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Application of GRA for Optimal Machining Parameter Selection in EDM

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Abstract

Electrical discharge machining (EDM) is one of the most extensively used non-conventional material removal process. The Taguchi method has been utilized to determine the optimal EDM conditions in several industrial fields. The method was design to optimize only a single performance characteristic. To remove this limitation, the Grey relational theory has been used to resolve the complicated interrelationship among the multiple performance characteristics. In the present study, we attempt to find the optimal machining conditions under which the Material removal rate(MRR) to be maximize and Tool wear rate(TWR) to be minimize. This paper summarizes the Grey relation theory and Taguchi optimization technique in order to optimize the cutting parameters in EDM for SS304. The Taguchi method was used to determine the relations between the machining and Response parameters. GRA was used to investigate the optimal machining parameters, among which the pulse on-time, pulse off-time are found to be the most desirable. Finally optimal machining conditions are pulse on time (50 µs), pulse off time (35 µs), discharge current (12A), and voltage (50V). Experimentation was planned as per Taguchi's L9 (3^3) orthogonal array. Analysis of variance (ANOVA) is applied to identify the level of importance of the machining parameters on the multiple performance characteristics considered. Finally confirmation result was carried out to identify the effectiveness of this proposed method.

Keywords: *EDM, performance characteristics (MRR, TWR), Grey relational Analysis (GRA), ANOVA*

1. Introduction

Electric discharge machine (EDM) is one of the non conventional machining processes, which is used to produce intricate shapes on any conducting metal and alloy irrespective of their hardness and toughness [1, 2]. EDM is achieved by applying a succession of discrete discharges between tool and an electrically conducting work piece separated by a dielectric fluid medium. A suitable gap, known as spark gap, the spark discharge is produce between the tool and the work piece [3]. The Selection of appropriate machining parameters for any particular material in EDM is an important step, and relies heavily on operator experience [4]. Electrical Discharge Machining (EDM) process is focused on machining and improving MRR and TWR. Stainless Steel (S304) is used as a work piece. Stainless Steel is a nickel and chromium based alloy, which is widely used in valves, refrigeration equipment, evaporators and cryogenic vessels due to its exceptional corrosion resistance, high ductility, non-magnetic, and it retains solid phase up to 1400 degree Celsius [5]. Now a day, Optimization of process parameters is the important criterion in the machining process to achieve high quality [6]. To optimize the data based on the experimental results, the conventional statistical

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regression requires large amount of data that causes the difficulty in treating the typical normal distribution of data and the lack of variant factors. B. Sidda Reddy, *et al.*, [7] Studied that influence by design four factor such as current, servo control, duty cycle and open circuit voltage over the outputs on MMR, TWR and SR and hardness on the die-sinker EDM of machining AISI 304 SS. M.M Rahman, *et al.*, [8]. Experimentally found out the machining characteristics of austenitic stainless steel 304 through electric discharge machining. The investigation shows that with increasing current increase the material removal and decreases the tool wear rate. Optimization of multiple response characteristics is more complicated than the single response parameters [9]. Taguchi methodology is a single parameter, optimization based on the signal to noise ratio. Grey relational analysis is applied to optimize the parameters having the multi responses through grey relational grade. T. M. Chenthil Jegan, *et al.*, [10] determines the assortment of machining setting like Peak Current, Pulse on-time, Pulse off-time in EDM intended for the machining of AISI202 stainless steel metal. Grey relational technique is used to optimize the response parameters MRR and TWR. The greatest nominal influence in addition to the order of significance of the manageable influences to the multi performance physical characteristics on EDM machining procedure stayed determined. The result shows that discharge current was influencing parameter on MRR. Furthermore, a statistical analysis of variance (ANOVA) is performed to see which statistical parameter is significant. Taguchi's method is applied to plan the experiments [11]. Orthogonal arrays were introduced in 1940s and has been widely used in design of experiments. It is used to reduce the no. of experiments needed to perform than the full factorial experiment. Dhar, *et al.*, [12] developed a second order non linear mathematical model to establish a relationship between parameter settings. ANOVA has been perform to verify the fit and adequacy of the model. Dewangan, *et al.*, [13] investigated the machining parameter settings like pulse on time, discharge current, diameter of tool of AISI P20 tool steel material using U-shaped copper electrode using internal flushing technique. For the practical machining of SS 304, it is necessary to determine the optimal machining parameters to achieve less tool wear rate, MRR etc. Jangra, *et al.*, [14] used the Grey relational analysis along with Taguchi method to optimize multiple machining characteristics in wire-EDM of punching die, D3 steel was used as a work piece. Lin et al. [15] applied the method to obtain the optimal machining parameter of a hybrid process of EDM incorporating ball-burning machining. Masuzawa, *et al.*, [16] fabricated micro pins, micro nozzles and micro pipes using EDM and Allen uses micro EDM technology to manufacture ink jet nozzle. The Taguchi method has been widely used in several industrial field and relevant research work. Saha, *et al.*, [17] studied the process of dry-EDM with copper as tool and mild steel as work piece. Nipanikar, *et al.*, [18] used the Taguchi methods to determine the optimal parameter setting in EDM using AISI D3 steel as a work piece. The grey relation theory can handle both incomplete information and fuzzy problems very precisely. It also provides an efficient solution to the uncertainty, multiple inputs and discrete data problem like machining. S. Dhanabalan, *et al.*, [19] have done EDM process optimization with multiple performance characteristics based on orthogonal array with grey relational analysis for Titanium grades with brass electrode. Rao, *et al.*, [20] highlighted the development of mathematical models using response surface modelling for correlating the relationship of various process WEDM parameters such as, pulse on-time, pulse off-time, peak current and servo feed setting on the machining speed and surface roughness. Mahapatra, *et al.*, [21] derived a mathematical quadratic model to represent the process behaviour of WEDM operations. Experiments has been conducted with six process parameters: wire speed, discharge current, pulse duration, pulse frequency, dielectric flow rate and wire tension; to be varied in three different level. Process responses such as Material Removal rate, surface finish and kerf have been measured. These data have been utilized to fit a mathematical quadratic model for each of the responses. GRA has been adopted to convert this multi-objective criterion into a single objective function; Optimal setting has been verified through confirmatory test; showed good agreement to the predicted value.

2. Multi-Objective Optimization: GRA

In GRA, the data pre-processing is required since the range and unit in one data sequence is vary from the others data. Data pre-processing is also required when the sequence scatter is large enough, 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 normalized in the range between 0 and 1. Depending on the characteristics of data sequence, there are various methodologies of data pre processing available for the GRA. The procedure is given below.

• Identify the response and process parameters to be evaluated.

• Determine the levels for the process parameters.

• Select the appropriate orthogonal array and assign the process parameters to the orthogonal array.

• Conducts the experiments based on the arrangements of the OA.

• Normalize the experimental results of MMR and TWR.

• Perform the Grey relation generating and calculate the Grey relation coefficient.

• Calculate the Grey relational grade (GRG) by averaging the Grey relational coefficient (GRC).

• Analyze the experimental results using the Grey relational grade and Analysis of Variance (ANOVA).

• Select optimal level of process parameters.

2.2 MATERIALS USED

The workpiece material used for the experiments was 304 Stainless steel. The hardness value of the 304 Stainless steel was 35 HRc. The commercial EDM oil, IPOL spark erosion 450 (specific gravity 0.75, kinematic viscosity (at 40°) 23 cSt and dielectric strength 12 kV min) was used as a dielectric fluid.

2.1 EXPERIMENTAL SETUP

The experiments were conducted using a ram EDM machine, model C-425 manufactured by Electronic Industries, India. The electrode is fed downwards into the work piece under servo control in this EDM machine. A special rotary head has been fabricated and attached to the quill of the EDM machine to provide rotary motion to the electrode. The electrode-rotating device consists of a precision spindle, a timer belt drive mechanism, and a speed control unit. The spindle was designed with built-in seals to effect flushing through the electrode. Figure 1 depicts the photograph of experimental setup used for the experimentation.

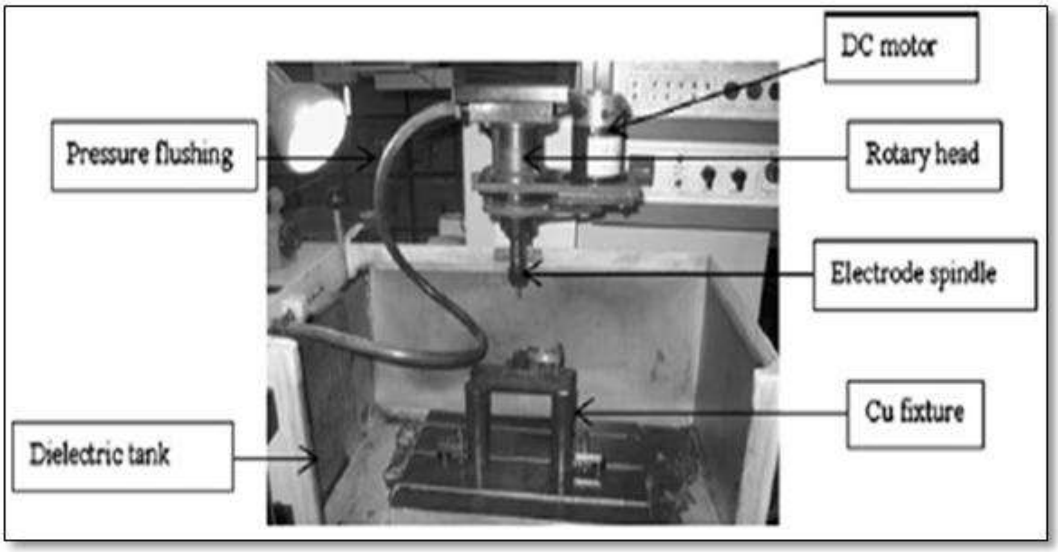

Figure 1. Schematic Setup for EDM

The objective of the research work is to improve the machined surface on 304 stainless steel. Since machined surface is influenced by various parameters such as MMR, TWR, and hence these parameters are considered as response variables. Singh, *et al.*, **[22]** machined hot die steel (H-11) on WEDM. They studied the effects of process parameter on MRR. Finally conclude that by increasing the pulse on-time MRR also increases and vice versa. Secondly, the literature indicates that the selected response variables are influenced by the process parameters. Therefore, three levels of each process parameters are selected and experiments are performed as shown in **Table 1. 1**

Table 1. Process Variable Values with Different Levels

Sr.No	symbols	Cutting parameters	Levels			units
			1	2	3	
1	A	Voltage	40	50	60	volts
2	B	Current	8	12	16	amps
3	C	Pulse on time (T_{ON})	50	100	150	µs
4	D	Pulse off time (T_{OFF})	20	35	50	µs

In GRA, The first step of grey relational analysis is to normalize (in the range between 0 and 1) the experimental data according to the type of performance response is known as the grey relational generation. Muthu, *et al.*, [23] investigated experimentally the influence of the machining parameter on the kerf width, metal removal rate and surface roughness of the machined work piece after using Taguchi method. There are three data pre-processing methods for the grey relational generation. The larger-the-better, smaller-the-better, characteristics have identical levels to compare with each other.

In this study, a L9 (3^3) OA was chosen. In the L9 array can be used to assign test factors and their interactions. For a 4 factor-3 level setup the total number of experiments to be conducted is given by $3^2 = 9$ as shown in Table 2**.**

Table 2. Experimental Layout using L 9 OA

Experiment No.	Discharge Current	Pulse on Time	Pulse off Time	Voltage
1	8	50	20	40
2	12	100	35	40
3	16	150	50	40
4	8	100	50	50
5	12	150	20	50
6	16	50	35	50
7	8	150	35	60
8	12	50	50	60
9	16	100	20	60

2.3 Normalization the S/N ratio

Depending on the characteristics of data sequence, linear normalization can be performed by different methodologies. In this study, the original sequence for Tool wear rate, which is the smaller-the better performance characteristic can be expressed as:

$$y_i^*(k) = \frac{\max y_i^{(o)}(k) - y_i^{(o)}(k)}{\max y_i^{(o)}(k) - \min y_i^{(o)}(k)} \text{......Eq. (1)}$$

Where $y_i^*(k)$ and $y_i^{(o)}(k)$ are sequences after data pre-processing and comparability sequence respectively, k = 1, 2 for Tool wear rate. i = 1, 2, 3 . . . 9 for experiment number 1–9.

The Material removal rates, which is the larger-the better performance characteristic can be expressed as:

$$y_i^*(k) = \frac{y_i^{(o)}(k) - \min y_i^{(o)}(k)}{\max y_i^{(o)}(k) - \min y_i^{(o)}(k)} \text{..............Eq. (2)}$$

Where $y_i^*(k)$ and $y_i^{(o)}(k)$ are sequences after data pre-processing and comparability sequence respectively, k = 3 for Material removal rates .i = 1, 2, 3,. . .9 for experiment number 1–9.

The normalized values of TWR, MRR measured by Equation (1) and (2) are shown in Table 3

Table 3. Data Processing of Each Performance Characteristic (Grey Relational Generation)

Trail. No	MRR	TWR
Ideal Sequence	1	1
1	0.366	0.453
2	0.628	0.783
3	0.312	0.272
4	0.000	0
5	0.173	0.247

6	1.000	1
7	0.393	0.476
8	0.746	0.98
9	0.132	0.324

$\Delta_{oi}(k)$ is deviation sequence of reference sequence $y^*_o(k)$ and Comparability sequence $y_i^{(o)}(k)$. Deviation sequence Δ_{oi} can be expressed as:

$\Delta_{oi}(k) = \left| y^*_o(k) - y_i^{(o)}(k) \right|$................**Eq.(3)**

Table 4. Deviation Sequence of Each Performance Characteristic

Exp. No	TWR	MRR
1	0.634	0.547
2	0.372	0.217
3	0.688	0.728
4	1.000	1.000
5	0.827	0.753
6	0.000	0.000
7	0.607	0.524
8	0.254	0.020
9	0.868	0.676

The Deviation sequence of TWR, MRR measured by Equation (3) are shown in Table 4

2.4 Grey Relational Coefficient (GRC)

Grey relational coefficient for all the sequences gives the relationship between the ideal (best) and actual normalized experimental results. The GRC can be expressed as:

$\gamma_{i(k)} = \frac{\Delta_{min} + \phi\Delta_{max}}{\Delta_{oi}(k) + \phi\Delta_{max}}$.....................**Eq. (4)**

Table 5. Grey Relational Coefficient of Each Performance Characteristics (With MMR ζ= 0.68 & TWR ζ= 0.32)

Trail No.	MRR	TWR
1	0.52	0.369
2	0.65	0.596
3	0.50	0.305
4	0.40	0.242
5	0.45	0.298
6	1.00	1.00
7	0.53	0.379
8	0.73	0.941
9	0.44	0.321

Where ϕ is the distinguishing coefficient between the range of $0 \le \phi \le 1$, it is considered as 0.5 is chosen in this study [26]. $\Delta_{oi} = \| y^*_o(k) - y^*_i(k) \|$ the absolute value of the difference of $y^*_o(k)$ and $y^*_i(k)$. $\Delta_{max} = \forall j^{max} \in i \forall k^{max} \| y^*_o(k) - y^*_j(k) \|$,Δ_{max} is the largest value of Δ_{oi} and $\Delta_{min} = \forall j^{min} \in i \forall k^{min} \| y^*_o(k) - y^*_j(k) \|$, Δ_{min} is the smallest value of Δ_{oi}

2.5 Grey Relational Grade (GRG)

The overall evaluation of the multiple performance characteristics is based on the GRG. The grey relational grade is an average sum of the GRC, and can be expressed as:

$\xi_i = \frac{1}{n}\sum_{k=1}^{n} w_k \gamma_i(k)$.................... **Eq. (5)**

Where, ξ_i is GRG for the j^{th} experiment and n the number of performance characteristics. W_k denotes the normalized weight of factor k. A real engineering system, the importance of various factors to the system varies the real condition of unequal weight being carried by the various factors. The same weight is given in Eq. (5) is equal. The order of the experiments according to the magnitude of GRG. **Table 6** shows that the corresponding experimental results are closer to the ideally normalized value and **Figure 2** indicate the response table for grey relational grade.

Table 6. Grey Relational Grade and their Order

Trail No.	Voltage	Current	Pulse on time (T_{ON})	Pulse off time (T_{OFF})	GRG	Rank
1	40	8	50	20	0.443	5
2	40	12	100	35	0.621	3
3	40	16	150	50	0.401	6
4	50	8	100	50	0.324	9
5	50	12	150	20	0.375	8
6	50	16	50	35	0.950	1
7	60	8	150	35	0.454	4
8	60	12	50	50	0.834	2
9	60	16	100	20	0.380	7

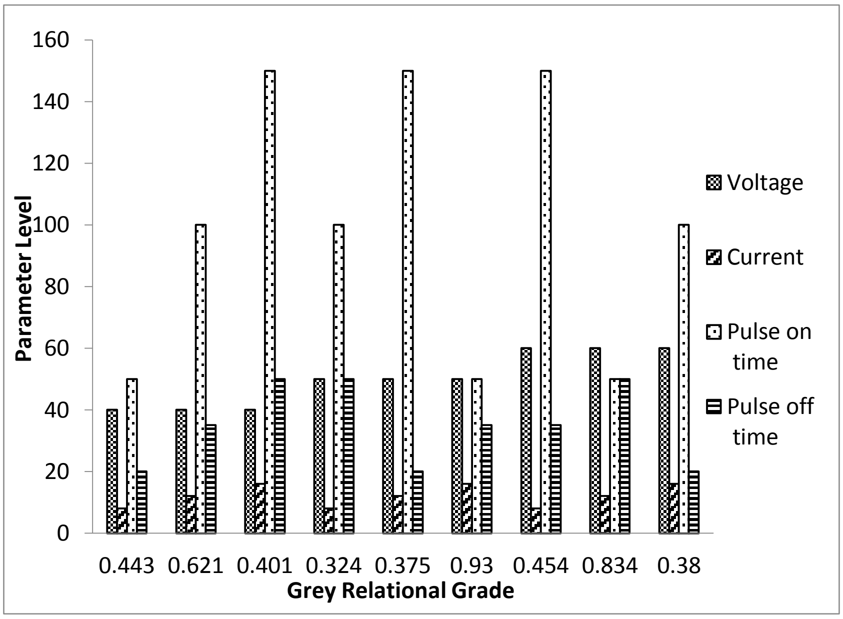

Figure 2. Variation of Grey Relational Grade with Experimental Run

Table 7. Mean Response Table for the Grey Relational Grade (GRG)

Level	Discharge current	Pulse on Time	Pulse off Time	Voltage
1	0.4069	0.7592	0.3995	0.4886
2	0.6101	0.4417	0.6916	0.5661
3	0.5939	0.4099	0.5197	0.5561
Max-Min.	**0.2031**	**0.3493**	**0.2922**	**0.0775**
Rank	**3**	**1**	**2**	**4**

Average Grey relational grade: 0.537

Table 7 indicates the response Table for grey relational grade. That is obtained by calculating the average value of each process variable at its corresponding level. The max–min row indicates that Pulse on-time is the most significant factor among the four process variable. In order to produce the optimized output, the optimal combination of the Process parameters is determined from the response table shows that discharge current must be maintained at level 3, pulse on time at level 2, and pulse off time at level 3and voltage at level 1. **Figure 3** shows the response graph plotted for the calculated grey relational grade. The graph illustrates that all the four input parameters have a grey relational grade above 0.3. The slope of the curves in the graph is found to be more for discharge current indicating it as the most influential parameter. In this graph, (8, 12, 16) amps in the x-axis corresponds to that of three levels of discharge current. Similarly the (50,100,150) µs and (20, 35, 50) µs and (40, 50, 60) volts corresponds to the three levels of pulse on time, pulse off time and voltage respectively. However, in order to obtain an improved quality in output.

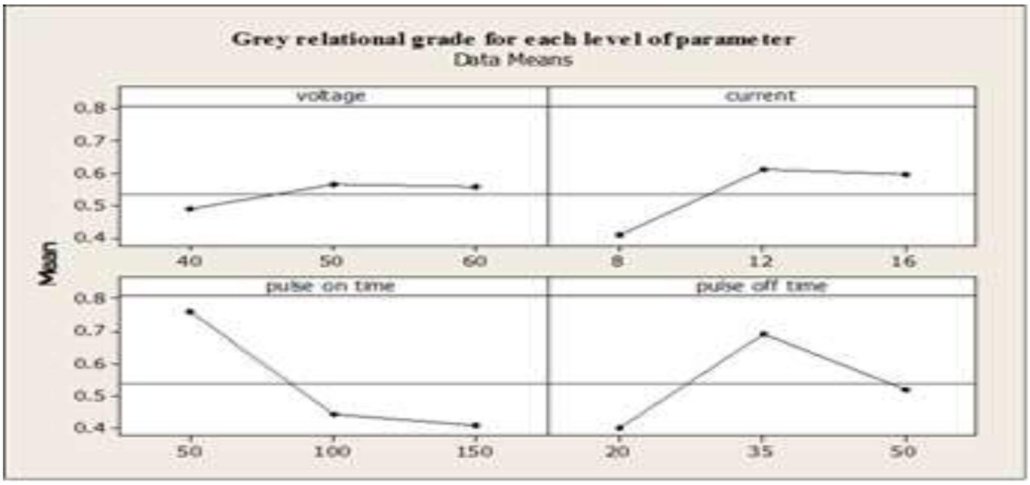

Figure3. Effect of input parameters on Grey Relational Grade

Table 8. ANOVA Results Grey Relational Grade with A, B, C & D

Source of Variation	DOF	Sum of Squares	Mean Square	P %
Voltage	2	0.010671	0.005335	**0.024**
Current	2	0.076478	0.038239	**0.17**

Pulse on time (t_{on})	2	0.223888	0.111944	**0.516**
Pulse off time (t_{off})	2	0.129375	0.064688	**0.29**
Error	0	0.00	0.00	**0.00**
Total	8	0.440411	0.2202055	**100**

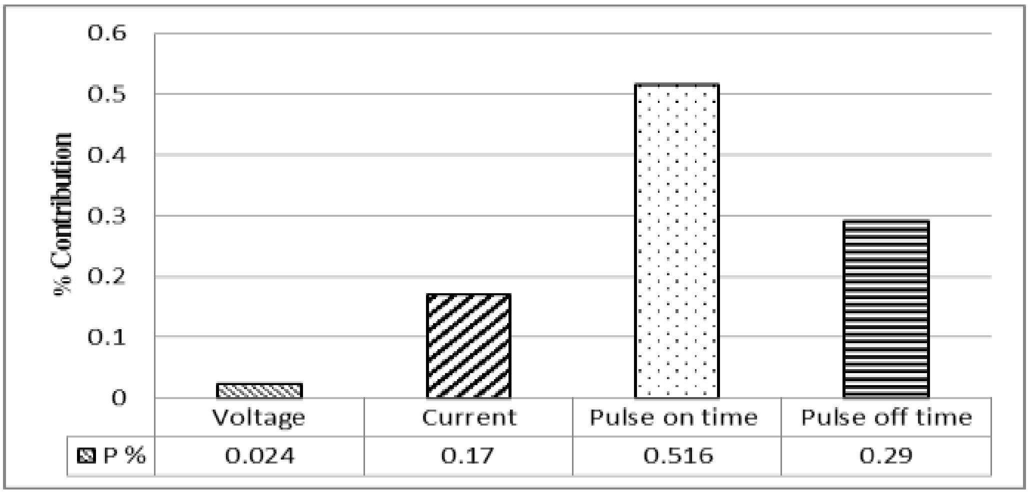

Figure 4. Percentage Contribution of Factors on Grey Relational Grade

3. Analysis of variance (ANOVA)

The purpose of analysis of variance (ANOVA) is used to elucidate which EDM parameters significantly affect the Performance Parameter. Statistical analysis was carried out on the experimental data obtained through Taguchi's experimental design using statistical software (MINITAB 17). Is using the grey relational grade value, Analysis of variance is indicated for identifying the significant factors. The ANOVA results for the grey relational grade values are shown in **Table 8.** According to ANOVA the percentage of contributions indicate the relative power of a factor to reduce variation. The factor with high per cent contribution has a great influence on the performance. The percentage contribution of pulse on time (51.6%) was found to be the major factor affecting the Response performance. Whereas the Pulse off time (29%) found to be second influential factor followed by discharge current (17%) and voltage (2.4%) as shown in **Figure 5**. The present work data by grey relational analysis are in good agreement with the experimental investigations.

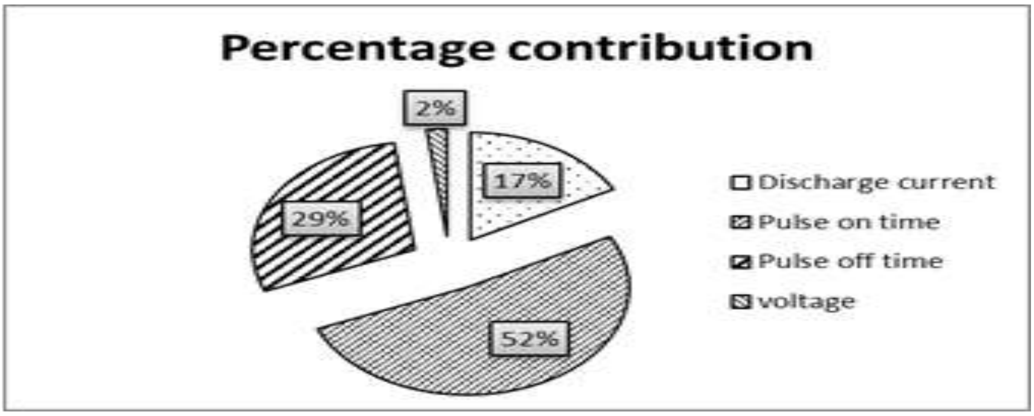

Figure 5. Contribution Percentage of Factors on Grey Relational Grade

4. Confirmation Test

After evaluating the optimal performance characteristics settings is to predict and verify the improvement of quality characteristics using the optimal parametric combination. The optimal predicted value can be evaluated by means of additive law as given by:

$$\hat{\gamma} = \gamma_n + \sum_{i=1}^{\alpha} (\bar{\gamma}_i - \gamma_n)$$

Where, γ_n is the total mean GRG, $\bar{\gamma}_i$ is the mean GRG at the optimal level and α is number of machining parameters that significantly affect multiple performance characteristics. Thus, the predicted or estimated GRG (optimal) is equal to the mean GRG plus the summation of the difference between the overall mean GRG and the mean GRG for each of the significant factors at optimal level. The results of the confirmation experiments using the optimal machining parameters are presented in **Tables 9.** It is found that there is a good agreement between predicted and experimental GRG. This ensures the usefulness of grey relational approach in relation to product/process optimization in a multiple quality criteria have to be fulfilled simultaneously.

Table 9. Results of the Response Performances Indicating the Initial and Optimal Settings

	Initial Machining Parameters	**Optimal Machining Parameters**	
		Prediction	**Experiment**
Setting level	A2B3C1D2	A2B2C1D2	A1B3C1D2
MRR (mm3/min)	36.56		
TWR (mm3/min)	19.28		
S/N ratio of Grey relational grade	0.1	0.72	0.81
Grey relational grade	0.93	0.68	0.95

5. Conclusions

The present work has successfully demonstrated the application of Taguchi based Grey relational analysis for multi objective optimization of process parameters in Electric Discharge Machining of 304 Stainless Steel. The experimental result for the optimal setting shows that there is considerable improvement in the process. After using this technique converts the multi response variable to a single response Grey relational grade and, then, simplify the optimization procedure. The results are summarized as follows:

- This study proposed the orthogonal array combined with grey relational analysis to optimize the multiple performances characteristics of MRR, TWR.
- From the analysis of variance for the grey relational grade, it is observed that pulse on time (51.6%), Pulse off time (29%), discharge current (17%) and voltage (2.4%) exerted a significant influence on multiple responses.
- As a result, the effectiveness of this approach is verified by the test experiment. The grey relational grade of the performance characteristics can be significantly improved by 0.02 through this method.
- Grey relational analysis transformed the multiple responses: MRR, TWR and into a single response A1B3C1D2 combination. The computational value of grey relational grade is 0.95.
- The parameters interaction also has effect on the grey relational grade & the accuracy can be improved by including more number of parameters and levels.

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