A Fuzzy Modelling for Selection of Machining Parameters in Wire Electrical Discharge Machining of D2 Steel

Santosh Patro, I. Harish, P. Srinivasa Rao

***Abstract:** Wire Electrical Discharge Machining (WEDM) is a widely used non-traditional machining process used for machining of hard and difficult-to-machine materials. Proper selection of machining parameters in WEDM is required for better output performance, such as Material Removal Rate (MRR), Wire Wear Rate (WWR) and Surface Roughness (SR) etc. In the present paper, Pulse ON time, Pulse OFF time, Peak Current, Spark Voltage, Wire Feed and Wire Tension were taken as the input parameters to optimize MRR, WWR and SR. A set of 27 experiments were performed as per Taguchi Design. A Fuzzy model has been proposed to select the optimum values of machining parameters. The proposed fuzzy model was found to predict the experimental values with more than 90 percent accuracy.*

***Keywords:** Material Removal Rate, Wire Wear Rate, Surface Roughness, Orthogonal Array.*

I. INTRODUCTION

Wire Electrical Discharge Machining (WEDM) is a widely used non-traditional machining process used for machining of hard and difficult-to-machine materials. The basic concept of WEDM process is cratering out of metal due to sudden stoppage of electron beam by the solid metal surface leading to reaching of the surface to its boiling point temperature and evaporation [1]. WEDM can be used for machining of any material provided the material should have some electrical conductivity. It has been used for manufacturing of components used in automobile, aerospace and machine tool industries [2]. Proper selection of machining parameters in WEDM is required for better output performance. The traditional Taguchi technique used widely is suitable for single response optimization. In order to have multi response optimization, a number of techniques have been developed. Kumar et. al. [4] used fuzzy approach for the optimization of process parameters in the machining of Aluminium Metal Fuzzy modelling is one of the widely used multi response optimization technique as it predict the optimal values with greater accuracy. Shabgard et. al. [3] investigated the machining of Tungsten Carbide-Cobalt (WC-Co) metal matrix composite in EDM and Ultrasonic assisted EDM using Fuzzy approach. In their result, they showed that proposed fuzzy model was in accordance to the experimental findings. Matrix Composite (AMMC). They found the optimal set of parameters to get the desired outputs. Dewangan et. al. [5] experimented the machining of AISI P20 tool steel to get the optimal machining parameters using Grey-Fuzzy logic based hybrid optimization technique. The optimum EDM parameters were obtained for minimum surface integrity of AISI P20 tool steel. Ramanan et. al. [6] adopted Grey-Fuzzy technique to obtain the optimum machining parameters during machining of AA7075-PAC composite. They found that the technique gives the optimal combination of process parameters to obtain the corresponding values of maximum material removal rate and minimum surface roughness. Puhan et. al. [7] investigated the machining of Aluminium Silicon Carbide (AlSiC$_p$) metal matrix composite in EDM and adopted a hybrid approach combining Principal Component Analysis (PCA) and Fuzzy Inference System (FIS) to optimize the machining parameters. It was observed that process parameters such as discharge current, pulse on time, duty factor and flushing pressure have significant effect on the output characteristics. Rao et. al. [8] studied the effect of input parameters like current, duty cycle, servo control and open – circuit voltage on the output performance like MRR, TWR, Surface Roughness and Hardness during machining of AISI 304 Stainless Steel. They developed the Fuzzy model to study the effect of input parameters on output performance. Caydas et. al. [9] adopted ANFIS modelling to improve the machining performance during the machining of AISI D5 tool steel. The result shows that ANFIS modelling can greatly improve the process responses such as surface roughness and white layer thickness. Maji et. al. [10] performed the machining of mild steel in EDM and developed the input-output parameters relationship of EDM process both in forward and reverse directions using ANFIS. The modelling was done using linear as well as non-linear membership function distributions. They found that ANFIS modelling with non-linear membership function distribution gives better results than that with linear membership function distribution. In the present paper, the Fuzzy approach has been utilized to select the machining parameters in WEDM for machining of D2 steel.

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The fuzzy model developed for the selection of process parameters is compared with the experimental results.

II. FUZZY LOGIC

Fuzzy logic technique is used when there is some degree of uncertainty in making decision. Some cases decision is partially true.

In those cases, trueness is assigned with a membership function which range from 0 to 1. The value '1' means completely true and '0' means completely false. The statements which are partially true lies between 0 and 1 [11]. Fuzzy logic technique can be implemented by developing a Fuzzy Logic Controller (FLC). The performance of FLC depends on the Knowledge Base (KB) which consists of Data Base (DB) and Rule Base (RB). The Data Base is the information about the input and output variables involve in the process. These variables are expressed with the help of some linguistic terms like Low, Medium and High etc. The relationship between the input and output variables are developed which are called Rule Base. These rules are expressed as if-then statements.

The fuzzy logic approach (Mamdani approach) consists of four modules: Data Base, Fuzzification, Fuzzy Inference System (Rule Base) and Defuzzification [12].

The steps involve in fuzzy logic approach is shown in fig.1 and are described as follows:

Step – 1: Input and output variables are defined. Input variables are called conditions and output variables are called actions. These variables are expressed with the help of some linguistic terms like Small, Medium and Large etc.

Step – 2: Then we go for fuzzification. Each input and output variables are assigned with a membership function (linear or non-linear). Linear membership functions like triangular, square, trapezoidal membership functions are generally used as they are easy to express.

Step – 3: Next we go for fuzzy inference system. Here, the input-output relationship are developed which are called fuzzy rules and are expressed in the form of 'if-then' statements.

Step – 4: After getting the combined fuzzified output, the defuzzification is carried out. In defuzzification, the combined fuzzified output is converted into a single crisp value. Centroid method is mostly used for defuzzification as it is easy to implement.

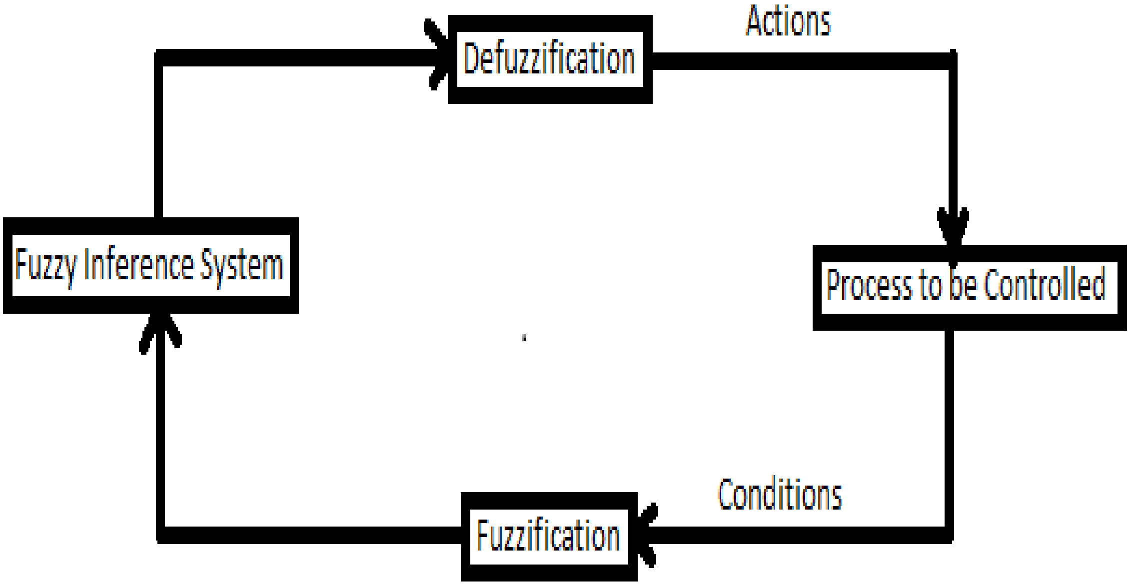


Fig. 1 Fuzzy Logic Approach

III. EXPERIMENTAL SETUP

The experiments were performed on a Wire Electrical Discharge Machine (EZEECUT NXG) 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 the input variables with their levels are shown in table 1. The output responses considered in these experiments were Material Removal Rate (MRR), Wire Wear Rate (WWR) and Surface Roughness (SR). Apart from the parameters mentioned above, the following parameters listed in table 2, were kept constant during the experiments. The machining of D2 steel was carried out using a 0.25mm diameter brass wire. A set of 27 experiments were performed as per the Taguchi design. Cube shapes of size 10 mm were cut using different combination of input parameters as shown in fig.3. The L_{27} orthogonal array used for the experiments and the values of MRR, WWR and SR calculated are shown in table 3.

The MRR was calculated using the expression:

$$\text{MRR} = \frac{Wi-Wf}{\rho t}, \ \text{mm}^3/\text{s}$$

where w_i is the weight of workpiece before machining in grams, w_f is the weight of workpiece after machining in grams, ρ is the density of the workpiece material in gram/mm^3 and t is the machining time in seconds.

The WWR was calculated by using the relation:

$$\text{WWR} = \frac{Vi-Vf}{t}, \ \text{mm}^3/\text{s}$$

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 and t is the machining time in seconds.

Fig. 2 Wire Electrical Discharge Machine

The Surface Roughness was measured using Talysurf (Mitutoyo) and the R$_a$ values were expressed in microns.

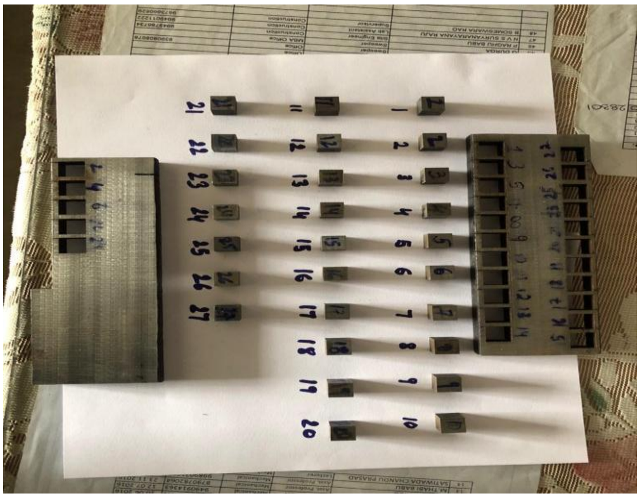


Fig. 3 Workpiece

Table 1 Input Parameters with their levels

Input Parameters	Symbol	Unit	Levels		
			1	2	3
Pulse ON Time	A	µs	0.35	0.875	1.4
Pulse OFF Time	B	µs	14	33	52
Spark Voltage	C	volt	10	30	50
Peak Current	D	amp	70	150	230
Wire Feed	E	m/min	4	8	12
Wire Tension	F	gram	500	1150	1800

Table 2 Parameters kept constant during the experiments

Parameters	Values
Peak Voltage	110 volts
Flushing Pressure	15 kgf/cm^2
Servo Feed	2050 units
Conductivity of Dielectric	20 mho
Workpiece Height	10 mm

IV. FUZZY MODELLING

The experimental values were modelled using fuzzy approach (Mamdini approach) in Matlab 2007b software to get the optimal machining conditions. The input parameters, each having 3 levels were expressed using triangular membership function. The levels were expressed using linguistic terms like Small (S), Medium (M) and Large (L).

The expressions of membership function for each input variable are shown in fig.4 to 9. Similarly, the output variables are also expressed using triangular membership function with linguistic terms like Very Small (VS), Small (S), Medium (M), Large (L) and Very Large (VL) as shown in fig. 10 to 12.

Table 3 L27 orthogonal array used for the experiments

Exp. No.	A	B	C	D	E	F	MRR (mm^3/s)	WWR (mm^3/s)	SR (µm)
1	1	1	1	1	2	3	0.0315	6.03×10^{-3}	2.650
2	1	1	2	2	3	1	0.0791	8.30×10^{-3}	3.457
3	1	1	3	3	1	2	0.1162	2.30×10^{-3}	3.752
4	1	2	1	2	3	1	0.0676	8.30×10^{-3}	3.240
5	1	2	2	3	1	2	0.1063	2.30×10^{-3}	3.375

6	1	2	3	1	2	3	0.0353	6.03 x 10^{-3}	4.254
7	1	3	1	3	1	2	0.1111	2.30 x 10^{-3}	4.841
8	1	3	2	1	2	3	0.0827	6.02 x 10^{-3}	3.780
9	1	3	3	2	3	1	0.0793	8.30 x 10^{-3}	5.055
10	2	1	1	1	2	3	0.0945	5.53 x 10^{-3}	4.822
11	2	1	2	2	3	1	0.122	8.30 x 10^{-3}	4.326
12	2	1	3	3	1	2	0.079	2.30 x 10^{-3}	4.978
13	2	2	1	2	3	1	0.0838	8.30 x 10^{-3}	5.141
14	2	2	2	3	1	2	0.1053	2.30 x 10^{-3}	3.623
15	2	2	3	1	2	3	0.0194	6.03 x 10^{-3}	5.035
16	2	3	1	3	1	2	0.0978	2.30 x 10^{-3}	3.772
17	2	3	2	1	2	3	0.0423	6.03 x 10^{-3}	4.824
18	2	3	3	2	3	1	0.0836	8.30 x 10^{-3}	4.583
19	3	1	1	1	2	3	0.0496	6.01 x 10^{-3}	4.619
20	3	1	2	2	3	1	0.0961	8.28 x 10^{-3}	5.175
21	3	1	3	3	1	2	0.1206	2.30 x 10^{-3}	5.109
22	3	2	1	2	3	1	0.1011	8.30 x 10^{-3}	5.085
23	3	2	2	3	1	2	0.1015	2.30 x 10^{-3}	4.884
24	3	2	3	1	2	3	0.0338	6.03 x 10^{-3}	3.731
25	3	3	1	3	1	2	0.0921	2.30 x 10^{-3}	5.019
26	3	3	2	1	2	3	0.0624	6.03 x 10^{-3}	4.862
27	3	3	3	2	3	1	0.0104	8.30 x 10^{-3}	4.590

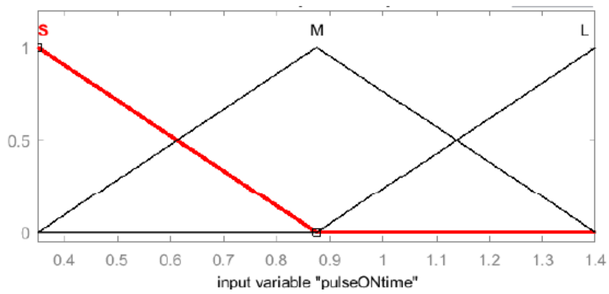


Fig. 4 Membership Function for Pulse ON time

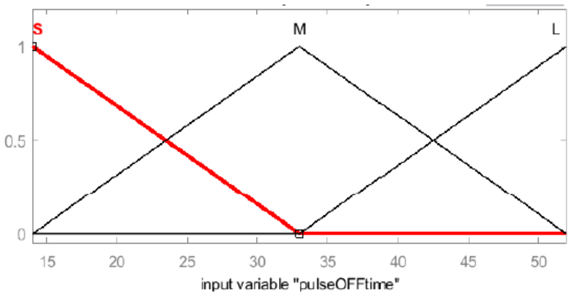


Fig. 5 Membership Function for Pulse OFF time

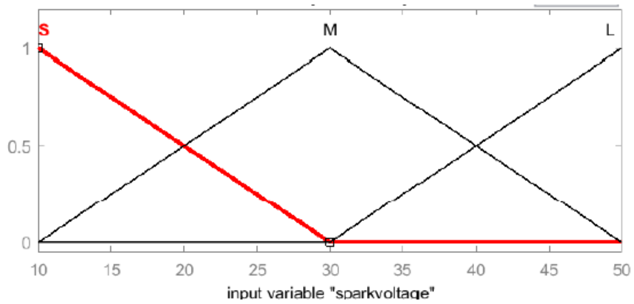


Fig. 6 Membership Function for Spark Voltage

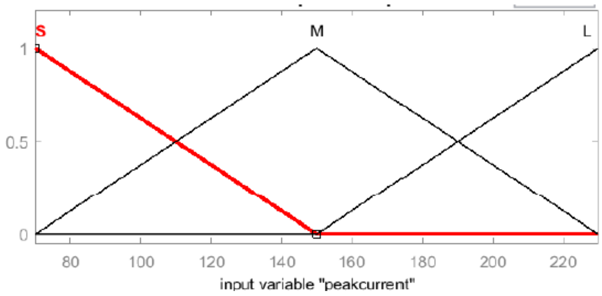


Fig. 7 Membership Function for Peak Current

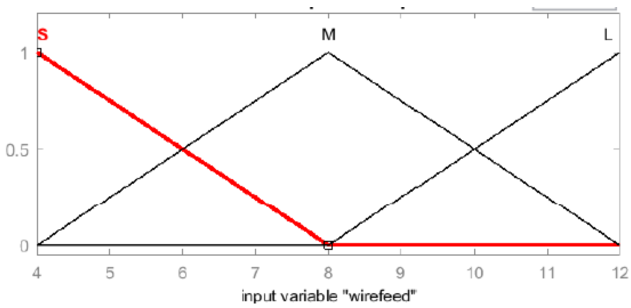


Fig. 8 Membership Function for Wire Feed

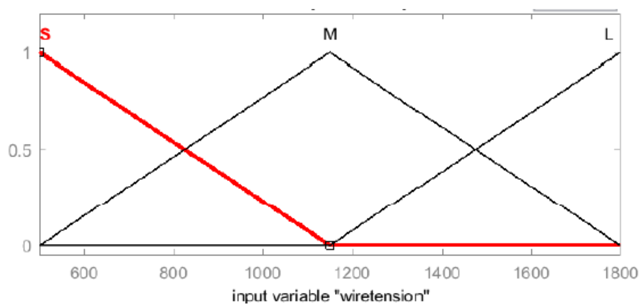


Fig. 9 Membership Function for Wire Tension

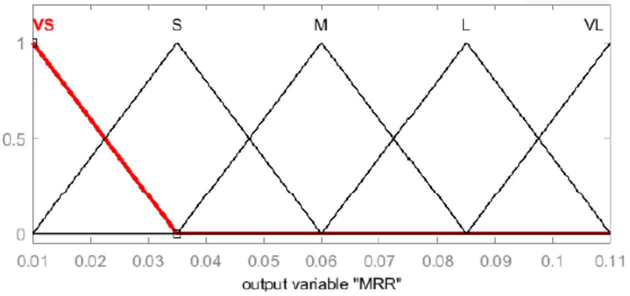


Fig. 10 Membership Function for MRR

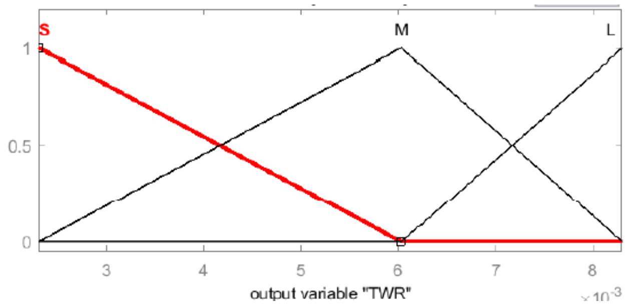


Fig. 11 Membership Function for WWR

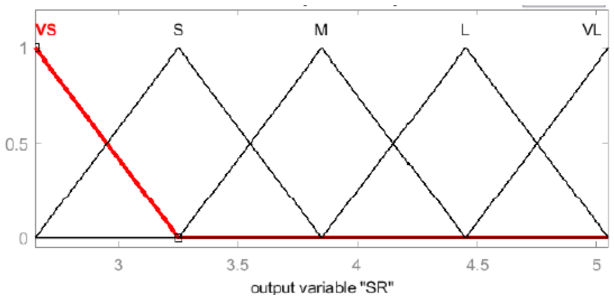


Fig. 12 Membership Function for SR

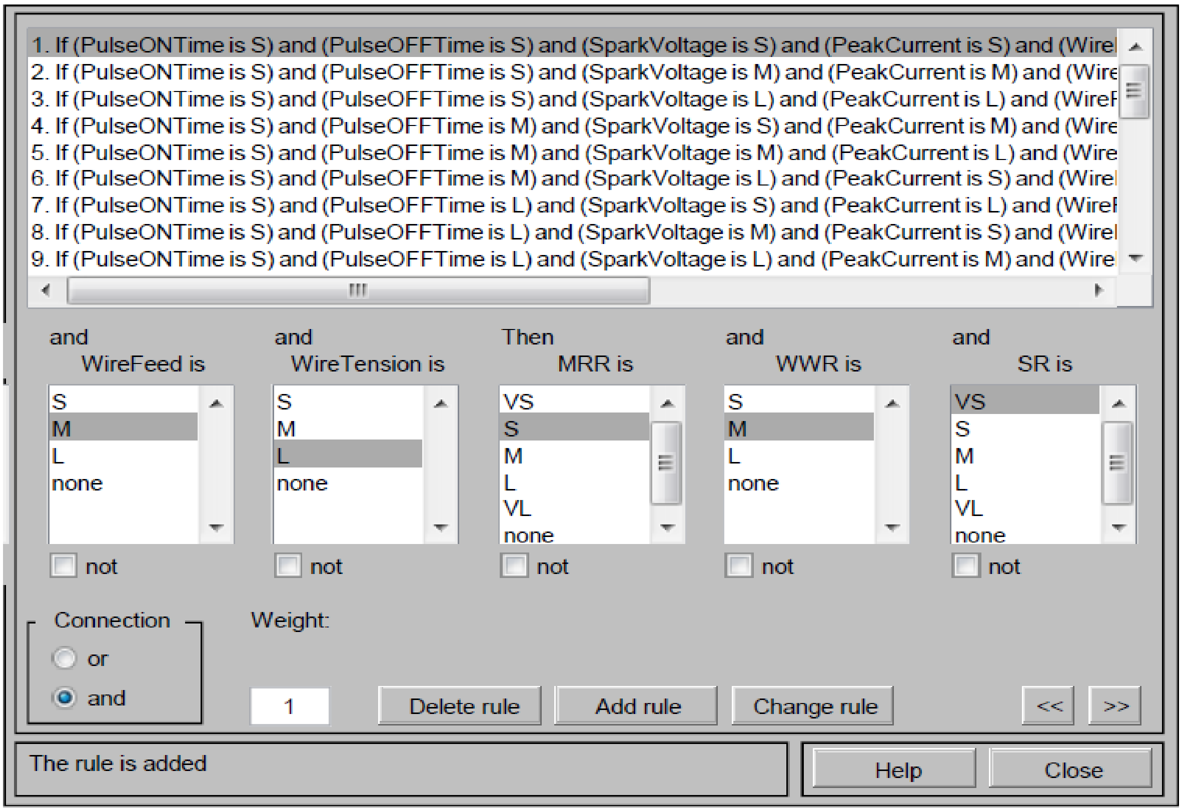
V. RESULTS AND DISCUSSIONS

The input-output relationships were developed by setting the rules in the form of if-then statements. A total of 27 rules were fired in the modelling as shown in fig. 13. The expression of a rule is as follows:

Rule 1: If Pulse ON time is Small and Pulse OFF time is Small and Servo Voltage is Small and Peak Current is Small and Wire Feed is Medium and Wire Tension is Large then MRR is Small and WWR is Medium and SR is Very Small.

The fuzzified output as obtained using fuzzy modelling is defuzzified using centroid method to get a crisp value. The graphical representation of modelled values obtained using fuzzy approach is shown in fig. 14. These modelled values are then compared with the experimental values and the accuracy of modelled values was checked.

The modelled values obtained using fuzzy logic approach (Mamdani approach) is compared with the experimental values as shown in table 4. It was found that the modelled values were comparable with the experimental values with more than 90 percent accuracy in most of the cases. The graphical representation of variation of MRR, WWR and SR for different values of input parameters is shown in fig. 15 to 17.



1. If (PulseONTime is S) and (PulseOFFTime is S) and (SparkVoltage is S) and (PeakCurrent is S) and (Wire
2. If (PulseONTime is S) and (PulseOFFTime is S) and (SparkVoltage is M) and (PeakCurrent is M) and (Wire
3. If (PulseONTime is S) and (PulseOFFTime is S) and (SparkVoltage is L) and (PeakCurrent is L) and (WireF
4. If (PulseONTime is S) and (PulseOFFTime is M) and (SparkVoltage is S) and (PeakCurrent is M) and (Wire
5. If (PulseONTime is S) and (PulseOFFTime is M) and (SparkVoltage is M) and (PeakCurrent is L) and (Wire
6. If (PulseONTime is S) and (PulseOFFTime is M) and (SparkVoltage is L) and (PeakCurrent is S) and (Wire
7. If (PulseONTime is S) and (PulseOFFTime is L) and (SparkVoltage is S) and (PeakCurrent is L) and (WireF
8. If (PulseONTime is S) and (PulseOFFTime is L) and (SparkVoltage is M) and (PeakCurrent is S) and (Wire
9. If (PulseONTime is S) and (PulseOFFTime is L) and (SparkVoltage is L) and (PeakCurrent is M) and (Wire

and WireFeed is: S, M, L, none — ☐ not

and WireTension is: S, M, L, none — ☐ not

Then MRR is: VS, S, M, L, VL, none — ☐ not

and WWR is: S, M, L, none — ☐ not

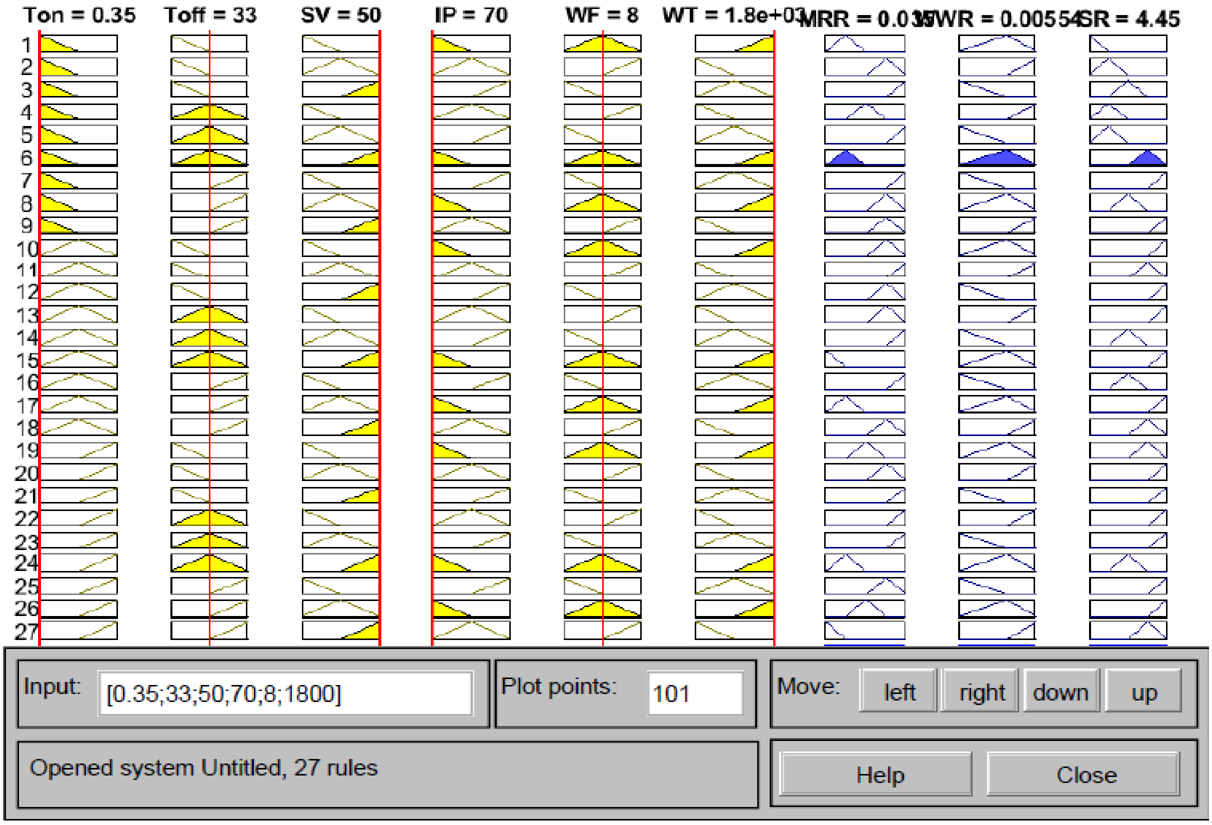
and SR is: VS, S, M, L, VL, none — ☐ not

Connection: ○ or ● and

Weight: 1

The rule is added

Fig. 13 Fuzzy Rules



Input: [0.35;33;50;70;8;1800]

Plot points: 101

Opened system Untitled, 27 rules

Fig. 14 Graphical Representation of Modelled values

Table 4 Comparison between Experimental Values and Modelled Values

Exp. No.	Experimental Values			Modelled Values			Percentage Accuracy		
	MRR	WWR	SR	MRR	WWR	SR	MRR	WWR	SR
	mm^3/s	mm^3/s	µm	mm^3/s	mm^3/s	µm	%	%	%
1	0.0315	6.03x10^{-3}	2.650	0.035	5.5x10^{-3}	2.84	89	91.21	92.83
2	0.0791	8.30x10^{-3}	3.457	0.085	7.6x10^{-3}	3.25	92.54	91.56	94.01
3	0.1162	2.30x10^{-3}	3.752	0.102	3.5x10^{-3}	3.85	87.78	47.83	97.38
4	0.0676	8.30x10^{-3}	3.240	0.06	7.6x10^{-3}	3.25	88.76	91.56	99.69
5	0.1063	2.30x10^{-3}	3.375	0.102	3.5x10^{-3}	3.25	95.95	47.83	96.29
6	0.0353	6.03x10^{-3}	4.254	0.035	5.5x10^{-3}	4.45	99.15	91.21	95.39
7	0.1111	2.30x10^{-3}	4.841	0.102	3.5x10^{-3}	4.86	91.81	47.83	99.61
8	0.0827	6.03x10^{-3}	3.780	0.085	5.5x10^{-3}	3.85	97.29	91.21	98.15
9	0.0793	8.30x10^{-3}	5.055	0.085	7.6x10^{-3}	4.86	92.81	91.56	96.14
10	0.0945	5.50x10^{-3}	4.822	0.085	5.5x10^{-3}	4.86	89.95	100	99.21
11	0.122	8.30x10^{-3}	4.326	0.102	7.6x10^{-3}	4.45	83.61	91.56	97.13
12	0.079	2.30x10^{-3}	4.978	0.085	3.5x10^{-3}	4.86	92.40	47.83	97.63
13	0.0838	8.30x10^{-3}	5.141	0.085	7.6x10^{-3}	4.86	98.56	91.56	94.53
14	0.1053	2.30x10^{-3}	3.623	0.102	3.5x10^{-3}	3.85	96.86	47.83	93.73
15	0.0194	6.03x10^{-3}	5.035	0.018	5.5x10^{-3}	4.86	92.78	91.21	96.52
16	0.0978	2.30x10^{-3}	3.772	0.102	3.5x10^{-3}	3.85	95.70	47.83	97.93
17	0.0423	6.03x10^{-3}	4.824	0.035	5.5x10^{-3}	4.86	82.64	91.21	99.25
18	0.0836	8.30x10^{-3}	4.583	0.085	7.6x10^{-3}	4.45	98.33	91.56	97.09
19	0.0496	6.01x10^{-3}	4.619	0.06	5.5x10^{-3}	4.45	79.03	91.21	96.34
20	0.0961	8.28x10^{-3}	5.175	0.085	7.6x10^{-3}	4.86	88.40	91.56	93.91
21	0.1206	2.30x10^{-3}	5.109	0.102	3.5x10^{-3}	4.86	84.58	47.83	95.12
22	0.1011	8.30x10^{-3}	5.085	0.102	7.6x10^{-3}	4.86	99.11	91.56	95.58
23	0.1015	2.30x10^{-3}	4.884	0.102	3.5x10^{-3}	4.86	99.51	47.83	99.51
24	0.0338	6.03x10^{-3}	3.731	0.035	5.5x10^{-3}	3.85	96.45	91.21	96.81
25	0.0921	2.30x10^{-3}	5.019	0.085	3.5x10^{-3}	4.86	92.29	47.83	96.83
26	0.0624	6.03x10^{-3}	4.862	0.06	5.5x10^{-3}	4.86	96.15	91.21	99.96
27	0.0104	8.30x10^{-3}	4.590	0.018	7.6x10^{-3}	4.45	27.75	91.56	96.95

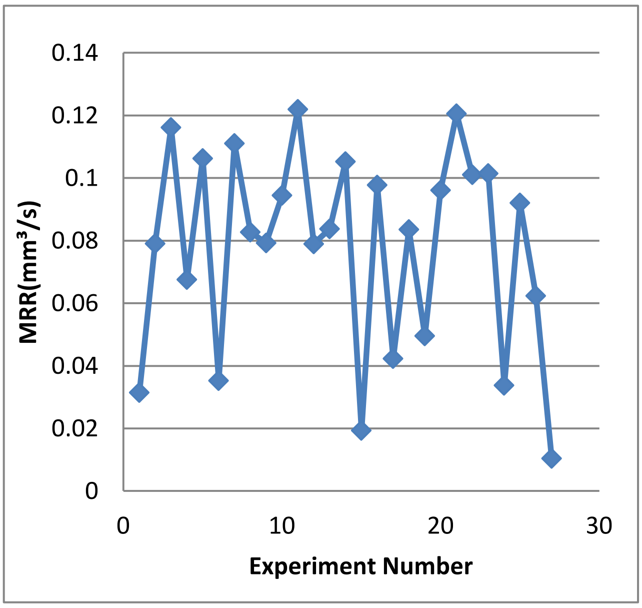


Fig. 15 Graphical Representation of Variation of MRR

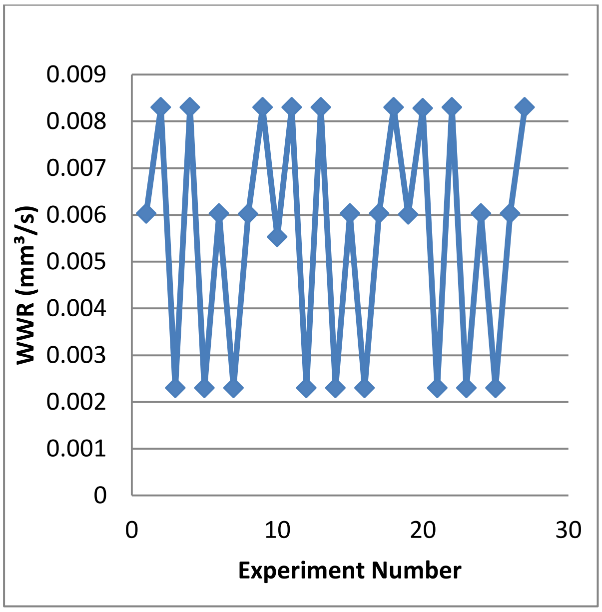


Fig. 16 Graphical Representation of Variation of WWR

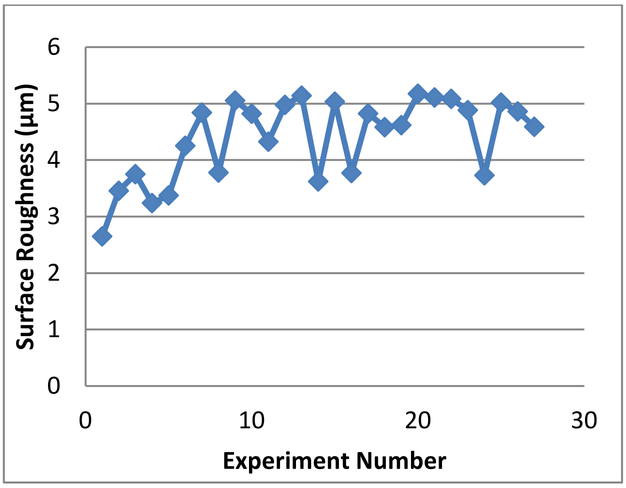


Fig. 17 Graphical Representation of Variation of SR

VI. CONCLUSIONS

The conclusions drawn from the present study are as follows:

1) The proposed fuzzy model was found to be in agreement with the experimental results.
2) With increase in Pulse ON time and Peak Current the Material Removal Rate increases.
3) With increase in Peak Current and decrease in Wire Feed the Wire Wear Rate decreases.
4) With decrease in Spark Voltage and Peak Current the Surface Roughness decreases.

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