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Experimental Investigation On Machining Performance of Ti6Al4V On Electro Discharge Machining Using Stationary and Rotary Electrode

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Abstract: Titanium alloys are commonly used in different industries due to its high strength and less in weight. Even though the machinability of titanium alloys is very less, due to its high strength, it becomes more useful in aerospace and medical industries. In this paper, the performance of stationary and rotary copper electrodes on machining of Titanium alloy Ti-6Al-4V with Electro Discharge Machining (EDM) have been studied. Material removal rate (MRR), tool ware rate (TWR) and surface roughness (SR) were analyzed with three controllable input parameters such as pulse on time (T_{on}), Peak Current (I_p) and Gap Voltage (V). The design of experiment is chosen for the experimentation as the Box-Behnken response surface design method. The results are analyzed using grey relational analysis (GRA) coupled with firefly algorithm. In both the case of stationary and rotary electrode, it was revealed that gap voltage is significant for overall grey relational grade. The machining performance of Titanium alloy Ti-6Al-4V in the case of rotary mode of electrode is quite better as compared to the stationary mode of operation.

Keywords: Material removal rate, tool wear rate, Electro Discharge Machining

1. Introduction

Titanium alloy Ti6Al4V is the single largest user in aerospace industries due to its strength to weight ratio, high temperature and corrosion resistance. Ti6Al4V alloys are used in jet engine parts, aero frames etc. As the titanium alloy Ti6Al4V has the low thermal conductivity which leads to increase in temperature and tool wear during machining in dry condition. When the conventional machining puts its limit for high strength material, then non-traditional machining process come into picture to mitigate the difficulties of machining. Out of the various non-traditional machining processes, electro-discharge machining (EDM) is one of them. Many researchers have been carried out the investigation during machining on EDM with various high strength materials. S Tiwari conducted an experiment to find out the effect of different process parameters on over cut [1]. The tool material and work piece material are selected as copper and medium carbon steel respectively with positive polarity of electrode. The over cut in electro-discharge machining process were calculated by taking the process parameter as peak current, pulse on time and pulse off time from different process parameters like peak current, gap voltage, pulse on time, pulse off time, current density etc. For machining of hard materials, EDM is suggested over traditional machining process due to less tool wear and more machining time [2]. Chatter and vibration during machining can be avoided because of a gap of approx. 0.025 to 0.05 mm is maintained between tool and work piece. Sidhu *et al.* [3] have investigated effect of rotary tool on EDM performance. The acting forces are not present also. The debris from the machining gap can be removed by whirl condition and centrifugal force applied by rotary tool electrode which gives the greater flushing condition and enhances the MRR, TWR and surface finish. The debris are got rid of from machining gap by the applied magnetic field which results in improved surface finish and better surface quality. The high input discharge energy may impute high valued current which gives deep

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craters, greater MRR and poor surface finish. The MRR and TWR decrease with increase in pulse on time from 50 **μs** to 150 **μs** because of inefficient flushing of debris by machining. Smart *et al.* [4] have studied the design and development of rotary tool setup with variable speed arrangement for EDM also investigated the effect of EDM machine parameters on MRR, surface finish and ware rate of electrode. With increasing rotary speed of EDM tool the surface roughness increases and electrode ware rate decreases. For higher MRR the pulse off time and pulse on time to be restricted to $25\mu s$ and $50\mu s$ respectively. To machining of Titanium and its alloys as a continuous operation, straight grade (WC/Co) cemented carbides are considered to be most suitable commercially available tool material [5].

Flank wear, crater wear, notch wear, chipping and catastrophic failure are considered to be the important failures during machining of titanium alloys. The appropriate employment of coolants and chemically active cutting fluids at the time of machining operations increase the life of the cutting tool and shrink the cutting force between the tool and workpiece. The feature size as small as $25\mu m$ may be attained by successful utilization of micro EDM for the fabrication biocompatible micro device [6]. If the work piece is vibrated ultrasonically the surface roughness is reduced to 20-40%. For the rapid fabrication of greater precision prototype this method is extremely worthy due to the total fabrication process takes time (including setup and tooling) approximately 4 hours. Use of micro EDM for making biocompatible device for bio experiments signifies due to the small feature size and greater surface finish. Successful selection of trained neutral network model and optimized input conditions, greater MRR and R_a may be achieved [7-8]. Patil *et al.* [9] have studied using combination of dimensional analysis and non-linear estimation method in the modelling of WEDM of difficult-to-cut MMCs. Pulse on-time and thermo-physical properties such as coefficient of thermal expansion, thermal diffusivity and melting point temperature are remarkably influence MRR. The RSM and the semi-empirical model is found to be more than 99%, the matter such as wire performance, gap status and surface integrity of the machined components may be disclosed by it The wire electro-discharge machining of A6061/Al_2O_3P composite with varying volume fractions of 10% and 22% was experimented by Patil *et al.* [10] by using Taguchi's method. Volume fraction of ceramic reinforcement, pulse on-time, off-time, and servo reference voltage influence cutting speed, surface finish, kerf width remarkably. By utilization of higher flushing pressures, correct pulse off-times, and suitable value of servo reference voltage wire breakages can be minimized. Pulse off-time, servo voltage, on-time, and open circuit voltage are significantly influencing the wire shifting which decays the machined surface.

Assarzadeh *et al.* [11] have investigated Statistical modelling and optimization of process parameters in electro-discharge machining of cobalt-bonded tungsten carbide composite (WC/6%Co). The MRR, TWR and Ra are mostly influenced by discharged current, duty cycle, pulse on time and their interactions and the discharge energy has the ability to melt and vaporize the work surface faster. Morgan et al have illustrated the potential of electro discharge micro-machining, micro-cutting or micro-grinding tool to fabricate conductive and non-conductive materials [12]. For a wide range of tool geometries and materials a variable depth of cut micro-grinding technique is found to be the best micro-machining parameters. Better geometric accuracy, surface finish and MRR for micro-cutting and micro-grinding for engineered materials can be achieved by optimizing process parameters (e.g. feed rates, depths-of-cut, etc.) and tool parameters (e.g. dimensions, flutes, rake angles). Employing micro-EDM micro tools can be formed from polycrystalline diamond which may be utilized efficiently in machining of glass in ductile form [13-18]. The grooves in soda-lime glass and pockets in ultra-low expansion glass are made by micro machining utilizing PCD tools with conical tips.

Many articles are published, and research works are done on machinability of Titanium alloys specifically on Ti6Al4V. But very less research work is done on Electro Discharge Machining of Ti6Al4V by using copper electrode by steady and rotary movement of electrodes. More study has to be carried out to optimize the performance in Rotary EDM on Ti-6Al-4V. In this study, the machining performance of Ti-6Al-4V has been analyzed using the copper electrode in both stationary and rotary mode of machining.

2. Experimental Details

2.1 Selection of Tool Material

For machining of Titanium alloy Ti6Al4V in electro-discharge machine, copper has been chosen as the tool material. Copper is selected as a tool material as it has following characteristics: High electrical conductivity, sufficiently high melting point and easily available [19]. The tool diameter is taken as 10mm.

2.2 Selection of Work Piece Material

For this experimentation, Titanium alloy Ti6Al4V has been selected as a work piece material which having the following composition as shown in Table 1.

Table 1 - Composition of Ti 6Al 4V

Symbol	Ti	Al	V	C	O	N	H
Element	**Titanium**	**Aluminium**	**Vanadium**	**Carbon**	**Oxygen**	**Nitrogen**	**Hydrogen**
% by weight	90.0	6.0	4.0	<0.1	<0.2	<0.05	<0.125

2.3 Experimental Setup

Die-sinking type Electric Discharge Machine (Model: GF+ Agie Charmilles ED005 with servo-head) is used for experimentation. The copper electrode is connected with positive polarity to conduct the experiments. Commercial grade EDM oil (specific gravity= 0.763) was used as dielectric fluid. The pulse discharge current was applied in various steps in positive mode [20]. Fig.1 portrays the EDM experimental setup with stationary and rotary electrodes. In this study three set of experiments have been conducted according to the design of experiment and average value of the responses are shown in the Table 3.

a

b

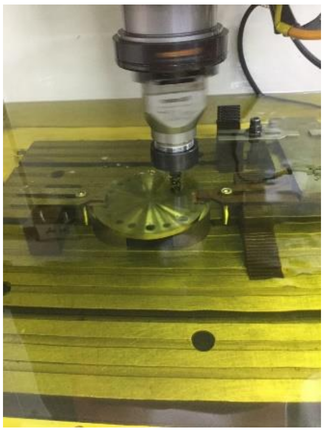

Fig. 1 - Experimental setup of Electric Discharge Machining (a) with stationary copper electrode; (b) with rotary copper electrode

2.4 Experimentation and Data Collection

According to the Box-Behnken response surface design [21], the experiments are performed in three levels of process parameters such as current, pulse-on time and voltage to obtain material removal rate (MRR), tool wear rate (TWR) and surface roughness (R_a). This particular design involves 15 number of experiments. According to the previous literatures on EDM of titanium alloys, it has been observed that the above three process parameters have significant influence on MRR, TWR and R_a. Thus, the levels of these parameters are selected carefully keeping an eye on previous literatures and trial experiments. These process parameters with their levels, notations and units are displayed in Table 2. MRR and TWR are measured by following weight loss approach. For measuring of these two responses experimentally, a precision electronic balance weight machine is employed which has an accuracy of 1 mg. These two responses are computed by measuring the weight loss of workpiece before and after the experiment. (Eq. 1) and tool (Eq. 2), respectively.

$$MRR = \frac{W_f - W_i}{t \times \rho_w} \tag{1}$$

$$TWR = \frac{T_f - T_i}{t \times \rho_t} \tag{2}$$

Where W_f and W_i are weights of workpiece before and after machining respectively. T_f and T_i are the weights of tool before and after machining respectively. t is the machining time. The density of Ti6Al4V titanium alloy is $\rho_w = 4.41\times10^{-3}$ g/mm^3 and density of copper electrode is $\rho_t = 8.92 \times10^{-3}$ g/mm^3. The measurement of SR (R_a) is performed with portable style type profilometer, Talysurf (Model: Taylor Hobson, Surtronic 3+), with parameters like cut-off length, L_c = 4 mm, sample length, L_s = 0.8mm and filter = 2CR ISO. These process parameters with their levels, notations and units are displayed in Table 2. The measured responses are provided in this Table 3.

Table 2 - Control factors and their selected levels

Control Factor	Levels			
	1	**2**	**3**	**Units**
A: Current	10	15	20	Amp
B: T_{on}	100	150	200	sec
C: Voltage	20	25	30	Volt

Table 3 - Experimental data during machining of Ti6Al4V using stationary copper electrode

Test run	Current (A)	T_{on} (B)	Voltage (C)	MRR (mm^3/h)	TWR (mm^3/h)	R_a (μm)
1	10	200	25	38.6	5.7	8.99
2	10	150	20	169.3	6.5	2.50
3	15	150	25	58.7	25.4	3.55
4	15	100	30	29.1	12.2	2.40
5	20	100	25	126.6	11.7	7.19
6	20	150	30	115.1	9.5	2.52
7	20	150	20	126.0	6.2	4.51
8	15	200	30	6.1	1.8	5.55
9	10	100	25	83.3	6.0	3.45
10	15	150	25	58.7	25.4	3.55
11	20	200	25	46.7	6.0	5.86
12	15	150	25	58.7	25.4	3.55
13	10	150	30	20.3	3.2	3.90
14	15	200	20	46.7	9.2	4.81
15	15	100	20	148.3	4.9	3.74

3. Methodology

3.1 Grey Relational Analysis:

Grey Relational Analysis (GRA) is one of the most widely used statistical measurement technique in grey theory which analyses the uncertain and insufficient correlation between the key factor and other input parameters in a system [20-22]. Moreover, this technique has the ability to convert the multi-response optimization problem to single response optimization problem using few steps. In the present work, the RSM design of experiment with GRA is discussed. The steps of the GRA process was executed through the following steps:

1. Normalising the performance measure results like MRR, TWR and SR for all the 15 numbers of experimental runs to avoid large variances in the data set.
2. Computing the individual Grey Relational Coefficient (GRC) to showcase the correlation between the required and real experimental results.
3. Calculating the overall Grey Relational Grade (GRG) by taking average of the three GRCs.
4. Performing Analysis of Variance (ANOVA) statistical method on GRG and the input factors to uncover their effects on the performance measures.
5. Finally, the optimum parametric levels are selected where the desired responses are obtained.

In the current EDM experimentation, the desired values of MRR is "higher-the-better (HB)" criteria where as it is "lower-the-better (LB)" for TWR and SR. In this analysis, the normalization of MRR where the HB criterion was used expressed by Eq. (3), and when LB criterion was used on TWR and SR then, the normalization can be calculated as Eq. (4).

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

$$x_i^*(k) = \frac{\max\ y_i(k) - y_i(k)}{\max\ y_i(k) - \min\ y_i(k)} \tag{4}$$

Where $x_i^*(k)$ and $y_i(k)$ are the normalized and experimented data for i^{th} experimental run using k^{th} response. The smallest and largest values of $y_i(k)$ for k^{th} response are represented as min $y_i(k)$ and max $y_i(k)$ respectively.

After pre-processing of the experimental data, the individual GRC ($\zeta_i(k)$) for k^{th} response in the i^{th} experimental run can be expressed as Eq. (5). It demonstrates the degree of relationship between ideal value i.e. $y_0(k)$ and the observed value i.e. $y_i(k)$

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

Where $\Delta_{0i}(k)$ is the difference of absolute values between $y_0(k)$ and $y_i(k)$. $\Delta_{\max}$, $\Delta_{\min}$ are treated as the global maximum and minimum values of the different output factors dataset. The distinguishing factor (ζ) represents the weight of each response, and it varies between 0 to 1. This factor is usually selected by the decision makers using their own judgement and intelligence. If all the responses are given equal weightage then, $\zeta = 0.33$ is preferred without any hesitation. After calculation of individual GRCs, the overall GRG (γ) can be expressed using the Eq. (6).

$$\gamma = \frac{1}{n}\sum_{i=1}^{n}\xi_i(k) \qquad (6)$$

The magnitude of GRG reflects the degree of close relationship between $y_0(k)$ and $y_i(k)$, or it is standard deviation of the i^{th} experimental data from the reference data sets. The parameter combination relates to the higher GRG is the favourable one.

3.2 Firefly Algorithm

The firefly algorithm (FA) has been developed to address all types optimization related manufacturing problems successfully. As every metaheuristic algorithm have some restrictions, the FA has certain limitations on providing best solutions in few cases/problems [25]. In order to overcome these limitations and improvisation of results, the hybridization of various optimization methods has been gaining popularity in recent years. Xin-She Yang [26] has developed this nature inspired algorithm inspired from the rhythmic flashing behaviour of fireflies. This flashing characteristics of the tropical fireflies is due to the bioluminescence process. This flash works mainly for the two reasons i.e. to attract mating partners and to remain alert from the possible threat of potential prey. The degree of attraction of the fireflies is according to the intensity of flash lights. This light intensity (I) reduces when the distance between the two fireflies' increases. It can be represented as:

$$I \propto 1/r^2 \qquad (7)$$

Meanwhile, the attraction among the fireflies may be local or global according to the degree of absorption coefficient. The fireflies are further divided into subgroups based upon their light intensity. Thus, the neighboring fireflies swarm around locally. This algorithm provides efficient solution in case of multimodal optimization problem.

The FA follows the three principles such as:

1. The nature of all fireflies are unisex, and at a time, single firefly is pulled towards to other brighter fireflies irrespective of their sex.
2. The degree of attractiveness of the fireflies is directly proportional to the brightness of the fireflies, and it also decreases if the distance between two fireflies' increases. Thus, the less flashing fireflies will attract towards the brighter fireflies. The fireflies will move randomly if there is a tie between their flashing characteristics.
3. The objective function is the brightness of the fireflies.

It is a population based algorithm which can provide global optimum solution. In the current EDM problem, the objective function is acquired from the regression modelling of GRG. The fireflies represent the input factors, and they are randomly distributed over the defined search domain.

In order to get most accurate solution, the relationship between light intensity (I) and distance between fireflies (r) is modified, and it is represented in Eq. (8)

$$I(r) = I_0 e^{-\gamma r^2} \qquad (8)$$

Where I_0 is the light intensity, γ is the light absorption coefficient which controls the increase or decrease of light intensity

The attractiveness (β) can be evaluated by a decreasing distance (r) function due to their degree of absorption of light in the medium as presented in Eq. (9)

$$\beta(r) = \beta_0 e^{-\gamma r^2} \qquad (9)$$

Where β_0 is the initial attractiveness value at $r=0$.

The Cartesian or Euclidean distance between two fireflies like i and j at positions x_i and x_j can be represented as in Eq. (10).

$$r_{ij} = \left| x_i - x_j \right| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k} \right)^2} \qquad (10)$$

Where $x_{i,k}$ and $x_{j,k}$ are the k^{th} components of the spatial coordinate x_i and x_j of the i^{th} and j^{th} fireflies respectively, and d is the number of dimensions.

The movement of i^{th} firefly towards the brighter j^{th} firefly can be determined from the Eq. (11).

$$x_i = x_i + \beta_0 e^{-\gamma r^2} \left(x_j - x_i \right) + \alpha \left(rand - \frac{1}{2} \right) \qquad (11)$$

The first term of the equation indicates present position of the firefly i. second term stands for attractiveness of the adjacent fireflies, and the last term denotes free random movement of a firefly when no brighter firefly is present. In most of the situations, the randomization parameter (α) is considered between 0 to 1. Likewise, the light absorption coefficient (γ) is selected between 0.1 to 10.

4. Results and Discussions

4.1 Experimental Data Analysis During Machining of Titanium Alloy Ti6Al4V Using Stationary Electrode

Table 3 represents the data obtained from EDM experimentation. One of the objectives of this study is to determine a single parametric combination which will provide a compromised solution i.e. higher MRR and lower TWR and SR. ANOVA technique is employed in this study to substantiate the significance of process parameters on the responses. Thus, from this study, the most influencing parameter can be identified. A higher mean result consistently depicts a superior quality characteristic. Consequently, the domains of input factors which confirms the best mean result is chosen as optimum level. In this investigation, it is feasible to separate the impact of each EDM factors at various levels by averaging the mean results. Figs. 2, 3 and 4 address the main effects plot for MRR, TWR and SR individually. For a wide range of quality characteristics (i.e. LB or HB), the higher mean result is always preferred. It demonstrates that the changes of MRR, TWR and SR are more modest around the preferred target.

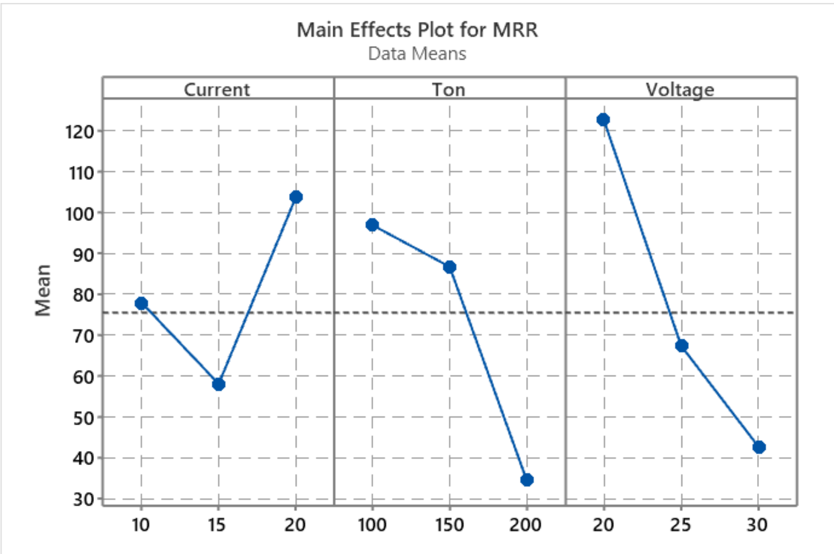

Fig. 2 - Main effect plots for MRR

ANOVA results are appeared in Tables 4, 5 and 6 for MRR, TWR and SR. This investigation has been performed with the assistance of statistical programming bundle MINITAB. It uses a hypothesis named as P-value (i.e. probability of significance). It is processed based on the determined F-value. At that point, this P-value is contrasted with alpha-level. When the P-value is under 0.05, it may be induced that the particular factor remarkably affects the quality characteristics at a confidence interval of 95%. The interaction effect among the process parameters is ignored in the current study.

From Table 4, it tends to be deduced that the impact of current is seemed to be insignificant as its P-value is more than 0.05. Nonetheless, the most impelling parameter is the voltage followed by pulse-on time. These two elements have beneficial outcome on the MRR. In the meantime, ANOVA results of TWR in Table 5 uncovers that each factor essentially influence the response. It implies that the test domain is reasonable to catch the vigorous deviation in the process parameter combinations. Similarly, the ANOVA aftereffects of SR introduced in Table 6 explored the most affecting parameter as the pulse-on time.

4.1.1 Data Analysis and Results by Grey Relational Technique

The normalized experimental results are attained first to eliminate the enormous differences in the data collection set. The normalized outcomes for MRR, TWR and SR are determined by utilizing Eq. (2) and (3), and they have been outfitted in Table 7. For TWR and SR, lower-the-better (LB) and for MRR, higher-the-better (HB) conditions have been chosen. Quality loss estimates (Δ_{0i}) identified with different quality characteristics have been given in Table 8.

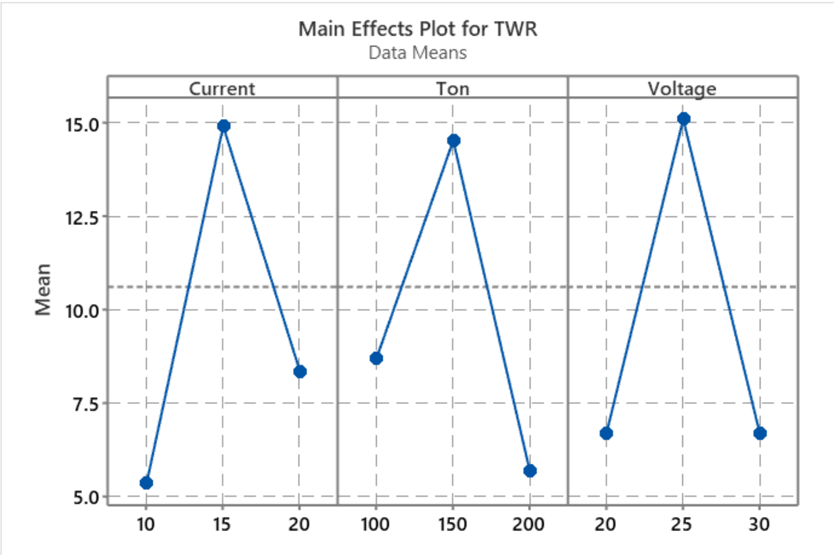

Fig. 3 - Main effect plots for TWR

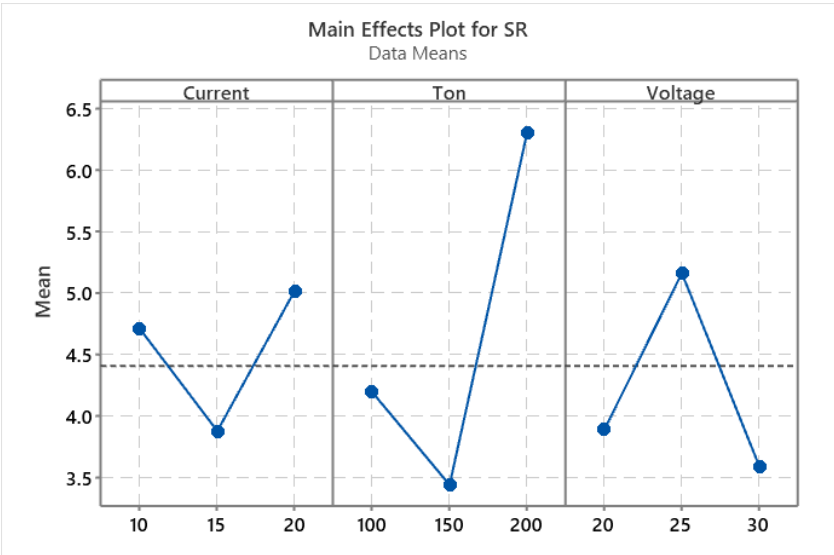

Fig. 4 - Main effect plots for SR

Table 4 - Analysis of variance results for MRR

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Current	2	5250.6	2625.30	3.17	0.097
Ton	2	8895.0	4447.48	5.37	0.033
Voltage	2	13764.6	6882.28	8.31	0.011
Error	8	6622.2	827.77		
Total	14	34772.3			

Table 5 - Analysis of variance results for TWR

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Current	2	341.654	170.827	18.93	0.001
Ton	2	296.970	148.485	16.45	0.001
Voltage	2	346.516	173.258	19.20	0.001
Error	8	72.205	9.026		
Total	14	931.249			

Table 6 - Analysis of variance results for SR

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Current	2	4.0904	2.0452	1.04	0.397
Ton	2	20.7798	10.3899	5.28	0.035
Voltage	2	5.6726	2.8363	1.44	0.292
Error	8	15.7539	1.9692		
Total	14	47.3862			

Table 7 - Normalized results of each quality characteristics

Experiment No.	MRR	TWR	SR
Ideal sequence	1.0000	1.0000	1.0000
1	0.1991	0.8347	0.0000
2	1.0000	0.8008	0.9848
3	0.3223	0.0000	0.8255
4	0.1409	0.5593	1.0000
5	0.7384	0.5805	0.2731
6	0.6679	0.6737	0.9818
7	0.7347	0.8136	0.6798
8	0.0000	1.0000	0.5220
9	0.4730	0.8220	0.8407
10	0.3223	0.0000	0.8255
11	0.2488	0.8220	0.4750
12	0.3223	0.0000	0.8255
13	0.0870	0.9407	0.7724
14	0.2488	0.6864	0.6343
15	0.8713	0.8686	0.7967

Table 8 - Computation of Δ_{0i} for each output

Experiment No.	MRR	TWR	SR
Ideal sequence	1.0000	1.0000	1.0000
1	0.8009	0.1653	1.0000
2	0.0000	0.1992	0.0152
3	0.6777	1.0000	0.1745
4	0.8591	0.4407	0.0000
5	0.2616	0.4195	0.7269
6	0.3321	0.3263	0.0182
7	0.2653	0.1864	0.3202
8	1.0000	0.0000	0.4780
9	0.5270	0.1780	0.1593
10	0.6777	1.0000	0.1745
11	0.7512	0.1780	0.5250

12	0.6777	1.0000	0.1745
13	0.9130	0.0593	0.2276
14	0.7512	0.3136	0.3657
15	0.1287	0.1314	0.2033

The Eq. 6 has been used to figure out individual GRC for each quality characteristics, and this information are outfitted in Table 9. In this investigation, the weightage of each response is thought to be equivalent. Consequently, the distinguishing factor (ζ) has been taken as 0.33. These GRCs have been collected to assess the overall GRG utilizing Eq. 6. It addresses the multi-quality highlights of EDM attributes with the presumption that every quality is equally significant. The overall GRG is also introduced in Table 10.

ANOVA analysis of GRG in Table 11 has uncovered that voltage is the most affecting parameter. Current and pulse-on time are discovered to be unimportant parameters as their P-values are more than 0.05. In the current investigation, the multi-modal optimization issue has been changed over to a single-modal optimization issue utilizing the GRA. The regression modelling is likewise done to uncover the correlation between input parameters and overall GRG. In this study, the R^2 is 0.9571 and adjusted R^2 is found to be 0.9129. The R^2 demonstrates that the model can clarify the difference in GRG up to 95.71%, and the adjusted R^2 represents the number of predictors in the regression model. The regression equation is introduced in Eq. 12.

Table 9 - Individual GRC of each performance (with ψ=0.33)

Experiment No.	MRR (ξ_1)	TWR (ξ_2)	SR (ξ_3)
Ideal sequence	1.0000	1.0000	1.0000
1	0.2918	0.6663	0.2481
2	1.0000	0.6236	0.9560
3	0.3275	0.2481	0.6541
4	0.2775	0.4282	1.0000
5	0.5578	0.4403	0.3122
6	0.4984	0.5028	0.9477
7	0.5543	0.6390	0.5076
8	0.2481	1.0000	0.4084
9	0.3851	0.6496	0.6744
10	0.3275	0.2481	0.6541
11	0.3052	0.6496	0.3859
12	0.3275	0.2481	0.6541
13	0.2655	0.8476	0.5918
14	0.3052	0.5128	0.4743
15	0.7195	0.7153	0.6187

Table 10 - Evaluation of overall GRG

Experiment No.	Overall grey relational grade (γ)
1	0.4021
2	**0.8599**
3	0.4099
4	0.5686
5	0.4368
6	0.6497
7	0.5670
8	0.5522
9	0.5697
10	0.4099
11	0.4469
12	0.4099
13	0.5683
14	0.4308
15	0.6845

Table 11 - Analysis of variance results for overall GRG

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Current	2	0.033739	0.016869	2.04	0.193
Ton	2	0.024999	0.012499	1.51	0.278
Voltage	2	0.115954	0.057977	7.00	0.017
Error	8	0.066243	0.008280		
Total	14	0.238457			

$$\mathrm{GRG} = 8.319 - 0.2214\,\mathrm{A} - 0.00678\,\mathrm{B} - 0.4433\,\mathrm{C} + 0.003123\,\mathrm{A2} - 0.000010\,\mathrm{B2} + 0.006929\,\mathrm{C2} + 0.000178\,\mathrm{A} \times \mathrm{B} + 0.003743\,\mathrm{A} \times \mathrm{C} + 0.000237\,\mathrm{B} \times \mathrm{C} \quad (12)$$

4.1.2 Data Analysis and Results by Firefly Algorithm

Firefly Algorithm is a metaheuristic procedure, and it is executed in the current investigation utilizing the MATLAB programming software. This algorithm is tried with different population sizes and emphases for getting the ideal solution of GRG with the optimal parametric conditions. As the current study includes a quadratic regression model subsequently, it is a perplexing situation. The population size of 25 fireflies and 40 iterations are utilized in this calculation to get ideal parametric combination, and there is no much change in the convergence nature of the solution. The optimal parametric combination and the ideal solution is accomplished at 30th iteration as outlined in Fig. 5.

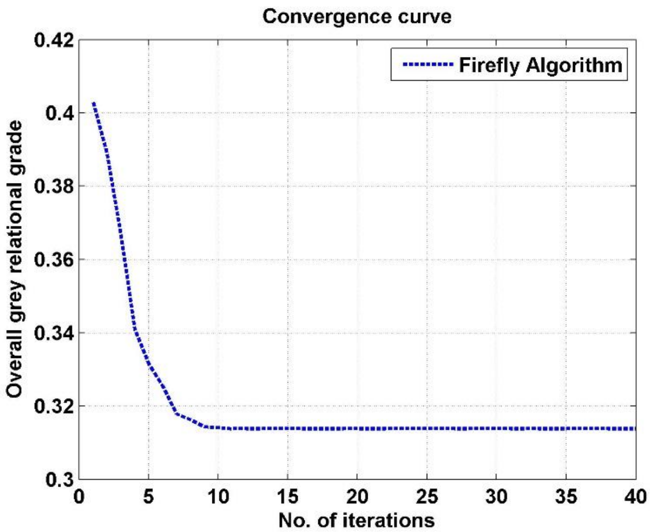

Fig. 5 - Overall GRG convergence plot using FA

4.1.3 Confirmatory Test Results

In the wake of getting the ideal process parametric settings from the main effects plot, the subsequent stage is to foresee and check the improvement of performance measure results utilizing this condition. Table 12 depicts the correlation results of the predicted GRG with their related experimental values by utilizing the ideal EDM machining conditions. There is a decent arrangement between these two outcomes has been noticed. This implies that the RSM technique and the GRA coupled FA hybrid methodology corresponding to manufacturing process optimization have been effectively applied to this intricate problem.

Table 12 - GRA coupled FA confirmation test results

	Initial Machining Parameters	**Optimal Machining Parameters**	
		Prediction	Experiment
Level	$A_1B_1C_2$	$A_2B_3C_2$	$A_2B_3C_2$
MRR	83.3	72.4	72.6
TWR	6	4.2	4.3
SR	3.45	9.3	9.4
Overall grey relational grade	0.33	0.31	0.56
Improvement in Overall grey relational grade = 0.23			

4.2 Experimental Data Analysis During Machining of Titanium Alloy Ti6Al4V Using Rotary Tool Electrode

The experimentation was carried out in a die sinking electro-discharge machine, Agiecharmiles FORM S-350, manufactured by GF machining solutions, Switzerland. In this case, the same copper tool is connected with negative polarity and the tool rotation was fixed at100 rpm for all set of experiments. A suitable fixture was used to handle the work material as shown in Fig.2(b). In this experimentation, same input parameters as well as same levels of input parameters are chosen. The experimental results of machining on Ti6Al4V using rotary electrode copper are shown in Table 13.

4.2.1 Data Analysis and Results by Grey Relational Technique

The experimental results are analysed as like the previous section. By using Grey relational analysis, the overall grey relational grade has been found out for all three responses (MRR, TWR and Surface roughness) as shown in the Table 14. ANOVA analysis results of the overall grey relational grade is presented in Table 15. It has revealed that voltage is the most influencing factor. Current and pulse-on time are found to be insignificant factors as their P-values are more than 0.05.

The regression model equation for the rotary electrode mode is presented in Eq. 13.

$$GRG = 0.4689 + 0.0389\ A + 0.0056\ B + 0.0852\ C - 0.0199\ A^2 + 0.0567\ B^2 - 0.0711\ C^2 - 0.0695\ A\times B + 0.0225\ A\times C + 0.0177\ B\times C \quad (13)$$

Table 13 - Observation data with rotary copper electrode on extruded Ti6-Al-4V work material

Sl. no.	I_p(A)	T_{on}(μs)	V	MRR (mm^3/h)	EWR (mm^3/h)	Ra(μm)
1	10	200	25	57.3	8.072	3.405
2	10	150	20	28	5.381	**2.274**
3	15	150	25	46.7	4.691	3.09
4	15	100	30	53.3	5.381	3.11
5	20	100	25	60	13.45	3.599
6	20	150	30	122.7	21.52	3.608
7	20	150	20	101.3	10.76	3.334
8	15	200	30	48	5.381	3.131
9	10	100	25	121.3	21.52	3.626
10	15	150	25	70.7	10.76	3.722
11	20	200	25	56	2.691	3.794
12	15	150	25	240	23.22	2.644
13	10	150	30	218.7	24.22	3.358
14	15	200	20	24	3.691	2.546
15	15	100	20	85.3	10.76	4.098

Table 14 - Evaluation of overall grey relational grade

Experiment No.	Overall grey relational grade (γ)
1	0.399006
2	**0.658994**
3	0.491416
4	0.473421
5	0.331252
6	0.320952
7	0.389955
8	0.469559
9	0.319069
10	0.352712
11	0.520963
12	0.625470
13	0.458359
14	0.604497
15	0.343922

Table 15 - ANOVA analysis results for overall grey relational grade

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Current	2	0.01358	0.006789	0.71	0.518
Ton	2	0.01212	0.006062	0.64	0.553
Voltage	2	0.07679	0.038393	4.53	0.041
Error	8	0.07606	0.009508		
Total	14	0.1809			

4.2.2 Data Analysis and Results by Firefly Algorithm

Like previous section 5.1.2, the firefly algorithm is utilized to find out the optimal parametric combination. In this case also, population size of 25 fireflies and 40 iterations are utilized in this calculation to get ideal parametric combination. It has been found that convergence is achieved at 35th iteration as shown in the Fig.6.

4.2.3 Confirmatory Test Results

After getting the optimal parameter settings from the main effects plot, the next step is to predict and verify the enhancement of performance characteristics using this condition. Table 16 shows the comparison results of the predicted GRG with their corresponding experimental values by using the optimal machining conditions. There is a good agreement between these two results has been observed. This signifies that the RSM method and the GRA coupled FA hybrid approach in relation to product/process optimization have been successfully applied to this complex problem. It has been found that the overall grey relational grade improves as 0.44.

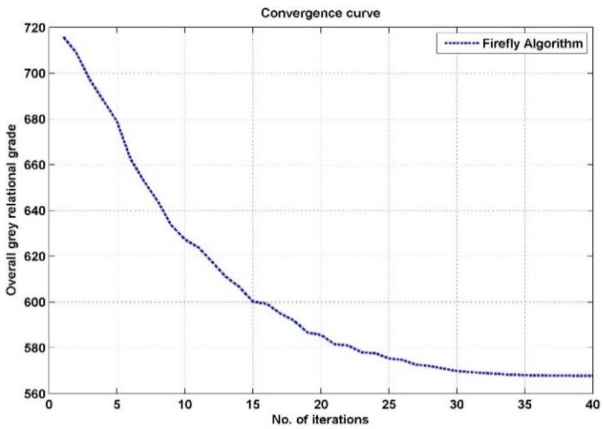

Fig. 6 - Overall GRG convergence plot using FA

Table 16 - Confirmation test results for GRA coupled FA

	Initial machining parameters	**Optimal machining parameters**	
		Prediction	Experiment
Level	$A_1B_3C_2$	$A_2B_3C_2$	$A_2B_3C_2$
MRR	57.3	61.4	62.4
TWR	8.072	7.8	7.2
SR	3.405	2.9	2.3
Overall grey relational grade	0.39	0.43	0.83
Improvement in Overall grey relational grade = 0.44			

4.2.4 Scanning Electron Micrographs

To check the surface integrity of machined surface scanning electron microscope (Model: Zeiss-Supra 55) is used. SEM micrographs have been taken in the optimized parametric setting in both stationary and rotary EDM process. It is observed that surface texture in rotary mode is finer than stationary mode as shown in the Fig.7a &7b. Furthermore, it has been found that stationary tool EDM has a greater crater size as compared to rotary tool EDM because debris of spark area is effectively cleaned.

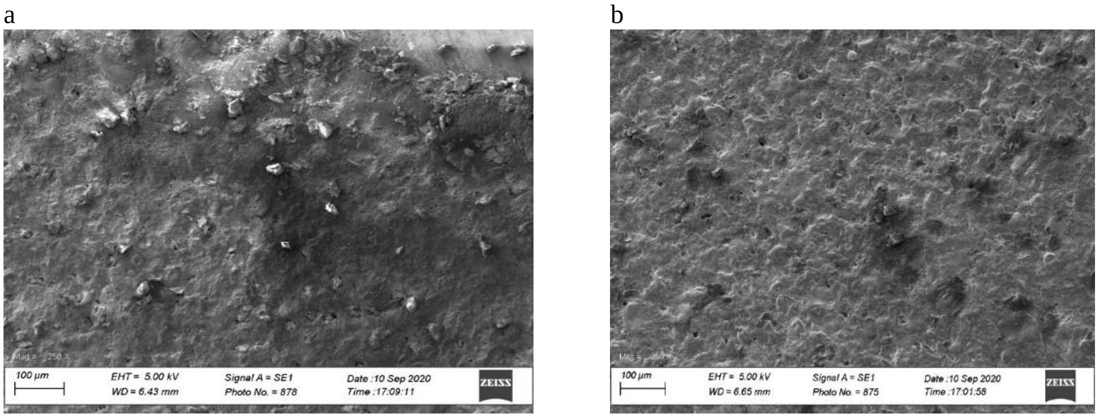

Fig. 7 - (a) Scanning electron micrograph showing stationary tool EDMed work piece at optimized parametric setting; (b) rotary tool EDMed work piece at optimized parametric setting

5. Conclusions

Major conclusions of this experiment can be summarised as follows:

- The optimal parametric settings are uncovered by the RSM DOE procedure to accomplish acceptable features of EDM test that yields outputs like MRR, TWR and SR. The voltage followed by pulse-on time are the two significant elements which impact MRR. Each input factor is significant in TWR investigation. Similarly, pulse-on time is the most impacting parameter which influence the SR result. RSM strategy is an effective manufacturing process optimization method which can give significant outcomes in a limited number of test runs.
- The MRR, TWR and SR quality characteristics are combined together to a single response by GRA technique. The quadratic regression modelling between the GRG and the input parameter shows 0.9571 R^2 value. Thus, it explains the variance in GRG up to 95.71%.
- This work uncovers the exactness and quick convergence offered by FA. As this EDM experimentation is a multi-modal problem, a novel optimization method is recommended in the current research work by pairing the GRA with FA. In this method, an optimal solution is reached with 40 iterations, and the ideal quality attributes is acquired.
- Rotary Electrode in EDM on Ti6Al4V improves machining performance. MRR, TWR and surface finish.

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