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OPTIMIZATION OF MULTIPLE PERFORMANCE CHARACTERISTICS IN WIRE ELECTRICAL DISCHARGE MACHINING (WEDM) PROCESS OF BUDERUS 2080 TOOL STEEL USING TAGUCHI-GREY-FUZZY METHOD

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ABSTRACT

This paper presents an optimization of machining parameters on the material removal rate (MRR), cutting width (kerf), surface roughness (SR) and recast layer thickness (RL) of WEDM process. Buderus 2080 tool steel was selected as workpiece material. The combinations of machining parameters were determined by using Taguchi experimental design method. The four important machining parameters such as arc on time, on time, open voltage and servo voltage were taken as process variables. Optimal machining parameter were obtained by grey relational analysis and fuzzy logic method. Experimental results show that on time gives the highest contribution for reducing the total variation of the multiple responses, followed by open voltage, servo voltage and arc on time. The maximum material removal rate and minimum cutting width, surface roughness and recast layer thickness could be obtained by using the values of arc on time, on time, open voltage and servo voltage of 1 A, 2 µs, 75 V and 30 V respectively.

Keywords: WEDM, buderus 2080, taguchi method, grey relational analysis, fuzzy logic.

INTRODUCTION

WEDM process is widely used in machining of complex components made of high hardness, high toughness and conductive materials. Cutting process in WEDM is caused by thermal energy of discrete sparks between the workpiece and the electrode. The sparks erode workpiece and small part of wire electrode. The eroded materials are flushed away from the machining zone by the dielectric fluid [1].

Material removal rate (MRR), cutting width (kerf), surface roughness (SR) and recast layer thickness (RL) are several responses that used to evaluate the performances of WEDM process. Cutting speed or MRR affects the production rate. However, the maximum MRR is limited by the wire rupture possibility. Kerf determine the degree of accuracy of workpiece dimensions [2]. SR is also an aspect requiring special attention because of its effect to the surface quality. The thick RL formed during WEDM process reduces the surface mechanical properties and increases the surface roughness.

Optimizing multiple performance characteristics at the same time in the WEDM process needs proper machining parameters setting. Based on the review literatures [3-7] and preliminary research, the most important machining parameters of WEDM process are on time, open voltage, servo voltage and arc on time. Hence, those machining parameters need to be selected properly in terms of the machining tool, material properties and wire electrode in order to maximize MRR and minimize SR, kerf and RL simultaneously.

The grey relational analysis method was developed by Deng [8]. This method provides techniques for determining a good solution for the unknown information. The grey relational analysis can find out the relation between machining parameters and machining performances. The term of fuzzy logic was introduced by Zadech [9]. Taguchi method only focused on optimizing single performance characteristic [3]. However, product in some machining processes have more than one machining performance which should be considered. By using fuzzy logic multiple objective optimization problem can be solved by transforming multiple quality characteristics into single quality characteristic. In fact, there are three definitions of performance characteristics, namely lower-is-better, higher-is-better, and nominal-is-better.

The main purpose of this research is to identify the combination of the machining parameters for achieving required multiple performance characteristics in WEDM process using grey relational analysis, fuzzy logic and orthogonal array based on the Taguchi method.

EXPERIMENTAL DESIGN

Equipments and Material

In this study, a five axis CNC Wire-cut EDM (CHMER CW32F) was used as the experimental machine. A 0.25 mm diameter of AC CUT VS 900 zinc coated brass wire used in this experimental as an electrode to erode a work piece of Buderus 2080 tool steel plate with hardness of 62 HRC. A typical composition of

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Buderus 2080 tool steel consists of 2.10% C, 0.30% Si, 0.30% Mn and 12.00% Cr. During the experiments 10 mm length of cut was performed on the workpiece with 200 mm in length, 30 mm in width and 15 mm in thickness. MRR is defined as volume of removed material per unit time [2]. Measurements of the SR were taken by using a Mitutoyo Surftest 301 with sampling length of 0.8 mm. Scanning electron microscope (SEM) was used to measures the RL thickness and the kerf was measured by using Nikon measurescope 20. Based on the review literature and preliminary investigation, the machining parameters were selected and shown in Table-1.

Table-1. Machining parameters.

Machining parameters	Level 1	Level 2	Level 3
Arc on time [AN, ampere]	1	2	-
On time [ON, μs]	0.2	0.4	0.6
Open voltage [OV, volt]	75	90	105
Servo voltage [SV, volt]	30	40	50

Design of Experiment

Taguchi method with an orthogonal array was used to design the experiment. The total degrees of freedom (DOF) need to be calculated to select a proper orthogonal array. This experiment has seven DOF because three machining parameters having three levels and one machining parameters having two levels as shown in Table-1. The DOF for the orthogonal array should be equal to or greater than DOF of the machining parameters [11]. Therefore, a mixed L_{18} (2^1x3^3) orthogonal array was chosen for the design of experiment and it is shown in Table-2. To reduce noise factors a random order was applied for running the tests.

Table-2. A mixed L_{18} (2^1x3^3) orthogonal array.

S. No	Machining parameter			
	AN [ampere]	ON [μs]	OV [volt]	SV [volt]
1	1	0.2	75	30
2	1	0.2	90	40
3	1	0.2	105	50
4	1	0.4	75	30
5	1	0.4	90	40
6	1	0.4	105	50
7	1	0.6	75	40
8	1	0.6	90	50
9	1	0.6	105	30
10	2	0.2	75	50
11	2	0.2	90	30
12	2	0.2	105	40
13	2	0.4	75	40
14	2	0.4	90	50
15	2	0.4	105	30
16	2	0.6	75	50
17	2	0.6	90	30
18	2	0.6	105	40

Optimization of Multiple Performance Characteristic with Taguchi-Grey-Fuzzy Method

The multi objective optimization problem can be solved with Taguchi-grey-fuzzy method. Figure-1 shows the calculation sequence of Taguchi grey fuzzy method.

Experimental Result and Analysis

The experimental results and signal-to-noise ratios (S/N ratios) of MRR, kerf, SR and RL are shown in Tabel-3. The S/N ratio is an effective value to find out the significant machining parameters by evaluating minimum variance. S/N ratio is used to measure the quality characteristic deviating from the targeted value [8]. There are three different types of the quality performance characteristics to calculate the S/N ratio, i.e., higher-is-better, lower-is-better and nominal-is-better. The better machining performance can be obtained through the maximum MRR and the minimum kerf, SR and RL. The determination of which equation to be employed for calculating S/N ratio is based on the types of the quality performance characteristic of each response. In this experiment the quality performance characteristic of MRR is higher-is-better and the quality performance characteristics of kerf, SR and RL are lower-is-better. The S/N ratio for each performance characteristic can be expressed by the following equations [8]:

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- Lower-is-better:

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

- Higher-is-better:

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

where n represent the number of the test, and y_i is the measured value. However, whatever the type of the performance characteristics is, the greater value of S/N ratio indicates the better machining performance.

Table-3. Experimental result of all responses and the S/N ratios.

No.	MRR [mm³/min]	S/N	Kerf [mm]	S/N	SR [µm]	S/N	RL [µm]	S/N
1	6.050	15.630	0.320	9.897	1.370	-2.738	4.728	-13.534
2	6.165	15.802	0.328	9.682	1.335	-2.511	5.148	-14.244
3	6.115	15.719	0.335	9.512	1.380	-2.798	5.819	-15.338
4	11.670	21.339	0.336	9.486	1.870	-5.447	6.085	-15.686
5	12.030	21.599	0.348	9.184	1.925	-5.689	7.361	-17.344
6	11.545	21.248	0.347	9.193	1.865	-5.415	8.967	-19.102
7	17.610	24.915	0.370	8.633	2.145	-6.630	6.796	-16.648
8	17.775	24.993	0.374	8.554	2.260	-7.086	7.902	-18.007
9	17.710	24.963	0.356	8.971	2.420	-7.676	8.695	-18.788
10	4.950	13.886	0.343	9.307	1.205	-1.620	6.065	-15.689
11	8.525	18.616	0.328	9.683	1.695	-4.592	6.020	-15.677
12	8.100	18.170	0.330	9.643	1.435	-3.138	7.283	-17.246
13	10.980	20.801	0.347	9.206	1.830	-5.250	5.836	-15.399
14	11.605	21.277	0.360	8.886	1.850	-5.344	8.605	-18.724
15	16.345	24.265	0.339	9.399	2.260	-7.082	8.814	-18.992
16	13.140	22.365	0.382	8.370	2.275	-7.140	9.473	-19.559
17	25.580	28.155	0.366	8.745	2.680	-8.566	9.951	-20.077
18	23.360	27.365	0.360	8.886	2.555	-8.148	10.513	-20.461

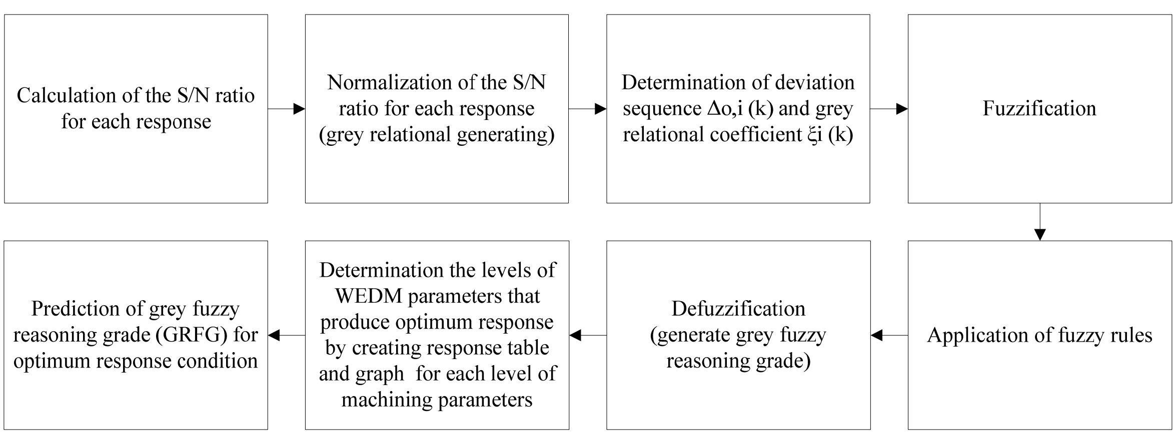

Figure-1. Optimization steps using the Taguchi-grey-fuzzy method.

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Determination of Optimal WEDM Process

The S/N ratios that shown in Table-3 should be normalized. Because the higher value of S/N ratio shows the better performance, the normalization can be obtained using the following equation [3]:

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{3}$$

where $x_i^*(k)$ is the sequence after data preprocessing, $x_i^0(k)$ is the original sequence, $\min x_i^0(k)$ is the minimum value of $x_i^0(k)$ for the k^{th} response, and $\max x_i^0(k)$ is the maximum value of $x_i^0(k)$ for the k^{th} response.

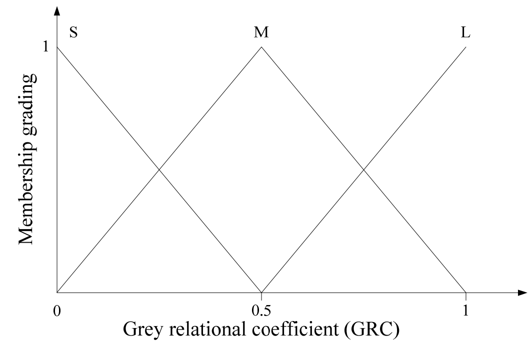
The $x_i^*(k)$ of each response needs to be converted into grey relational coefficient (ξ_i) or GRC by using the formula below [3]:

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta \cdot \Delta_{\max}}{\Delta_{0,i}(k) + \zeta \cdot \Delta_{\max}} \tag{4}$$

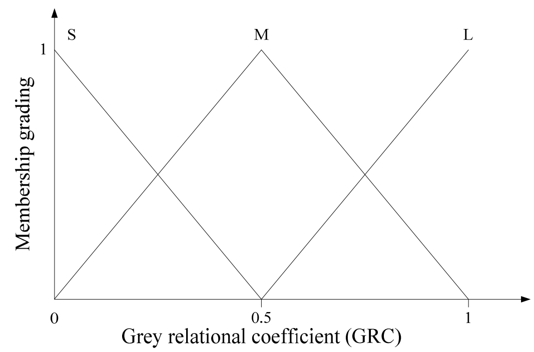
where $\Delta_{0,i}(k) = |x_0^*(k) - x_i^*(k)|$ is the absolute value of difference between $x_0^*(k)$ and $x_i^*(k)$, $x_0^*(k)$ is the reference sequence, $x_i^*(k)$ is the comparative sequence, $\Delta_{\min}$ is the minimum value of $\Delta_{0,i}(k)$ = min $_i$ min $_k$ $|x_0^*(k) - x_i^*(k)|$, $\Delta_{\max}$ is the maximum value of $\Delta_{0,i}(k)$ = max $_i$ max $_k$ $|x_0^*(k) - x_i^*(k)|$ and $\zeta \in (0,1)$ is the distinguishing coefficient. In this experiment, the selected value of ζ was 0, 5 [10].

The GRC of each response should be converted into a single value by using fuzzy logic method. Fuzzy logic has three basic components, i.e., fuzzifier, inference engine and defuzzifier. As a result, a single value performance characteristic called grey fuzzy reasoning grade (GFRG) was generated.

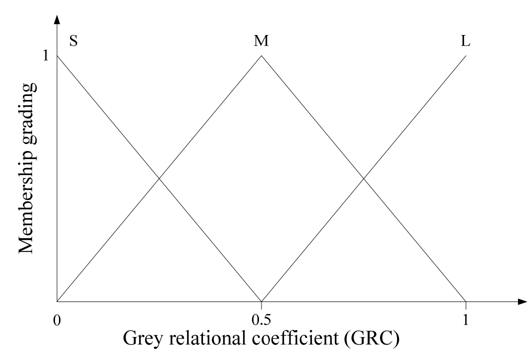
In this research, the input variables such as GRC of MRR, kerf, SR and RL have been represented by membership function with three fuzzy subsets: small (S), medium (M) and large (L) (Figure-2). The output variable (GFRG) is represented by membership function with nine fuzzy subsets: tiny (T), very small (VS), small (S), medium small (MS), medium (M), medium large (ML), large (L), very large (VL) and huge (H) (Figure-3). The triangle membership function was used for both input and output variables. Table-4 shows GRC and GFRG. The larger GFRG the better multiple performances is. The mean GFRG for each level of the machining parameters is shown in Table-5.



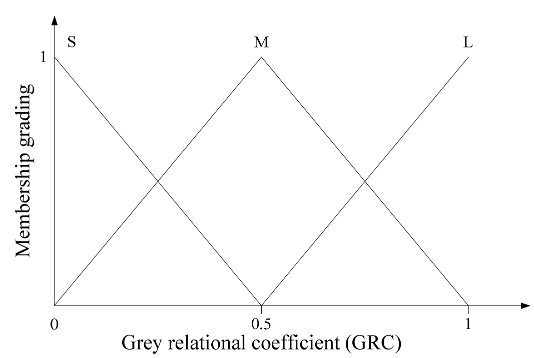
(a)



(b)



(c)



(d)

Figure-2. Membership functions for input parameter (a) MRR, (b) kerf, (c) SR, (d) RL.

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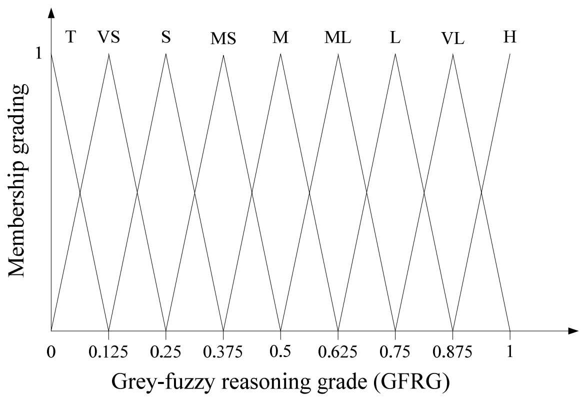

Figure-3. Membership functions for output parameter GFRG.

Table-4. GRC and GFRG.

No.	GRC				GFRG
	MRR	Kerf	SR	RL	
1	0.333	0.564	1.000	0.616	0.8297
2	0.428	0.781	0.539	0.618	0.6659
3	0.417	0.750	0.696	0.483	0.6197
4	0.492	0.525	0.489	0.650	0.6219
5	0.509	0.430	0.483	0.400	0.4749
6	0.647	0.605	0.389	0.388	0.4251
7	0.552	0.333	0.386	0.365	0.5019
8	1.000	0.399	0.333	0.346	0.4438
9	0.900	0.430	0.347	0.333	0.4310
10	0.333	0.564	1.000	0.616	0.6570
11	0.428	0.781	0.539	0.618	0.6233
12	0.417	0.750	0.696	0.483	0.5724
13	0.492	0.525	0.489	0.650	0.5929
14	0.509	0.430	0.483	0.400	0.4006
15	0.647	0.605	0.389	0.388	0.4586
16	0.552	0.333	0.386	0.365	0.3767
17	1.000	0.399	0.333	0.346	0.4359
18	0.900	0.430	0.347	0.333	0.4352

Based on Table-5, the maximum MRR and minimum kerf, SR and RL could be obtained by combination of machining parameters of AN at level 1, ON at level 1, OV at level 1 and SV at level 1 ($AN_1ON_1OV_1SV_1$). Figure-4 shows the grey-fuzzy reasoning grade (GFRG) graph.

Table-5. Response table for the mean GFRG.

Machining parameters	Level 1	Level 2	Level 3	Delta
AN	0.5571	0.5058	-	0.0513
ON	0.6613	0.4957	0.4374	0.2239
OV	0.5967	0.5074	0.4903	0.1064
SV	0.5667	0.5405	0.4871	0.0796
Average	0.5315			

Analysis of Variance and Confirmation Experiment

In order to find out which machining parameters of WEDM process that significantly affect the multiple machining performance, analysis of variance (ANOVA) and F test are used to analyze the experimental data. The result of ANOVA in Table-6, shows that ON gives the highest contribution for reducing the total variation of the multiple responses, followed by OV, SV and AN.

When the combination level of machining parameters which result optimal machining performance has been obtained, the next step is predicting and verifying the improvement of the machining performance. The predicted GFRG $(\hat{\gamma})$ can be obtained by using following equation [12]:

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q} \left(\bar{\gamma}_i - \gamma_m\right) \tag{5}$$

where γ_m is the total mean of GFRG, $\bar{\gamma}_i$ is the mean of GFRG taken at the optimal condition and q is the number of machining parameters that significantly affect the multiple machining performance. Table-7 shows the comparison of the result of confirmation experiment using the optimal machining parameters and the result of the confirmation experiment using the initial machining parameters. As shown in Table-7, the optimum setting level improves the machining performance. The kerf is decreased from 0.347 mm to 0.319 mm, SR is decreased from 1.91 µm to 1.37 µm and RL is decreased from 6.989 µm to 4.86 µm. The GFRG is also greatly improved through this study by 61.45%.

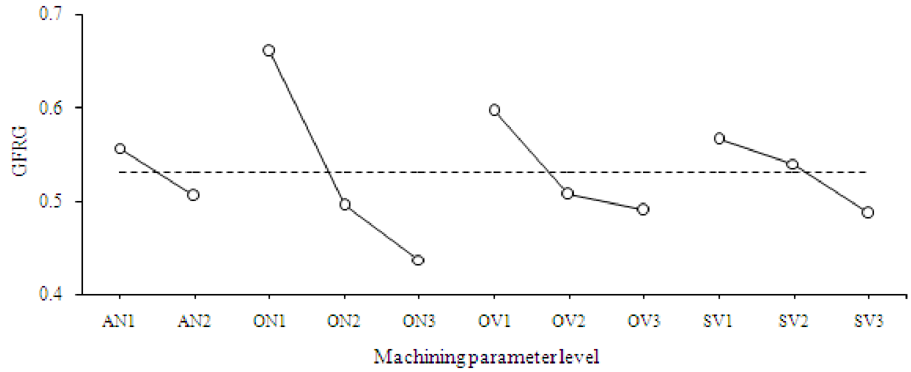

Figure-4. GFRG graph.

Table-6. Result of the ANOVA for GFRG.

Source	DF	SS	MS	F	P	Contribution
AN	1	0.01182	0.011822	6.6	0.028	4.00 %
ON	2	0.16195	0.080977	45.2	0.000	63.20 %
OV	2	0.03915	0.019573	10.93	0.003	14.19 %
SV	2	0.01974	0.009870	5.51	0.024	6.45 %
Error	10	0.01791	0.001791			12.15 %
Total	17	0.25058				100 %

Table-7. Result of the confirmation experiment.

	Initial machining parameter	Optimal machining parameter	
		Prediction	Experiment
Setting level	$AN_1ON_2OV_2SV_2$	$AN_1ON_1OV_1SV_1$	$AN_1ON_1OV_1SV_1$
MRR [mm^3/min]	12.29		6.02
Kerf [mm]	0.347		0.319
SR [µm]	1.91		1.37
RL [µm]	6.989		4.860
GFRG	0.5136	0.7874	0.8292
Improvement in GFRG = 61.45 %			

The Experimental Results and Confirmation Test Show that:

- On time gives the highest contribution for reducing the total variation of the multiple responses in WEDM process, followed by open voltage, servo voltage and arc on time.
- The maximum material removal rate and minimum cutting width, surface roughness and recast layer thickness could be obtained by using the values of arc on time, on time, open voltage and servo voltage of 1 A, 2 µs, 75 V and 30 V respectively.
- A grey-fuzzy reasoning grade (GFRG) of 0.7874 was predicted and 0.8292 was obtained experimentally. The GFRG greatly improved through this study by 61.45%.

CONCLUSIONS

The study has confirmed the use of grey relational analysis and fuzzy logic based on the Taguchi method to optimize multiple performance characteristic problem of WEDM operation. As a result, the performance characteristics such as cutting width (kerf), surface roughness (SR) and recast layer thickness (RL) can be improved through this method.

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