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MULTI-RESPONSE OPTIMIZATION USING GREY-FUZZY METHODOLOGY FOR PURE TITANIUM IN FINISH CUT WEDM

RUPESH CHALISGAONKAR[1] AND JATINDER KUMAR[2]

[1] *Department of Mechanical Engineering, KIET Group of Institutions, Ghaziabad, Uttar-Pradesh, India, Email: rupesh_chalisgaonkar2000@yahoo.com*
[2] *Department of Mechanical Engineering, National Institute of Technology, Kurukshetra, Haryana, India, Email: jatin.tiet@gmail.com*

Abstract: In this research work, development of a multi response optimization technique has been undertaken using grey-fuzzy logic approach for finish cut WEDM process selecting pure titanium as workiece. The process parameters (wire type (zinc coated and uncoated brass wire), pulse on time (T_{ON}), pulse off time (T_{OFF}), peak current (IP), wire feed (WF), spark gap voltage (SV) and wire offset (W_{OFF})) with considering machining characteristics (machining rate (MR), surface roughness (SR) and wire weight consumption (WWC)) has been found to be successful. Taguchi's L-18 orthogonal array, grey relational generating, grey relational coefficient, grey-fuzzy reasoning grade and analysis of variance have been found to be effective tools to optimize concurrently the performance characteristics of the machining process.

Keywords: Grey relational analysis, Fuzzy logic, Multi-response optimization, Finish cut WEDM, Titanium

1. INTRODUCTION

Single response optimization process can only focus on an individual quality characteristic at a time. In case of product/processes having more than one quality characteristic, the single optimal parametric setting creates conflicts with output of other quality characteristic. To avoid such type of situation product/process parametric setting should be set at a compromising level to satisfy the output of all quality characteristic. In past, various researchers have explored the fuzzy logic methodology in various forms for distinguished processes with selective materials. Lin & Lin [1] optimized multiple machining characteristics such as (electrode wear ratio, material removal rate and surface roughness) with the help of grey-fuzzy logic in EDM process. Rajyalaxami & Venkata [2] performed multi-response optimization using grey-fuzzy methodology in assistance with Taguchi's experimental design for Inconel 825 in WEDM process. Dewangan et al. [3] performed multi-response optimization of surface integrity characteristics such as white layer thickness (WLT), surface crack density (SCD) and surface roughness (SR) with the help of grey-fuzzy logic-based hybrid approach in EDM process. Hashmi et al. [4] presented the fuzzy logic based selection of machining parameters (cutting speed, feed rate and depth of cut) for machining medium carbon leaded steel and free machining carbon wrought steel with conventional machining. Lin et al. [5] optimized multi response EDM process based on the orthogonal array with fuzzy logic and grey relational analysis method. Parameters such as pulse on time, duty factor and discharge current was selected for SKD11 alloy to find the influence on material removal rate, electrode wear ratio and surface roughness in EDM process. Hashmi et al. [6] implemented the fuzzy based intelligent system for selection of input parameters (material hardness and depth of cut) for desired output parameter (cutting speed). Ghose et al. [7] presented the Taguchi-fuzzy investigation methodology for mapping of EDM process for aluminum foam. Kumar & Giriprasad [8] investigated the simultaneous optimization of responses (material removal rate and surface roughness) with applying fuzzy-logic concept enabled with Taguchi experimental design for Aluminum silicon carbide composite in EDM process. Shabgard et al. [9] developed fuzzy model for EDM and ultrasonic assisted EDM process selecting tungsten carbide (WC–10%Co) as a workpiece material. It was observed that developed fuzzy model were in agreement with experimental results and 90% predictions were achieved. Sengottuvel et al. [10] proposed fuzzy modeling to validate the experimental results for EDM process considering material removal rate, surface roughness and tool wear ratio as an output parameters selecting Inconel 718 as workpiece material. Finish cut WEDM operation is performed subsequently after rough cut operation to improve surface finish and job inaccuracies produced after first rough cut. Recast layer, heat affected zone (HAZ) and several types of micro-cracks are developed due to higher pulsed discharge energy developed during WEDM rough cut operation which necessitate subsequent finish cut operation [11]. It has been observed from past studies that the concept of grey-fuzzy logic methodology for multi-response optimization of response parameters such as machining rate, surface roughness and wire weight consumption in finish phase of WEDM process for pure titanium has not been used. Grey-fuzzy method for optimizing quality characteristics of finish cut WEDM concurrently may prove to be capable for yielding best results.

2. EXPERIMENTAL PROCEDURE

2.1. Experimental Methodology

In finish cut experimentation, two different types of wire electrodes (uncoated brass wire and zinc coated brass wire) were used to assess the effect of wire material on the machining characteristics. Each experiment consists of initial rough cut, which was performed by same type of wire; followed by single pass finish cut. Rough cut operation was performed using high pulse discharge condition [using 21st experimental setting of rough cut stage: pulse on time(T_{ON}3)- 0.9 µs, pulse off time(T_{OFF}1)- 7 µs, peak current (IP3)- 200 A, wire feed rate(WF2)- 8 m/min, wire tension(WT1)- 850 g, spark gap voltage(SV2)- 50 V [12], while finish cut was made to start by taking selective values of wire offset and other pulse parameters as shown in Fig. 1. The wire path program was made using ELAPT software, by inclusion of wire offset in program for machining profile of 6 mm × 6 mm square cut. The provision for leaving the length of 2mm was left in rough cut path so that finish cut can be initiated as shown in Fig. 1. The wire path planning of finish cut is shown in Fig. 1. In the finish cut stage, seven factors such as wire type (zinc coated and uncoated brass wire), pulse on time (T_{ON}), pulse off time (T_{OFF}), peak current (IP), wire feed (WF), spark gap voltage (SV) and wire offset (W_{OFF}) were selected for evaluation of their effects on three response variables- machining rate (MR), surface roughness (SR) and wire weight consumption (WWC) through experimentation. L18 orthogonal array (OA) was used for planning the experiments. Initial nine experiments (1-9) were performed with uncoated brass wire (for both rough and finish cut) while rest of the nine experiments (10-18) were conducted with zinc coated wire (for both rough and finish cut), as per the design matrix obtained by using L18 orthogonal array (OA). The experiments were conducted with fixed values of wire tension (10 units), dielectric fluid pressure Based on the experimental layout depicted in Table 2, the experiments were performed in random order and each specific run was repeated two times, in order to get a measure of the experimental error. Three machining characteristics namely MR, SR and WWC were recorded under varying experimental conditions. Machining rate (MR) is defined as material removal (in terms of area) during experimental run. MR is defined by following formula.

$$\text{MR (mm}^2\text{/min)} = \text{Cutting speed} \times \text{plate thickness [13]}$$

(WP=1unit), pulse peak voltage (VP=2 unit) and de-ionized water as a dielectric fluid. The input parameters and their levels are shown in Table 1.

A roughness tester (Mitutoyo make) was used for measurement of average surface roughness (Ra) of the machined surface. The cut off length (ëc) and the sampling number were chosen as 0.8 mm and 5 respectively. Three independent readings were taken on each surface of machined component and an average was computed. Eroded wire after completion of each experiment was obtained from the collection spool and weighted by weighing machine (SHIMADZU electronic balance with 0.01 gm LC). Table 1 shows the factors and their levels for finish cut. The parameters were assigned in

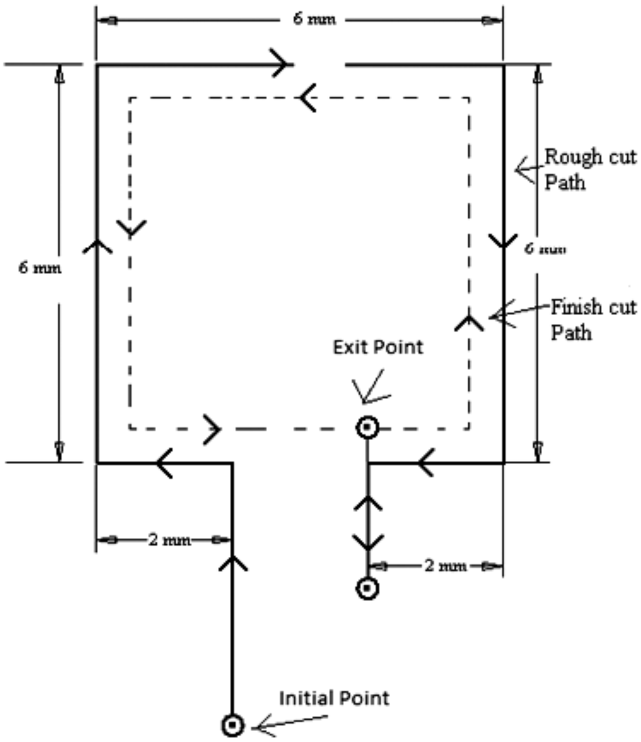


Figure 1: Wire path profile during machining

their respective columns of Taguchi's L-18 mix orthogonal array (Table 2). Each experiment was repeated two times to reduce experimental errors and obtain S/N ratio. Table 2 depicts the experimental results.

3. MULTI-MACHINING CHARACTERISTICS OPTIMIZATION USING GREY-FUZZY LOGIC METHODOLOGY

In this section multi response optimization was performed using grey-fuzzy logic methodology. Following steps were performed for achieving optimal process parametric setting for multi response optimization of machining rate (MR), surface roughness (SR), and wire weight consumption (WWC).

Table 1
Factors and their levels for finish cut

Factor	*Level-1*	*Level-2*	*Level-3*
Wire type	*1(Uncoated Brass wire)*	*2(Zn coated brass wire)*	–
Pulse on time (T_{ON})	0.2 µs	0.35 µs	0.5 µs
Peak current (IP)	40 A	60 A	80 A
Wire offset (W_{OFF})	0.07mm	0.09mm	0.11mm
Wire feed rate(WF)	6 m/min	8 m/min	10 m/min
Pulse off time(T_{OFF})	18 µs	26 µs	36 µs
Spark gap voltage(SV)	65 V	75 V	85 V

Table 2
Experiment Design Matrix (L18 OA) and Results

Exp.No.	*Wire type*	T_{on}	*IP*	W_{off}	*WF*	T_{off}	*SV*	*MR(mm²/min)*	*SR(µm)*	*WWC(gm)*
1	1	1	1	1	1	1	1	10.791	1.23	115.93
2	1	1	2	2	2	2	2	32.010	1.44	74.825
3	1	1	3	3	3	3	3	45.711	1.42	70.84
4	1	2	1	1	2	2	3	20.613	1.35	90.905
5	1	2	2	2	3	3	1	28.009	1.66	85.685
6	1	2	3	3	1	1	2	92.392	2.02	45.695
7	1	3	1	2	1	3	2	36.618	1.82	40.66
8	1	3	2	3	2	1	3	91.786	2.22	22.72
9	1	3	3	1	3	2	1	58.321	2.21	21.225
10	2	1	1	3	3	2	2	73.841	1.51	34.785
11	2	1	2	1	1	3	3	14.550	1.27	86.88
12	2	1	3	2	2	1	1	106.700	2.00	24.895
13	2	2	1	2	3	1	3	66.688	1.97	34.825
14	2	2	2	3	1	2	1	176.904	2.48	11.325
15	2	2	3	1	2	3	2	59.412	1.92	45.7
16	2	3	1	3	2	3	1	171.084	2.47	11.665
17	2	3	2	1	3	1	2	128.767	2.80	21.24
18	2	3	3	2	1	2	3	117.370	2.71	20.125

3.1. Determination Of Grey Relation Coefficient

In this step, raw data of machining characteristics (MR, SR and WWC) has been normalized in the range between 0 and 1. Then the grey relational coefficient is calculated from the normalized experimental data to express the relationship between the desired and actual experimental data. The machining rate (MR) has been selected as "larger the better" while wire wear consumption (WWC) and surface roughness (SR) have been considered as "lower the better type" characteristics.

The experimental data has been normalized for MR ("larger the better" characteristic) as following.

$$x_i^*(k) = \frac{y_i^*(k) - \min y_i^0(k)}{\max y_i^0(k) - \min y_i^0(k)} \quad (1)$$

While SR and WWC ("Lower is better" characteristics) have been normalized as following.

Eroded wire collected after machining with WEDM is not reusable as it could affect the dimensional accuracy and the machining efficiency. Hence, the focus of this experimental study is on minimizing the wire consumption from the economical considerations.

$$x_i^*(k) = \frac{\max y_i^0(k) - y_i^*(k)}{\max y_i^0(k) - \min y_i^0(k)} \quad (2)$$

Where $y_i^*(k)$ the experiment result in i^th^ experiment, $x_i^*(k)$ is the normalized result in i^th^ experiment and [max $y_i^0(k)$-min $y_i^0(k)$ is the difference between maximum and minimum value of the experimental results. After normalizing of the experimental results, the deviation sequence is found out. The deviation sequence $\Delta_{01}(1) = \left|x_0^*(k) - x_1^*(k)\right|$ is calculated, where $x_0^*(k)$ is the reference sequence which is generally set to be equal to 1 and $x_1^*(k)$ is normalized results of first experiment. Table 3 shows normalized experimental results.

Table 3
Normalized experimental result of Machining Rate (MR), Surface Roughness (SR) and Wire Weight Consumption (WWC)

Exp. No.	*MR*	*SR*	*WWC*
1	0.00	1.00	0.00
2	0.13	0.87	0.39
3	0.21	0.88	0.43
4	0.06	0.92	0.24
5	0.10	0.73	0.29
6	0.49	0.49	0.67
7	0.16	0.62	0.72
8	0.49	0.37	0.89
9	0.29	0.38	0.91
10	0.38	0.82	0.78
11	0.02	0.97	0.28
12	0.58	0.51	0.87
13	0.34	0.53	0.78
14	1.00	0.20	1.00
15	0.29	0.56	0.67
16	0.96	0.21	1.00
17	0.71	0.00	0.91
18	0.64	0.18	0.92

3.2. Grey Relational Coefficient and Grey Relational Grade

Grey relation coefficient is calculated for each of the performance characteristics which express the relationship between ideal and actual normalized experimental results.

The grey relational coefficient is calculated in following manner:

$$\xi_1(k) = \frac{\Delta\min + \varsigma\Delta\max}{\Delta 0i + \varsigma\Delta\max} \quad (3)$$

Where Δ_{0i}(k) is the deviation sequence of the reference sequence $x_0^*(k)$ and the comparability sequence $x_i^*(k)$.

$$\Delta 0i(k) = \left\|x_0^*(k) - x_i^*(k)\right\| \quad (4)$$

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \left\|x_0^*(k) - x_i^*(k)\right\| \quad (5)$$

$$\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} \left\|x_0^*(k) - x_i^*(k)\right\| \quad (6)$$

Where T is distinguishing coefficient and its value is generally taken as 0.5. Table 4 shows the deviation sequence and grey relational coefficient for each experiment using the L18 orthogonal array.

Table 4
Deviation sequence, grey relational coefficient and grey relational fuzzy grade

Exp. No.	Δ_{0i} (MR)	Δ_{0i} (SR)	Δ_{0i} (WWC)	ξ_{IMR}	ξ_{ISR}	ξ_{IWWC}	GRFG
1	1.000	0.00	1.00	0.33	1.00	0.33	0.485
2	0.872	0.13	0.61	0.36	0.79	0.45	0.495
3	0.790	0.12	0.57	0.39	0.80	0.47	0.513
4	0.941	0.08	0.76	0.35	0.87	0.40	0.471
5	0.896	0.27	0.71	0.36	0.65	0.41	0.44
6	0.509	0.51	0.33	0.50	0.50	0.60	0.518
7	0.845	0.38	0.28	0.37	0.57	0.64	0.477
8	0.512	0.63	0.11	0.49	0.44	0.82	0.579
9	0.714	0.62	0.09	0.41	0.44	0.84	0.544
10	0.620	0.18	0.22	0.45	0.74	0.69	0.608
11	0.977	0.03	0.72	0.34	0.95	0.41	0.519
12	0.423	0.49	0.13	0.54	0.50	0.79	0.573
13	0.664	0.47	0.22	0.43	0.51	0.69	0.522
14	0.000	0.80	0.00	1.00	0.39	1.00	0.875
15	0.707	0.44	0.33	0.41	0.53	0.60	0.484
16	0.035	0.79	0.00	0.93	0.39	0.99	0.838
17	0.290	1.00	0.09	0.63	0.33	0.84	0.605
18	0.358	0.82	0.08	0.58	0.38	0.86	0.585

3.3. Fuzzy Logic Optimization

Fuzzy logic tool box applies linguistic terms making fundamental relationship between input and output parameters. A fuzzy-rule based inference engine constitutes three basic components: fuzzifier, inference engine and defuzzifier (Fig. 2). Fuzzy logic builds the mapping between input and output parameters. The mapping mechanism is relied on the concept of human knowledge, experience and logics represented in linguistic terms (if-then rules). The term GRFG (Grey Relation Fuzzy Grade) was computed and optimized for setting the best process parameters for multi response optimization of machining characteristics. The output variable GRFG was set in the range between 0 and 1 in FIS editor. Grey relation coefficient (Table 4) of MR, SR and WWC was selected as fuzzy input variable while grey relation fuzzy grade (GRFG) as output variable for establishing the mapping. Fuzzy logic inference system has been developed using MathWorks MATLAB 7.8.0 (Release 2009a), Fuzzy Logic Toolbox. The fuzzy logic scheme has been represented in the Fig. 2.

The input variables such as grey relation grade (î) of MR, SR and WWC have been represented by membership functions having three levels, namely low (L), middle (M) and high (H) as shown in Fig. 3. The output variable (grey relational fuzzy grade) is represented by membership functions having nine levels namely extremely small (ES), very small (VS), small (s), small medium (SM), medium (M), large medium (LM), large (L), very large (VL) and extremely large (EL) (Fig. 4). The trapezoidal membership function was selected for both input and output parameters. The fuzzy rule base consists of a group of if–then control

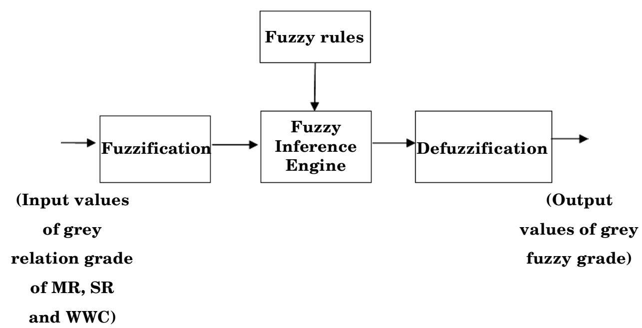
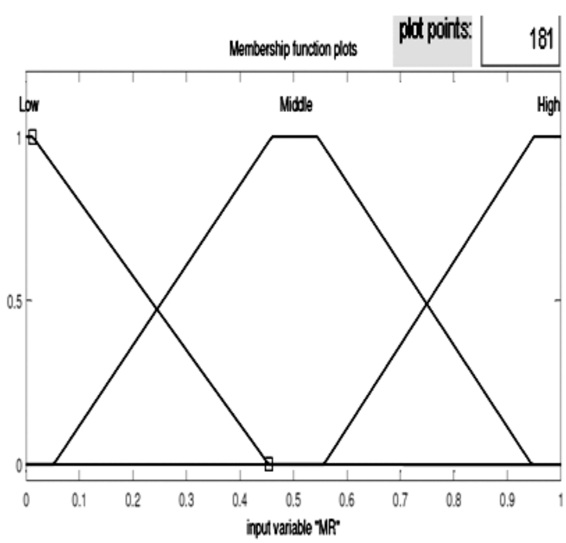
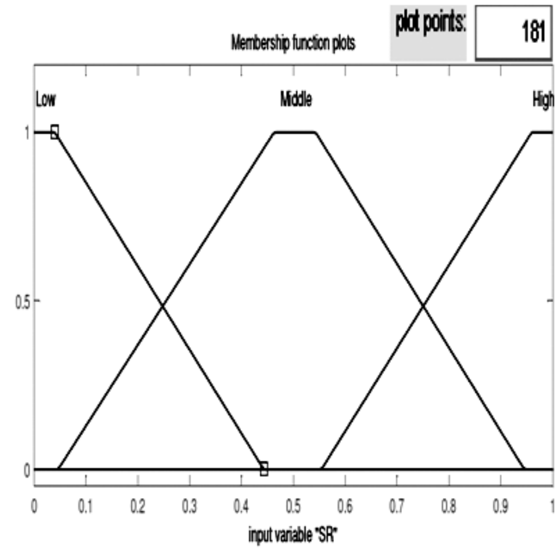


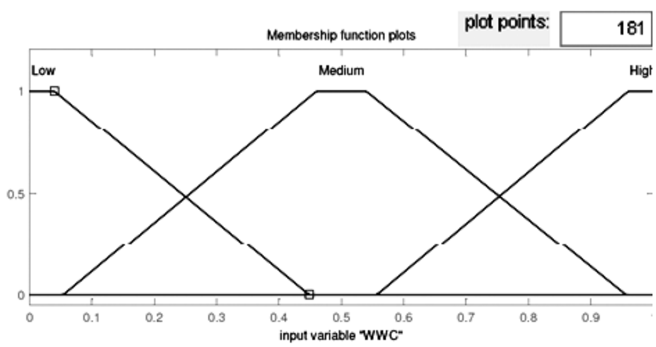
Figure 2 Fuzzy logic mechanism



(a)



(b)



(c)

Figure 3: Membership functions for input variables (MR, SR and WWC)

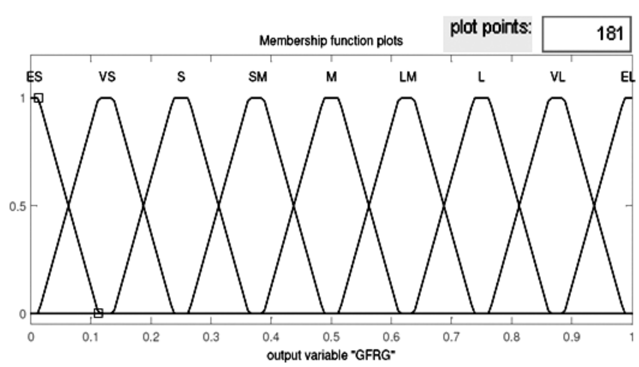


Figure 4: Membership function of output variable (GRFG)

rules with the three grey relational coefficients of MR, SR and WWC and one multi-response output of grey fuzzy grade. Twenty-seven fuzzy rules are directly derived based on the fact that the larger grey relational fuzzy grade is the better process response.

Some examples of fuzzy rules have been given below:

Rule 1: if grey relational coefficient (MR) is low (L) and grey relational coefficient (SR) is low (L) and grey relational coefficient (WWC) is low (L) then grey fuzzy grade is extremely small (ES).

Rule 2: if grey relational coefficient (MR) is low (L) and grey relational coefficient (SR) is low (L) and grey relational coefficient (WWC) is middle (M) then grey fuzzy grade is very small (VS).

Rule 27: if grey relational coefficient (MR) is High (H) and grey relational coefficient (SR) is High (H) and grey relational coefficient (WWC) is High (H) then grey fuzzy grade is extremely large (EL).

4. MULTI-RESPONSE OPTIMIZATION

Further, the grey relational coefficient of each machining characteristics (MR, SR and WWC) was used as an input in the rule editor of fuzzy inference engine (Fig. 5). The de-fuzzified values of grey relation fuzzy grade obtained for each experimental run are tabulated in the Table 4. Since the experimental layout is orthogonal, so it is possible to separate out the effect of each process parameter at selected levels of this experimental study. Fig. 6 shows main effect plot of grey fuzzy grade. The optimal parametric setting for multi-response output parameter was found out as following.

Wire type- zinc coated brass wire, Pulse on time (T_{ON})- 0.5 µs, Peak current (IP)- 60 A , Wire offset (W_{OFF})- 0.11 mm, Wire feed rate (WF)- 6 mm/min, Pulse off time (T_{OFF})- 26 µs and Spark gap voltage (SV)-65V. ANOVA was performed on the GRFG data which revealed that wire type (28.05%) and wire offset (32.79%) are the most influencing parameters affecting the variation in the overall GRFG data (see Table 5).

5. CONFIRMATION EXPERIMENTATION

The Taguchi approach for predicting the mean performance characteristics and determination of confidence intervals for the predicted mean has been applied. Two confirmation experiments for each of the performance characteristics have been performed at optimal settings of the process parameters and the average value has been reported. The average values of the performance

Table 5
ANOVA table

Factor	DOF[a]	SS[b]	MS[c]	F-ratio	Contribution
Wire type	1	0.066	0.065	16.22	28.05%
T_{ON}	2	0.017	0.0084	2.09	7.21%
IP	2	0.007	0.0037	0.92	3.18%
W_{OFF}	2	0.077	0.0383	9.48	32.79%
T_{OFF}	2	0.005	0.0026	0.65	2.25%
WF	2	0.011	0.0050	1.25	4.32%
SV	2	0.034	0.0178	4.41	15.26%
Error	4	0.016	0.0040		6.91%
Total	17	0.234			

Note: a- Degree of freedom, b- sequential sums of squares and c- adjusted mean of squares

Table 6
Confirmatory Experiment Values

Quality characteristics	*Confirmatory experimental value*
MR	184.56 mm²/min
SR	2.35μm
WWC	11.25 g

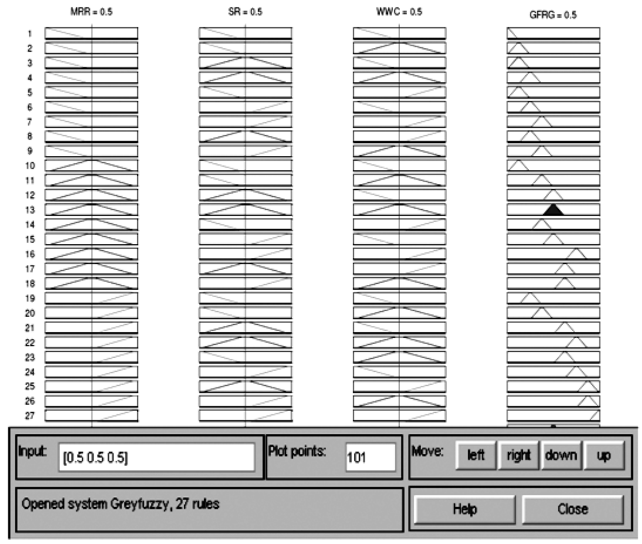


Figure 5: Rule editor for GRFG

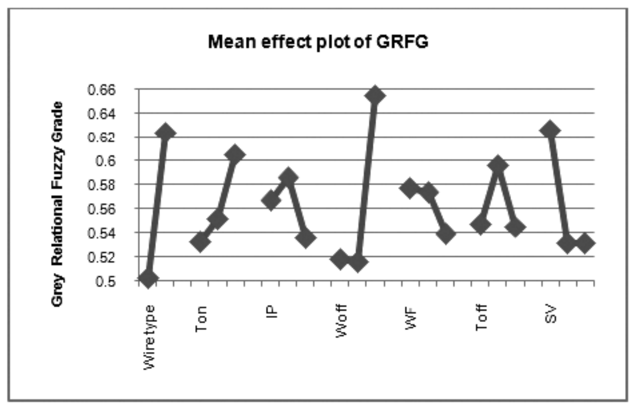


Figure 6: Mean effect plot of GRFG

characteristics obtained through the confirmation experiments (two runs) must be within the 95% confidence interval, CI_{CE} (fixed number of confirmation experiments).

The optimum values of response parameters (μ) have been predicted for the optimized setting identified though the grey-fuzzy technique, i.e. Wire type- zinc coated brass wire, Pulse on time (T_{ON})- 0.5 μs, Peak current (IP)- 60 A , Wire offset (W_{OFF})- 0.11 mm, Wire feed rate (WF)- 6 mm/min, Pulse off time (T_{OFF})- 26 μs and Spark gap voltage (SV)-65V.

CI_{CE} is given by following equation.

$$CI_{CE} = \sqrt{F_a(1, fe)\left\{\frac{1}{\eta_{eff}} + \frac{1}{R}\right\}Ve} \quad (7)$$

Where Fα (1, fe) = the F-ratio at a confidence level of (1-α) against DOF 1 and error degrees of freedom.

Ve = error variance (Ve= 0.004048, from ANOVA of GFG)

$$\eta_{eff} = \frac{1}{1 + Total\ DOF\ used\ in\ estimating\ mean} \quad (8)$$

Where N stands for total number of experiments (18 × 2 = 36) and R is the sample size for confirmatory experiments (R = 2).

Predicted confidence interval for confirmation experiment is given below.

$$\mu_{mean} - CI_{CE} < \mu_{mean} < \mu_{mean} + CI_{CE} \quad (9)$$

By putting the values of μ_{mean} and CI_{CE} in above equation we get.

$$0.544 < \mu_{\mathbf{MR,\ SR,\ WWC}} < 0.876 \quad (10)$$

Two confirmation experiments were conducted at optimal parametric setting. The average values of quality characteristics are reported in Table 6.

The experimental value of mean value of grey fuzzy grade was calculated by using above values of quality characteristics and was found 0.87.

Since this value falls within 95% CI limit (equation 10), the optimal results are validated.

6. CONCLUSIONS

Multi-response optimization was successfully implemented for finish cut WEDM process using grey-fuzzy method. Parameters namely Wire type and wire offset were established as the most significant from the analysis of their contributions in the variation of grey relational fuzzy grade data.

- The optimized parametric setting for multiple responses by grey fuzzy logic was identified as; Wire type- zinc coated brass wire, Pulse on time (T_{ON})- 0.5 μs, Peak current (IP)- 60 A , Wire offset (W_{OFF})- 0.11 mm, Wire feed rate (WF)- 6 mm/min, Pulse off time (T_{OFF})- 26 μs and Spark gap voltage (SV)-65V.
- The confirmation experiments results validated the predicted optimal values of the responses considered in the study.

REFERENCES

[1] C.L. Lin, J.L. Lin, & T.C. Ko, "Optimization of the EDM process based on the orthogonal array with fuzzy logic and grey relational analysis method", International Journal of Advanced Manufacturing Technology, Vol. 19, 2002, pp 271-277.

[2] Rajyalakshmi G. & Venkata Ramaiah P., "Optimization of process parameters of wire electrical discharge machining using fuzzy logic integrated with taguchi method", International Journal of Scientific Engineering and Technology, Vol. 2(6), 2013, pp 600-606 ISSN: 2277-1581.

[3] S. Dewangan, S. Gangopadhyay & C.K. Biswas, "Multi-response optimization of surface integrity characteristics of EDM process using grey-fuzzy logic-based hybrid approach", Engineering Science and Technology, an International Journal, 2015, DOI: 0.1016/j.jestch.2015.01.009.

[4] K. El. Hashmi, M.A Baradle & M. Ryan, "Fuzzy logic based intelligent selection of machining parameters", Computers industrial Engineering Vol. 35, 1998, pp 571-574.

[5] C.L. Lin, J.L. Lin, & T.C. Ko, "Optimization of the EDM process based on the orthogonal array with fuzzy logic and grey relational analysis method", International Journal of Advanced Manufacturing Technology, Vol. 19, 2002, pp 271-277.

[6] K. Hashmi, I.D. Graham & B. Mills, "Data selection for turning carbon-steel using a fuzzy logic approach", Journal of Materials Processing Technology, Vol. 135, 2003, pp 44-58.

[7] J. Ghose, V. Sharma, N. Kumar, A. Krishnamurthy, S. Kumar & Z. Botak, "Taguchi-fuzzy based mapping of EDM- Machinability of Aluminum foam", Technical Gazette Vol. 18(4), 2011, pp 595-600.

[8] Pradeep Kumar J. & Giriprasad C R, " Investigation on application of fuzzy logic concept for evaluation of electric discharge machining characteristics while machining aluminum silicon carbide composite", International Journal of Science, Engineering and Technology Research (IJSETR), Vol. 2(10), 2013, pp 1804-1809.

[9] M.R. Shabgard, M.A. Badamchizadeh, G. Ranjbary & K Amini, "Fuzzy approach to select machining parameters in electrical discharge machining (EDM) and ultrasonic-assisted EDM processes", Journal of Manufacturing Systems, Vol. 32, 2013, pp 32– 39.

[10] P. Sengottuvel, S. Satishkumar & D. Dinakaran, "Optimization of multiple characteristics of EDM parameters based on desirability approach and fuzzy modeling", Procedia Engineering, Vol. 64, 2013, pp 1069 – 1078.

[11] K.K. Jangra, "Study of unmachined area in intricate machining after rough cut in WEDM", International Journal of Industrial Engineering Computations, Vol. 3, 2012, pp 887–892.

[12] R. Chalisgaonkar & J. Kumar. " Optimization of WEDM process of pure titanium with multiple performance characteristics using Taguchi's DOE approach and utility concept", Frontiers of Mechanical Engineering, Vol. 8(2), 2013, pp 201-214, doi: 10.1007/s11465-0.

[13] R. Ramakrishnan & L. Karunamoorthy, "Modeling and multi-response optimization of Inconel 718 on machining of CNC WEDM process", Journal of Material Processing Technology, Vol. 207, 2008, pp 343-349.