melted and vaporized by an erosion spark between the electrode and workpiece. Recently, Fonda et al. [8] used EDM technology to machine Ti–6Al–4V alloy to examine the effect of thermal and electrical properties on the productivity.

Table 1 Material properties of the Ti–6Al–4V alloy

Density (g/cm3)	Hardness (HRC)	Elastic modulus (kg/mm2)	Yield strength (kg/mm2)	Thermal (Cal/s•cm•C)
4	35	11,200	80	0.013

Chen et al. [9] noted a higher material removal rate (MRR) and lower electrode wear ratio (EWR) using distilled water as the dielectric compared to using kerosene. Ahmet et al. explored the influence of EDM parameters on the surface integrity of Ti–6Al–4V alloy with different electrode materials [10].The researchers found outcomes concerning the optimization of process parameters in EDM of Ti–6Al–4V alloy have rarely been reported up to now [11] Lin et al. examined the effects of attached magnetic forceon EDM and optimised the machining parameters of the magnetic-force-assisted EDM by the Taguchi method [12] .On the other hand, grey relational analysis can be recommended as a method for optimizing the complicated inter-relationships among multiple performance characteristics [13,14]. In this paper, the optimization of parameters considering multiple performance characteristics of the EDM process to Ti–6Al–4Valloy using the Taguchi method and grey relational analysis is reported. Performance characteristics including electrode wear ratio, material removal rate and surface roughness are chosen to evaluate the machining effects. Those process parameters that are closely correlated with the selected performance characteristics in this study are the discharge current, open voltage, pulse duration and duty factor.

Table 2 Machining parameters and their levels

Symbol	Control factors	Unit	Level 1	Level 2	Level 3
A	Discharge current	A	5	10	20
B	Open voltage	V	100	150	200
C	Pulse duration	µs	100	200	400
D	Duty factor	(%)	25	50	75

The duty factor is defined as the discharge ON time divided by the sum of the discharge ON and OFF times. Experiments based on the appropriate orthogonal array are conducted first. The normalized experimental results of the performance characteristics are then introduced to calculate the coefficient and grades according to grey relational analysis. Optimized process parameters simultaneously leading to lower electrode wear ratio, higher material removal rate and better surface roughness will then be verified through a confirmation experiment. The details of the procedures are addressed in the following sections.

2. EXPERIMENTAL PROCEDURE

2.1 Machining parameters selection

A series of experiments were performed on an Electrical Discharge Machine Electronica 4025 equipped with an iso-frequent pulse generator. The electrolytic copper of diameter 10 mm was used as an electrode. Commercial-grade kerosene was used as the dielectric fluid and the side injection of dielectric fluid was adopted. A jet flushing system was employed to assure adequate flushing of the debris from the gap zone.A pure cylindrical copper rod 10 mm in diameter was used as the electrode the workpiece of Ti–6Al–4V alloy (20×20×5mm) in this study. The material properties of the alloy is shown in Table 1.

In this study, there are several machining parameters to be considered in the EDM process. As a result, a preliminary experiment for determining the optimal process parameters indicates the machining parameters such as discharge current, open voltage, pulse duration and duty factor have a clear effect on the EDM performance of Ti–6Al–4V alloy.Table 2 shows they have discharge current with levels of 5, 10 and 20 amp; open voltage with levels of 100, 150 and 200 V; pulse duration with levels of 100, 200 and 400 μsand duty factor with levels of 25%, 50% and 75%. Moreover, some researchers have shown that positive electrode polarity gives a much higher material removal rate, lower electrode depletion and better surface roughness [15,16]. Therefore, the experiments used a positive polarity electrode. Besides, kerosene was used as the dielectric fluid in all experiments.

2.2 Machining performance evaluations

The machining performance evaluated based on the response variables namely MRR,TWR and surface roughness. The MRR and TWR was calculated based on the weight difference of the workpiece and tool before and after undergoing the EDM process. A high-precision electronic weighing balance Electric Balance, Model: AX 200, Capacity: Max: 200 gms, Readability: 0.1mg, Make: Shimadzu Corporation, Japan was used for this purpose. The surface roughness measurement was then carried out using a Talysurf 10, Rank Taylor Hobson. A traverse length of 5 mm with a cut-off evaluation length of 0.8 mm was selected. The centre line average value of the surface roughness (Ra) is the most widely used surface roughness parameter in industry is selected in this study. For the efficient evaluation of the EDM process, the MRR, TWR and the surface roughness are regarded as "larger-the-better" and "smaller-the-better" characteristics, respectively, in this study.

2.3 Selection of orthogonal array

The orthogonal array with the grey relational analysis is used to determine the optimal machining parameters with considerations of the multiple-performance characteristics. To select an appropriate orthogonal array, total degrees of freedom need to be computed. The degrees of freedom are the number of comparisons to be made between design parameters. For example, a three-level design parameter counts for two degrees of freedom. Therefore, in the present work, total degrees of freedom are 9, 8 owing to four parameters with three levels and one for overall mean[17]. Basically, degrees of freedom for an orthogonal array should be greater than or at least equal to number of design parameters. Each parameter was assigned to each column of the orthogonal array. Therefore, only nine experiments were required to study the entire parameter space using L9 orthogonal array. Normally, the full-factorial design would require (3^4= 81) experimental runs. However, the effort and experimental cost for such a design could be prohibitive and unrealistic. In the present study, nine experimental runs based on the L_9 orthogonal array with four columns and nine rows is used and is presented in Table 3. The working time for each experiment was 15 minutes and each experiment was repeated three times with the average being taken.

3. GREY RELATIONAL ANALYSES OF THE EXPERIMENTAL DATA

The Taguchi method is a systematic application of design 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. Most Taguchi experiments are concerned with the optimisation of a single quality characteristic.

Table 3 Experimental layout using an L_9 orthogonal array and performance results

		Expt. No				Control factors	
	A	B	C	D	MRR (mg/min)	TWR (mg/min)	Surface Roughness (µm)
1	1	1	1	1	10.30	1.47	3.61
2	1	2	2	2	6.30	0.18	2.27
3	1	3	3	3	4.86	0.13	2.16
4	2	1	2	3	10.16	0.66	3.13
5	2	2	3	1	15.01	1.69	4.53
6	2	3	1	2	11.47	1.89	3.88
7	3	1	3	2	19.70	4.26	4.12
8	3	2	1	3	13.86	3.25	4.8
9	3	3	2	1	24.46	6.1	4.47

Antony [18] attempted simultaneous optimisation of multiple quality characteristics in manufacturing processes using Taguchi's quality loss function. The use of Taguchi method with the grey relational analysis can greatly simplify the optimization of process parameters for multiple-performance characteristics[19] .In grey relational analysis, grey relational coefficient for different process characteristics is calculated and average of these coefficients is called grey relational grade which is used as a single response for the Taguchi's experimental plan, and same is illustrated in Fig. 2. Therefore, in the present work, grey relational analysis based on the Taguchi method's response table has been used to optimise EDM of Ti–6Al–4V alloy for multiple responses namely MRR ,TWR and surface roughness.

3.1 Data pre-processing

In grey relational analysis, data pre-processing is required since the range and unit in one data sequence may differ from the others. Data pre-processing is also necessary when the sequence scatter range is too large, or when the directions of the target in the sequence are different. Data pre-processing is a process of transferring the original sequence to a comparable sequence. For this purpose, the experimental results are normalised in the range between zero and one. Depending on the characteristics of data sequence, there are various methodologies of data pre-processing available for the grey relational analysis [20].

$$x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)} \qquad (1)$$

Where $x_i^*(k)$ and $x_i(k)$ are the sequence after the data preprocessingand comparability sequence respectively, k=1 for MRR; i=1,2,3....9 for experiments 1to 9.

The tool wear rate and surface roughness is also one of the important measures of EDM performance. Selection of optimum process parameters of Ti–6Al–4V alloy is at the development stage and their effects on surface roughness have yet to be clarified. To obtain optimal cutting performance, the "smaller-the-better" quality characteristic has been used for minimising the surface roughness.

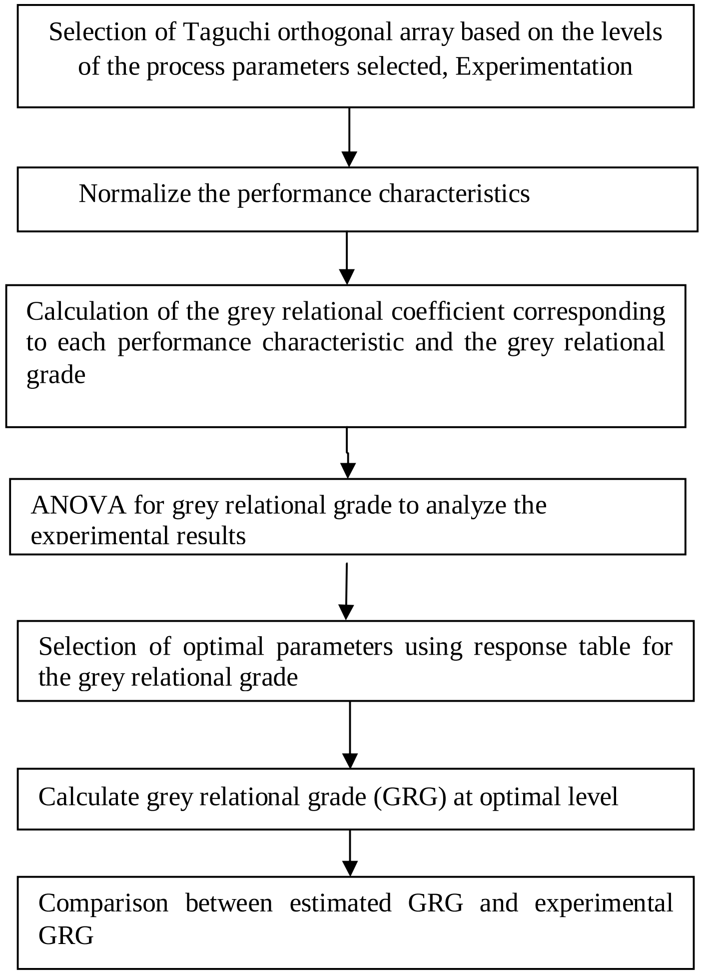

Fig. 2 Grey relational analysis to optimize the process with multiple performance characteristics

When the “smaller-the-better” is a characteristic of the original sequence, then the original sequence should be normalised as follows:

$$x_i^*(k) = \frac{max\ x_i(k) - x_i\ (k)}{\max x_i(k) - \min x_i(k)} \qquad (2)$$

Where $x_i^*(k)$ and $x_i(k)$ are the sequence after the data preprocessing and comparability sequence respectively, k=2 for TWR, surface roughness: i=1,2,3....9 for experiments 1 to 9 [20].All the sequences after data pre-processing using Eqs. 1 and 2 are listed in Table 4.

Table 4 Sequences of each performance characteristic after data processing

Expt.No	MRR	TWR	Surface roughness
Reference Sequence	1.0000	1.0000	1.0000
1	0.2774	0.7755	0.4519
2	0.0732	0.9910	0.9582
3	0.0000	1.0000	1.0000
4	0.2700	0.9101	0.6316
5	0.5178	0.7375	0.1025
6	0.3370	0.7046	0.3481
7	0.7569	0.3070	0.2582
8	0.4591	0.4762	0.0000
9	1.0000	0.0000	0.1240

Now, Δ_{oi} (k) is the deviation sequence of the reference $x_i^*(k)$ and the comparability sequence $x_i^*(k)$, i.e.

$$\Delta_{oi}(k) = |x_0^*(k) - x_i^*(k)| \qquad (3)$$

The deviation sequence Δ01 can be calculated using Eq. 3 as follows;

$\Delta_{oi}(1) = |x_0^*(1) - x_i^*(1)| = |1.00 - 0.2774| = 0.7226$

$\Delta_{oi}(2) = |x_0^*(2) - x_i^*(2)| = |1.00 - 0.7755| = 0.2244$

$\Delta_{oi}(3) = |x_0^*(3) - x_i^*(3)| = |1.00 - 0.4519| = 0.5481$

So Δ_{01} = (0.7226,0.2245,0.5481)

Similar calculation was performed for i=1 to 9 and the results of all Δ_{oi} for i=1–9 are listed in Table 5.Investigating the data presented in Table 5, Δ_{max} (k) and Δ_{min} (k) are obtained and are follows

$\Delta_{max} = \Delta_{03}(1) = \Delta_{o9}(2) = \Delta_{08}(3) = 1.00$

$\Delta_{min} = \Delta_{09}(1) = \Delta_{03}(2) = \Delta_{03}(3) = 0.00$

Table 5 The deviation Sequences

Deviation Sequences	Δ_{oi} (1)	Δ_{oi} (2)	Δ_{oi} (3)
Expt.no.1	0.7226	0.2244	0.5481
Expt.no.2	0.9267	0.0089	0.0417
Expt.no.3	1.0000	0.0000	0.0000
Expt.no.4	0.7299	0.0898	0.3683
Expt.no.5	0.4821	0.2624	0.8974
Expt.no.6	0.6629	0.2953	0.6519
Expt.no.7	0.2430	0.6929	0.7417
Expt.no.8	0.5408	0.5237	1.0000
Expt.no.9	0.0000	1.0000	0.8759

3.2 Computing the grey relational coefficient and the grey relational grade

After data pre-processing is carried out, a grey relational coefficient can be calculated with the pre-processed sequence. It expresses the relationship between the ideal and actual normalised experimental results. The grey relational coefficient is defined as follows [20]

$$\xi_i(k) = \frac{\Delta_{min} + \xi\Delta_{max}}{\Delta_{oi}(k) + \xi\Delta_{max}} \quad (4)$$

Where Δ_{0i} (k) is the deviation sequence of the reference sequence $x_i^*(k)$and the comparability sequence $x_i^*(k)$, ξ is distinguishing or identification coefficient. If all the parameters are given equal preference, ξ is taken as 0.5. The grey relational coefficient for each experiment of the L_9 orthogonal array can be calculated using Eq. 4 and same is presented in Table 6.After obtaining the grey relational coefficient, the grey relational grade is computed by averaging the grey relational coefficient corresponding to each performance characteristic. The overall evaluation of the multiple performance characteristics is based on the grey relational grade, that is:

$$\gamma_i = \sum_{k=1}^{n} \xi_i \ (k) \quad (5)$$

Where γ_i is the grey relational grade for the ith experiment and n is the number of performance characteristics. Table 6 shows the grey relational grade for each experiment using L_9 orthogonal array. The higher grey relational grade represents that the corresponding experimental result is closer to the ideally normalized value. Experiment 3 has the best multiple-performance characteristics among nine experiments because it has the highest grey relational grade as shown in Table 6. It can be seen that in the present study optimisation of the complicated multiple-performance characteristics of EDM of Ti–6Al–4V alloy has been converted into optimisation of a grey relational grade.

Table 6 Grey relational coefficient and grey relational grade

Expt No.	Grey relational coefficient			Grey relational grade	Order
	MRR $\xi_i(1)$	TWR $\xi_i(2)$	Surface Roughness $\xi_i(3)$		
1	0.4089	0.6901	0.4770	0.5253	
2	0.3504	0.9824	0.9228	0.7519	
3	0.3333	1	1	0.7777	
4	0.4065	0.8476	0.5758	0.6099	
5	0.5090	0.6558	0.3577	0.5075	
6	0.4299	0.6286	0.4340	0.4975	
7	0.6729	0.4191	0.4026	0.4982	
8	0.4803	0.4884	0.3333	0.4340	
9	1	0.3333	0.3633	0.5655	

Since the experimental design is orthogonal, it is then possible to separate out the effect of each machining parameter on the grey relational grade at different levels. For example, the mean of the grey relational grade for the discharge current at levels 1, 2 and 3 can be calculated by averaging the grey relational grade for the experiments 1 to 3, 4 to 6 and 7 to 9, respectively (Table 7).The mean of the grey relational grade for each level of the other machining parameters, namely, pulse-on time, duty cycle and gap voltage can be computed in the same manner. The mean of the grey relational grade for each level of the machining parameters is summarized and shown in the multi response performance index Table 7.

Table 7 Response table for Grey relational grade.

Level	Discharge current A	Voltage B	Pulse duration C	Duty factor D
1	0.6850*	0.5445	0.4857	0.5328
2	0.5384	0.5645	0.6425*	0.5826
3	0.4993	0.6136*	0.5945	0.6073*
Max-Min	0.1857	0.0691	0.1568	0.0744
Rank	1	4	2	3

* Levels for optimum grey relational grade, Total mean value of the grey relational grade=0.5742

In addition, the total mean of the grey relational grade for the nine experiments is also calculated and listed in Table 7. Figure 3 shows the grey relational grade obtained for different process parameters. The mean of grey relational grade for each parameter is shown by horizontal line. Basically, the larger the grey relation grade is, the closer will be the product quality to the ideal value. Thus, larger grey relational grade is desired for optimum performance. Therefore, the optimal parameters setting for better MRR and improved surface quality is (A1B3C2D3) as given in Table 7. Optimal level of the process parameters is the level with the highest grey relational grade. Furthermore, ANOVA has been performed on grey relational grade to obtain contribution of each process parameter affecting the two process characteristics jointly and is discussed in the forthcoming section.Experiment 3 shows the highest grey relational grade, indicating the optimal process parameter set of A1B3C3D3 has the best multiple performance characteristics among the nine experiments. The mean value of the grey relational grade for each EDM process parameter level is summarised in Table 11 and shown in Fig. 4. It shows the predicted optimal process parameter set is A1B3C2D3 based on the grey relational analysis.

4. ANALYSIS OF VARIANCE

ANOVA is a standard statistical technique to interpret the experimental results. It is extensively used to identify the performance of a group of parameters under investigation. The purpose of ANOVA is to investigate the parameters, whose combination to total variation is significant. In ANOVA, the total sum of squares deviations (SST) is calculated by[21] .

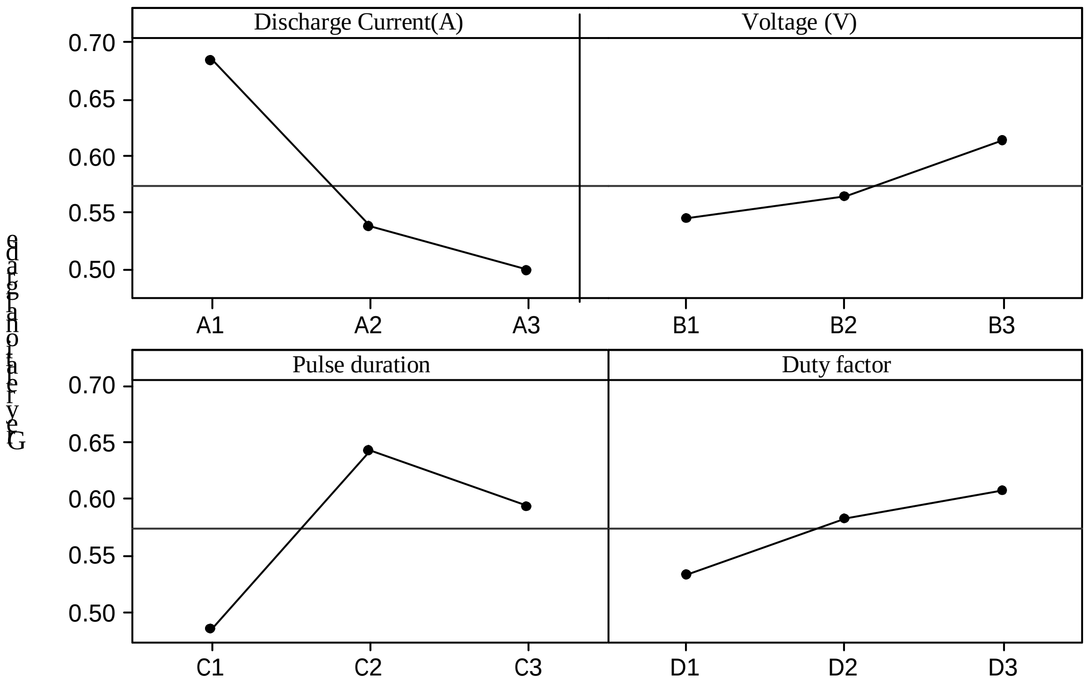

Fig.3 Effect of EDM parameters on the multi-performance characteristics

$$SS_T = \sum_{I=1}^{N} (\eta_i - m)^2 \qquad (6)$$

where m is the overall mean S/N ratio.

The total sum of squared deviations, $SS_{T,}$ is divided into two sources

$$SS_T = \sum_{j=1}^{n_p} SS_j + SS_e \qquad (7)$$

where, SS_J is the sum of squared deviations for each design parameter and is given by

$$SS_j = \sum_{I=1}^{l} (\eta_i - m)^2 \qquad (8)$$

where $n_p$is the number of significant parameters and l is the number of levels of each parameter. SS_e is the sum of squared error without or with pooled factor, which is the sum of squares corresponding to the insignificant factors. Mean square of a factor (MSj) or error (MSe) is found by dividing its sum of squares with its degrees of freedom. Percentage contribution (ρ) of each of the design parameters is given by following equation [18].

$$\rho_j = \frac{SS_j}{SS_T} \qquad (9)$$

Table 7 ANOVA results for the Grey relational grade

Process parameters	DOF	Sum of squares	variance	% contribution
Discharge Current(A)	2	11.5	5.778	49.50
Voltage (V)	2	1.49	1.495	6.41
Pulse duration	2	8.91	4.455	38.35
Duty factor	2	1.27	0.63	5.46
Total	8	23.23		100

Table 7 lists the grey relational grade based on the results of ANOVA analysis. It shows that the discharge current is the significant control factor affecting multiple performance characteristics with nearly 49.5% of contribution ratio and the pulse duration has 38.35% contribution.

4.1 Confirmation tests

Confirmation test has been carried out to verify the improvement of performance characteristics while EDM of Al2O3–SiCw–TiC ceramic composite. Optimum parameters are selected for the confirmation test as given in Table 7. The estimated grey relational grade using the optimal level of the machining parameters can be calculated using following equation.

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q} (\gamma_i - \gamma_m) \qquad (10)$$

Where γ_m is the total mean of the grey relational grade, is the mean of the grey relational grade at the optimal level and q is the number of the machining parameters that significantly affects multiple-performance characteristics. The obtained process parameters, which give higher grey relational grade, are presented in Table 8. The predicted MRR, surface roughness and grey relational grade for the optimal machining parameters are obtained using Eq. 10 and also presented in Table 8. Table 8 also shows the comparison of experimentally obtained MRR and surface roughness of a trial which gives maximum MRR (trial 9 of the OA) and experimentally obtained MRR and surface roughness at optimum EDM process parameters. It can be seen that the overall performance of EDM process has been improved.

5. CONCLUSION

An application of the Taguchi method and grey relational analysis to improve the multiple performance characteristics of the electrode wear ratio, material removal rate and surface roughness in the electrical discharge machining of Ti–6Al–4V alloy has been reported in this paper. As a result, this method greatly simplifies the optimization of complicated multiple performance characteristics. The optimal process parameters based on grey

Table 8 Comparison between machining performance using the initial and optimal level

	Machining parameters in Third trial of OA	Optimal Machining parameters	
		Prediction	Experiment
Setting Level	A1B3C3D3	A1B3C2D3	A1B3C2D3
Material removal rate (mg/min)	4.86	5.31	5.26
Tool wear rate (mg/min)	0.13	0.10	0.12
Surface roughnessRa (µm)	2.16	1.85	1.88
Grey relational grade	0.5742	0.8437	0.8560

relational analysis for the EDM of Ti–6Al–4V alloy include 5 amp discharge current, 200 V open voltage, 200 µs pulse duration and 75% duty factor. The machining performance of the electrode wear ratio decrease from 0.13 to 0.10mg/min, the material removal rate increases from 4.86 to 5.31 mg/min and the surface roughness decreases from 2.16 to 1.85µm, respectively.

To conclude, as per the findings, GRA, an advanced statistical method of multi-factorial analysis, embodies rich philosophical thought of the unity of opposites, such as continuity and discontinuity, quality and quantity, staticsand dynamics, etc. Empirical research on high-tech industries and systems are often constrained, since traditionalstatistical methods require large sets of data. On the other hand, grey system theory is designed to work with system where the available information is insufficient to characterise the system.

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