Multi-Responses Optimization Of Edm Sinkingprocess of Aisi D2 Tool Steel using Taguchi Grey–Fuzzy Method

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Abstract— **Rough machining with Electro Discharge Machining (EDM) process gives a large Material Removal Rate (MRR) and high Surface Roughness (SR), while finish machining gives low SR and very slow MRR. In this study, Taguchi method coupled with Grey Relational Analysis (GRA) and fuzzy logic has been applied for optimization of multiple performance characteristics. The EDM machining parameters (gap voltage, pulse current, on time and duty factor) are optimized with considerations of multiple performance characteristics, i.e., MRR and SR. The quality characteristic of MRR is larger-is-better, while the quality characteristic of SR is smaller-is-better. Based on Taguchi method, an L_{18} mixed-orthogonal array is selected for the experiments. By using the combination of GRA and fuzzy logic, the optimization of complicated multiple performance characteristics was transformed into the optimization of a single response performance index. The most significant machining parameters which affect the multiple performance characteristics were gapvoltage and pulse current. Experimental results have also shown that machining performance characteristics of EDM process can be improved effectively through the combination of Taguchi method, GRA and fuzzy logic.**

Keywords— **Taguchi, Grey relational analysis, Fuzzy logic, EDM, AISI D2**

Abstrak*—*Rough Machiningyang menggunakan proses Electro Discharge Machining (EDM) menghasilkan Material Removal Rate (MRR) yang sangat rendah. Dalam penelitian ini, metode Taguchi bersamaan dengan Grey Relational Analysis (GRA) dan fuzzy logic telah diaplikasikan untuk mengoptimalkan karakteristik performansi multiple. Parameter dari EDM Machining (gap voltage, pulse current, on time dan duty factor) dioptimalkan dengan pertimbangan dari karakteristik performansi multiple, seperti MRR dan SR. Semakin besar kualitas karakteristik MRR maka akan semakin baik, sedangkan semakin kecil kualitas karakteristik SR maka akan semakin baik. Sesuai dengan metode Taguchi, sebuah L_{18} mixed-orthogonal array telah dipilih untuk digunakan dalam penelitian ini, dengan menggunakan kombinasi dari GRA dan fuzzy logic, optimalisasi performance single response. Parameter yang terpenting dari

Keywords—***probe spektrofotometer,analysis real time, fiber optik, rhodamine B, in-situ***

I. INTRODUCTION

Electric Discharge Machining (EDM) is one of the most popular modern non-conventional machining methods. The removal of material in EDM is based upon the erosion effect of electric sparks occuring between an electrode (the cutting tool) and the workpiece in the presence of a dielectric fluid. Minute the particles of metal or chips, generally in the form of hollow spheres, are removed by melting and vaporization, and are washed from the gap by dielectric fluid which is continuously flushed between the tool and workpiece.

Nowdays, EDM technology is widely used in tool, die and mould making industries, for machining of heat treated tool steels and many advanced materials which require high precision, complex shapes and high surface finish. Heat treated tool steels are very difficult to machine using conventional processes, due to rapid tool wear, inability to generate complex shapes and imparting better surface finish [1].

Based on the types of processes, EDM can be classified as rough cutting and finishing cutting. The main issue of rough cutting is to remove the material as quickly as possible so that both processing time and production cost can be reduced.

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Generally, the performance of the rough cutting processes can be evaluated based on Material Removal Rate (MRR), Surface Roughness (SR) and Electrode Wear Ratio (EWR), which are correlated with the machining parameters such as on time, off time, discharge current, servo voltage, etc.

The machining parameters are usually selected based on either the experience or the proposed guidelines of the manufacturers [2]. However, this selection procedure does not lead to the optimal and economically effective use of the machines. Taguchi method has been used extensively for optimization of a single performance characteristic. Solving the more complex and demanding multiple performance characteristics is still an interesting and challenging research problems [3-4].

The grey system theory developed by Deng [5] in 1982 has been proven to be useful for dealing with unclear, uncertain and incomplete information. The grey relational analysis based on the grey system theory can be used to solve the complicated interrelationships among multiple performance characteristics or responses effectively. A grey relational grade is obtained from the average of the grey relational coefficient to analyze the relational degree of the multiple responses [6].

The theory of fuzzy logics was initiated by Zadeh in 1965 [7] has been proven to be useful for dealing with uncertain and vague information. It is a fact that the definition of performance characteristics such as lower-the-better, higher-the-better, and nominal-the-better contains a certain degree of uncertainty and vagueness.

Therefore, optimization of the performance characteristics with fuzzy logics has been considered in this study. In this case, a fuzzy reasoning of the multiple performance characteristics has been developed based on fuzzy logics. As a result, optimization of the complicated multiple performance characteristics can be transformed into optimization of a single grey-fuzzy reasoning grade.

The purpose of this paper is to demonstrate an application of grey relational analysis and the fuzzy-based Taguchi method to identify the optimum MRR and surface roughness with a particular combination of machining parameters in EDM sinking process of AISI D2 tool steel.

II. METHOD

A. Materials and Equipment

The experimental studies were performed on a EDM sinking Aristech LS-550machine tool. The schematic diagram of the experimental set-up isshown in Fig. 1. As work piece material, AISI D2 tool steel with 40 mm x 15 mm x 10 mm size was used. Fig. 2 shows the geometric of workpiece. A rectangular copper was used as electrode in the experiments, and its geometric is shown in Fig. 3. The shape of workpiece after machining is shown in Fig. 4. Different setting of gap voltage,pulse current, on time andduty factor were used in the experiments as shown in Table 1. The surface roughness measurements were performed by using a Mitutoyo Surftest 301 with a cut-off length of 0.8 mm and sampling length of 5 mm.

B. Experimental

An experiment was designed using Taguchi method [8], which uses an orthogonal array to study the entire parametric space with a limited number of experiments. The four EDM sinking parameters (control factors) are gap voltage, pulse current, on time and duty factor. As shown in Table 1, one of them was set at two different levels while the other three were set at three different levels. Therefore, the total degrees of freedom were seven. L_{18} orthogonal array that used for the experiment is shown in Table 2 and led to a total 18 tests. The L_{18} orthogonal array is generated by using statistical software. A random order was also determined for running the tests.

C. Taguchi Grey Fuzzy Optimization

Taguchi's loss function is estimates the deviation between the experimental value and the desired value. The value of the loss function is further transformed into a signal-to-noise (S/N)ratio. Basically, there are three categories of the process response in the analysis of the S/N ratio, i.e., the lower-the-better, the higher-the-better, and the nominal-the-better. The S/N ratio for each level of process parameters is computed based on the S/N analysis. Regardless of the category of the process response, a larger S/N ratio corresponds to a better process response. Therefore, the optimal level of the process parameters is the level with the highest S/N ratio. This is true for the optimization of a single process response. However, optimization of multiple responses cannot be as straight forward as the optimization of a single process response. A higher S/N ratio for one process response may correspond to a lower S/N ratio for another process response. As a result, an overall evaluation of the S/N ratios is required for the optimization of a multi-response process.

The steps of Taguchi grey fuzzy optimization are:

1. *Calculation of S/N ratio for each response*

The signal-to-noise (S/N) ratio is a measure of the data set relative to the standard deviation. If the S/N is large, the magnitude of the signal is large relative to the noise, as measured with the standard deviation. There are three S/N ratios available, depending on the type of the performance characteristics; the LB, HB, and NB. In EDM process lower surface finish, cutting force, feed force and higher tool life are indications of better performance. Therefore, for obtaining optimum machining performance, the "LB" and "HB" ratios were selected for surface finish, cutting force, feed force and tool life respectively. The S/N ratios for each type of characteristic can be calculated as follows:

a. Low is better (minimize):

$$\frac{S}{N} = -10\log\left[\sum_{i=1}^{n}\frac{{y_i}^2}{n}\right] \quad (1)$$

b. High is better (maximize):

$$\frac{S}{N} = -10\log\left[\sum_{i=1}^{n}\frac{\frac{1}{y_i}^2}{n}\right] \quad (2)$$

Where n is the number of measurements, and y_i^2 is the measured characteristic value. Regardless the category of performance characteristics, the greater S/N ratio corresponds to the better performance characteristics.

2. *Normalization of S/N ratio*

In the grey relational analysis, experimental data (material removal rate and surface roughness) are first normalized in the range between 0 and 1, which is also called the grey relational generating. The normalization of S/N ratio was conducted by using the following equation [9]:

$$X_i^*(k) = \frac{X_i(k) - \min\ X_i(k)}{\max\ X_i(k) - \min\ X_i(k)} \quad (3)$$

$X_i^*(k)$ is the value after the grey relational generating, min $X_i(k)$ is the smallest value of $X_i(k)$ for the k^{th} response and max $X_i(k)$ is the largest value of $X_i(k)$ for the k^{th} response.

3. *Calculation of grey relational coefficient (GRC)*

The grey relational coefficient is calculated from the normalized experimental data to express the relationship between the desired and actual experimental data. All $X_i^*(k)$ then converted into $\xi_i(k)$ or Grey Relational Coefficient (GRC) by using the following equation [5]:

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{0.i}(k) + \zeta\Delta_{max}} \quad (4)$$

where $\Delta_{0i} = \|x_0(k) - x_i(k)\|$ is the difference of the absolute value between $x_0(k)$ and$x_i(k)$; ζ the distinguishing coefficient; $\Delta_{min} = \forall j^{min} \in i \forall k^{min}\|x_0(k) - x_j(k)\|$ is the smallest value o fΔ_{0i}; and $\Delta_{max} = \forall j^{max} \in i \forall k^{max}\|x_0(k) - x_j(k)\|$ is the largest value ofΔ_{0i}.

The definition of the grey relational coefficient in the grey relational analysis is to show the relational degree between the nine sequences ($x_0(k)$ and $x_i(k)$, i = 1, 2, . . . , 18; k = 1, 2, . . . , 18).

4. *Fuzzification (using membership function)*

A fuzzy logic unit consist of a fuzzifier, membership function, a fuzzy rule base, an inference engine, and a defuzzifier. The implementation of fuzzy logic includes the following steps. First, the fuzzifier uses membership function to fuzzify the grey relational coefficient. The inference engine then performs a fuzzy inference on fuzzy rules in order to generate a fuzzy value. Finally, the defuzzifier converts the fuzzy value into a grey fuzzy reasoning grade or GFRG.

In the following, the concept of fuzzy reasoning is described briefly based on the two-input (material removal rate and surface roughness)-one output fuzzy logic unit. The fuzzy rule base consists of a group of if-then control rules with two inputs or two grey relational coefficient x_1 and x_2, and one multi-response output y, that is:

Rule 1: if x_1 is A_1 and $x_2$is B_1 then y is C_1, else

Rule 2: if x_1 is A_2 and x_2 is B_2 then y is C_2, else

. . .

Rule n: if x_1 is A_k and x_2 is B_k then y is C_n.

A_i, B_i, and C_i are fuzzy subsets defined by the corresponding membership functions, i.e., μA_i, μB_i, and μC_i.Various degrees of membership of the fuzzy sets are calculated based on the values of x_1, $x_2$and y. Nine fuzzy rules are directly derived based on the fact that the larger grey relational coefficient is, the better is the process response. By taking the max–min compositional operation [10], the fuzzy reasoning of these rules yields a fuzzy output. Supposing that x_1 and x_2 are the two input values of the fuzzy logic unit, the membership function of the output of fuzzy reasoning can be expressed as

$$\mu D_0(y) = (\mu A_1(x_1) \wedge \mu B_1(x_2) \wedge \mu C_1(x_2) \wedge \mu D_1(y)) \Lambda\_ \vee (\mu A_n(x_1) \wedge \mu B_n(x_2) \wedge \mu C_n(x_3) \wedge \mu D_n(y)) \quad (5)$$

where $\wedge$ is the minimum operation and $\vee$is the maximum operation. Finally, a defuzzification method, called the center-of-gravity method [7], is adopted here to transform the fuzzy inference output μD_0 into a non-fuzzy value y_0, i.e.,

$$y_0 = \frac{\sum y \mu D_0(y)}{\sum \mu D_0(y)} \quad (6)$$

In this paper, the non-fuzzy value y_0 is called grey fuzzy reasoning grade or GFRG (Lin et al., 2002). It can be summarized that the larger is the GFRG, the better is the performance characteristic.

III. RESULT & DISCUSSION

Table 3 shows the experimental results and S/N ratio for the MRR and surface roughnes based on the experimental parameter combinations (Table 2). Fuzzy rules which are applied in fuzzification is shown in Table 4. T is tiny, VS is very small, S is small, SM is smaller middle, M is middle, LM is larger middle, L is large, VL is very large and H is huge.

Table 5 shows the sequences after the grey relational generating. An ideal sequence ($X_0(k)$ = 1, k = 1, 2, . . . , 18) for MRR and surface roughness Table 6 shows the grey relational coefficient for each experiment using the L_{18} orthogonal array.Table 7 shows the experimental results for the grey-fuzzy reasoning grade using the experimental layout (Table 2). In this paper, three (3) fuzzy subsets are assigned in the grey relational coefficient of the material removal rate and surface roughness (Fig. 5). For both input, i.e., material removal rate and surface roughness, the interval is between 0 and 1. Nine (9) fuzzy subsets are assigned in the multi-response output in the interval between 0 and 1 (Fig 6.)

Since the experimental design is orthogonal, it is then possible to separate out the effect of each process parameter at different levels. The mean of the grey-fuzzy reasoning grade for each level of the process parameters is calculated (Table 8). Basically, the larger the mean of the grey-fuzzy reasoning grade, the better is the multiple process responses.

The analysis of variance (ANOVA) investigates those process parameters which significantly affect the performance characteristics. This is accomplished by separating the total variability of the multi-response performance from the total mean of the GFRG, into contributions by each of the process parameter and the error. First, the total sum of the squared deviations (SS_T) from the total mean of the GFRG μ_m can be calculated as

$$SS_T = \sum_{i=1}^{n} (\mu_i - \mu_m)^2 \quad (7)$$

where n is the number of experiments in the orthogonal array and μ is the mean of the GFRG for the i^{th} experiment.

The total sum of the squared deviations SS_T is decomposed into two sources: the sum of the squared deviations SS_d due to each process parameter and the sum of the squared error SS_e. The percentage contribution by each of the process parameter in the total sum of the squared deviations SST can be used to evaluate the importance of the process parameter change on the performance characteristics. In addition, the F-test can also be used to determine which process parameters have a significant effect on the performance characteristic. Usually, the change of the process parameter has a significant effect on the performance characteristic when the F-value is large. Results of ANOVA (Table 9) indicate that gap voltage and on time are the most significant processparameters for affecting the multiple process responses.

Hence, based on the GFRG graph (Fig. 7) and the results of ANOVA (Table 8), the optimal machining condition for EDM sinking process of AISI D2 tool steel are gap voltage (A) at level 1, pulse current (B) at level 2, on time (C) at level 3 and duty factor (D) at level 1.

After selecting the optimal level of parameters setting, the final step is to predict and verify the improvement of the performance characteristics by using the optimal level of the EDM parameters. The estimated GFRG $\hat{\alpha}$ using the optimal level of the process parameters can be calculated by using the following equation [3]:

$$\hat{\alpha} = \alpha_m + \sum_{i=1}^{q} (\overline{\alpha_i} - \alpha_m) \quad (8)$$

where α_m is the total mean of the GFRG, α_i is the mean of the GFRG at the optimal level and q is the number of the machining parameters that significantly affects the multiple response characteristics.

Based on Eq. 8, the estimated GFRG using the optimal machining parameters can then be obtained. Table 10 shows the results of the confirmation experiment using the optimal machining parameters, and also a comparison of the multiple process responsesfor initial and optimal machining parameters. As shown in Table 8, MRR is increased from 34.68048 to 39.52387 mm^3/min and SR is decreased from 8.58 to 5.37μm. It is clearly shown that the GFRG in the EDM process of AISI D2 tool steel are greatly improved through this study.

IV. CONCLUSION

In this study, the Taguchi-Grey-Fuzzy method has been implemented for the optimization of the EDM process of AISI D2 tool steel with multiple performance characteristics. The combination of grey relational and fuzzy logic analysis of material removal rate and surface roughness obtained from the Taguchi method reduced from the multiple performance characteristics to a single performance characteristic which is called the grey fuzzy reasoning grade. Hence, the optimization of the complicated multiple performance characteristics of the EDM process can be significantly simplified by using Taguchi-grey-fuzzy method. It is also shown that the performance characteristics of EDM process such as material removal rate and surface roughness are also greatly improved by implementing this method.

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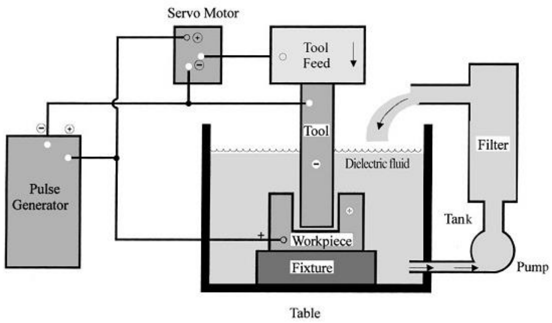

Figure 1. Schematic diagram of the EDM process.

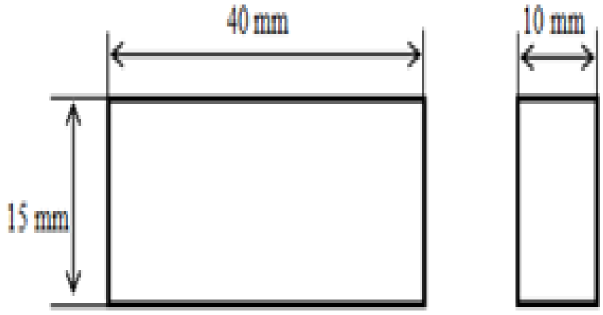

Figure 2.Geometric of workpiece.

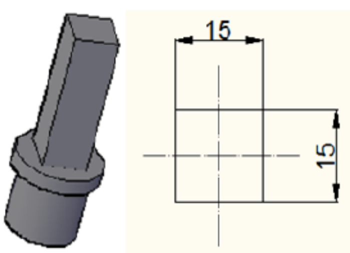

Figure 3. Geometric of electrode.

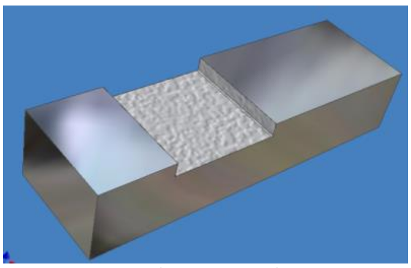
Figure 4.Shape of workpiece after machining.

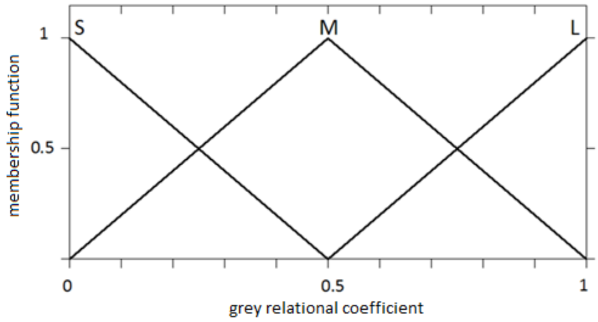

Figure 5. Membership functions for material removal rate and surface roughness.

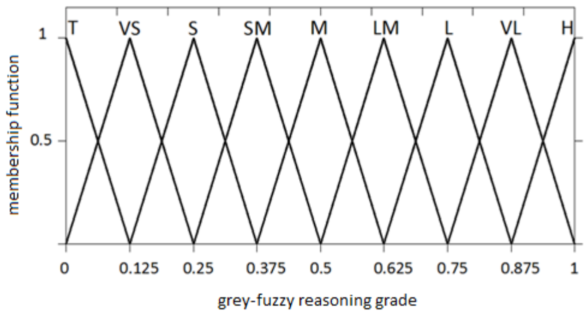

Figure 6. Membership functions for multi-response output.

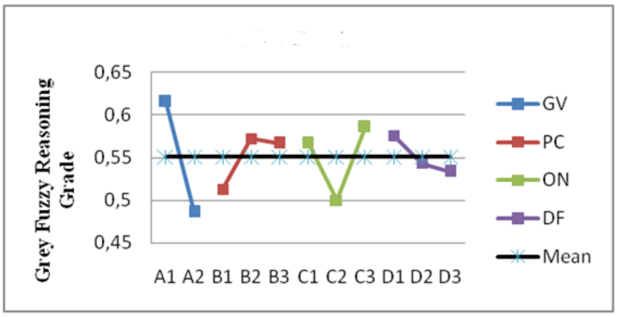

Figure 7. Grey Fuzzy Reasoning Grade (GFRG) Graph.

TABLE1.
Machining parameters and their levels

Machining Parameters	Unit	Level 1	Level 2	Level 3
Gap Voltage (GV)	Volt	30	60	-
Pulse current (PC)	Ampere	10	15	20
On time (ON)	µs	180	250	300
Duty Factor (DF)	-	0.4	0.5	0.6

TABLE 2.
ORTHOGONAL ARRAY L_{18}

No.	GV	PC	ON	DF
1	30	10	180	0.4
2	30	10	250	0.5
3	30	10	300	0.6
4	30	15	180	0.4
5	30	15	250	0.5
6	30	15	300	0.6
7	30	20	180	0.5
8	30	20	250	0.6
9	30	20	300	0.4
10	60	10	180	0.6
11	60	10	250	0.4
12	60	10	300	0.5
13	60	15	180	0.5
14	60	15	250	0.6
15	60	15	300	0.4
16	60	20	180	0.6
17	60	20	250	0.4
18	60	20	300	0.5

TABLE 3.
EXPERIMENTAL RESULTS FOR MRR AND SR AND THEIR S/N RATIO

No	Metal Removal Rate (mm^3/min		Surface Roughness (µm)		S/N Ratio	
	MRR 1	MRR 2	Ra 1	Ra 2	MRR	Ra
1	18.30541	18.34606	6.82	6.89	25.26121	-16.7224
2	16,60325	16,7167	7,12	7,18	24,43334	-17,0902
3	11,27363	10,80774	5,1	5,2	20,85412	-14,2677
4	38,95352	38,69229	5,47	5,35	31,78161	-14,6725
5	36,97405	32,38692	8,9	8,62	30,74468	-18,8712
6	22,10034	23,46231	5,31	6,09	27,13994	-15,1455
7	51,06545	50,95541	9,04	9,13	34,15317	-19,1714
8	34,02374	35,08084	10,85	10,56	30,76649	-20,5925
9	44,28382	44,23083	6,59	6,36	32,9197	-16,2284
10	10.29907	9.731915	6.92	6.15	20.003	-16.3176
11	12.59843	12.53793	9.97	10.01	21.98537	-19.9971
12	9.260284	10.08412	6.93	7.1	19.68687	-16.9253
13	23.83328	23.92866	7.74	7.54	27.56099	-17.6645
14	17.30939	17.2795	10.16	10.08	24.75812	-20.1037
15	29.26018	28.22768	8.14	8.13	29.16672	-18.2125
16	24.60562	21.70249	11.18	11.16	27.2413	-20.9637
17	38.81515	38.76608	10.12	9.99	31.77453	-20.0507
18	33.17885	33.6587	12.7	12.14	30.47914	-21.9049

TABLE 4.
Fuzzy Rules

No	MRR	SR	GFRG
1	S	S	T
2	S	M	VS
3	S	L	S
4	M	S	SM
5	M	M	M
6	M	L	LM
7	L	S	L
8	L	M	VL
9	L	L	H

TABLE 5.
THE DATA PREPROCESSING OF EACH INDIVIDUAL QUALITY CHARACTERISTICS

No	Material removal rate	Surface Roughness
Ideal sequence	1	1
1	0.61467	0.32141
2	0.67189	0.36957
3	0.91931	0.00000
4	0.16394	0.05300
5	0.23562	0.60277
6	0.48480	0.11494
7	0.00000	0.64208
8	0.23411	0.82816
9	0.08527	0.25673
10	0.97815	0.26841
11	0.84111	0.75020
12	1.00000	0.34798
13	0.45569	0.44477
14	0.64944	0.76415
15	0.34469	0.51652
16	0.47779	0.87676
17	0.16443	0.75721
18	0.25397	1.00000

TABLE 6.
THE GREY RELATIONAL COEFFICIENT OF EACH INDIVIDUAL QUALITY CHARACTERISTICS

No	Material Removal Rate	Surface Roughness
1	0.44856	0.60871
2	0.42666	0.57500
3	0.35228	1.00000
4	0.75308	0.90415
5	0.67970	0.45340
6	0.50772	0.81309
7	1.00000	0.43780
8	0.68110	0.37646
9	0.85431	0.66074
10	0.33826	0.65069
11	0.37282	0.39994
12	0.33333	0.58964
13	0.52318	0.52923
14	0.43499	0.39552
15	0.59193	0.49187
16	0.51136	0.36317
17	0.75253	0.39770
18	0.66315	0.33333

TABLE 7.
THE GREY FUZZY REASONING GRADE

No	Grey Fuzzy Reasoning Grade
1	0.5301
2	0.5009
3	0.6673
4	0.7146
5	0.5641
6	0.6507
7	0.7097
8	0.5233
9	0.6814
10	0.4957
11	0.4185
12	0.4658
13	0.5213
14	0.4334
15	0.5503
16	0.4305
17	0.5591
18	0.4987

TABLE 8.
RESPONSE TABLE FOR THE MEAN GFRG

Factor	Level 1	Level 2	Level 3	Max-min
Gap voltge (GV)	0.6158	0.4859	-	0.1299
Pulse current (PC)	0.5130	0.5724	0.5671	0.0594
On time (ON)	0.567	0.4999	0.5857	0.0858
Duty Factor (DF)	0.5757	0.5434	0.5335	0.0422

TABLE 9.
THE ANOVA FOR GFRG

Source	Df	SS	MS	F	Contribution (%)
GV	1	0,0758	0,0758	20,46	46,20
PC	2	0,0129	0,0064	1,74	14,20
ON	2	0,0244	0,0122	3,29	28,90
DF	2	0,0058	0,0029	0,79	5,09
Error	10	0,0371	0,0037		5,58
Total	17	0,1562			100

TABLE 10.
RESULTS OF CONFIMATION EXPERIMENT

	Initial	**Optimal Process Condition**		**Improvement**
		Prediction	**Experiment**	
Level of process parameters	$GV_1PC_2ON_2DF_2$	$GV_1PC_2ON_2DF_2$	$GV_1PC_2ON_3DF_1$	
Material Removal Rate (mm^3/min)	34.68048		39.52387	increased 13.97%
Surface Roughness (µm)	8.78		5.37	decreased 38.84%
GFRG	0.5789	0.6970	0.7714	increased 24.95%