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Multi-Objective Optimization of WEDM Machining Parameters on SS-317 Using Grey Integrated Fuzzy

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Abstract- The present study applied Grey integrated Fuzzy technique to optimize the Multi-objectives of Wire Electrical Discharge Machining parameters of SS 317. Process parameters viz., Pulse-on time, Pulse-off time and Peak Current and L9 orthogonal array is adopted for design of experiments. The objectives selected are of maximum material removal rate and minimum surface roughness. The optimal process parameters results in the lower roughness and more metal removal.

Index Terms-Wire EDM, SS 317, L9 Array, Multi-Objective, Grey Fuzzy

1. INTRODUCTION

In the field of structural and engineering applications, advanced metals and alloys [1] with lower density, higher strength and better properties compared to the existing one are the prior requirement. To fulfill the requirement, intense research of new Alloys and Composites [2] are in study at present research field.

SS 317 stainless steel is an advanced steel to SS 316 with the increase in nickel and molybdenum, which increases strength and corrosion resistance. SS 316 is used in numerous applications like heat exchangers, fittings & valves, vessels, desalination plants, piping, fasteners, and constructions as a replacement to austenitic stainless steels.

In perspective of industries at the present phase and pace, the product is to be manufactured rapidly with better finish and economical to meet the demands of the market. To fulfill the needs of the market, the process of manufacturing is to be advanced and the identification of the suitable parameters and their ranges. Optimization methodology plays a vital role in fulfilling the needs of the industries.

Wire Electric Discharge Machining (WEDM) is an advanced machining process using in many industries all over the world for rapid machining with better surface finish and high precision, and the process utilizes thermal energy to remove the metal on electrically conductive parts.

Taguchi methodology is to optimize the single objective [3], which is impractical for the industries has multi objectives for a single product. Optimization of multiple objectives by Grey integrated Fuzzy [4] is one of the best technique adopted among many other techniques. Grey relational analysis converts multi response into single.response as Grey relational grades. Fuzzy logic was performed to the Grades to achieve optimal parameters and determined [5].

2. LITERATURE REVIEW

2.1 Single objective – Surface Roughness (Ra)

Raju et al. [6] studied the effect of Pulse on time, Peak current, Servo voltage and Wire tension on SS 316L and observed that Pulse on time is the most significant factor followed by peak current, servo voltage and wire tension respectively. Faiyaz et al. [7] conducted experiments on EN36 steel and found that Peak current plays important role than Pulse on time, Pulse off time and servo voltage**.**

Vijaya babu et al. [8] conducted experiments on AISI 316L steel and found that Pulse on time is a significant factor. Rajesh Khanna et al. [9] also studied and observed that Pulse off time has the most influent parameter on determining response characteristics of SS316.

2.2 Multi- objective – MRR and Ra

Rajmohan et al. [10] investigated on SS 304L using taguchi integrated Grey relational analysis, and observed that Pulse off time is the most significant factor that affects the Grey relational grade. Shunmuga Priyan et al. [11] observed that Pulse on, Pulse off, Servo Voltage and Wire feed has the effect on the Ra in the order and Pulse off time has opposite effect to pulse on time, in machining of SS 304 using GRA. MRR decrease with increase of pulse off time, while surface roughness reduces.

Manish et al.[12] investigated on 316L using taguchi integrated GRA and studied that the cutting speed is mostly affected by pulse-on time (Ton) , Pulse off time (T_{Off}) and Servo Voltage (SV) and Ra is mostly affected by the peak current (Ip), pulse-on time (Ton) , Pulse off time (T_{Off}) and Servo Voltage (SV). Debasish Mohanty et al. [13] observes that all the WEDM Parameters plays significant role on MRR and Ra individually on machining of EN 31 steel.

Chandra Sekhar [14] investigated on SS 317 using grey relational analysis and observed that Pulse on time found to be the most significant factors influencing all responses and the grey relational grade is increased by 30% with the optimal parameters which improves the MRR and SR.

It is noted, from the literature review that most of the research work has been carried out using Grey relational analysis. In the present investigation, an attempt is made to determine and confirm the optimal process parameters using Grey integrated fuzzy. Minimizing surface roughness (Ra) and Maximizing material removal rate (MRR) are chosen as objectives. Pulse on, Pulse off and Peak Current are chosen as the machining parameters with a L9 array of DOE.

3. EXPERIMENTAL DETAILS:

In the present investigation, SS 317 is used as target material and the experiments were performed using Electronica Maxicut Wire EDM as shown in "Fig.1.

Fig - 1 Wire Electric Discharge Machine

Fig - 2 Material in Fixture

A brass wire of 0.25 mm dia was used as electrode to erode the metal under distilled water, maintaining a small gap of 0.025 mm to 0.05 between the wire and work-piece. The dimensions of 10 * 10 * 10 mm3 of the work piece selected for machining. Experiments were performed as per the DOE in Table 2 by setting the process parameters in the WEDM machine. A stopwatch is used to measure the time required for material removal of workpiece and talysurf instrument is used to measure surface roughness, and the results were tabulated in Table 2.

In the present study, three machining parameters with three levels were chosen for experimentation, which have more influence on material removal rate and surface roughness. The parameters and its levels are tabulated in Table 1, with L_9 ($3^{3-1} = 3^2 = 9$ runs) orthogonal array of DOE instead of L_{27} array ($3^3 = 27$ runs) to minimize the cost of experimentation.

Table 1. Machining parameters and levels

Process parameters	**Levels**		
	1	**2**	**3**
Pulse-on (μs) – 'A'	8	9	10
Pulse-off (μs) – 'B'	1	2	3
Pulse Current (A) – 'C'	3	4	5

Table 2. Design of Experiments and Responses

S.No	**A (μs)**	**B (μs)**	**C (A)**	**MRR (mm^3/sec)**	**Ra (μ)**
1	8	1	3	0.906	4.288
2	8	2	4	0.758	3.133
3	8	3	5	0.612	2.160
4	9	1	4	0.873	3.870
5	9	2	5	0.635	3.735
6	9	3	3	0.758	4.413
7	10	1	5	0.931	5.045
8	10	2	3	0.980	3.600
9	10	3	4	1.022	5.430

Fig -3 Specimens after machining.

4. GREY INTEGRATED FUZZY

4.1 Grey relational analysis:

Grey relational analysis methodology is used by many researchers in solving complicated interrelationships among the multiple res among factors in the system are certain.

The analysis includes the following steps:

1. Conduct the experiments as per DOE.
2. Convert the experimental results into signal-to-noise (S/N) ratio.
3. Normalize the values of S/N ratio.
4. Calculate the grey relational coefficient.
5. Calculate the grey relational grade by averaging the grey relational coefficient.

4.1.1 Normalization:

Convert the original sequences to a set of comparable sequences by normalizing the data. Depending upon the response characteristic, three main categories for normalizing the data is as follows:

'Larger the better' $$a_i^{(*)}(k) = \frac{b_i^{(*)}(k) - \min b_i^{(*)}(k)}{\max b_i^{(*)}(k) - \min b_i^{(*)}(k)} \quad (1)$$

'Smaller the better' $$a_i^{(*)}(k) = \frac{\max b_i^{(*)}(k) - b_i^{(*)}(k)}{\max b_i^{(*)}(k) - \min b_i^{(*)}(k)} \quad (2)$$

'Nominal the better' $$a_i^{(*)}(k) = 1 - \frac{b_i^{(*)}(k) - OV}{\max(\max b_i^{(*)}(k) - OV, OV - \min b_i^{(*)}(k))} \quad (3)$$

. (1)

4.1.2 Grey relational coefficient and grey relational grade

Grey relational coefficient and grey relational grade: Grey relation coefficient (α_{ij}) is calculated for each of the performance characteristics, which expresses the relationship between ideal and actual normalized experimental results, as shown in "Eq.(4)."

$$\alpha_{ij} = \frac{\Delta\min + \xi\Delta\max}{\Delta oi(k) + \xi\Delta\max} \quad (4)$$

Grey relational grade can be calculated by taking the average of is the weighted grey relational coefficient and defined as follows:

$$\Sigma\beta_k\gamma(x_0^{(*)}(k), x_i^{(*)}(k)) = 1 \quad (5)$$

Table 3. Grey Relational Grades

Expt. No	Normalized values		Grey Relational Coefficients		Grey Relational Grades
	MRR	Ra	MRR	Ra	
1	0.7157	0.3494	0.637	0.435	0.536
2	0.3545	0.7023	0.437	0.627	0.532
3	0.0000	1.0000	0.333	1.000	0.667
4	0.6348	0.4771	0.578	0.489	0.533
5	0.0569	0.5183	0.346	0.509	0.428
6	0.3545	0.3112	0.437	0.421	0.429
7	0.7773	0.1177	0.692	0.362	0.527
8	0.8974	0.5596	0.830	0.532	**0.681**
9	1.0000	0.0000	1.000	0.333	0.667

4.2 Determination of fuzzy grade

Fuzzy defines the relationship between system input and desired outputs in linguistic form. A fuzzy logic unit comprises a fuzzifier, membership functions, a fuzzy rule base, an inference engine and a defuzzifier as shown in "Fig. 1".

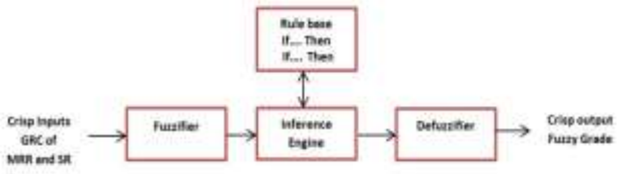

Fig – 4 Fuzzy Logic Unit

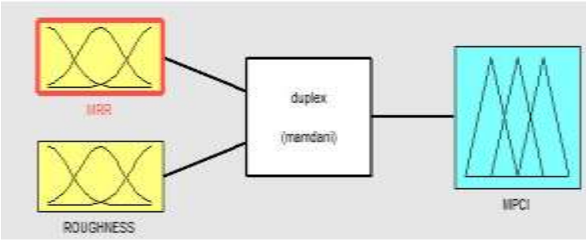

Fig - 5 Fuzzy Structure

In this study, grey relation coefficient of Material removal rate (MRR) and surface roughness(SR) has been taken as fuzzy inputs using triangular membership functions form and grey relation fuzzy grade (MPCI) as output for finding out optimal process parameters. The input and output 'fuzzy set' has been defined in the range between 0 and 1. The desired output is targeted on maximizing grey relation fuzzy grade. The fuzzy inputs are uniformly assigned into five fuzzy subsets – very low (VL), low (L), medium (M), High (H) and very High (VH) grade, as shown in "Fig. [4-5]". Unlike the input variables, the output variable is assigned into relatively nine subsets i.e., very very low (VVL), very low (VL), Low (L), medium low (ML), medium (M), medium high (MH), high (H), very high (VH), very very high (VVH), as shown in "Fig.6."

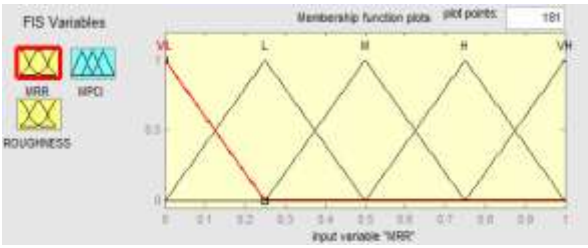

Fig – 6 Fuzzy input – MRR

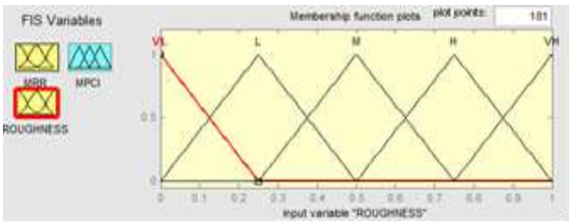

Fig – 7 Fuzzy input - SR

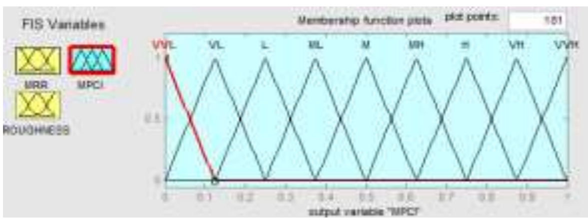

Fig - 8 Fuzzy output – MPCI

The relationship between the two fuzzy inputs are defined in the form of if-then fuzzy rules as listed in Table 4.

Table 4. Fuzzy Rules

Rules		Grey relational coefficients of MRR				
		VL	**L**	**M**	**H**	**VH**
Grey relational coefficients of SR	**VL**	VVL	VL	L	ML	M
	L	VL	L	ML	M	MH
	M	L	ML	M	MH	H
	H	ML	M	MH	H	VH
	VH	M	MH	H	VH	VVH

Table 5. MPCI (Grey Fuzzy Grades)

Expt. No	Fuzzy Inputs MRR	Fuzzy Inputs SR	GRG	MPCI (Fuzzy Output)	Order
1.	0.637	0.435	0.536	0.5262	5
2.	0.437	0.627	0.532	0.5238	6
3.	0.333	1.000	0.667	0.6704	2
4.	0.578	0.489	0.533	0.5353	4
5.	0.346	0.509	0.428	0.4329	8
6.	0.437	0.421	0.429	0.4130	9
7.	0.692	0.362	0.527	0.5211	7
8.	0.830	0.532	0.681	**0.6937**	**1**
9.	1.000	0.333	0.667	0.6704	2

Table 5. presents the MPCI obtained from the FIS, and exhibits an improvement in the values of MPCI, which indicates the reduction of uncertainty in data. The larger MPCI value indicates the optimal combination of parameters among the other and confirmed that the experiment number 8 has the optimal combination of process parameters for machining. The averages of MPCIs for each level of the machining factors are then computed and tabulated in Table 6. The darkened number in each column of factors indicates the best level for each factor. The delta, indicates the difference between maximum and minimum, of MPCIs. Rank 1 represents the largest delta among their levels and have more influence on the machining process.

Table 6. Response table for Grey-Fuzzy grade

LEVEL	PULSE ON	PULSE OFF	PEAK CURRENT
1	-4.889	-5.556	-5.478
2	-6.794	-5.355	**-4.839**
3	**-4.104**	**-4.876**	-5.469
DELTA	2.69	0.68	0.639
RANK	1	2	3

5. ANALYSIS OF VARIANCE (ANOVA)

ANOVA is performed to identify the contribution of process parameters of WEDM on MPCI's. An ANOVA table as shown in Table 7. consists of degrees of freedom, sums of squares and the percentage of contribution.

Table 7. Analysis of Variance

Source	DF	Seq SS	Adj SS	% Contribution
Pulse on	2	0.04153	0.02076	55.16%
Pulse off	2	0.00497	0.00248	6.62%
Pulse Current	2	0.0022	0.00111	2.96%
Error	2	0.02637	0.01318	35.11%
Total	8	0.07512	--	

From Table 7, it shows that the process parameters Pulse on and Pulse off have the most influence on the MPCI, which coincides with the results of Table 6. It is observed that the Pulse On (55.16%) is most significant factor followed by Pulse off (6.62%), and Pulse current (2.96%).

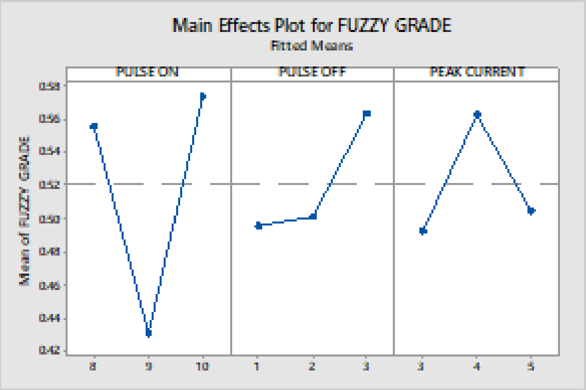

Fig - 9 Optimal Parameters – MPCI

6. CONFIRMATION TEST

After determining the optimal combination of parameters, the last phase is to verify the MRR, surface roughness by conducting the confirmation experiment. The $A_3B_3C_2$ is an optimal parameter combination of the machining process by Grey Fuzzy Methodology. The confirmation test is carried out with the optimal parameter combination $A_3B_3C_2$, and the results are tabulated in Table.8 and the grey fuzzy grade is increased by 31%. It is clear that the MRR and SR increased greatly with the optimal parameters.

Table 8. Confirmation test results

Type	Optimal / Predicted	Optimal/ Experimental	% Error
Level combination	$A_1B_3C_3$	$A_3B_3C_2$	$A_3B_3C_2$
MRR (mm^3/sec)	0.612	0.8872	0.843
SR (µm)	2.16	2.12	2.21
Grey fuzzy grade (MPCI)	0.667	0.93	0.96

CONCLUSIONS:

- The effect of process parameters i.e. pulse on-time, pulse off-time, Pulse current on response variables such as material removal rate, surface roughness has been thoroughly studied. The levels of significance of process parameters for each response variable has been investigated using ANOVA.

- Pulse on time found to be the most significant factors influencing all responses investigated for both the experiment sets.

- The $A_3B_3C_2$ is an optimal parameter combination of the machining process by Grey Fuzzy Methodolgy.

- The grey relational grade is increased by 31%. It is clear that the MRR and SR increased greatly with the optimal parameters.

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