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ORIGINAL RESEARCH

Multi-objective optimisation of electrical discharge machining for Inconel 825 using Taguchi-fuzzy approach

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Abstract This paper employs Taguchi-fuzzy approach for parametric optimisation of electric discharge machining with multiple performance measures. In this work, seven input parameters (one of two levels and six of three levels) and two performance measures have been considered and the experiments are designed using Taguchi's L_{36} orthogonal array. A fuzzy model is formed using mamdani inference system and optimal combination of process parameters has been obtained on basis of multi-performance fuzzy index (MPFI) value calculated using different shapes of membership functions (MF) viz. triangular, trapezoidal and gaussian. Gaussian MF is found to provide better results as compared to triangular and trapezoidal MF. ANOVA analysis has also been carried out on MPFI to find out percentage contribution. It is shown with the help of confirmatory experiments that MRR and SR are improved by 103.25 and 32.11% respectively by employing the proposed approach.

Keywords ANOVA · EDM · Metal removal rate · Taguchi-fuzzy · Surface roughness · Multi-objective optimization

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1 Introduction

Inconel 825 find immense applications in aerospace, chemical and nuclear industries because of its mechanical and metallurgical properties at higher temperature [1]. This alloy holds some distinctive properties like resistance to pitting and crevice corrosion, stress corrosion cracking and inter-granular corrosion because of the addition of various alloying elements like molybdenum, nickel, chromium, and titanium. Despite all these features, it has a tendency for work hardening, poor thermal diffusivity and high dynamic shear strength which makes it difficult to machine by conventional methods [2]. Due to these properties, it is put in the category of hard-to-cut materials. EDM is one of the most widely and successfully applied machining processes to shape this material. In EDM, thermal energy is utilized for machining of electrically conductive parts with regardless of material hardness. The metal removal takes place by discharging an electric current across a narrow dielectric field gap between the work piece and the tool electrode. The heat produced from the sparks is enough to create a tiny crater by melting and vaporization phenomenon. Approximately thousands of sparks per second are produced which is eroding the shape of the tool into the work piece.

To understand the relationship between the various process parameters and the performance measures, the EDM process has been investigated by various researchers with different range and machine set up [3–6]. The selection of process parameters combination/levels in EDM is a tough task due to complex nature of EDM process. To overcome this problem, multi-objective optimisation of EDM process has been undertaken by considering in general the higher MRR with low SR. For that purpose, many researchers have suggested various statistical multi-objective optimization techniques. Kumar et al. [7] have done optimization of abrasive mixed EDM process using OA and grey relational analysis (GRA). They added silicon powder (2 g/l) in dielectric fluid to study the effect of powder in MRR and SR. They have concluded that by the use of optimisation technique there is an improvement in the performance measures. Similarly, Chakravorty et al. [8] have applied principal component analysis (PCA) based utility approach for the multi-response optimisation of EDM process. This approach takes accounts for the correlations among the responses. They concluded that PCA based utility approach leads to better optimisation performance. Talla et al. [9] presented the experimental investigation on mild steel by taking reverse EDM process. The experiments were planned using response surface methodology. The author concluded that by applying optimization technique like PCA and GRA there is an improvement in the SR, taper and cylindricity error. Ramakrishnan and Karunamoorthy [10] did the parametric optimization of Inconel 718 using multi-response signal to noise ratio technique in wire-EDM process. They have taken MRR and SR as the performance measures. They have done the parametric optimization by assigning different weights in three different cases. However, these statistical techniques have some limitation as they do not take into account the uncertainty associated with a sophisticated process like EDM. As a solution, the researchers started employing intelligent computational techniques. Joshi and Pande [11] did process modeling and optimization of the electric discharge machining process using finite element method integrated with the artificial neural network (ANN) and genetic algorithm (GA). Guojunzhang et al. [12] presented the experimental investigation of medium-speed wire-EDM of SKD11 material. SR and MRR were taken as performance measures. They designed the experiments using response surface methodology (RSM) approach. For optimization and modeling they have used the back propagation neural network (BP-ANN) combined with GA. Aich and Banerjee [13] applied support vector machine which is a supervised learning method for developing the model of EDM process. They developed a mathematical model using support vector machine technique for MRR and SR. Finally optimization is carried out using particle swarm optimization technique. Similarly, Bharti et al. [14] obtained the pareto optimal solution for EDM of Inconel 718. They modeled EDM process by ANN and then employed controlled elitist non-dominated sorting genetic algorithm to find the pare to optimal solution. These computational techniques are known as intelligent techniques but these are complex and sophisticated in nature as they require expertise in computational programming. As a solution, we need a robust and effective analysing method to solve the problem of multi-objective optimization of the stochastic manufacturing process like EDM. As Taguchi approach is robust in nature and fuzzy logic is popular for its uncertainty accountability, these approaches can provide solutions for such problems. Combining the advantages of Taguchi and fuzzy approach, in this work Taguchi-fuzzy approach is applied for multi-objective optimization of the EDM process.

In this work, an optimal combination set of process parameter is obtained using the proposed approach. In the following sections, experimental details are elaborated followed by methodology adopted of Taguchi- fuzzy. Then, the results of the Taguchi- fuzzy approach are explained ending with confirmations of the experiments.

2 Experimental details

2.1 Materials

The research was carried out in a Die sinking EDM machine Elektra 5535 PS ZNC as shown in Fig. 1a. Inconel 825 alloy steel was selected as work piece material for the study. The work pieces were cut from the metal plate of Inconel 825 (305 × 210 × 5 mm) into the shape of rectangles. The size of the work piece was made as 75 mm × 40 mm with the help of surface grinder. The electrodes used in the study are copper, copper-tungsten (Cu20%, W80%), and graphite as shown in the Fig. 1b.

2.2 Measurement of responses

MRR and SR are taken as a performance measure. The L_{36} ($2^1 \times 3^6$) OA is selected for experiment design. The parameters and their levels are represented in Table 1. MRR have been calculated by finding the weight loss of material before and after divided by machining time. To perform the computation of MRR, weighing balance of make Shimadzu having a capacity of 300 g and accuracy of 10 mg is used which is shown in the Fig. 1c. SR has been computed by centre line average method, 0.4 mm has been taken as cut off length with 4 mm evaluation length. For measuring the SR a Mitutoyo surface roughness tester SJ2100 is used which is shown in the Fig. 1d. Table 2 depicts the design experimental array with different parametric level.

3 Methodology

3.1 Taguchi's methodology

Taguchi method deals with all features of the design that affect the deviation of performance measure of the sample

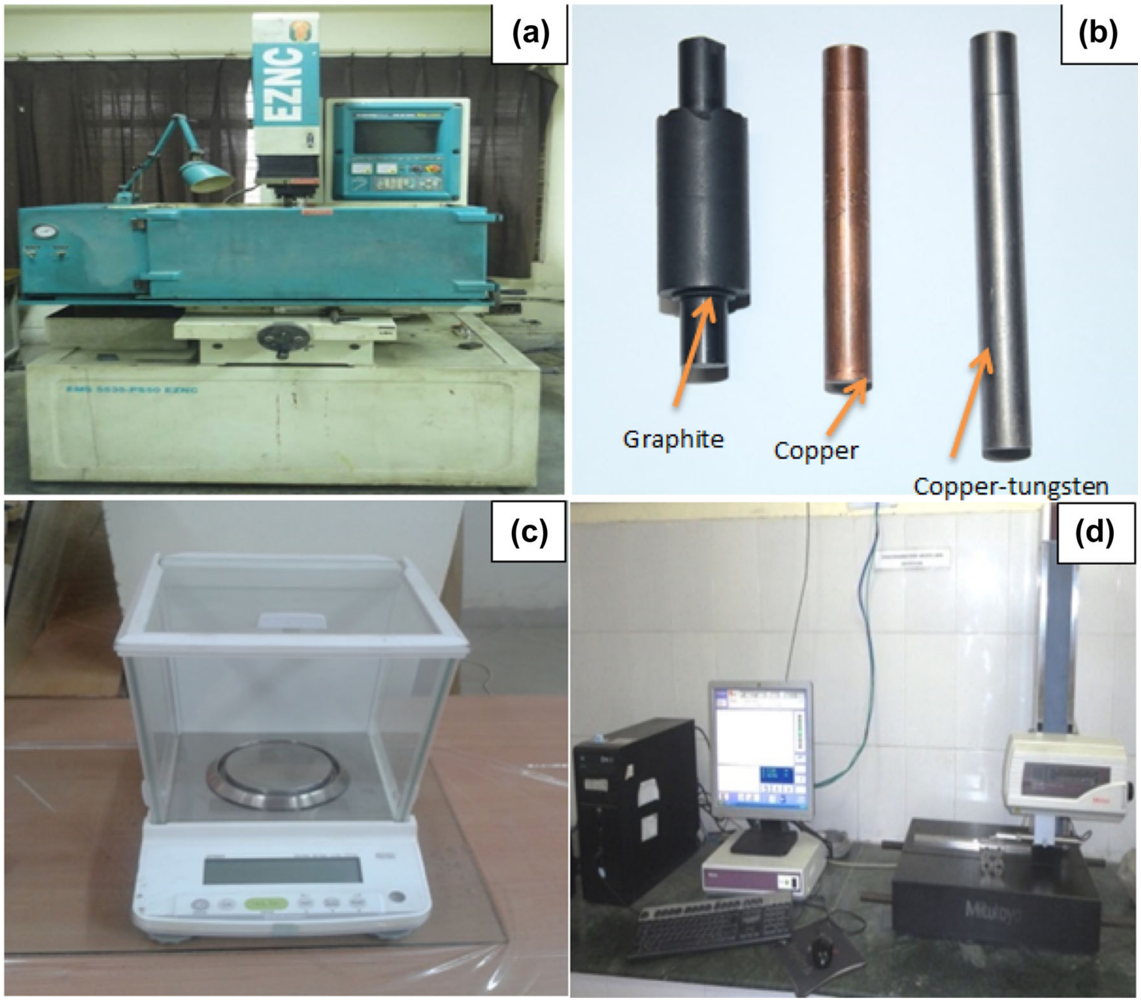

Fig. 1 Equipment and apparatus used in this experiment. **a** EDM PS50. **b** Electrodes used in the Study. **c** Weighing balance used for MRR. **d** Mitutoyo Surface Roughness Tester SJ2100

Table 1 Process parameters and their levels used in the orthogonal experiment

Input parameters	Unit	Symbol	Levels and values		
			1	2	3
Dielectric fluid (A)	–	D_F	Oil 1	Oil 2	–
Pulse-on-time (B)	μs	T_{on}	20	40	75
Discharge Current (C)	A	I_d	4	8	12
Duty cycle (D)	%	ζ	10	11	12
Gap voltage (E)	V	V_g	40	60	80
Tool Electrode Material (F)	–	T_M	Copper (Cu)	Copper tungsten (CuW)	Graphite (Gr)
Tool electrode lift time(G)	sec	T_L	0.1	0.2	0.3

from the final value [15]. This optimization method reduces influence of undesirable and uncontrollable factors which cause functional deviations [16]. Taguchi method starts with designing of experiments using OA approach. OA deals with a set of levels to study all the machining parameter [17]. In the OA, the numbers of experiments are minimized and accordingly quality characteristics are examined. For deciding a particular OA, degree of freedom is calculated from the number of factors, number of interactions and number of levels of each factor. In orthogonal array design, each level of every parameter appears equally in the column. Taguchi approach comprises of signal-to-noise ratio also; in this loss function is used to calculate the variation between the experimental

Table 2 Design experiment of L_{36} (2^1x3^6) array with different experimental parametric levels

Exp no.	D_F	T_{on} (µs)	I_D (A)	ζ (%)	V_g (V)	T_M	T_L (s)	MRR (mm^3/min)	S/N	SR (µm)	S/N
1	1	1	1	1	1	1	1	3.063	9.723	4.347	− 12.76
2	1	2	2	2	2	2	2	4.812	13.64	6.53	− 16.29
3	1	3	3	3	3	3	3	11.51	21.22	7.777	− 17.81
4	1	1	1	1	1	2	2	2.147	6.638	3.864	− 11.74
5	1	2	2	2	2	3	3	4.318	12.70	5.789	− 15.25
6	1	3	3	3	3	1	1	3.981	11.99	8.284	− 18.36
7	1	1	1	2	3	1	2	1.191	1.522	5.741	− 15.18
8	1	2	2	3	1	2	3	5.068	14.09	6.492	− 16.24
9	1	3	3	1	2	3	1	5.507	14.81	8.388	− 18.47
10	1	1	1	3	2	1	3	2.260	7.085	4.544	− 13.14
11	1	2	2	1	3	2	1	3.427	10.7	5.916	− 15.44
12	1	3	3	2	1	3	2	5.303	14.49	7.859	− 17.90
13	1	1	2	3	1	3	2	4.445	12.95	4.644	− 13.33
14	1	2	3	1	2	1	3	4.281	12.63	6.824	− 16.68
15	1	3	1	2	3	2	1	1.657	4.390	5.844	− 15.33
16	1	1	2	3	2	1	1	3.746	11.47	5.287	− 14.46
17	1	2	3	1	3	2	2	5.1329	14.20	6.872	− 16.74
18	1	3	1	2	1	3	3	3.590	11.10	5.093	− 14.14
19	2	1	2	1	3	3	3	10.44	20.37	4.689	− 13.42
20	2	2	3	2	1	1	1	4.887	13.78	7.426	− 17.41
21	2	3	1	3	2	2	2	1.762	4.922	5.605	− 14.97
22	2	1	2	2	3	3	1	3.378	10.57	4.991	− 13.96
23	2	2	3	3	1	1	2	4.368	12.80	6.204	− 15.85
24	2	3	1	1	2	2	3	2.478	7.883	6.528	− 16.29
25	2	1	3	2	1	2	3	10.01	20.01	5.387	− 14.62
26	2	2	1	3	2	3	1	1.836	5.280	5.309	− 14.5
27	2	3	2	1	3	1	2	8.077	18.14	8.386	− 18.47
28	2	1	3	2	2	2	1	5.741	15.17	5.488	− 14.78
29	2	2	1	3	3	3	2	2.443	7.761	5.192	− 14.30
30	2	3	2	1	1	1	3	4.790	13.60	7.432	− 17.42
31	2	1	3	3	3	2	3	4.845	13.70	5.53	− 14.85
32	2	2	1	1	1	3	1	2.303	7.247	4.988	− 13.95
33	2	3	2	2	2	1	2	4.498	13.06	8.635	− 18.72
34	2	1	3	1	2	3	2	4.420	12.90	4.995	− 13.97
35	2	2	1	2	3	1	3	2.542	8.104	5.646	− 15.03
36	2	3	2	3	1	2	1	3.136	9.9297	7.081	− 17.00

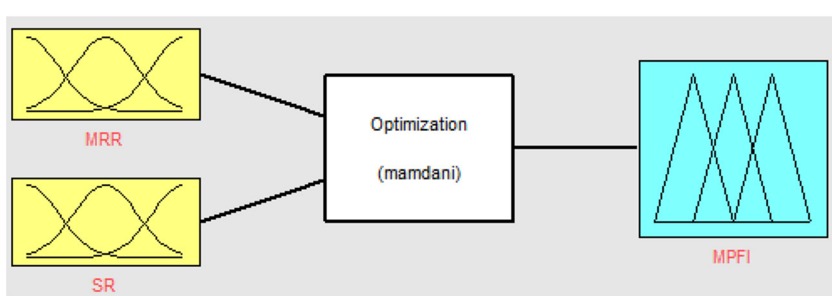

Fig. 2 Overview of fuzzy inference system

value and the desired value. Signal-to-noise ratio (S/N) evaluate the statistical performance characteristics deviating from the desired value. For MRR, as its higher value is always desired therefore S/N ratio is calculated using Eq. (1). Lower value of SR indicate the better finished surface hence, Eq. (2) for lower the better characteristics is used to calculate its S/N ratio.

Larger-the-better characteristics

$$S/_N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \quad (1)$$

Smaller-the-better characteristics

$$S/_N = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right) \quad (2)$$

where y_i is the experimentally observed value and n is the repeated numbers of each experiment.

3.2 Anova

Analysis of variance (ANOVA) which determines the effect of each process variable on the observed performance measures [18]. In ANOVA, *f* value defines the result at some confidence level (95 or 99% confidence level) and indicates that variations of process parameter change the performance of the responses [16, 19]. *f* test basically gives the comparison of the variances. *P* values are determined for each process parameter which informs about the significance of that parameter at a particular level of confidence. In ANOVA analysis, the percentage contribution of each process parameter is also determined for a response which helps in screening out the important parameters.

3.3 Fuzzy logic

Fuzzy logic is explained by mathematical theory for inexact reasoning that permits the modeling of the reasoning process of human in linguistic terms [20]. It establishes the relation between an input system and desired output. Fuzzy logic basically involves the problems having uncertainty in their outputs. The present study deals with designing of a fuzzy model for selecting the parameters for EDM machining operations. The response of EDM machining MRR and SR are provided as input signals to the fuzzy model. The output from the fuzzy model is obtained as single score called multi-performance fuzzy index (MPFI) for each experiment as shown in Fig. 2.

To perform the fuzzy logic function, we have to normalize the data so that they have the same uniformity. In our case, the data for MRR and SR is normalized. After normalization, each variable lies in the range of 0 & 1.

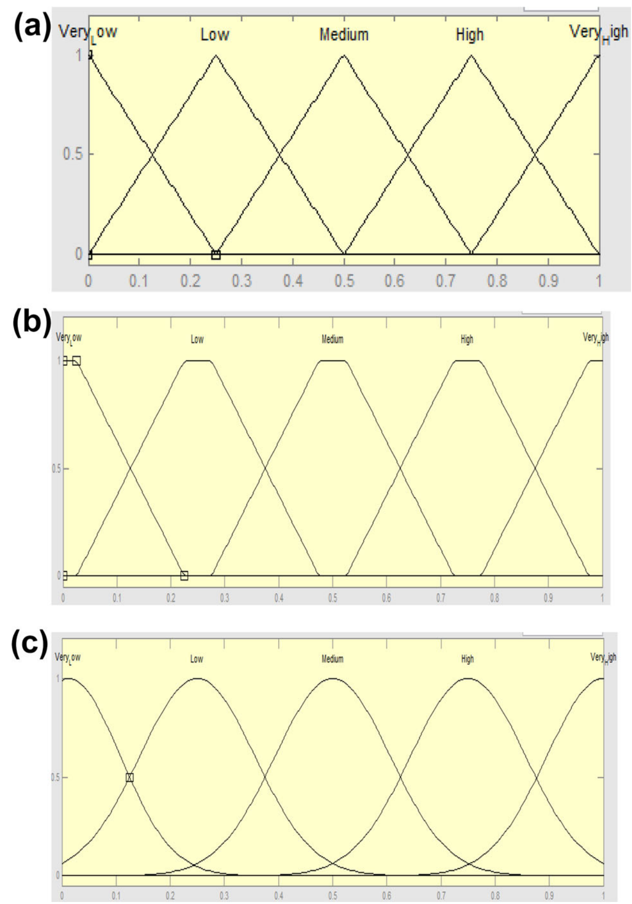

Fig. 3 Membership shape function **a** Triangular, **b** Trapezoidal, and **c** Gaussian

Table 3 Fuzzy rules for MPFI

MPFI	MRR				
SR	VL	L	M	H	VH
VL	VL	L	L	M	M
L	L	L	M	M	M
M	L	M	M	H	H
H	M	M	H	H	H
VH	M	H	H	H	VH

Furthermore, when we required the maximum value of a variable like MRR Eq. (3) is used.

$$y_i^*(k) = \frac{y_i^0(k) \; - \min y_i^0(k)}{\max y_i^0(k) \; - \min y^0{}_i(k)} \quad (3)$$

For lower the better value of SR, normalization is done according to Eq. (4)

$$y_i^*(k) = \frac{\max y_i^0(k) \; - y_i^0(k)}{\max y_i^0(k) \; - \min y_i^0(k)} \quad (4)$$

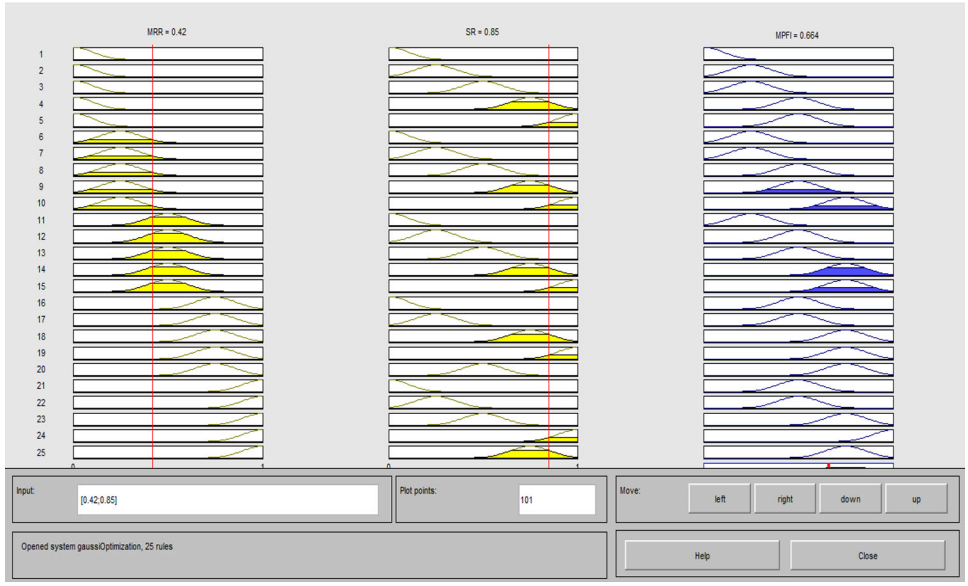

Fig. 4 Screen shot of rule base viewer for mamdani inference system using Gaussian MFs

Table 4 Details of the proposed fuzzy model

Type of fuzzy inference system (FIS)	Mamdani
Inputs/output	2/1
Input membership function types	Triangular, trapezoidal, gaussian
Output membership function types	Triangular, trapezoidal, gaussian
Number of input membership functions	5/5
Number of output membership function	5
Rules weight	1
Number of fuzzy rules	25
And method	Min
Implication method	Min
Aggregation method	Max
Defuzzification method	Centroid

where y_i^o (k) is the original sequence, min y_i^o (k) is the minimum y_i^o (k) value, max y_i^o (k) is the largest y_i^o (k) value and y^0 is the desired value.

A fuzzy system is made up of various stages viz. fuzzifier, inference engine, database, a rule base and defuzzifier. The role played by fuzzifier is to use the membership function for converting the crisp input into fuzzy sets, and then inference engine performs the fuzzy reasoning on fuzzy rules to generate fuzzy values. In the present study, three different membership function (MF) shapes such as triangular, trapezoidal and gaussian are applied. Various MFs for input and output variables used in this study are depicted in Fig. 3.

After applying membership function, next is to use fuzzy rule base for fuzzy inference system. Fuzzy rules are nothing but they establish a relation between input and the output in a fuzzy model which is characterized by a set of linguistics statements called fuzzy rules. Fuzzy rule base comprises of a group of "if and then" with two inputs normalized MRR, normalized SR and one output MPFI. In this work, a total of 25 fuzzy rules are made as shown in Table 3.

For input as well as output measures, five MFs—very low (VL), low (L), medium (M), high (H), and very high (VH) are used. Rule base viewer is represented in Fig. 4.

Complete details about the fuzzy model used in this work are summarized in Table 4.

Therefore, after using fuzzification process next is to apply fuzzy implication and aggregation. Based on fuzzy rules, mamdani inference method is applied due to its simplicity and easiness for performing the computational ability. In this, we take max–min compositional operation [21], a fuzzy output is established. If we take x_1 and x_2 as a two input values of the fuzzy logic unit, the membership function of the output of fuzzy reasoning can be determined by the following equation:

$$\mu_{co}(y) = \{\mu_{A1}(x_1) \wedge \mu_{B1}(x_2) \wedge \mu c_i(y)\}\, v \ldots \{\mu_{A_n}(x_1) \wedge \mu_{B_n}(x_2) \wedge \mu_{C_n}(y)\} \quad (5)$$

where $\wedge$ is the minimum operation and $\vee$ is the maximum operation.

In centroidal defuzzification method, the values of the two input variable are combined into one single crisp output MPFI which is denoted by y_o

$$y_0 = \frac{\sum y\mu_{co}(y)}{\sum \mu_{co}(y)} \tag{6}$$

4 Results and discussion

The results of MRR and SR as well as their corresponding S/N ratio values are presented in Table 2. The process begins with normalization of MRR and SR values as they are not in the standardized form. To do the normalization Eqs. (3) and (4) is applied. Normalization is done to make the data easy for calculation and for comparison purpose. Normalized values are tabulated for MRR and SR in Table 5.

After getting the normalized values, it is presented to fuzzy inference system (FIS) as an input. FIS generate the single output called MPFI through rule base.

Ranking of all the 36 experiments is done to optimize the EDM process parameters. The rankings are done according to MPFI score of that experiment. The highest MPFI score is ranked first while the lowest MPFI score is ranked last. However, other experiments are ranked accordingly as per their MPFI scores. In this study, three MF shapes are used for calculating the MPFI. MPFI-1 corresponds to FIS when triangular shape MF is taken. Similarly, MPFI-2 and MPFI-3 scores are determined using trapezoidal and Gaussian shape MF respectively. According to MPFI-1 ranking, a combination of EDM process variable in experiment number 4 ($D_F - 1$, T_{on} 20 µs, I_d 4A, ζ 10%, V_g 40 V and T_M CuW, T_L 0.2 s) is suggested as optimum as its score is highest with 0.75 in MPFI-1.Similarly, experiment number 14 ($D_F - 1$, T_{on} 40 µs, I_d 12A, ζ 10%, V_g 60 V and T_M Cu, T_L 0.3 s) and experiment number 19 ($D_F - 2$, T_{on} 20 µs, I_d 8A, ζ 10%, V_g 80 V and T_M Graphite, T_L 0.3 s) are ranked first in MPFI-2 and MPFI-3 scores respectively.

In manufacturing industry to obtain high production of good quality products, higher values of MRR and lower value of SR are always desired. According to MPFI-1 ranking, experiment number 4 [MRR = 2.1474 mm^3/min (0.26) and SR = 3.864 µm (1.0)] suggested as optimal gives more weightage to SR whereas in ranking according to MPFI-2 score, experiment number 14 [MRR = 4.2817 mm^3/min (0.56) and SR = 6.824 µm (0.29)] suggested as optimal does not leads to optimal result of any process response. In above sentence, the values in the bracket next to response units indicate the normalized values of that response. On the other hand, in experiment number 19 (ranked first by MPFI-3 score), the results obtained are MRR = 10.445 mm^3/min, SR = 4.689 µm. corresponding normalized values of MRR and SR for this experiment are 0.96 and 0.76 respectively which are near to their desired value i.e. 1. Therefore the results of MRR and SR for experiment number 19 are more logical and optimal as compared to the results of experiment number 4 as well as 14.

ANOVA analysis helps to determine the percentage contribution of each input process parameter on the process response and its individual contribution on MPFI score are identified through ANOVA analysis. The results of MPFI-3 scores corresponding to Gaussian MF are further analysed using ANOVA to find out the influence of process parameters on it.

To do this analysis, a confidence level of 95% is taken called as fisher test or f test. f test further indicates the change in the process parameter which has a prominent effect on multiple performance measures. As seen from the Table 6, pulse-on-time has the largest f value which indicates the stronger influence on performance characteristics. After that tool electrode material and gap voltage have significant influence on MPFI-3. Percentage contribution of pulse-on-time, tool electrode material, and gap voltage are 45.41, 11.18, and 5.82 respectively.

5 Confirmation test

The confirmation test is the final step to validate the results drawn during the analysis phase. The readings of the initial parameters are taken itself from the designed experiments i.e. experiment number 17 because of the moderate values of the parameters. Experiment number 19 shows the highest MPFI index corresponding to Gaussian MF. It indicates that the optimal process parameter set of- D_F 2, T_{on} 20 µs, I_d 8A, ζ 10%, V_g 80 V and T_M Graphite, T_L 0.3 s has the best multiple performance characteristics among the 36 experiments. The findings of the confirmatory experiment at initial as well as optimized levels are depicted in Table 7. The response values obtained from the confirmation experiment are MRR = 10.431 mm^3/min, SR = 4.663 µm. The material removal rate shows an increased value of 5.132–10.431 mm^3/min, the SR shows a reduced value from 6.872 to SR = 4.663 µm. The corresponding improvement in material removal rate is 103.25% and SR is 32.144% respectively.

6 Conclusions

The present work proposes a combination of Taguchi and Fuzzy logic to solve the multi-objective parameter optimization problem in EDM process. Following conclusions are drawn from the outcomes of this study.

Table 5 Values of input variables with their corresponding MPFI

Exp. no.	Normalized responses		MPFI-1	Rank acc. to MPFI-1	MPFI-2	Rank acc. to MPFI-2	MPFI-3	Rank acc. to MPFI-3
	MRR	SR						
1	0.42	0.85	0.658	5	0.602	10	0.664	8
2	0.62	0.35	0.611	9	0.402	28	0.603	12
3	1.00	0.13	0.5	19	0.685	3	0.501	22
4	0.26	1.00	0.75	1	0.668	5	0.725	4
5	0.57	0.50	0.579	13	0.609	8	0.563	16
6	0.53	0.05	0.31	32	0.51	18	0.304	35
7	0.00	0.51	0.264	33	0.435	25	0.28	36
8	0.64	0.35	0.608	10	0.75	1	0.598	13
9	0.67	0.04	0.412	26	0.578	11	0.425	30
10	0.28	0.80	0.56	14	0.511	17	0.542	17
11	0.47	0.47	0.461	21	0.349	30	0.474	24
12	0.66	0.12	0.395	28	0.62	7	0.405	32
13	0.58	0.77	0.75	1	0.607	9	0.73	3
14	0.56	0.29	0.552	16	0.75	1	0.539	19
15	0.15	0.49	0.395	29	0.526	15	0.408	31
16	0.50	0.61	0.613	8	0.491	21	0.605	11
17	0.64	0.28	0.547	17	0.435	24	0.537	20
18	0.49	0.66	0.653	6	0.423	26	0.66	9
19	0.96	0.76	0.75	1	0.5	19	0.748	1
20	0.62	0.19	0.418	25	0.698	2	0.44	27
21	0.17	0.54	0.412	27	0.438	23	0.431	29
22	0.46	0.68	0.671	3	0.289	32	0.679	6
23	0.57	0.41	0.583	12	0.401	29	0.566	15
24	0.32	0.35	0.355	30	0.338	31	0.351	33
25	0.94	0.59	0.75	1	0.75	1	0.744	2
26	0.19	0.60	0.423	22	0.75	1	0.446	25
27	0.84	0.04	0.5	20	0.569	12	0.499	23
28	0.69	0.56	0.68	2	0.565	13	0.687	5
29	0.32	0.63	0.591	11	0.525	16	0.577	14
30	0.61	0.19	0.421	23	0.441	22	0.443	26
31	0.62	0.55	0.621	7	0.539	14	0.616	10
32	0.29	0.68	0.553	15	0.662	6	0.54	18
33	0.59	0.00	0.347	31	0.684	4	0.34	34
34	0.58	0.68	0.669	4	0.25	33	0.677	7
35	0.33	0.53	0.542	18	0.423	27	0.529	21
36	0.43	0.25	0.421	24	0.5	20	0.437	28

1. S/N ratios and their normalization for process responses prove to be an effective and efficient approach to bring the variables at same scale.
2. As compared to triangular and trapezoidal shape MF, Gaussian shape MF has led to more logical and optimized results of MRR and SR for an EDM process.
3. For the given range of process parameters, a combination D_F 2, T_{on} 20 μs, I_d 8A, ζ 10%, V_g 80 V and T_M Graphite, T_L 0.3 s comes out be the optimized level combination by employing fuzzy logic with Gaussian MF.
4. It has been illustrated with the help of the confirmatory experiments that fuzzy logic proves to be an effective and efficient solution for the multi-response parameter optimization problem in the area of EDM process.
5. From ANOVA analysis pulse-on-time, tool electrode material and gap voltage are found to have significant

Table 6 ANOVA analysis for MPFI

Source	DF	Seq SS	Adj MS	*F* value	*P*	% contribution
Dielectric fluid	1	0.000971	0.000971	0.12	0.729	0.170216
Pulse-on-time	2	0.259043	0.129521	16.43	0	45.41029
Discharge current	2	0.01335	0.006675	0.85	0.442	2.340258
Duty cycle	2	0.004257	0.002128	0.27	0.766	0.746253
Gap voltage	2	0.033203	0.016601	2.11	0.146	5.820493
Tool electrode material	2	0.063756	0.031878	4.04	0.032	11.17644
Tool electrode lift time	2	0.022473	0.011237	1.43	0.262	3.939521
Residual error	22	0.173407	0.007882			30.39828
Total	35	0.570459				100.0016

Table 7 Confirmatory experimental results and comparison of optimized and initial results

Test condition	D_F	T_{on} (µs)	I_d (A)	ζ (%)	V_g (V)	T_M	T_L (s)	MRR (mm^3/min)	SR (µm)
Initial	Oil 1	40	12	10	80	CuW	0.2	5.132	6.872
Optimised	Oil 2	20	8	10	80	Gr	0.3	10.431	4.663
Percentage improvement	–	–	–	–	–	–	–	103.25	32.144

influence on MPFI-3 having percentage contribution of 45.41, 11.18, and 5.82 respectively.

6. The proposed technique of fuzzy logic provides the satisfactory results which are very useful for EDM practioners as well as researchers.

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