MULTI-RESPONSE OPTIMIZATION AND MODELLING OF WEDM USING GREY–FUZZY AND RESPONSE SURFACE METHODOLOGY

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Abstract: Wire Electric discharge machining (WEDM) is a thermoelectric process in which workpiece is eroded by a series of discrete sparks between the workpiece and a traveling wire electrode immersed in a liquid dielectric medium. Al5083AA alloyed with 0.15Zr is difficult to machine using conventional methods as it exhibits poor machinability and average workability for producing intricate shapes with high precision and accuracy. WEDM is one of the promising machining techniques to process this alloy. This research is focused on parametric optimization of WEDM of Al5083AA with 0.15Zr in terms of Material removal rate (MRR) and Surface roughness (Ra). Input parameters considered here are Pulse on time (T_{on}), Pulse off time (T_{off}), Current (I) and Driving motor speed (N). The experiment is conducted as per CCD (Central composite design) design and modelled and optimized using RSM (Response surface methodology) and Grey-fuzzy methodology. It was observed that N was the most significant factor followed by T_{on} in both MRR and Ra. The optimum value of Input parameters for maximum MRR and minimum Ra was obtained. The obtained optimum values are experimentally verified and percentage error in the output is depicted.

Key words: CCD, Grey-fuzzy, RSM, WEDM, MRR, Ra, Optimization

1. INTRODUCTION

Machining Aluminium alloys using conventional methods produces continuous thick chips and can form long ribbons and become entangled in workpiece [1]. Thus impairing the surface quality [2]. In drilling, they can cause production stoppages as a result of drills breaking due to clogging of their grooves [2,3]. When surface quality and tolerances are of concern, non-conventional machining methods, such as WEDM, WAJM (Water Abrasive jet machining), etc can be used. WEDM offers good surface finish and also do not produce problems related to long chips and built up edges. But this is a slow operation, and the MRR can be very small. Wire Electric Discharge Machining (WEDM) is a method that uses a thin wire electrode (usually brass) to cut a conductive material that follows a computer numerically controlled (CNC) path. As compared to tooling marks left by milling cutters and grinding wheels, WEDM leaves a totally random pattern on the surface. Here, through a series of discrete sparks generated by spark generators, electrical energy is transformed into thermal energy. Sparks are created by a series of fast electrical pulses generated by the power supply of the machine, and these are thousands of times a second. Under extremely high temperature and pressure, each spark forms an ionization path in which particles migrate between the wire electrode and the workpiece, resulting in localized parts being vaporized.

To achieve the best possible outputs for the given constraints, optimization of the process is needed. Many outputs would be feasible, but optimization is defined as choosing the most favorable and probable combination of input outputs. If outputs are associated with each other and various inputs vary the outputs in different amounts separately, this is necessary. The simulation of mathematical and computational processes experiments provides us insight into the process and helps us forecast the output for the given input range.

Only after initial exploratory trials and defining the most relevant parameters can the RSM modeling and optimization approach be implemented. To forecast random trials that have a high degree of fuzziness, fuzzy logic is used. The Grey relationship is used to describe the outcomes between high and low in the grey zone.

In optimization, there are several research works performed using the methods selected on WEDM. In [4] are illustrated the effects of input parameters such as pulse on time (Ton) pulse off time (Toff) on machining characteristics such as material removal rate (MRR), surface roughness (SR) and wire weight usage (WWC) on commercially pure titanium as work material, such as peak current (IP), wire feed (WF), wire tension (WT) and servo voltage (SV). The answers were optimized by the approach of grey-fuzzy logic. For prediction of the response parameter (MRR) over a large range of input variables, a mechanistic model has also been developed and validated. A study and modeling of WEDM on Al / SiC Metal matrix composite (MMC) workpieces was conducted in [5]. It is to be noticed that during experimentation, there was no dielectric used. The dissertation relies on the use of gaseous dielectric technology. Adaptive neuro-fuzzy inference systems (ANFIS) have been used to correlate the relationship between process inputs and reactions. A grey relational analysis was eventually used to optimize Cutting Velocity (CV) and concurrently minimize Surface Roughness (SR). Results have shown that oxygen gas and brass wire ensure superior cutting speed. Pulses on time and current were also observed to have a major impact on CV and SR, according to ANOVA. In [6] the multi-performance characteristics of the WEDM mechanism were conducted using grey-ANFIS. Grey grade variance analysis is used to assess the essential parameters. For the training of the suggested adaptive neuro fuzzy inference method, a regression model is generated and used to produce datasets. In [7] multi-objective optimization of wire electrical discharge machining (WEDM) of 5083 aluminum alloy was conducted. It was observed that the, additive model was employed for prediction of all possible machining combinations. In [8] RSM has been used to refine WEDM Process Parameters for Friction-Stir-Welded 5754 Aluminum Alloy Machining. The findings have shown that the use of Box–Behnken design(BBD) will reduce the number of experiments needed to improve the parameters of the WEDM method. This thesis, [9], describes the development of the model and its implementation using multiple regression analysis (MRA), group method data handling technique (GMDH) and artificial neural network (ANN) to estimate machining efficiency. For each experiment, three responses were considered, namely accuracy, surface roughness and volumetric material removal rate. Using MRA, GMDH and ANN, calculation and comparison of responses was carried out. In [10] the properties related to the material used in experimentation can be seen.

2. METHODOLOGY

2.1 Modelling

RSM is a technique based on regression that can be used for system output estimation, determination and optimization. RSM is a set of computational and mathematical techniques needed for a process to be developed, enhanced and optimized. It is used in situations where several parameters depend on the output. The output correlated with multi-parameters is called reaction. RSM requires strategy preparation to establish a relationship between various input parameters and production output. Using this, it is possible to obtain a model that describes the relation between input and output parameters. The experiment is designed using Central Composite Design (CCD). CCD and RSM are used in quantifying the interaction of various process parameters with various machining requirements and identify the impact of these process parameters on calculated responses.

2.2 Multi-Parameter optimization

This section explains the methodology followed during optimization of the process.

2.2.1 Grey relational analysis

The grey theory is used to solve uncertain and discrete data that have dynamic interrelationships within the different problems of multiple characteristics in results. Since there is always vagueness, one is always somewhere in the centre, somewhere between the poles, somewhere in the grey zone. A simple set of assertions about machine solutions is then arrived at by Grey analysis. At one extreme, no solution for a device with no data can be specified. The following measures are included in determining the grey relational analysis.

Step 1: Calculation of signal to noise ratio (S/N ratio)

The MRR is quantified as "Higher the better" while Ra is quantified as "Lower the better". The S/N ratio is determined using the following equations, as seen in equation (1a) for higher the better and equation (1b) for lower the better.

Higher the better:

$$\eta = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_{ij}^2}\right] \tag{1a}$$

Lower the better:

$$\eta = -10\log_{10}\left[\frac{1}{n}\sum_{i=1}^{n}y_{ij}^2\right] \tag{1b}$$

Where:

y_{ij} is the response variable, i=1,2,…n; j=1,2,…m (m is the number of response) and n is the number of tests.

Step 2: Normalization of S/N ratio of the quality characteristics

The data cannot be simply reduced to grey relational coefficients if the data range is too wide or the data range is different in size or the units are different. Therefore, data is normalized first, so that the scale of all the data is the same. Using equation (2), the normalization is performed:

$$X_{ij}(m) = \frac{\eta_i(m) - \min\eta_i(m)}{\max\eta_{ij} - \min\eta_{ij}} \tag{2}$$

Where:

$\eta(m)$ denotes the corresponding S/N ratio and max η_{ij} and min η_{ij} are the largest and smallest values of $\eta_{ij}(m)$, respectively; $X_{ij}(m)$ are the normalized data of mth element in the i^{th} sequence;

Step 3: Grey relational coefficient calculation

For deciding how near $X_i(m)$ and $X_0(m)$ are, the Grey relational coefficient is used. As per equation (3), it can be determined.

$$\xi(m) = \frac{\Delta_{\min} + \Delta_{\max}}{\Delta_{oi}(m) + \Delta_{\max}} \quad (3)$$

I=1,2,3,….,m

Where

$\Delta_{oi}(m) = \left| X_o(m) - X_i(m) \right|$

where Δ_{min} is the minimum deviation sequence of i^{th} sequence of m^{th} element=min{Δ_i(m)} Δ_{max} is the maximum deviation sequence of i^{th} sequence of m^{th} element=max{Δ_i(m)} and ζ is the differentiating coefficient and its value is in between 0 and 1. The smaller ζ implies higher distinguishability.

Step 4. Multiple performance characteristics index

By feeding the grey relational coefficient value of each response into the fuzzy system, multiple responses are transformed into a single equivalent response (called MPCI). The MPCI is counted as the weighted sum of the grey relational coefficients. Here, using fuzzy rules to calculate MPCI, the weightage of individual responses is generated. Using main effect plots and ANOVA, the largest MPCI value is determined.

2.2.2 Fuzzy logic

There is a certain degree of complexity and vagueness in the grey relational coefficient ξi(m). Initially, the fuzzifier utilizes membership functions of fuzzy logic processing to fuzzify the grey relational coefficient. To produce a fuzzy value, the inference engine executes a fuzzy reasoning on fuzzy rules. The defuzzifier eventually transforms the fuzzy attribute to an MPCI. There are essentially four components in a general fuzzy inference system: fuzzification, base of fuzzy rules, fuzzy output engine and defuzzification.

Every grey relational coefficient is transformed into degrees of membership by fuzzification. A membership function is a curve that determines how a membership value between 0 and 1 is mapped to each input value. Due to their convenience, trapezoidal membership functions are used here and are simple to incorporate in a computer programme. After fuzzification of the parameters of the input method and linguistic representation of the output variable, a fuzzy relationship was defined by fuzzy laws. In order to produce a fuzzy value, the fuzzy inference engine executes a fuzzy interface on fuzzy rules. The final step is defuzzification, the method of transforming a fuzzy set into a non-fuzzy value, which in this analysis will be called the MPCI.

2.3 Interpretation and validation of results

The results of experiment will be used for prediction of values of input parameters for which there will be maximum MRR and minimum Ra (This condition occurs when MPCI is maximum). And also to construct a mathematical model for relating input and output parameters. Experiment is conducted at the predicted input values at which maximum MPCI occurs and percentage of error is calculated.

3. EXPERIMENTAL DETAILS

3.1 Procedure

The experiment was conducted on the CONCORD WEDM DK7732 VERSA CUT 01 machine which is shown in Figure 1. It is a four axes machine. Molybdenum wire of diameter 0.18mm was used as tool electrode. During all experiments deionized water was used as dielectric. The workpiece is made of Al5083 with 0.15 wt% addition of Zr. The Zr addition is mainly done to increase the plasticity of Al5083. The experiments were designed as per CCD. The MRR and SR was measured for each combination of input parameters. Pulse on time (Ton) Pulse off time (Toff), Current (I), Driving motor speed (N) were used as variable input parameters. 3 levels of input parameters were chosen as shown in Table 1.

Table 1. Input factors and their levels

Control factor/Level	Level			Units
	1	2	3	
Pulse On(T_{on})	25	30	35	μsec
Pulse Off(T_{off})	10	11	12	μsec
Current(I)	3	4	5	A
Driving Motor speed(N)	100	150	200	Hz

Fig. 1. CONCORD WEDM DK7732 VERSA CUT 01 [12]

3.2 Evaluation of performance characteristics

Average surface roughness (Ra) is the parameter which is related to surface integrity. Ra is the

arithmetic mean of absolute departures of roughness profile from mean line central line along sampling length. The average Ra for each trial was measured by using surface roughness tester. MRR is a characteristics related to machine performance. To calculate MRR, the time of cutting is obtained directly from the display of the WEDM machine. Then MRR is calculated using as shown in equation (4).
The draft of specimen can be seen in Figure 2.

$$MRR = V/t \quad \left[\mathrm{mm}^3/\mathrm{min}\right] \tag{4}$$

Where: t=Machining time [min]
V is the volume of material removed, [mm^3] given by the next relation V= P·T·W with
P=Perimeter = 2*(L+B)=2*(30+8)=76mm
T=Thickness=6mm
W=Width of cut =d+2s
d=wire diameter = 0.18mm
s=Distance between the electrodes=0.01mm

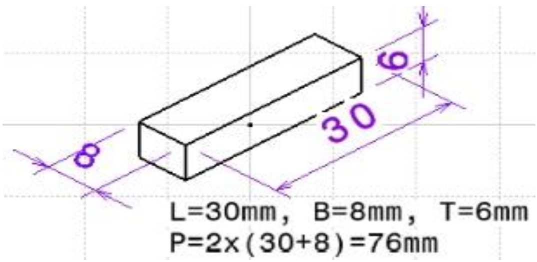


Fig. 2 . Draft of Isometric view of the specimen

3.3 Experimental design

The experiment is designed as per CCD. Blocked design is chosen since the experiment needs 2 days to complete. The experiment has about 30 runs. The results of experiments are shown in Table 2. The levels of the input parameters were chosen from prior experience with the machine. All the calculations were using Matlab, Design Expert 12, Minitab. The optimized results from analysis are verified by experimentation. The optimized input levels obtained by analysis are practically confirmed and any error is calculated.

4. RESULTS AND DISCUSSIONS

This section describes the results obtained from the experiments and discussions about it. For analysis of the results, initially the adequacy of model, lack of fit test are required. Hence ANOVA is performed for Ra, MRR and MPCI. In ANOVA p-value for terms that are less than 0.05 are considered to be significant. RSM Single objective models are used to predict single responses for any combination of inputs.

4.1 Analysis of MRR through RSM

As the adequacy measured by R2, modified R2 and projected R2 gives satisfactory performance, the established model was well satisfied. Parameters with a p-value smaller than 0.05 are statistically significant. From Table 3, it can be shown that *N* is the most important factor, followed by *I*. Two other variables of this selected substance are not important in WEDM. The key influence plots of each element on MRR are seen in Figure 3.
It can be observed that MRR is almost entirely dependent on the driving motor speed. Other factors have negligible effect compared to this factor. This is mainly because Al5083 being a soft material can be cut easily and the speed of the motor determines the speed of movement of wire. Increase or decrease in speed of wire increases or decreases the rate of erosion. Hence cutting speed will vary largely. Other factors will have negligible impact since the workpiece chosen has less melting point and also has higher thermal conductivity. The sequential sum of squares can be seen in Table 4 which is used to determine the significant model for MRR

Table 2. CCD design of experiment

A: Pulse on time [μsec]	B: Pulse off Time, [μsec]	C: Current, [A]	D: Driving Motor speed(N), [Hz]	MRR, [mm^3/min]	Ra, [μm]
25	12	3	200	11.5883	2.96
25	10	3	100	5.82004	3.17
35	10	3	100	5.82004	3.42
35	12	3	100	5.90291	3.58
25	10	5	100	5.94137	3.22
30	11	4	150	8.78613	3.42
35	12	5	200	11.6923	3.64
35	12	3	200	11.6178	3.24
25	12	5	100	5.92208	2.83
35	10	5	200	11.6923	3.52
35	10	3	200	11.3292	3.35
25	12	5	200	11.6178	3.14
35	12	5	100	5.89528	3.71
30	11	4	150	8.8716	3.39
30	11	4	150	8.7106	3.45
30	11	4	150	8.66097	3.41
25	10	5	200	11.6178	3.1
25	12	3	100	5.8725	3.08
35	10	5	100	5.92208	3.49
25	10	3	200	11.5443	3.04
40	11	4	150	8.6857	4.3
30	11	4	150	8.72727	3.47
30	13	4	150	8.7524	3.21
30	11	4	150	8.68571	3.45
30	11	6	150	8.85437	3.38
30	11	4	250	14.3622	2.83
30	11	4	100	5.88387	3.44
20	11	4	150	8.66097	3.25
30	11	2	150	8.68571	3.32
30	9	4	150	9.04762	3.46

The mathematical model of MRR is chosen as a linear model since it has sufficient fit and p-value of the model is less than 0.05 as can be seen in Table 4. The model is represented by equation (5):

$$MRR = 0.105527 - 0.000024 T_{on} - 0.007022 T_{off} + 0.047636 I + 0.056851 N \quad (5)$$

Table 3. ANOVA for MRR

Source	Sum of Squares	df	Mean Square	F-value	p-value
Block	0.5735	1	0.5735		
Model	168.93	4	42.23	4911.65	< 0.0001
A-Ton	3.40E-07	1	3.40E-07	0	0.995
B-Toff	0.0012	1	0.0012	0.1376	0.7139
C-I	0.0545	1	0.0545	6.33	0.0189
D-N	168.88	1	168.88	19640.13	< 0.0001

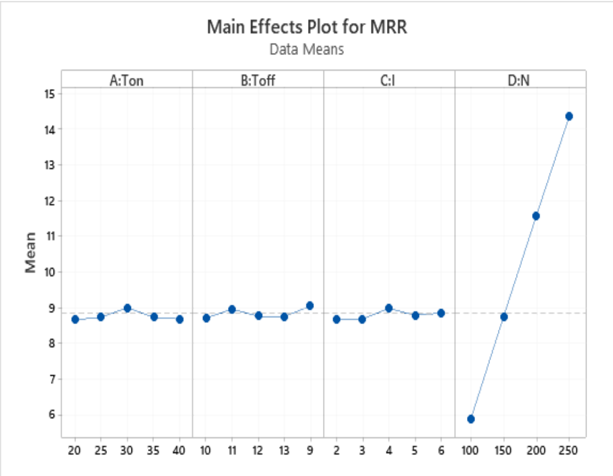


Fig. 3. Main Effect plot for MRR

4.2 Analysis of Ra using RSM

As the adequacy measured by R^2, modified R^2 and projected R^2 gives satisfactory performance, the established model was well satisfied. Parameters with a p-value smaller than 0.05 are statistically significant. It can be seen from Table 5 that T_{on} is the most significant factor followed by N. Interaction effect of factors is also significant. Figure 4 shows the main effect plots of each factors on R_a. ANOVA of the model can be seen in Table 5.

It can be seen that Ra is mainly dependent on Ton and N. Ra is increasing as T_{on} increases and decreases as N increases. This is because having more T_{on} time will transfer more energy which will melt more metal around the wire, after solidification the surface will be uneven. As N increases, speed of wire increases and hence the erosion of metal will increase and surface will be smoother. The mathematical model of Ra is chosen as a quadratic model since it has sufficient fit and p-value of the model is less than 0.05. As can be seen in Table 6, both Linear and Quadratic models have p-value less than 0.05 but ultimately quadratic model is chosen since it fares better in lack of fit test. The model is represented by equation (6).

$$\begin{aligned} Ra = {} & 4.17203 - 0.276752 \cdot T_{on} + 0.40158 \cdot T_{off} - 0.198062 \cdot I + 0.0140157 \cdot N + 0.011375 \cdot T_{on} \cdot T_{off} + \\ & + 0.009125 \cdot T_{on} \cdot I - 0.000097 \cdot T_{on} \cdot N + 0.006875 \cdot T_{off} \cdot I + +0.000088 \cdot T_{off} * N + 0.0010125 \cdot I \cdot N + \\ & + 0.00292781 \cdot T_{on}^2 + -0.0368048 \cdot T_{off}^2 + -0.0330548 \cdot I^2 + -5.61826e-05 \cdot N^2 \end{aligned} \quad (6)$$

In the Tables 3, 4 and 5, df is the degree of freedom of the parameter. It the number of values that can be changed independently.

Table 4. Sequential model sum of squares for MRR

Model	Sum of Squares	df	Mean Square	F-value	p-value
Mean vs Total	2343.86	1	2343.86		
Block vs Mean	0.5735	1	0.5735		
Linear vs Block	**168.93**	**4**	**42.23**	**4911.65**	**< 0.0001**
2FI vs Linear	0.0336	6	0.0056	0.5839	0.7387
Quadratic vs 2FI	0.0649	4	0.0162	2.1	0.1345
Cubic vs Quadratic	0.079	9	0.0088	1.52	0.3361
Residual	0.0289	5	0.0058		
Total	2513.57	30	83.79		

Table 5. ANOVA for R_a

Source	Sum of Squares	df	Mean Square	F-value	p-value
Block	0.0707	1	0.0707		
Model	2.15	14	0.1537	17.38	< 0.0001
A-T_{on}	1.27	1	1.27	143.04	< 0.0001
B-T_{off}	0.0165	1	0.0165	1.87	0.193
C-I	0.036	1	0.036	4.07	0.0631
D-N	0.0261	1	0.0261	2.95	0.1079
AB	0.0518	1	0.0518	5.85	0.0298
AC	0.0333	1	0.0333	3.77	0.0727
AD	0.0095	1	0.0095	1.07	0.3174
BC	0.0008	1	0.0008	0.0855	0.7743
BD	0.0003	1	0.0003	0.0346	0.855
CD	0.041	1	0.041	4.64	0.0492
A^2	0.1496	1	0.1496	16.91	0.0011
B^2	0.0378	1	0.0378	4.28	0.0576
C^2	0.0305	1	0.0305	3.45	0.0844
D^2	0.3085	1	0.3085	34.88	< 0.0001

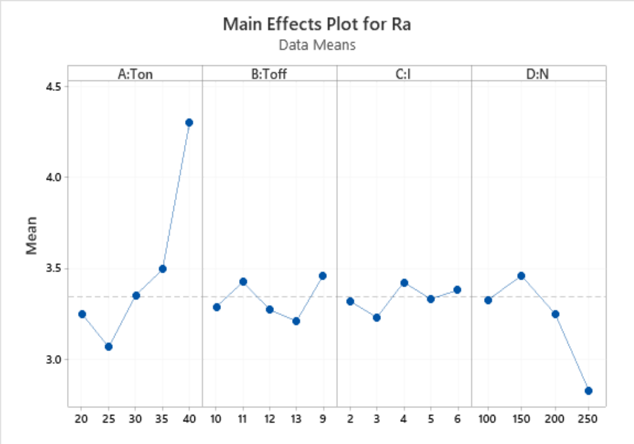


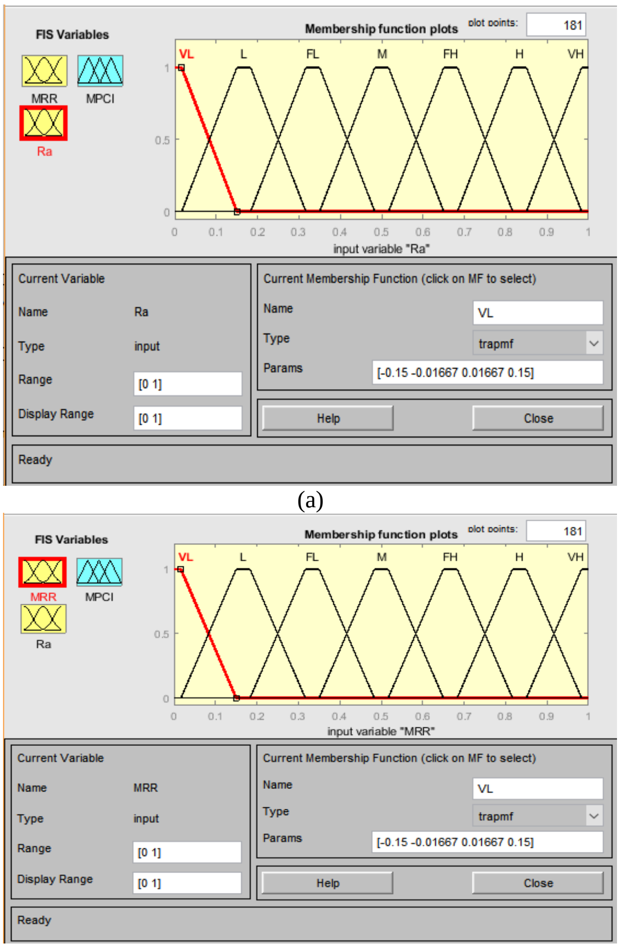
Fig. 4. Main effect plots for Ra

4.3 Multi-Objective Optimization

Both MRR and Ra are optimized together. MRR is optimized as higher the better and Ra is optimized as lower the better.

4.3.1 Grey-Fuzzy methodology

First of all, S/N ratio of MRR and Ra values obtained from experiments is normalized as shown in Table 6. This brings different data to same scale. The Grey relation coefficient is calculated which is fed to fuzzy logic system to obtain a MPCI. MPCI is considered as "Larger the better". The MPCI obtained is the single equivalent output which can be optimized by using ANOVA or main effect plots. MATLAB tool was used to obtain MPCI from the responses Ra, MRR. Mamdani type fuzzy inference methodology has been implemented for this present work. It uses a conjunction for inference and a disjunction to aggregate individual rules [11]. Seven linguistic variables were used to express each input element. Very Low (VL), Low (L), Fairly Low (FL), Medium(M), Fairly High (FH), High (H), Very High (VH) and fuzzy rules are formed as shown in Table 7. Also Figure 5(a) and Figure 5(b) shows fuzzy membership functions for Ra and MRR respectively.



(a)

(b)

Fig. 5. Membership functions for: (a) Ra; (b) MRR

Table 7. Fuzzy Rule matrix

MPCI		MRR						
		VL	L	FL	M	FH	H	VH
Ra	VL	VL	VL	L	L	FL	FL	M
	L	VL	VL	L	FL	FL	M	M
	FL	L	L	FL	FL	M	M	FH
	M	L	L	FL	M	M	FH	H
	FH	L	FL	FL	M	FH	H	H
	H	L	FL	M	FH	FH	H	VH
	VH	FL	FL	M	FH	H	H	VH

Table 8. Normalized, GRF, MPCI and S/N ratio of MPCI

Normalized		Grey relation coeff		MPCI	S/N Ratio for MPCI
Ra	MRR	Ra	MRR		
0.89264	0.76242	0.82324	0.67789	0.667	-3.517483322
0.7288	0	0.64834	0.33333	0.333	-9.55111533
0.54734	0	0.52485	0.33333	0.333	-9.55111533
0.43805	0.01565	0.47083	0.33685	0.333	-9.55111533
0.69139	0.02284	0.61834	0.33849	0.333	-9.55111533
0.54734	0.45596	0.52485	0.47891	0.492	-6.160697945
0.39832	0.77231	0.45385	0.68711	0.507	-5.899840813
0.67659	0.76524	0.60723	0.68049	0.609	-4.307654147
1	0.01924	1	0.33766	0.5	-6.020599913
0.47845	0.77231	0.48945	0.68711	0.507	-5.899840813
0.59678	0.73739	0.55357	0.65564	0.551	-5.176968023
0.75153	0.76524	0.66803	0.68049	0.667	-3.517483322
0.35278	0.01422	0.43584	0.33652	0.333	-9.55111533
0.5684	0.46668	0.53671	0.48388	0.5	-6.020599913

0.52647	0.4464	0.51359	0.47457	0.486	-6.267274615
0.55434	0.44008	0.52873	0.47173	0.481	-6.357098473
0.78217	0.76524	0.69655	0.68049	0.667	-3.517483322
0.79764	0.00993	0.71189	0.33556	0.375	-8.519374645
0.49891	0.01924	0.49946	0.33766	0.333	-9.55111533
0.82889	0.75821	0.74504	0.67404	0.667	-3.517483322
0	0.44323	0.33333	0.47314	0.333	-9.55111533
0.51265	0.44852	0.50641	0.47552	0.487	-6.249420776
0.69882	0.4517	0.62408	0.47696	0.489	-6.213822818
0.52647	0.44324	0.51359	0.47314	0.483	-6.321057385
0.57547	0.46453	0.54081	0.48287	0.499	-6.037989088
1	1	1	1	0.952	-0.427261032
0.5334	0.01208	0.51728	0.33604	0.333	-9.55111533
0.66922	0.44008	0.60184	0.47173	0.478	-6.411442068
0.61828	0.44324	0.56707	0.47314	0.48	-6.375175252
0.51955	0.48843	0.50997	0.49428	0.5	-6.020599913

The trapezoidal membership function is chosen since it gives more accurate values. Trapezoidal membership function is also used for MPCI. The outputs of each trial are fed to the fuzzy system and corresponding MPCI is obtained. The Table 8 shows normalized grey relation coefficient, MPCI and S/N ratio of MPCI.

The fuzzy rule base generated in MATLAB can be seen in Figure 6. The obtained MPCI values are analyzed as larger the better and then optimized using ANOVA. A relation between MPCI and other factors can be derived as shown in equation (7). The optimum value of factors for maximum value of MPCI are obtained as T_{on}=20, T_{off}=13, I=6, N=250. The analytical results were verified by practical experimentation and the error obtained can be as seen in Table 9.

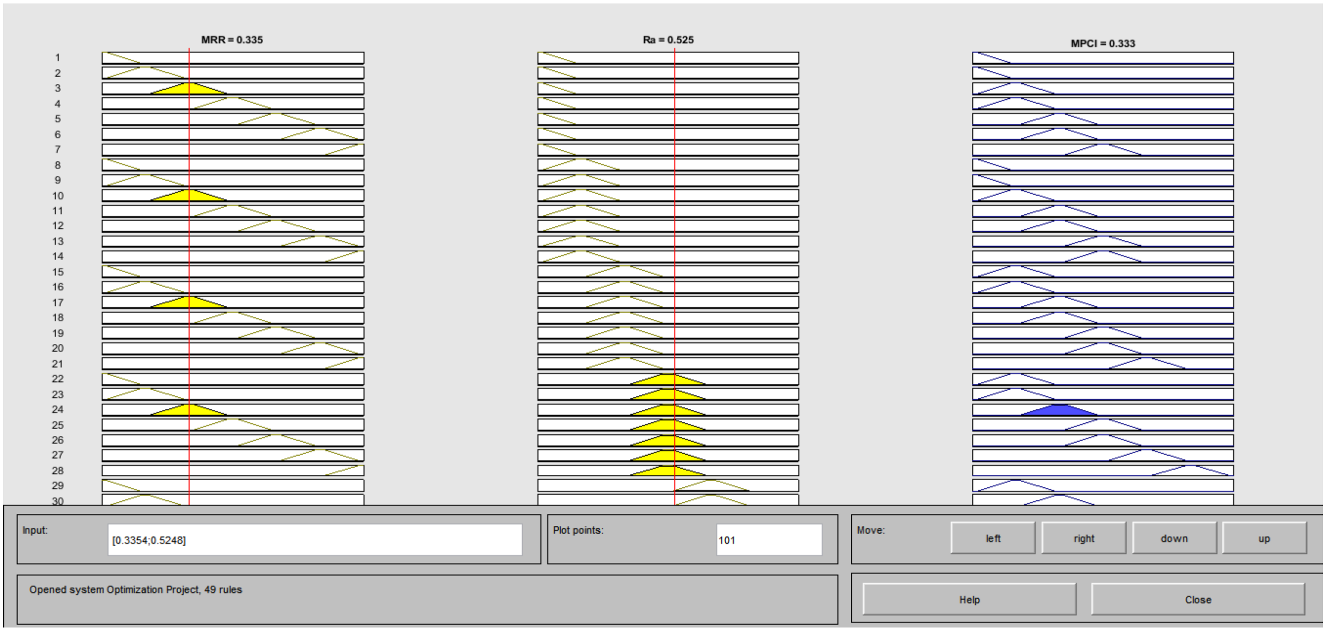


Fig. 6. Fuzzy Rule base

$$MPCI = 6.15293 - 0.047975 \cdot T_{on} - 0.415562 \cdot T_{off} - 0.7475 \cdot I - 0.0103533 \cdot N + 0.0050125 \cdot T_{on} \cdot T_{off} - 0.0016875 \cdot T_{on} \cdot I - 1.625e-05 \cdot T_{on} \cdot N + 0.0445625 \cdot T_{off} \cdot I + 0.00027375 \cdot T_{off} \cdot N + 0.00182375 \cdot I \cdot N \quad (7)$$

Table 9. Error percentage

T_{on}	T_{off}	I	N	MRR (Analytical)	MRR (Actual)	Error %	Ra (Analytical)	Ra (Actual)	Error%
20	13	6	250	14.54	14.28	1.8	2.35	2.49	-5.62

5. CONCLUSIONS

Based on the experimental study and data analysis the effects of process parameters on each out parameter and overall *MPCI* was investigated using *RS*M and Grey-Fuzzy methodology. Fuzzy logic and *RSM* are successfully applied for optimization. It was found out that T_{on}=20, T_{off}=13, I=6, N=250 are the optimal values based on grey-fuzzy. Though not many trials were conducted at T_{on}=20, *RSM* indicated that the optimal value is in that region and hence this value was chosen since *RSM* also indicated a similar value. Also it was observed that *N* is the most influencing factor on both *MRR* and *Ra*. The advantage of this using Grey fuzzy methodology along with *RSM* is that we are able to reduce the error and increase accuracy of prediction of points. However, this model is material and machine specific, more datasets can be obtained by experimentation on different materials and a material model can be developed. With the help of such model *WEDM* of different materials can be estimated and can be used in Industries for selection of materials and process parameters.

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