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A HYBRID GREY-FUZZY LOGIC APPROACH FOR OPTIMIZATION OF PROCESS PARAMETERS IN WIRE ELECTRICAL DISCHARGE MACHINING OF D2 STEEL

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ABSTRACT: Wire Electrical Discharge Machining (WEDM) is an extensively used non – traditional machining process for machining of hard and difficult - to - machine materials. In the present work, multi response optimization of the process parameters in WEDM machining of D2 Steel is carried out using hybrid Grey-Fuzzy logic technique. The input parameters such as Pulse ON time (T_{ON}), Pulse OFF time (T_{OFF}), Spark Voltage (SV), Peak Current (IP), Wire Feed (WF) and Wire Tension (WT) are used to optimize the output parameters like Material Removal Rate (MRR), Tool Wear Rate (TWR), Surface Roughness (SR) and Kerf Width. A set of 27 experiments are performed using Taguchi's Design of Experiment. Grey Relational Analysis (GRA) combined with Fuzzy Logic approach is used to find Grey Fuzzy Relational Grade (GFRG). The optimal combination obtained using this technique is found to be T_{ON} = 110μs, T_{OFF} = 45μs, SV = 15volts, IP = 210amps, WF = 6m/min and WT = 6 grams. Analysis of Variance (ANOVA) result shows that T_{ON} is having the highest significance on the output performance.

KEYWORDS: Material Removal Rate, Tool Wear Rate, Surface Roughness, Kerf Width, Grey Relational Analysis, Fuzzy Logic, Grey Fuzzy Relational Grade

I. INTRODUCTION

Wire Electrical Discharge Machining (WEDM) process is used for machining of hard and difficult-to-machine materials. The basic principle of WEDM process is the bombardment of electrons on the work piece surface causing the temperature on the surface to rise beyond melting point temperature leading to evaporation. WEDM is suitable for machining those materials which have some electrical conductivity. It is widely used in various industries for manufacturing of components generally in automobile, aerospace and machine tool industries. Various optimization techniques have been used to improve the output performance in the WEDM process. Bobbili et. al. [1] investigated the machining performance in WEDM during machining of Ballistic grade Aluminium alloy using Taguchi coupled with Grey Relational Analysis. They conclude that Pulse ON time, Peak Current and Spark Voltage are the significant variables in the WEDM process. Dongre et. al. [2] performed the multi response optimization based on Response Surface Method (RSM) technique during the machining of Silicon wafer using Molybdenum wire. They found that use of WEDM process reduces the kerf width from 250μm to 50μm. They also found that use of WEDM process improves the surface roughness to 2-3μm. Goswami et. al. [3] used the utility concept for multi response optimization during machining of Nimonic-80A using Brass wire. They found that the material removal rate and surface roughness increases with increase in pulse ON time and decreases with increase in pulse OFF time. Mohanty et. al. [4] investigated the machining of Inconel 718 using copper, graphite and brass electrodes using Utility concept and QPSO algorithm. It is observed that MRR can be improved through the use of graphite tool but SR and radial overcut are seriously affected due to higher discharge energy. Joshi et. al. [5] performed the machining of p-type polycrystalline silicon ingot using brass wire in WEDM. They used the RSM technique to get the optimal results. Their results show that the least wafer thickness of 140.5μm is obtained with the kerf width of 130μm and slicing rate of 0.96 mm/min. Puhan et. al. [6] adopted a hybrid approach combining Principal Component Analysis (PCA) and Fuzzy Inference System (FIS) to optimize the machining parameters during machining of Aluminium Silicon Carbide composite. From their analysis, it is observed that the process parameters such as discharge current, pulse ON time, duty factor and flushing pressure have the significant effect on the multi performance characteristics. Majumder et. al. [7] performed the machining of Inconel 800 using brass wire. They used the hybrid GRA-PCA technique to optimize the machining performance. The experimental result shows that with increase in the duration of charging cycle and servo voltage in WEDM, the cutting time reduces up to a

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threshold after which it increases. Also they found that surface roughness increases with increase of pulse ON time appreciably. Saha et. al. [8] performed the machining of Tubular coated nanocomposite based electrode (Nanocarb 110) using brass wire and zinc coated brass wire and applied GRA-PCA hybrid technique to optimize the output performance. It is observed that zinc coated brass wire gives better performance compared to brass wire. Shayan et. al. [9] performed the machining of Cemented Tungsten Carbide (WC-Co) using copper wire. A central composite rotatable method was employed to design the experiments based on RSM. In their work a parametric study, modelling and optimization of dry WEDM process on WC-Co has been fulfilled based on experimental results. Pramanick et. al. [10] adopted Regression analysis and GRA technique for the optimization of output performance during machining of Boron Carbide (B_4C) using brass wire. It is observed that pulse ON time and pulse peak current have strong effect on surface roughness and pulse ON time, water pressure and servo feed rate have strong effect on machining speed respectively. Harish et. al. [11] performed the machining of D2 Steel in WEDM using brass wire and applied the TOPSIS approach to optimize the output performance. They also performed the machining of D2 Steel in WEDM using coated copper wire using the same approach [12]. Patro et. al. [13] proposed a fuzzy model for selection of machining parameters in wire electrical discharge machining of D2 steel. In their work, they concluded that with the increase in pulse ON time and peak current, the MRR increases. Also with increase in peak current and decrease in wire feed, the WWR decreases. They also found that with the decrease in spark voltage and peak current, the surface roughness decreases. Caydas et. al. [14] adopted the Adaptive Neuro-Fuzzy Inference System (ANFIS) model for the optimization of machining parameters in WEDM machining of D5 tool steel. Their result shows that the ANFIS model can greatly improve the process response such as surface roughness and white layer thickness in the WEDM process. Maji et. al. [15] performed the machining of mild steel using copper tool electrode in EDM process. They find the input-output parameters relationships in both forward and reverse directions using ANFIS technique. They found that the ANFIS model with non-linear membership function distributions gives better performance compared to linear membership function distributions. Dewangan et. al. [16] used the Grey-Fuzzy logic based hybrid optimization technique during machining of P20 tool steel in EDM process. The result shows that pulse ON time is the most significant parameter followed by discharge current, whereas tool work time and tool lift time do not have significant effect. In the present work, Grey-Fuzzy approach is adopted to select the machining parameters during the machining of D2 steel in order to get the optimal output performance. Also, ANOVA is carried out to know the contribution of each input parameters on the machining performance.

II. METHODOLOGY

2.1 Grey Relational Analysis

Grey Relational Analysis (GRA) is a popular technique to find the optimal combination of machining parameters. Grey is a colour in between black and white. Here, white means best result and black means worst result. So, grey is a result in between the worst and the best [17]. This technique gives an intermediate result. The first step in GRA is to normalize the experimental data in the range of zero to one. The normalization is necessary as all the responses can be expressed in the range of zero to one.

If the response is of 'larger-the-better' type, the equation for normalization is as follows:

$$x_i(k) = \frac{yi(k) - minyi(k)}{maxyi(k) - minyi(k)} \tag{1}$$

where i = Experiment Number

k = Response Number

$x_i(k)$ = Normalized value of k^{th} response for i^{th} experiment

$y_i(k)$ = value of k^{th} response for i^{th} experiment

max $y_i(k)$ = Maximum value of k^{th} response in the total set of experiments

min $y_i(k)$ = Minimum value of k^{th} response in the total set of experiments

If the response is following 'smaller-the-better' criteria, then the following equation is to be used for normalization:

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$$x_i(k) = \frac{max yi(k) - yi(k)}{max yi(k) - min yi(k)} \quad (2)$$

After normalization, the next step is to calculate the Grey Relational Coefficient (GRC). GRC is calculated using the equation given as follows:

$$\xi_i(k) = \frac{\Delta min + \Psi \Delta max}{\Delta i(k) + \Psi \Delta max} \quad (3)$$

where $\Delta_i(k)$ is the absolute value of the difference between $x_o(k)$ and $x_i(k)$.

$$\Delta_i(k) = |xo(k) - xi(k)| \quad (4)$$

where $x_o(k)$ is the best normalized result and it is equal to 1. Δ_{max} and Δ_{min} are the global maximum and global minimum in the particular data set. Ψ is the distinguishing coefficient and is generally taken as 0.5.

2.2 Grey-Fuzzy Logic

The values obtained using GRA technique has some level of uncertainty. This uncertainty can be effectively examined by using Fuzzy Logic approach. So, this type of multi response optimization problem can be solved using hybrid Grey-Fuzzy Logic technique.

Fuzzy logic approach (Mamdani approach) consists of Fuzzifier, Membership Function, Fuzzy Rule Base, Fuzzy Inference Engine and Defuzzifier. In this method, the fuzzifier uses membership functions to fuzzify the Grey Relational Coefficient (GRC). The fuzzy inference engine uses the fuzzy rules to convert fuzzified data into fuzzy values. Finally, the defuzzifier converts the fuzzified values into equivalent Grey Fuzzy Relational Grade (GFRG) values.

2.3 Procedure in Grey-Fuzzy Logic technique

The steps involve in Grey-Fuzzy Logic technique is shown in fig. 1 and is as follows:

1. The experimental values of MRR, TWR, SR and kerf width are normalized in the range of 0 to 1.
2. The Grey Relational Coefficient (GRC) value of each response is calculated.
3. Then Fuzzy logic technique is applied. The GRC values are expressed in membership function using fuzzifier.
4. Then the fuzzy rules are fired and finally defuzzifier converts fuzzy values into Grey Fuzzy Relational Grade (GFRG).
5. The optimal combination of machining parameters is obtained with the help of main effect plots for GFRG.

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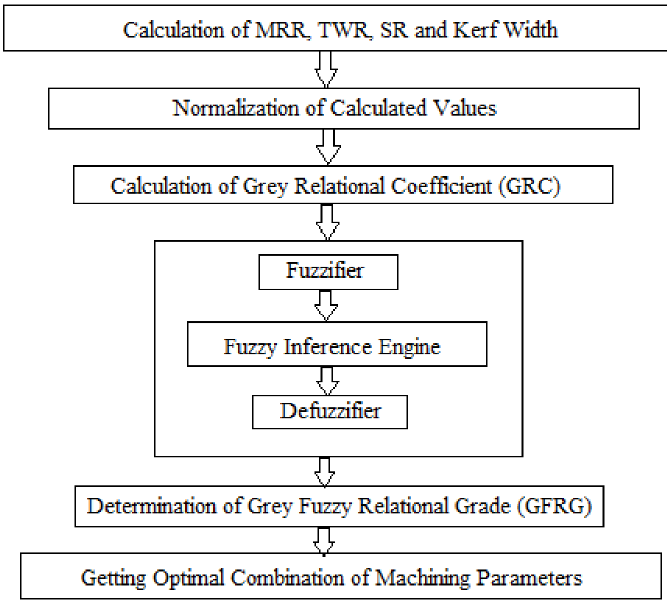

Fig. 1 Steps in Grey Fuzzy Logic Technique

III. EXPERIMENTAL DETAILS

The experiments were conducted on a wire electrical discharge machine (ELECTRONICA) as shown in fig.2. The input parameters taken in the experiments were pulse ON time, pulse OFF time, spark voltage, peak current, wire feed and wire tension. The details of input parameters with their levels are shown in table 1. The output parameters taken in the experiments were Material Removal Rate (MRR), Tool Wear Rate (TWR), Surface Roughness (SR) and Kerf Width. Apart from the parameters mentioned above, few parameters were kept constant as shown in table 2. The machining of D2 Steel was carried out using a 0.25 mm diameter brass wire. A set of 27 experiments were conducted as per the Taguchi's design of Experiments. The work piece material was cut in a shape of cube of size 10 mm. The set of experiments conducted and the values of MRR, TWR, SR and Kerf Width are shown in table 3.

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Fig. 2 Wire Electrical Discharge Machine

Table 1 Input Parameters with Details

Process Parameters	Symbol	Unit	Levels		
			1	2	3
Pulse ON time	A	μs	110	115	120
Pulse OFF time	B	μs	30	45	60
Spark Voltage	C	volt	15	18	21
Peak Current	D	amp	180	210	240
Wire Feed	E	m/min	2	4	6
Wire Tension	F	gram	6	8	10

Table 2 Constant Parameters

Parameters	Values
Peak Voltage	110 volts
Flushing Pressure	15 kgf/cm^2
Servo Feed	2100 units
Conductivity of Dielectric	20 mho
Work piece Height	10 mm

Table 3 Experimental Details

Exp. No.	A	B	C	D	E	F	MRR (mm^3/s)	TWR (mm^3/s)	SR (μm)	Kerf Width (mm)
1	1	1	1	1	2	3	0.058	0.020	1.60	0.264
2	1	1	2	2	3	1	0.058	0.080	1.60	0.270
3	1	1	3	3	1	2	0.056	0.008	1.73	0.277
4	1	2	1	2	3	1	0.086	0.016	2.32	0.252

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5	1	2	2	3	1	2	0.099	0.036	2.69	0.262
6	1	2	3	1	2	3	0.096	0.040	2.81	0.266
7	1	3	1	3	1	2	0.046	0.020	1.72	0.260
8	1	3	2	1	2	3	0.044	0.028	1.77	0.258
9	1	3	3	2	3	1	0.043	0.072	1.71	0.264
10	2	1	1	1	2	3	0.098	0.048	3.22	0.284
11	2	1	2	2	3	1	0.089	0.056	3.17	0.262
12	2	1	3	3	1	2	0.082	0.048	2.49	0.248
13	2	2	1	2	3	1	0.100	0.032	3.12	0.216
14	2	2	2	3	1	2	0.063	0.036	2.21	0.241
15	2	2	3	1	2	3	0.116	0.040	2.84	0.222
16	2	3	1	3	1	2	0.061	0.032	2.78	0.238
17	2	3	2	1	2	3	0.057	0.040	2.36	0.233
18	2	3	3	2	3	1	0.055	0.076	1.87	0.232
19	3	1	1	1	2	3	0.135	0.080	4.07	0.330
20	3	1	2	2	3	1	0.121	0.036	3.64	0.312
21	3	1	3	3	1	2	0.135	0.084	3.64	0.337
22	3	2	1	2	3	1	0.127	0.036	4.19	0.280
23	3	2	2	3	1	2	0.141	0.120	5.01	0.289
24	3	2	3	1	2	3	0.154	0.120	4.76	0.289
25	3	3	1	3	1	2	0.106	0.120	3.76	0.290
26	3	3	2	1	2	3	0.095	0.100	3.59	0.297
27	3	3	3	2	3	1	0.100	0.120	3.02	0.291

The MRR was calculated using the expression:

MRR = $\frac{wi-wf}{\rho t}$, mm^3/s

where w_i is the weight of work piece before machining in grams

w_f is the weight of work piece after machining in grams

ρ is the density of the work piece material in $gram/mm^3$

t is the machining time in seconds

The TWR was calculated using the expression:

TWR = $\frac{vi-vf}{t}$, mm^3/s

where v_i is the volume of the wire before machining in mm^3

v_f is the volume of the wire after machining in mm^3

t is the machining time in seconds

The Surface Roughness was measured using Talysurf (Mitutoyo) and the R_a values were expressed in microns. The Kerf Width was measured by projecting the machined work piece in the profile projector. It is given as follows:

Kerf Width = $\frac{OD-ID}{2}$, mm

where OD is the outer dimension or dimension of the hole generated after removal of cube material in mm

ID is the inner dimension or dimension of the cube material in mm.

IV. RESULTS AND DISCUSSION

4.1 Calculation of Grey Relational Coefficient (GRC)

The GRA technique was used to normalize the output response in the range of 0 to 1 using the eqn. 1 and 2. The Grey Relational Coefficient (GRC) values for each response were calculated using the eqn. 3. The details are shown in table 4. However, to obtain improved values of output performance and to reduce the uncertainty in the data, the Grey-Fuzzy logic technique is further used to find Grey Fuzzy Relational Grade (GFRG).

Table 4 Calculation of Grey Relational Coefficient (GRC) and Grey Fuzzy Relational Grade (GFRG)

Exp. No.	Normalized value				Grey Relational Coefficient (GRC)				GFRG	Ranking
	MRR	TWR	SR	Kerf Width	MRR	TWR	SR	Kerf Width		
1	0.1351	0.8928	1.0000	0.6033	0.3663	0.8234	1.0000	0.5576	0.6868	2
2	0.1351	0.3571	1.0000	0.5537	0.3663	0.4375	1.0000	0.5284	0.5830	13
3	0.1171	1.0000	0.9619	0.4959	0.3616	1.0000	0.9292	0.4979	0.6972	1
4	0.3874	0.9286	0.7888	0.7025	0.4494	0.8750	0.7030	0.6269	0.6636	6
5	0.5045	0.7500	0.6803	0.6198	0.5022	0.6667	0.6099	0.5680	0.5867	12
6	0.4775	0.7143	0.6452	0.5868	0.4889	0.6364	0.5849	0.5475	0.5644	16
7	0.0270	0.8928	0.9648	0.6364	0.3394	0.8234	0.9342	0.5789	0.6689	5
8	0.0090	0.8214	0.9501	0.6529	0.3353	0.7368	0.9092	0.5902	0.6428	7
9	0.0000	0.4286	0.9677	0.6033	0.3333	0.4667	0.9393	0.5576	0.5742	15
10	0.4955	0.6428	0.5249	0.4380	0.4978	0.5833	0.5128	0.4708	0.5162	21
11	0.4144	0.5714	0.5396	0.6198	0.4606	0.5384	0.5206	0.5680	0.5219	20
12	0.3514	0.6428	0.7390	0.7355	0.4353	0.5833	0.6570	0.6540	0.5824	14
13	0.5135	0.7857	0.5542	1.0000	0.5068	0.6999	0.5286	1.0000	0.6838	3
14	0.1802	0.7500	0.8211	0.7934	0.3788	0.6667	0.7365	0.7076	0.6224	8
15	0.6576	0.7143	0.6364	0.9504	0.5935	0.6364	0.5790	0.9098	0.6797	4
16	0.1622	0.7857	0.6539	0.8182	0.3737	0.6999	0.5909	0.7334	0.5995	11
17	0.1261	0.7143	0.7771	0.8595	0.3639	0.6364	0.6916	0.7806	0.6181	9
18	0.1081	0.3928	0.9208	0.8678	0.3592	0.4516	0.8632	0.7909	0.6162	10
19	0.8288	0.3571	0.2756	0.0578	0.7449	0.4375	0.4084	0.3467	0.4844	23
20	0.7027	0.7500	0.4018	0.2066	0.6271	0.6667	0.4553	0.3866	0.5339	19
21	0.8288	0.3214	0.4018	0.0000	0.7449	0.4242	0.4553	0.3333	0.4894	22
22	0.7568	0.7500	0.2405	0.4710	0.6728	0.6667	0.3969	0.4859	0.5556	17

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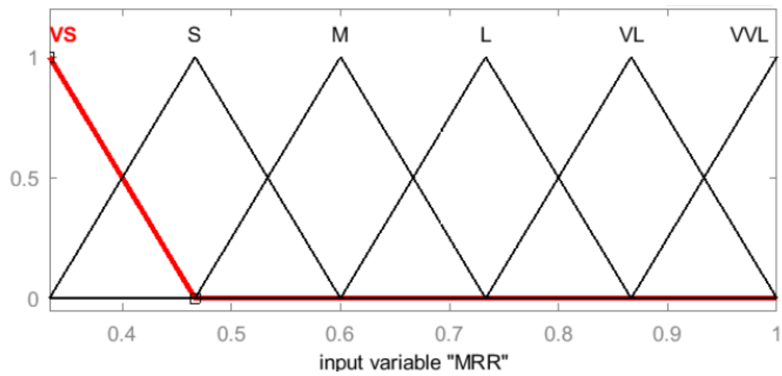
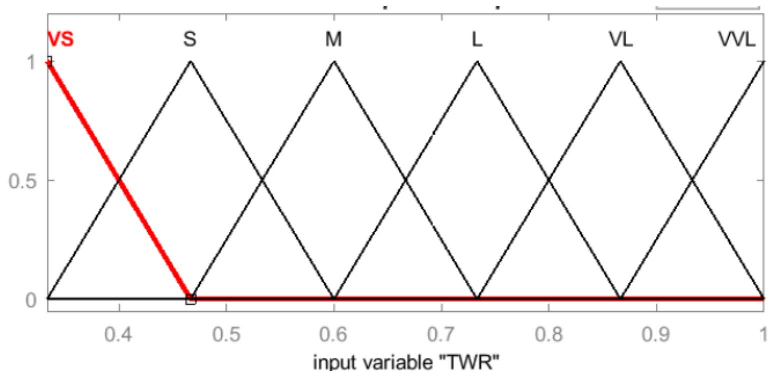
23	0.8288	0.0000	0.0000	0.3967	0.8101	0.3333	0.3333	0.4532	0.4825	24
24	1.0000	0.0000	0.0733	0.3967	1.0000	0.3333	0.3504	0.4532	0.5342	18
25	0.5676	0.0000	0.3666	0.3884	0.5362	0.3333	0.4411	0.4498	0.4401	26
26	0.4685	0.1786	0.4164	0.3306	0.4847	0.3784	0.4614	0.4276	0.4380	27
27	0.5135	0.0000	0.5836	0.3802	0.5068	0.3333	0.5456	0.4465	0.4580	25

4.2 Determination of Grey Fuzzy Relational Grade (GFRG)

The Grey Relational Coefficient (GRC) values of each response were modelled using fuzzy approach (Mamdani Approach) in Matlab 2007b software. The four responses, namely, MRR, TWR, SR and Kerf Width were taken as input parameters, each having six levels were expressed using triangular membership function. The levels were expressed using linguistic terms like Very Small (VS), Small (S), Medium (M), Large (L), Very Large (VL) and Very Very Large (VVL). Similarly, the output variable is also expressed in six levels using triangular membership function. The membership functions of input and output variables are shown in fig.3. The relationship between the inputs and output is expressed in the form of ‘if-then’ statements called as fuzzy rules. A total of 27 rules were fired in the modelling as shown in fig.4. The expression of a rule is as follows:

Rule 1: If MRR is Very Small and TWR is Very Large and SR is Very Very Large and Kerf Width is Medium then GFRG is Very Very Large.





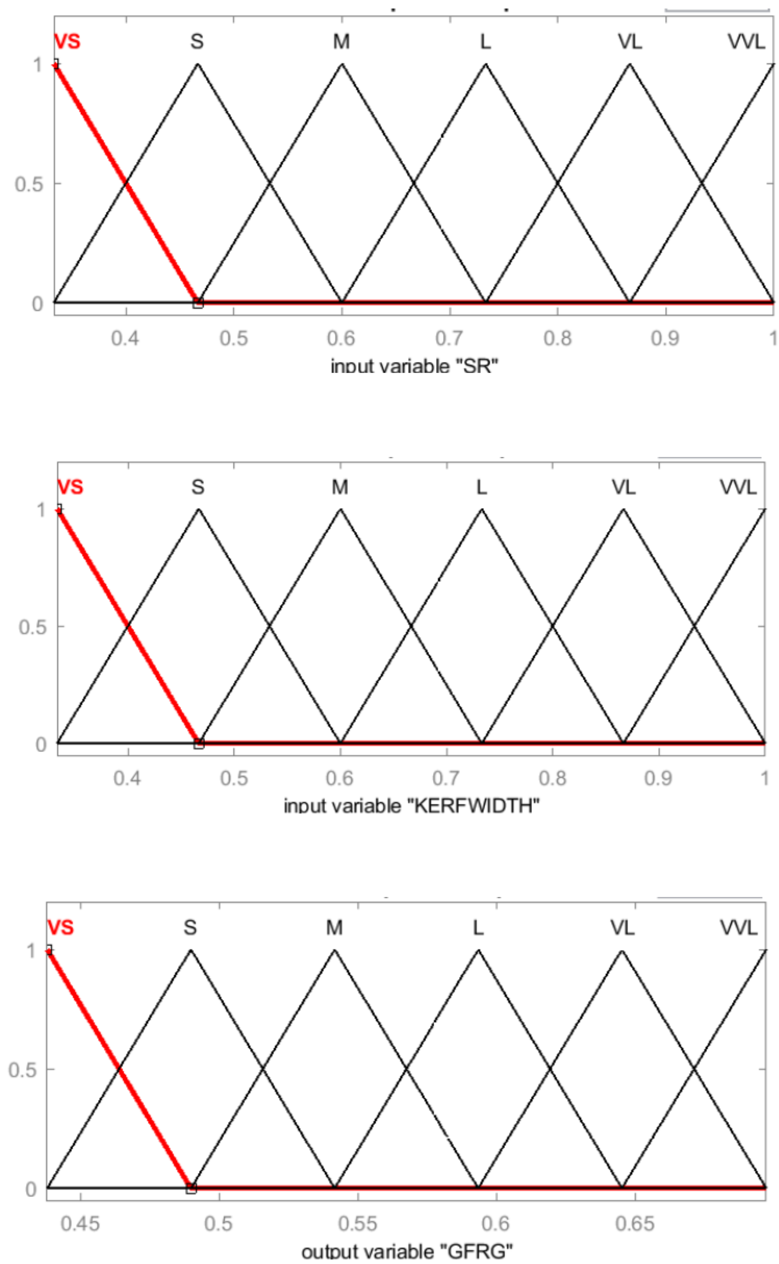


Fig. 3 Membership Function of Input and Output Variables

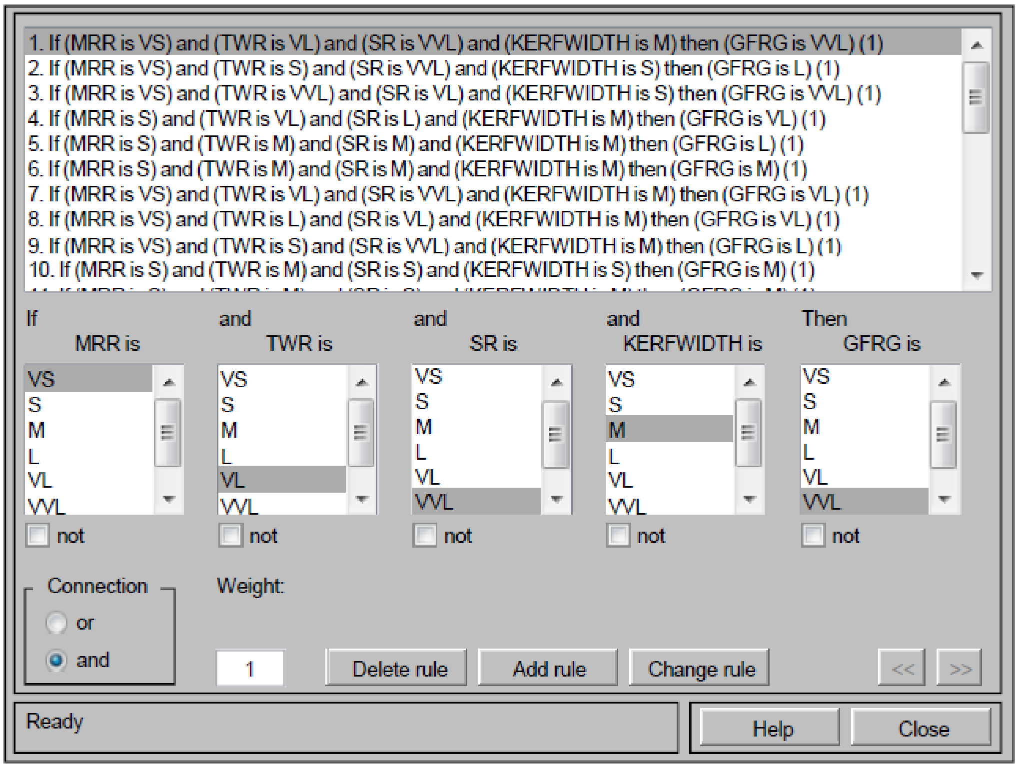


Fig. 4 Fuzzy Rules

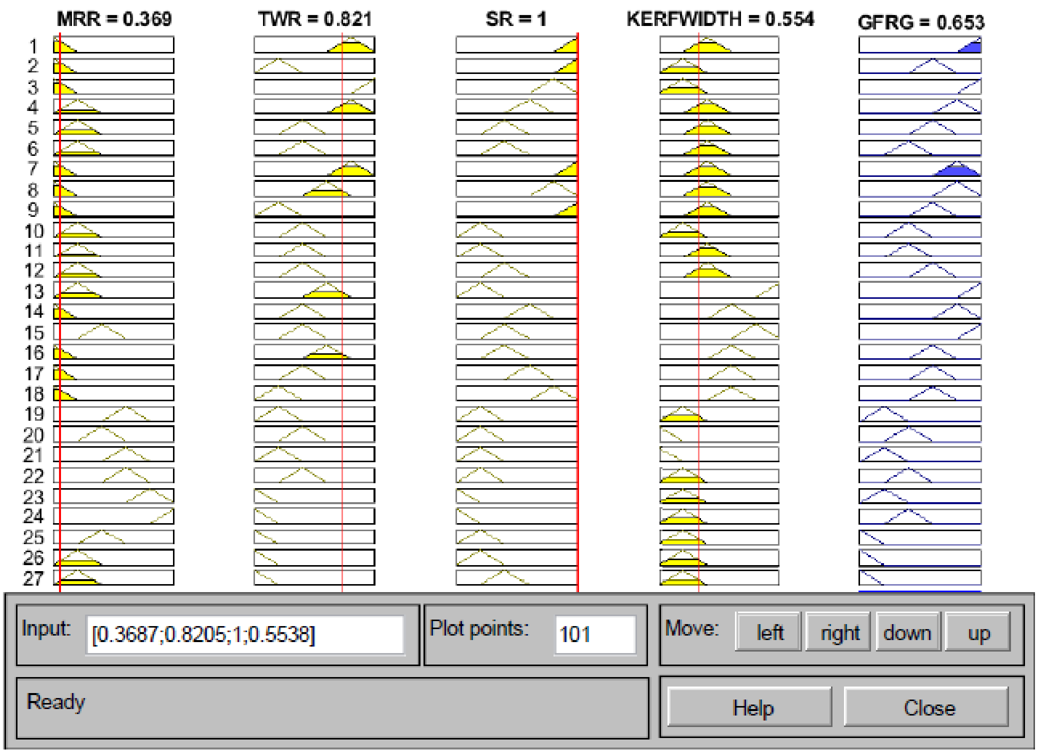


Fig. 5 Graphical Representation of Fuzzy Values

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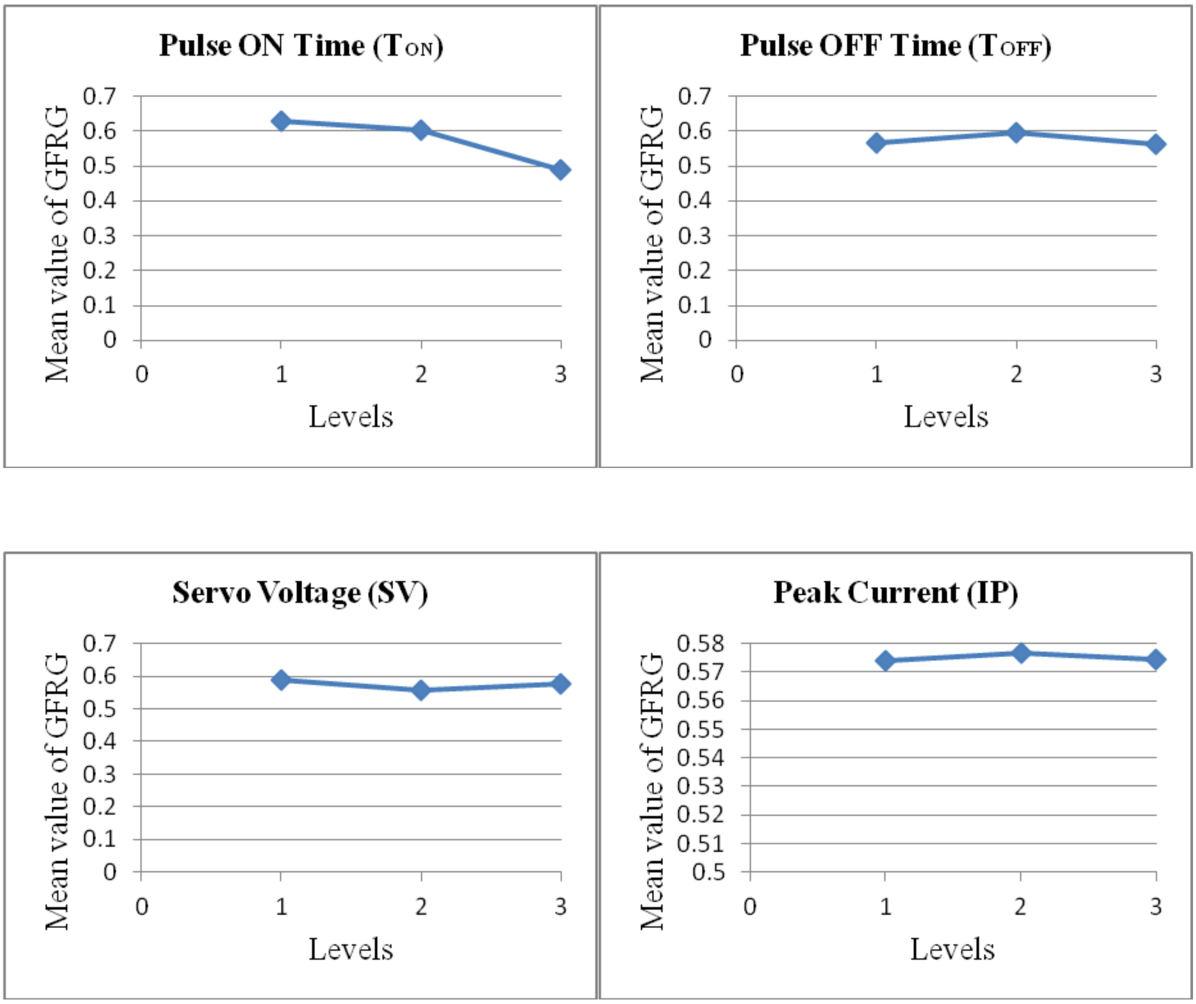
The graphical representation of the modelled values is shown in fig.5. The GFRG values were ranked from the highest value to the lowest value as shown in table 4. The higher value means most favourable condition. Based on table 5 and fig.6, the optimal combination of input parameters is found to be Pulse ON time (Level – 1), Pulse OFF time (Level - 2), Spark Voltage (Level - 1), Peak Current (Level - 2), Wire Feed (Level - 3) and Wire Tension (Level - 1). This corresponds to Experiment Number 4 where Pulse ON time is 110µs, Pulse OFF time is 45µs, Spark Voltage is 15volts, Peak Current is 210Amps, Wire Feed is 6m/min and Wire Tension is 6grams. The difference between the maximum and minimum values of GFRG is also calculated and shown in table 5.

Table 5 Mean value of GFRG at different levels

Levels	Input Parameters					
	T_{ON}	T_{OFF}	SV	IP	WF	WT
1	**0.6297**	0.5661	**0.5888**	0.5738	0.5743	**0.5767**
2	0.6045	**0.5969**	0.5588	**0.5767**	0.5738	0.5743
3	0.4907	0.5618	0.5773	0.5743	**0.5767**	0.5738
Δ = Max-Min	0.1390	0.0351	0.0300	0.0029	0.0029	0.0029
Ranking	1	2	3	4	5	6



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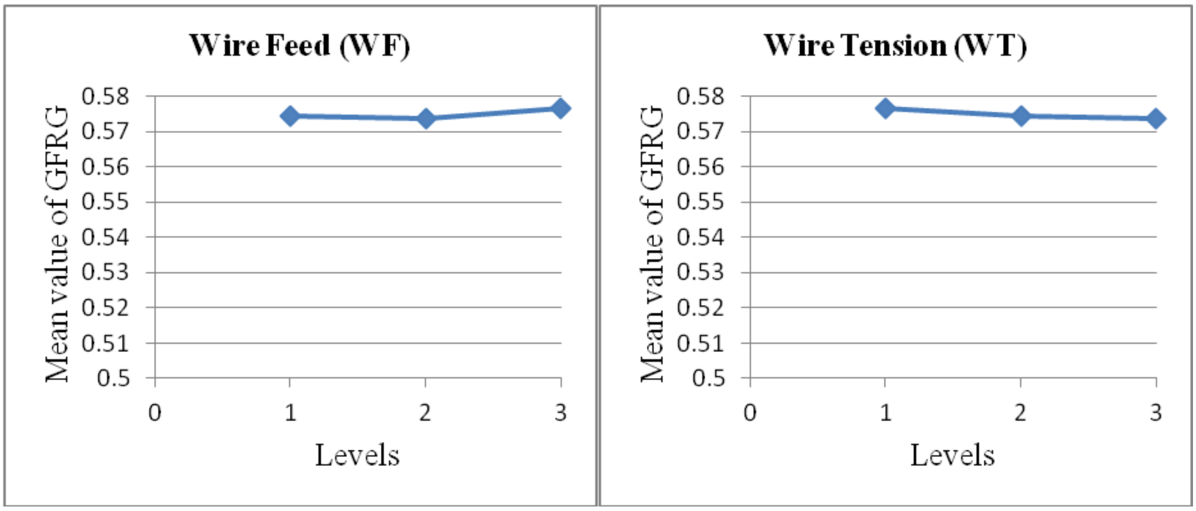

Fig. 6 Plot showing the Mean value of GFRG for the input parameters at different levels

4.3 Analysis of Variance (ANOVA)

Analysis of Variance (ANOVA) is carried out to know the contribution of each input parameter on the output performance. Here, the ANOVA of GFRG is carried out as shown in table 6. The result shows that Pulse ON time is the most significant parameter which influences the output performance. The error means the interaction between the input parameters which contributes next to Pulse ON time.

Table 6 ANOVA for Grey Fuzzy Relational Grade (GFRG)

Parameters	DOF	SS	MS	Percentage Contribution
Pulse ON time	2	0.0987	0.0494	60.63
Pulse OFF time	2	0.0066	0.0033	4.05
Spark Voltage	2	0.0041	0.0021	2.52
Peak Current	2	0.000043	0.000022	0.026
Wire Feed	2	0.000043	0.000022	0.026
Wire Tension	2	0.000043	0.000022	0.026
Error	14	0.0533	0.0038	32.74
Total	26	0.1628		100.00

V. CONCLUSIONS

The following conclusions were drawn from the present study:

1. The optimal combination was obtained as Pulse ON time = 110 µs, Pulse OFF time = 45 µs, Spark Voltage = 15 volt, Peak Current = 210 Amp, Wire Feed = 6 m/min and Wire Tension = 6 gram using Grey-Fuzzy logic technique.
2. The ANOVA result shows that Pulse ON time is having the highest influence on the output performance. The interaction between the input parameters contributes next to pulse ON time.
3. The Grey-Fuzzy logic technique is having the good potential to give an optimal result in WEDM process.
4. This technique does not give best result for one output parameter but gives an optimal result for multiple output parameters keeping equal importance to all output parameters.
5. This technique can be applied to other machining operations to get the optimal output performance.

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