Precision Multi-Response Optimization of Performance Characteristics in Wire-Cut Electric Discharge Machining (WEDM) Process

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ABSTRACT

In this paper, an effective two stage multi-response optimization technique (i.e. grey relational analysis coupled with Taguchi technique) has been applied to achieve a better performance characteristic in wire-cut electrical discharge machining (WEDM) process. A zinc coated brass wire of 0.25 mm diameter was used as tool electrode for machining a D2 tool steel specimen. Experiments were planned according to Taguchi's L_9 orthogonal array under different cutting parameters such as: pulse on time (T_{ON}), pulse off time (T_{OFF}), peak current (IP) and wire feed rate (WF). The three quality characteristics (i.e. performance characteristics), namely cutting rate, kerf width and surface roughness have been simultaneously optimized in two different stages. It wasobserved that the cutting speed is increased by 24.60% compared to first stage/primary optimization process. From the analysis of variance (ANOVA), pulse-on time is found to be the most influencing cutting parameter having 74.91% contribution towards overall performance of the WEDM process. Finally,a confirmatory experiment has been carried out at optimum set of cutting parameters obtained from the precision optimization stage to identify the effectiveness of this proposed method. It was observed that the predicted values of the responses obtained from regression models were in good agreement with the experimental findings.

Keywords: *Taguchi technique, WEDM, orthogonal array, grey relational analysis, ANOVA*

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Introduction

In the present manufacturing scenario, Wire-cut Electric Discharge Machining (WEDM) has grown tremendously in the field of electronics, aerospace, automobile, tool and dies industries owing to its high performance and capability of machining any conductive material (regardless of its hardness) into any complex and irregular shape by using a flexible thin metal wire as an electrode [1]. In this unconventional machining operation material is removed by generating repetitive spark discharges between the gap of wire electrode and workpiece immersed in a liquid dielectric medium. A metal wire of small diameter is continuously fed from the supply spool to the workpiece by constantly maintaining a gap of 0.025-0.05 mm between the workpiece and wire and the used wire is collected in the collection tank provided at the bottom of the machine [2].

Guo et al. adopted orthogonal design to determine the main cutting parameters that affect the cutting rate and surface roughness when machining Al_2O_3 particle-reinforced (6061 alloy) material at different machining conditions [3]. Tosun et al. optimized the effects of machining parameters on kerf width and MRR by using statistical regression models and ANOVA technique [4]. Hewidy et al. used the technique of response surface methodology (RSM) for determining optimal parameters setting in the WEDM process of Inconel 601 material [5]. Sarkar et al. formulated an additive model of the WEDM process to predict the most influencing cutting parameter by using constrained optimization and Pareto optimization algorithm [6]. Chiang and Chang applied grey analysis technique to evaluate the multiple performance characteristics of the WEDM process for Al_2O_3 particle reinforced material [7]. Yuan et al. proposed a Gaussian process regression model approach to optimize high speed wire electric discharge machining process [8]. Ramakrishnan and Karunamoorthy developed an artificial neural network (ANN) model and used multi-response signal-to-noise (MRSN) ratio method to predict the optimal performance characteristics of WEDM process [9]. Chen et al. proposed a method integrating back propagation neural network (BPNN) and simulated annealing algorithm (SAA) to study the effect of cutting parameters on cutting velocity and surface finish properties at various operating conditions [10]. Mukherjee et al. implemented six non-traditional optimization algorithms i.e. genetic algorithm (GA), sheep flock algorithm, ant colony optimization (ACO), particle swarm optimization (PSO), artificial bee colony (ABC) and biogeography based optimization for single and multi-objective attributes of WEDM process [11]. Nourbakhsh et al. adopted Taguchi's orthogonal design of experiment to investigate the effect of various process parameters on WEDM performance characteristics such as cutting speed, wire rupture and surface integrity of Ti6Al4V using different wire electrode materials [12]. Sharma et al. designed an experimental design based on one factor at a time (OFAT) approach for evaluating the effect of various control factors such as servo voltage, pulse on time, pulse off time, servo feed, wire feed and flushing pressure on WEDM performance characteristics, namely, MRR and SR of Inconel 706 alloy component [13]. Gurupavan et al. used pulse-on-time, pulse-off-time, current and bed speed as machining parameters for evaluating surface roughness, accuracy, volumetric material removal rate and electrode wear. ANN model was developed to predict performance parameters and they observed a good correlation between the predicted and experimental result [14].

From the study of past research works, it is found that a lot of research works have already been carried out in the field of WEDM technology by using numerous multi-response optimization techniques. However, a few published papers are available on machining of D2 steel with multi-objective performance optimization. D2 steel is a high-carbon, high-chromium, air-hardening tool steel having great wear and abrasion resistant properties. This is mostly used for making blanking or forming dies and thread rolling dies. In this study, three response variables, namely cutting rate (V_c), kerf width (K_w) and surface roughness (R_a) have been optimized in two stages to obtain better performance in machining of D2 steel by using Taguchi-based grey relational analysis (GRA) technique. This combined Taguchi-GRA approach eases in obtaining optimal cutting parameters setting as numerical value of grey relational grades by considering correlation of response characteristics [15].

Methodology

This research work uses Grey relational analysis (GRA) method coupled with Taguchi’s parametric design approach to determine the optimum parametric combination for achieving best surface quality (R_a) with optimum cutting rate (V_c) and minimum kerf width (K_w). According to Taguchi based methodology, the control factors/cutting parametersare categorised into three types, i.e. the smaller the better, the larger the better and nominal the best. Since each performance characteristic may not have the same impact on the process, therefore, for solving such multiple response optimization problems following analytic processing steps are used.

Step 1: Determination of loss function (L_{ij}) of each performance characteristics as follows,

(a) For smaller the better, $$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} y_{ijk}^{2} \quad (1)$$

(b) For larger the better, $L_{ij} = \frac{1}{n} \sum_{k=1}^{n} \frac{1}{y_{ijk}^{2}}$ (2)

where, *n* represents number of repeated experiments and y_{ijk} represents the experimental value of the *j*th response variable in *i*th trial at *k*th replication.

Step 2: Determination of S/N ratio (η_{ij}) value for each performance characteristics as given below,

$$\eta_{ij} = -10 \log L_{ij} \tag{3}$$

Step 3: Computation of normalised S/N ratio (Y_{ij}) values for all the responses for all the trials as follows:

(a) For larger the better: $Y_{ij} = \frac{\eta_{ij} - \eta_j^{min}}{\eta_j^{max} - \eta_j^{min}}$ (4)

(b) For smaller the better: $Y_{ij} = \frac{\eta_j^{max} - \eta_{ij}}{\eta_j^{max} - \eta_j^{min}}$ (5)

where, η_j^{min} = min $\{\eta_{1j}, \eta_{2j} \ldots\ldots \eta_{mj}\}$ and η_j^{max} = max $\{\eta_{1j}, \eta_{2j} \ldots\ldots \eta_{mj}\}$. Using the above equations, all the responses are linearly normalised in the range between zero and one.

Step 4: Determination of the grey relational coefficients (GRC), γ_{ij} i.e.

$$\gamma_{ij} = \frac{\Delta_j^{min} + \xi \Delta_j^{max}}{\Delta_{ij} + \xi \Delta_j^{max}} \tag{6}$$

where, $\Delta_{ij} = |1 - Y_{ij}|$, Δ_j^{min} = min$\{\Delta_{1j}, \Delta_{2j}, \ldots, \Delta_{mj}\}$, Δ_j^{max} = max$\{\Delta_{1j}, \Delta_{2j}, \ldots, \Delta_{mj}\}$. ξ is the distinguishing coefficient ($\xi \in [0,1]$).

Step 5: Calculation of the grey relational grade (GRG_i) for *i*th trial as follows,

$$GRG_i = \sum_{j=1}^{p} w_j \gamma_{ij} \tag{7}$$

where, w_j is the weight for the *j*th response, and $\sum_{j=1}^{p} w_j = 1$.

In this study, attempts have been made to determine the influence of four cutting parameters, i.e. pulse on time (T_{ON}), pulse off time (T_{OFF}), peak current (IP) and wire feed rate (WF) on the multiple performance characteristics by using analysis of variance (ANOVA). At last, a confirmatory experiment has been conducted at optimal parametric combination to validate the current study.

Experimental details

In the present research work, D2 tool steel of 12 mm thickness was used as work material for experimentation. The chemical composition of workpiece is listed in Table 1. A 0.25 mm diameter zinc coated brass wire was used as tool electrode. Experiments were carried out on CNC wire cut EDM machine (ECOCUT ELPULS 15) as shown in Figure 1. WEDM machine specification is illustrated in Table 2.

Based on detailed literature survey, four cutting parameters such as: T_{ON}, T_{OFF}, IP and WF were chosen to find out how these parameters affect V_c, R_a and K_w of D2 tool steel. Each parameter is varied in three levels, denoted as low, medium and high level respectively. Table 3 represents the four cutting parameters and their levels. Experiments were planned according to Taguchi's L_9 orthogonal array.

Figure 1: Experimental set up.

Table 1: Chemical composition of D2 tool steel

Element	Weight percentage (%)
C	1.55
Mn	0.6
Si	0.6
Cr	11.8
Ni	0.3
P	0.03
S	0.03
Mo	0.8
V	0.8
Co	1
Cu	0.25
Fe	Balance

Table 2: WEDM machine(ECOCUT ELPULS 15) specifications

Cutting parameter	Symbol	Range
Pulse on time	T_{ON}	000-131
Pulse off time	T_{OFF}	00-63
Peak current	IP	00-12
Pulse peak voltage	VP	1 or 2 (Not used in ELPULS 15)
Water dielectric flushing pressure	WP	0-Low pressure
Wire feed rate	WF	01-15
Wire tension	WT	01-15 (Not used in ELPULS 15)
Spark gap voltage	SV	00-99
Servo feed	SF	0000-0990 (Normal feed) 1000-1999 (Constant feed) 2000-2999 (Constant voltage)
Corner control factor	CC	Not used in ELPULS 15
Cutting speed override %	CS%	100

Table 3: Cutting parameters and their levels

Parameter	Unit	Symbol	Level		
			1	2	3
Pulse on time (T_{ON})	µs	A	105	110	115
Pulse off time (T_{OFF})	µs	B	30	40	50
Peak current (IP)	Amp	C	10	11	12
Wire feed rate (WF)	mm/min	D	4	6	8

Using different levels of the cutting parameters as shown in Table 3, nine experiments were conducted. In each experiment, a 5 mm width of work material was made to cut and machining time for each trial was measured using a stop watch. The cutting rate (V_c) for WEDM operation was calculated using Equation (8) as shown below:

$$V_C = \frac{L}{t}(\text{mm/min}) \tag{8}$$

where L is the length of the slot in mm and t is the machining time in min. The kerf width (K_w) was measured using scanning electron microscope. While a 2D portable surface profilometer (Talysurf, Surtronic 3+) with 0.8 mm cut off value was used to measure the surface roughness (R_a).The surface roughness value was measured on three different locations of each machined specimen by keeping it on a flat surface. The experimental results are illustrated in Table 4.

Table 4: Experimental results (first stage of experimentation)

Expt no.	T_{ON} µs	T_{OFF} µs	IP, Amp	WF, mm/min	V_c, mm/min	K_w, mm	R_a(µm)		
							R_{a1}	R_{a2}	R_{a3}
1	105	30	10	4	0.261	0.35	0.9	1.12	1.38
2	105	40	11	6	0.193	0.51	1.1	1.18	1.1
3	105	50	12	8	0.759	0.42	0.7	1.12	0.76
4	110	30	11	8	0.217	0.47	1.0	1.08	1.34
5	110	40	12	4	1.961	0.37	1.0	1.11	1.18
6	110	50	10	6	0.125	0.5	1.4	1.36	1.14
7	115	30	12	6	0.259	0.55	0.7	0.74	0.7
8	115	40	10	8	0.202	0.48	0.7	0.8	0.82
9	115	50	11	4	0.133	0.44	1.1	0.6	0.66

Results and Discussions

In this section, the experimental data given in Table 4 are analysed by using the grey relational analysis technique (GRA) which is described in the earlier section. In this study, cutting rate (V_c) is addressed as the larger-the-better type problem as larger value of V_c indicates better performance while smaller values of surface roughness (R_a) and kerf width (K_w) indicate better machining performance and thus treated as smaller-the-better type problems.

First stage optimization of multiple performance characteristics

First step in data analysis is to find out the quality losses of all the response variables using Equation (1) and Equation (2) as applicable. Then Equation (3) was applied to transform the loss functions into signal-to-noise (S/N) ratios. The corresponding S/N ratio values of the three response variables are shown in Table 5.

Table 5: Signal-to- noise (S/N) ratio values

Expt. no.	Signal-to-noise ratio values (η_{ij})		
	V_c	K_w	R_a
1	-11.6672	9.1186	-1.3769
2	-14.2889	5.8486	-1.0911
3	-2.3952	7.5350	1.1126
4	-13.2708	6.5580	-1.3413
5	5.8496	8.6360	-0.9915
6	-18.0618	6.0206	-2.5039
7	-11.734	5.1927	2.6069
8	-13.893	6.3752	1.9010
9	-17.523	7.1309	1.7488

The S/N ratio values of cutting rate were then normalised using Equation (4) while for surface roughness and kerf width Equation (5) was used. Basically, larger value of normalised data indicate better performance characteristic, and the best normalised result should be equal to 1. Next, in order to express the relationship between the optimal and actual normalised experimental results, the grey relational coefficients were calculated by using Equation (6). In this study, all the four cutting parameters are considered to be equally influencing the V_C, K_w and R_a. So, the distinguishing coefficient ξ is taken as 0.5 in Equation (6). Then, the grey relational grade was calculated by using Equation (7). Table 6 shows the values of GRC and GRG for each experiment. A higher value of GRG indicates a better performance as the corresponding result is closer to the ideal normalised value. In this way, the multi response optimization problem has been transformed into a single process performance index using the combination of grey relational analysis and Taguchi method.

Table 6: Grey relational coefficient (GRC) and Grey relational grade (GRG) values

Expt. no.	GRC, γ_{ij}			GRG_i
	V_c	K_w	R_a	
1	0.405	0.3333	0.6940	0.4776
2	0.372	0.7496	0.6440	0.5887
3	0.591	0.4559	0.4140	0.4873
4	0.384	0.5898	0.6873	0.5539
5	1.000	0.3631	0.6282	0.6638
6	0.333	0.7034	1.0000	0.6789
7	0.404	1.0000	0.3333	0.5794
8	0.377	0.6241	0.3671	0.4561
9	0.338	0.5032	0.3753	0.4056

Since the experimental design is orthogonal, it is possible to separate out the effect of each machining parameter at different factor levels. The calculated mean GRG values of each machining parameter at three different levels are shown in Table 7. The optimal level combination can then be easily determined by examining the values of level averages (as shown in Table 7) of various factors. Basically, a larger value of GRG (boldfaced in Table 7) signifies better performance characteristic. The optimal cutting conditions for the factors A, B, C and D with respect to GRG is found to be $A_2B_2C_3D_2$ i.e. a pulse on time of 110 μs, a pulse off time of 40 μs, a peak current of 12 A and a wire feed rate of 6 mm/min can be recommended as optimal cutting parameters for the WEDM operation.

Table 7: Response table for the grey relational grade (GRG)

Symbol	Parameters	Mean GRG			Max-
		Level 1	Level 2	Level 3	
A	T_{ON}	0.5179	**0.6322**	0.5715	0.1143
B	T_{OFF}	0.5370	**0.5695**	0.5239	0.0456
C	IP	0.5376	0.5161	**0.5768**	0.0607
D	WF	0.5157	**0.6156**	0.4991	0.1165
Total mean GRG= 0.5511					

Precision/second stage optimisation of performance characteristics

In order to get better performance characteristics, the optimum cutting parameters (i.e. $A_2B_2C_3D_2$) obtained in the previous section are again divided into three neighbouring values except for the peak current value. Due to some machining constraints the peak current could not be varied further (i.e. 12 Amp is the maximum peak current for ECOCUT ELPULS 15 WEDM machine). Table 8 shows the precised levels of cutting parameters. Again experiments were planned according to L_9 orthogonal array keeping the optimal peak current value constant at 12 A and the experimental findings are illustrated in Table 9.

Table 8: Precised levels of cutting parameters

Cutting Parameter	Unit	Symbol	Level		
			1	2	3
Pulse on time (T_{ON})	Ms	A	108	110	112
Pulse off time (T_{OFF})	Ms	B	38	40	42
Wire feed rate (WF)	mm/min	D	5	6	7

Again following the same procedure as described earlier, the experimental data given in Table 9 were analysed and the values of S/N ratio, grey relational coefficient and grey relational grades are shown in Table 10 and Table 11, respectively.

Table 9: Results of second stage experimentation

Expt. no.	T_{ON}	T_{OFF}	WF	V_c	K_w	R_a		
						R_{a1}	R_{a2}	R_{a3}
1	108	38	5	0.947	0.36	1.04	1.09	1.15
2	108	40	6	0.845	0.39	1.17	1.06	1.03
3	108	42	7	0.723	0.34	1.41	1.48	1.52
4	110	38	6	1.046	0.38	1.88	2.08	1.8
5	110	40	7	1.059	0.35	1.68	1.71	1.73
6	110	42	5	0.895	0.36	1.76	1.64	1.79
7	112	38	7	1.16	0.39	2.02	1.98	1.94
8	112	40	5	1.025	0.38	1.88	1.98	1.86
9	112	42	6	1.071	0.37	1.9	2	2.08

Table 10: S/N ratio values of second data set

Expt. no.	Signal-to-noise ratio values (η_{ij})		
	V_c	K_w	R_a
1	-0.4730	8.8739	-0.7824
2	-1.4629	8.1787	-0.7352
3	-2.8172	9.3704	-3.3505
4	0.3906	8.4043	-5.6823
5	0.4979	9.1186	-4.6436
6	-0.9635	8.8739	-4.7670
7	1.2892	8.1787	-5.9345
8	0.2145	8.4043	-5.6088
9	0.5958	8.6360	-5.9975

Table 11: Grey relational coefficient (GRC) and Grey relational grade (GRG) values

Expt. no.	Grey relational coefficient, γ_{ij}			Grey relational grade (GRG_i)
	V_c	K_w	R_a	
1	0.5381	0.4615	0.3353	0.4450
2	0.4273	1.0000	0.3333	0.5869
3	0.3333	0.3333	0.4985	0.3884
4	0.6956	0.7253	0.8930	0.7713
5	0.7218	0.3880	0.6603	0.5900
6	0.4768	0.4615	0.6814	0.5399
7	1.0000	1.0000	0.9766	0.9922
8	0.6564	0.7253	0.8713	0.7510
9	0.7476	0.5658	1.0000	0.7711

Next, the précised optimal level combination was determined to be $A_3B_1D_2$ by evaluating mean GRG value of each cutting parameter at three different levels as given in Table 12.

Table 12: Level averages of the factors

Symbol	Parameters	Mean GRG			Max-Min
		Level 1	Level 2	Level 3	
A	Pulse on time (T_{ON})	0.4734	0.6337	**0.8381**	0.3647
B	Pulse off time (T_{OFF})	**0.7362**	0.6426	0.5665	0.1697
D	Wire feed rate (WF)	0.5786	**0.7031**	0.6569	0.1245
Total mean GRG = 0.6477					

Comparison of both the optimum parameter settings

Figure 2 illustrates the variation of mean grey relational grades with the different levels of cutting parameters for both primary and precision optimization (refer to Table 7 and Table 12 respectively). From Figure 2, it is clearly seen that higher values of GRGs are obtained in the second stage optimization i.e. precision optimization and it indicates that the precision optimization leads to better performance characteristics as compared to single stage/primary optimization because higher the value of GRG better is the machining output.

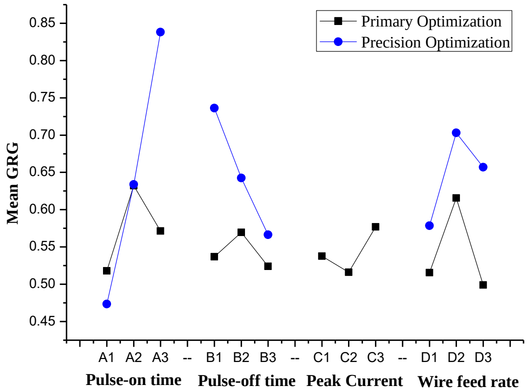

Figure 2: Variation of GRG with different levels of process parameters.

Regression analysis

Regression models for V_c, K_w and R_a have been developed (for both first and second stage optimization) to predict the correlation between the cutting parameters and the respective response characteristic. The following equations are obtained from multiple regression analysis:

a) First stage optimization:

$$V_C = -1.26 - 0.0206T_{ON} + 0.0047T_{OFF} + 0.399IP - 0.098WF \quad (9)$$

$$K_w = -0.359 + 0.00633T_{ON} - 0.00017T_{OFF} + 0.0017IP + 0.0175WF \quad (10)$$

$$R_a = 5.24 - 0.0273T_{ON} - 0.0013T_{OFF} - 0.0950IP - 0.0208WF \quad (11)$$

b) Precision/Second stage optimization:

$$V_C = -4.35 + 0.062T_{ON} - 0.039T_{OFF} + 0.012WF \quad (12)$$

$$K_w = 0.131 + 0.004T_{ON} - 0.005T_{OFF} - 0.003WF \quad (13)$$

$$R_a = -19.9 + 0.186T_{ON} + 0.017T_{OFF} + 0.072WF \quad (14)$$

It is observed that in the first stage of optimization, the set of optimum cutting parameters are $A_2B_2C_3D_2$ (i.e. T_{ON} = 110 µs, T_{OFF} = 40 µs, IP = 12 Amp and WF = 6 mm/min) and in the second stage of optimization (i.e. precision optimization), the set of optimum cutting parameters are $A_3B_1D_2$ (i.e. T_{ON} = 112 µs, T_{OFF} = 38 µs and WF = 6 mm/min). Using the corresponding regression equations, the cutting speed, kerf width and surface roughness are compared between both the stages of optimization and the results are shown in Table 13. It is observed that the cutting speed is increased by 24.60% due to application of precise optimization technique. However, the kerf width is improved by 2.78% with a decrease in surface roughness value. Hence it is found that with a slight increase in kerf width and surface roughness, the cutting speed is tremendously improved due to precision optimization as compared to first stage optimization. So going for precise optimization is justified and essential.

Table 13: Comparative results of regression analysis

	Initial cutting Parameters	Optimal cutting parameters	
		First stage	Precision
Level →	$A_1B_1D_1$	$A_2B_2C_3D_2$	$A_3B_1D_2$
V_c	0.947	0.862	1.18
K_w	0.36	0.45	0.37
R_a	1.09	0.92	2.01

Analysis of Variance (ANOVA)

In order to investigate the significance of each process parameter towards the multiple WEDM performance characteristics, analysis of variance (ANOVA) is applied, which is measured by the sum of squared deviations from the total mean of GRG. In ANOVA analysis, a F-test is conducted where the F-ratio value represent the percentage contribution of different cutting factors. A higher value of F-ratio indicates that any small variation in the respective cutting parameter can significantly affect the performance. Table 14 shows the results of ANOVA analysis. From the results, T_{ON} is found to be the most influencing factor with highest F-value (8.429) and percentage contribution (74.91%) towards the performance measures, followed by T_{OFF} (contributing

16.2%). Since WF has lowest F value and percentage contribution (i.e. 8.89), it is considered to be statistically insignificant.

Table 14: Results of ANOVA

Sources of variance	SS_f	DOF	SS_m	F	P (%)
T_{ON}	0.2005	2	0.1002	8.4290	74.91
T_{OFF}	0.0434	2	0.0217	1.8227	16.20
WF	0.0238	2	0.0119	1.0000	8.89
Error	WF	2	-	-	-
Total	0.5625	8	-	-	100.00

Validation of the precision optimization process

The final step is to validate the optimum cutting parameters by performing confirmatory experiment. Table 15 shows the comparison of the predicted machining performances with the actual values obtained from the confirmatory experiment conducted at the optimal level of cutting parameters i.e. $A_3B_1D_2$. Based on the experimental confirmation it is observed that, the cutting rate is increased by 34.11% and the kerf width is also improved by 5.56% as compared to initial parameters settings (i.e. $A_1B_1D_1$). In order to assess the prediction accuracy of the mathematical model developed from regression analysis, percentage error is calculated (Table 16). For all the three responses percentage error is less than 10%. Hence, the proposed methodology is efficient and effective for optimizing multiple performance characteristics in WEDM process [15, 16].

Table 15: Results of the confirmatory experiment

	Initial cutting Parameters	Optimal cutting parameters		
		Prediction	Experiment	Error percentage (%)
Level	$A_1B_1D_1$	$A_3B_1D_2$	$A_3B_1D_2$	
V_c	0.947	1.18	1.27	7.63
K_w	0.36	0.37	0.34	8.11
R_a	1.09	2.01	1.94	3.48
GRG	0.4450		0.6586	
Improvement of GRG = 0.2136				

Conclusion

The present research work has been focused on two stage multi-response optimization technique by using grey-Taguchi technique to achieve better performance characteristics in wire-cut EDM. The following conclusions have been obtained from the above study:

1. A pulse-on time of 112 μs, a pulse-off time of 38 μs, a peak current of 12 Amp and a wire feed rate of 6 mm/min, are recommended as the optimal cutting parameters for this WEDM process.
2. By following the precision optimization technique, cutting speed is significantly increased by 34.11% compared to primary optimization technique.
3. From the ANOVA analysis, pulse-on time is found to be the most significant cutting parameter having 74.91% contribution towards overall performance. Similarly, wire feed rate is the least significant cutting parameter having 8.89% contribution towards overall performance.

In order to achieve manufacturing quality and production objectives this proposed Taguchi-GRA precision optimization methodology may be used as standard in industrial as well as academic application. Production cost and time may also be reduced to a great extent. Further studies can be carried out by analysing the influence of other cutting parameters such as wire tension, wire diameter, wire types, dielectric fluid concentration on heat affected zone, surface crack density and recast layer thickness of the machined surface. This study is limited with the use of Zinc coated brass wire only.

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