Engineering Science and Technology, an International Journal 18 (2015) 361–368

Contents lists available at ScienceDirect

Engineering Science and Technology, an International Journal

journal homepage: http://www.elsevier.com/locate/jestch

Full length article

Multi-response optimization of surface integrity characteristics of EDM process using grey-fuzzy logic-based hybrid approach

Shailesh Dewangan, Soumya Gangopadhyay*, Chandan Kumar Biswas [1]

Department of Mechanical Engineering, National Institute of Technology, Rourkela 769008, India

ARTICLE INFO

Article history:
Received 22 October 2014
Received in revised form
28 December 2014
Accepted 15 January 2015
Available online 14 March 2015

Keywords:
AISI P20 tool steel
Grey-fuzzy logic
Multi-response optimization
Surface integrity
Electric discharge machining

ABSTRACT

Surface integrity remains one of the major areas of concern in electric discharge machining (EDM). During the current study, grey-fuzzy logic-based hybrid optimization technique is utilized to determine the optimal settings of EDM process parameters with an aim to improve surface integrity aspects after EDM of AISI P20 tool steel. The experiment is designed using response surface methodology (RSM) considering discharge current (Ip), pulse-on time (T_{on}), tool-work time (T_w) and tool-lift time (T_{up}) as process parameters. Various surface integrity characteristics such as white layer thickness (WLT), surface crack density (SCD) and surface roughness (SR) are considered during the current research work. Grey relational analysis (GRA) combined with fuzzy-logic is used to determine grey fuzzy reasoning grade (GFRG). The optimal solution based on this analysis is found to be Ip = 1 A, T_{on} = 10 μs, T_w = 0.2 s, and T_{up} = 0.0 s. Analysis of variance (ANOVA) results clearly indicate that T_{on} is the most contributing parameter followed by Ip, for multiple performance characteristics of surface integrity.

1. Introduction

EDM is one of the widely used non-traditional machining processes, where electrical energy is used to generate electrical spark and material removal occurs primarily due to thermal energy of the spark. EDM is most commonly recommended to cut difficult-to-machine materials including high strength and high temperature resistant alloys [1].

EDM is usually characterized by multiple performance measures primarily governed by productivity, quality and surface integrity which are in turn dependent on different process parameters like discharge current (Ip), pulse-on time (T_{on}), pulse-off time (T_{off}), voltage (V), flushing pressure (F_p), tool-work time (T_w), tool lift time (T_{up}) etc. Therefore, optimization of EDM process essential requires multi-objective optimization techniques. Significant amount of research work has been reported in this context. Bhattacharyya et al. [2] investigated the influence of EDM parameters like Ip and T_{on} on EDMed surface integrity of AISI D2 tool steel. Response surface methodology (RSM)-based modelling and optimization was carried out to find out the optimal setting of machining parameters. Similar study on surface integrity of the same material has also been reported recently using RSM combined with grey relational analysis (GRA) as multi-objective optimization technique [3]. Grey system is particularly designed for dealing with uncertain and complex interrelationship between input parameters and output responses. Therefore, GRA-based multi-response optimization techniques have become a topic of research interest in EDM. GRA was also adopted for multi-response optimization of micro EDM process considering tool wear entrance and exit clearances, machining time and number of shorts [4]. The same technique was utilized in optimization of multiple responses during EDM of Al–10%SiC$_P$ composites by converting the responses into single response grey relational grade [5]. Simultaneous increase in MRR as well as reduction in TWR could be achieved through successful implementation of GRA technique in EDM of AISI P20 tool steel [6].

The analysis based on fuzzy-logic finds applications in vague and uncertain environment. In the recent years, fuzzy-logic-based multi-criteria decision making approaches have become very popular in optimization of EDM and other manufacturing processes. Rupajati et al. [7] has optimized the multiple performances like recast layer thickness and surface roughness using fuzzy-logic method with the design of Taguchi L_{18} mixed- orthogonal array. It was observed that application of this optimization technique significantly improved multiple responses. The same technique was also used to predict material removal rate (MRR), tool wear rate

* Corresponding author. Tel.: +91 9439096336.
E-mail address: soumya.mech@gmail.com (S. Gangopadhyay).
Peer review under responsibility of Karabuk University.
[1] Present address: Department of Petroleum Engineering, Universiti Teknologi Petronas, Ipoh, Malaysia.

http://dx.doi.org/10.1016/j.jestch.2015.01.009
2215-0986/

Table 1
Machining parameters and their levels.

Parameters	Symbol	Levels			Unit
		Low	Middle	High	
Control parameters					
Pulse current	Ip	1	3	5	A
Pulse on time	T_{on}	10	80	150	μs
Work time	T_w	0.2	0.6	1.0	s
Lift time	T_{up}	0.0	0.75	1.5	s
Fixed parameters					
Duty cycle	(ζ)	70			%
Voltage	V	45			V
Flushing pressure	Fp	0.3			kgf/cm^2
Sensitivity	SEN	6			

(TWR) and surface roughness (SR) in ultrasonic-assisted EDM (US/EDM) process [8]. Different other manufacturing processes were also optimized using similar type of optimization technique [9–11].

Utility of fuzzy-logic based optimization technique can be further improved when it is integrated with other optimization methodologies. Sengottuvel et al. utilized fuzzy-logic to predict output responses (MRR, TWR and SR) while desirability approach was used to optimize the parameters during EDM of Inconel 718 [12]. Fuzzy-TOPSIS based multi-objective optimization was performed with a view to improve of EDM surface integrity as well as dimensional accuracy of AISI P20 tool steel [13].

GRA also has strong potential to further enhance the capability of fuzzy-logic in multi-objective optimization problems. Here, the optimization of complex multiple response characteristics can be effectively transformed into optimization of single grey fuzzy reasoning grade (GFRG). Lin and Lin [14] carried out optimization of EDM process of SKD11 alloy steel with multiple process responses using grey-fuzzy-logic method. Soepangkat and Pramujati applied integrated approach comprising of GRA and fuzzy-logic in order to optimize wire EDM of AISI D2 steel for minimizing surface roughness and recast layer thickness [15]. Similar optimization techniques have been successfully utilized in various manufacturing processes which are particularly carried out under complex and uncertain environment [16–20].

Fig. 1. Experimental setup.

Although some research work has been carried out to examine the influence of EDM parameters on quality and productivity aspects, it is also very essential to determine optimal parametric combination in order to obtain improved EDMed surface integrity. Moreover, surface integrity characteristics of AISI P20 tool steel is also rare although the same material is widely used in the manufacturing of plastic moulds, hydro forming tools and many other applications. Therefore, present work aims at utilizing grey-fuzzy logic-based hybrid optimization technique to optimize different surface integrity characteristics such as WLT, SCD, SR during machining AISI P20 tool steel using EDM.

2. Experimental details

2.1. Materials and methods

The experimental runs were conducted on Electronica Electraplus PS 50ZNC Die Sinking Machine. Commercial grade EDM oil (specific gravity = 0.763, false point = 94 °C) was used as dielectric fluid. The machining parameters and their levels are presented in Table 1. The work piece material was AISI P20 tool steel with semi-circular shape (100 mm diameter and 10 mm thickness). The composition of AISI P20 tool steel includes 0.4% C, 1% Mn, 0.4% Si, 1.2% Cr, 0.35% Mo, 0.25% Cu, 0.03% P 0.03% S and rest Fe. A cylindrical shaped commercially pure copper with a diameter of 12 mm was used as a tool. The workpiece (+ve polarity) and the tool (−ve polarity) are shown in Fig. 1.

2.2. Design of experiment using RSM

Response surface methodology (RSM) is a collection of mathematical and statistical techniques that are useful for modelling and analysis of problems in which output or response is influenced by

Table 2
Observation table.

Run order	Pt type	Blocks	Ip (A)	T_{on} (μs)	T_w (s)	T_{up} (s)	WLT (μm)	SCD (μm/μm^2)	SR (μm)
1	0	2	3	80	0.6	0.75	12.452	0.0210	4.86
2	1	2	5	150	1.0	1.50	28.379	0.0078	7.13
3	1	2	1	10	1.0	1.50	3.755	0.0662	1.73
4	1	2	1	150	1.0	0.00	7.479	0.0703	1.73
5	1	2	5	10	1.0	0.00	15.633	0.0210	3.40
6	0	2	3	80	0.6	0.75	15.209	0.0066	5.20
7	1	2	5	150	0.2	0.00	26.882	0.0066	5.86
8	1	2	1	150	0.2	1.50	10.271	0.0605	2.00
9	1	2	5	10	0.2	1.50	17.469	0.0004	3.66
10	**1**	**2**	**1**	**10**	**0.2**	**0.00**	**6.954**	**0.0202**	**2.06**
11	−1	3	3	80	0.6	0.00	18.243	0.0093	4.66
12	−1	3	3	80	0.2	0.75	13.717	0.0110	5.26
13	−1	3	3	10	0.6	0.75	7.299	0.0011	3.20
14	−1	3	5	80	0.6	0.75	23.166	0.0009	6.06
15	0	3	3	80	0.6	0.75	14.660	0.0096	5.06
16	−1	3	3	150	0.6	0.75	17.302	0.0186	5.06
17	−1	3	1	80	0.6	0.75	4.972	0.0637	2.89
18	0	3	3	80	0.6	0.75	17.993	0.0134	5.40
19	−1	3	3	80	0.6	1.50	16.305	0.0031	4.66
20	−1	3	3	80	1.0	0.75	13.001	0.0156	4.80
21	1	1	1	150	1.0	1.50	9.595	0.0690	1.73
22	1	1	5	150	1.0	0.00	29.842	0.0092	5.53
23	1	1	5	10	1.0	1.50	16.553	0.0370	3.26
24	0	1	3	80	0.6	0.75	16.435	0.0027	4.80
25	1	1	1	10	1.0	0.00	3.146	0.0730	1.66
26	0	1	3	80	0.6	0.75	18.275	0.0071	4.96
27	1	1	1	150	0.2	0.00	9.267	0.0650	1.86
28	1	1	5	150	0.2	1.50	24.615	0.0069	6.60
29	1	1	5	10	0.2	0.00	19.594	0.0010	3.00
30	1	1	1	10	0.2	1.50	6.684	0.0230	1.82

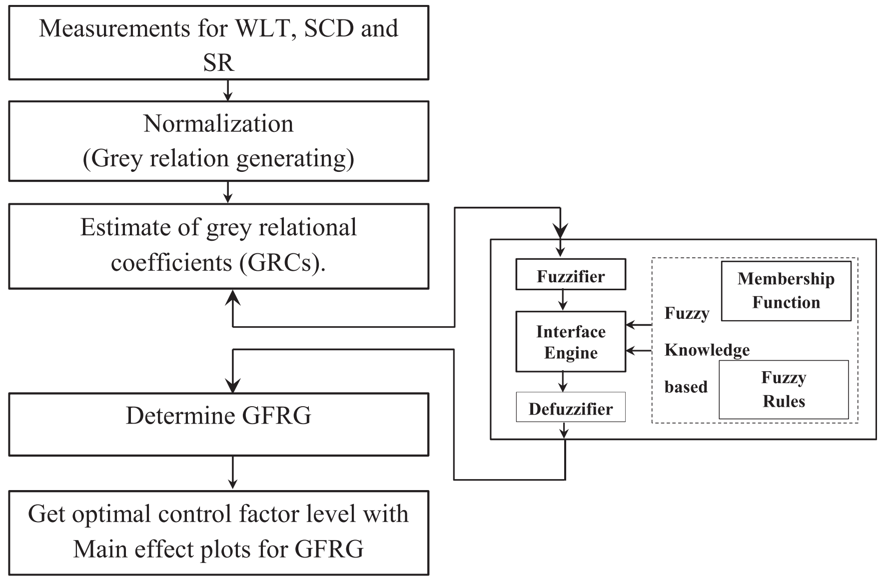

Fig. 2. Steps for grey-fuzzy logic method.

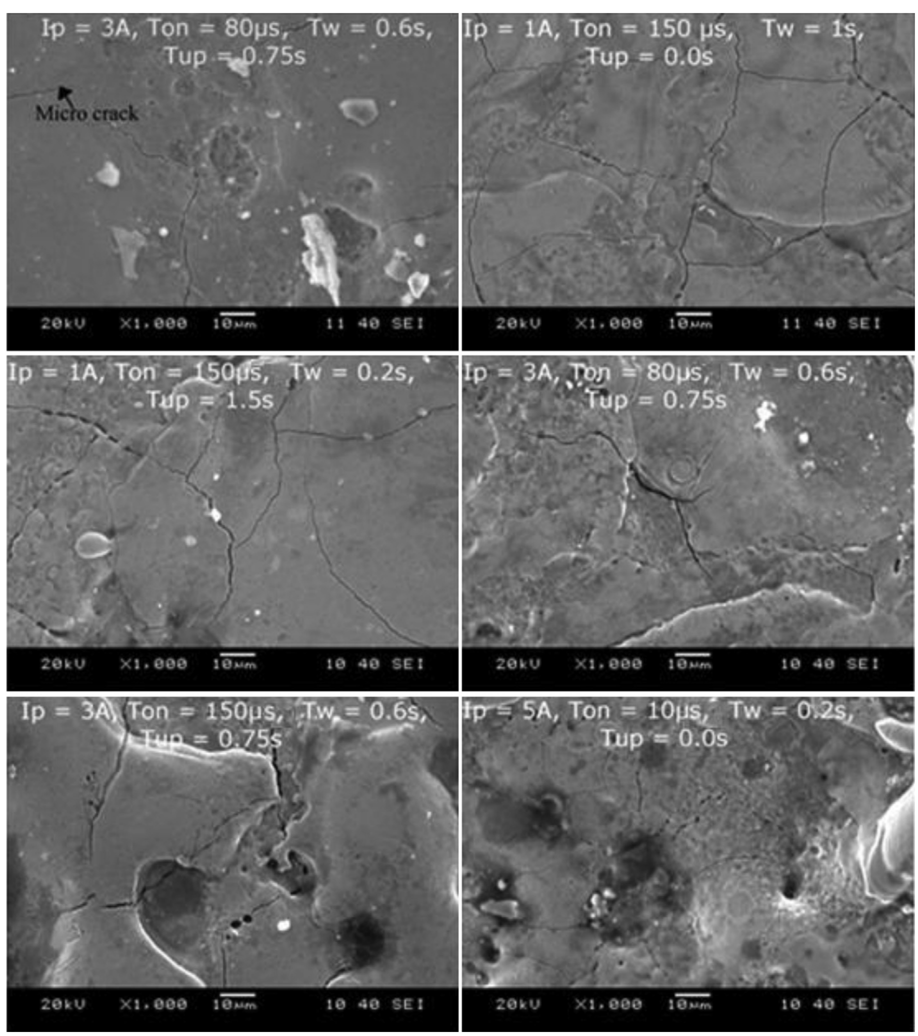

Fig. 3. Representative SEM images of SCD obtained with different parametric combinations.

several variables and the goal is to find the correlation between the response and the variables [21]. The RSM using central composite design with four variables (Ip, T_{on}, T_w and T_{up}) yield a total of 30 runs in three blocks, where the cardinal points used are sixteen cube points, eight axial points and six center points. The machining parameters and their levels are presented in Table 1. A second-order model is given in Eq. (1).

$$y = \beta_0 + \sum_{i=1}^{m} \beta_i x_i + \sum_{i=1}^{m} \beta_{ii} x_i^2 + \sum_{i,j=1, i \neq j}^{m} \beta_{ij} x_i x_j + \varepsilon \qquad (1)$$

where y = corresponding response, x_i = input variables and x_{ij}^2 and $x_i \cdot x_j$ are the squares and interaction terms respectively, of these input variables. The unknown regression coefficients are β_0, β_i and β_{ij} and ε = random error term.

Detailed observation for the entire sets of experiment is provided in Table 2. For each combination of experimental runs, corresponding responses such as WLT, SCD and SR were calculated.

2.3. Measurement of responses

During the current study, EDMed surface integrity was characterized by SR, WLT and SCD. After machining, each specimen was sectioned vertically. This was followed by polishing of the specimens with different grades of polishing papers with deceasing grit size. The polished surface was then etched with Nital solution to reveal micro-structure along with recast layer or white layer. Images were then captured on five different locations of each specimen using optical microscope (with model: SCD313 BPD and make: Radical Instrument) with a magnification of 400×. The measurement of WLT was carried out with an optical microscope with 400× magnification. Recast area was measured using software (PDF X-change viewer) and then the area was divided by total length of optical microscopic images, to get the average height of recast layer (i.e. WLT). In order to measure SCD, the top surface morphology of the EDMed surface was studied using scanning electron microscopy (SEM) with a magnification of 1000×. Randomly, five sample areas were selected on each specimen and the length of the cracks was measured using the same software. The average crack length on each specimen was divided by area of each micrograph (10649.072 μm^2) to measure the SCD. The similar measurement of SCD has been reported elsewhere [22]. EDMed Surface roughness (Ra) was measured using surface roughness tester (Make: Taylor Hobson, Model: Talysurf, Surtronic 3+).

3. Methodology

3.1. Grey relation analysis

Grey relational analysis (GRA) is an effective method in which analysis being done among the sequence groups requires that all sequences satisfy comparability conditions, for instance, non-

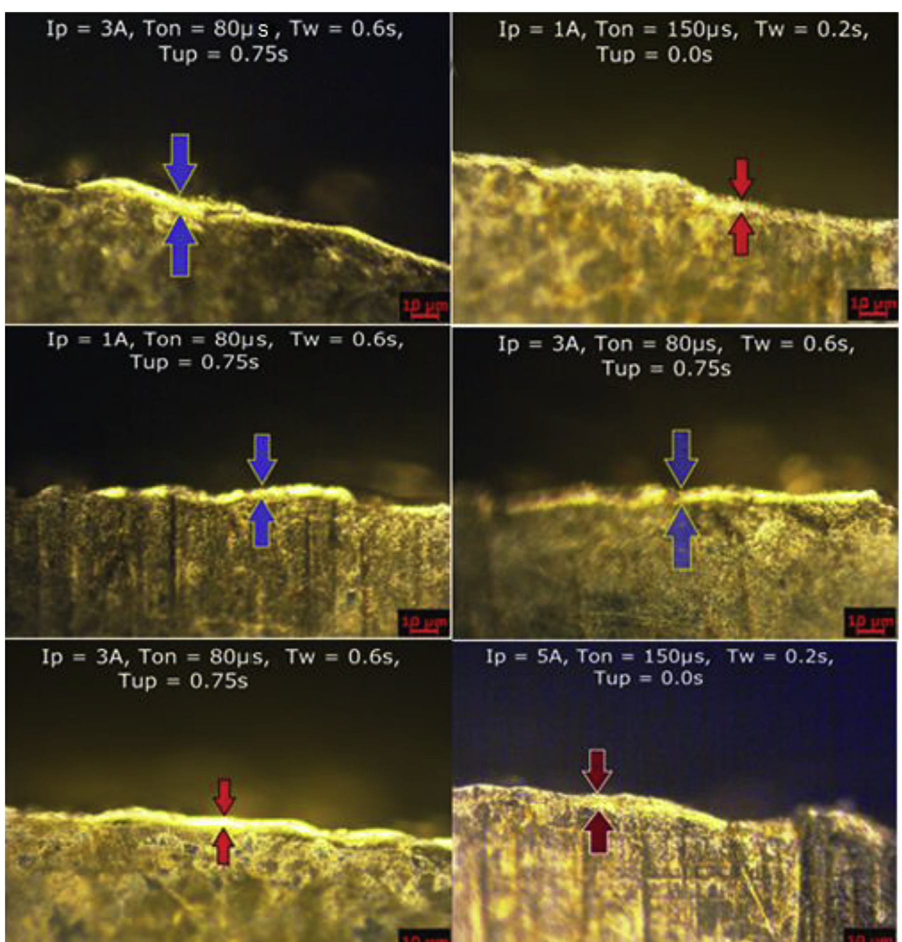

Fig. 4. Representative optical microscopic images of WLT obtained with different parametric combination.

dimension, scaling, and polarization attributes [23]. First step in GRA is to normalize all the experimental data in the range of zero to one. Such normalization is necessary because the range and the unit in one response may vary from the others. If the response is of 'higher-the-better' characteristics, equation for normalizing is as follows:

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

If 'lower-the-better' criterion is to be followed, then the following equation is to be utilized for normalizing the corresponding data:

$$x_i^*(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i - \min x_i(k)} \tag{3}$$

where $x_i^*(k)$ and $x_i(k)$ are the normalized data and observed data respectively for ith experiment using kth response. After normalizing the responses, the next step is to calculate the grey relation coefficient (GRC). GRC is denoted by for kth response. It can be calculated by using Eq. (4).

$$\zeta_i(k) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_i(k) + \zeta\Delta_{\max}} \tag{4}$$

where $\Delta_i(k)$ is the absolute value of the different between $x_i^o(k)$ and $x_i^*(k)$ and $\Delta_i(k) = |x_i^*(k) - x_i^o(k)|$. $\Delta_{\max}$ and $\Delta_{\min}$ are the global maximum and global minimum values in the different data series, respectively. The distinguishing coefficient lies between 0 and 1, which is to expand or compress the range of GRC, general, $\zeta = 0.5$ is taken.

3.2. Grey-fuzzy logic

In GRA, each response is categorized as either 'lower-the-better' or 'higher-the-better' or 'nominal-the-better' quality characteristics and the analysed results show some level of uncertainty. This uncertainty can be effectively examined by using fuzzy-logic approach [18]. Thus complicated multi-objective optimization problem can be solved by integrating GRA and fuzzy-logic techniques.

Fuzzy-logic system (Mamdani system) includes of a fuzzifier, membership functions, fuzzy rule base, inference engine and defuzzifier [24]. In this analysis, the fuzzifier uses membership functions to fuzzify the GRC, as it comprises some degree of uncertainty and vagueness with respect to performances characteristic. The inference engine performs fuzzy reasoning on fuzzy rules to generate a fuzzy value. Finally, the defuzzifier converts fuzzy predicted value into a single equivalent multi performance characteristics index.

3.3. Steps for grey-fuzzy-logic method

The steps of grey-fuzzy-logic method are illustrated in Fig. 2 and described as follows:

1. The experimental values of WLT, SCD and SR are normalized in the range of 0–1.
2. Grey relational coefficient (GRC) of each response is calculated.
3. Then fuzzy-logic system is applied. The fuzzifier uses the membership functions to fuzzify GRC of each performance characteristic.
4. Fuzzy rules (if-then control rules) are generated and finally defuzzifier converts fuzzy predicted value into a GFRG.
5. Optimal setting of machining parameters with the help of main effect plots for GFRG is finally evaluated.

4. Results and discussion

In this section, pre-processed data of WLT, SCD and SR along with the optical microscopic and SEM images depicting the formation of recast layer (white layer) and surface crack are presented. The experimental results are provided in Table 2. The representative SEM images of crack formation of machine surface and optical microscopic images of white layer obtained under different machining condition are shown in Figs. 3 and 4 respectively. The experimental data are utilized for determination of GRC and then GFRG followed by analyses of variance (ANOVA) for GFRG. Conformation test is also carried out with the optimal parametric combination.

4.1. Calculating the grey relation coefficients

For all the surface integrity characteristics i.e. WLT, SCD and SR, 'lower-the-better' criterion is chosen. Therefore, the output values that are listed in Table 2 have been normalized by using Eq. (3). GRCs for each response have been calculated using Eq. (4). Table 3 shows the normalized data and grey relational coefficients for corresponding to each experiment runs. However, in order to obtain an improved quality in the performances and to decrease the uncertainty in the data, grey-fuzzy logic method is further used for computing the GFRG.

4.2. Grey-fuzzy reasoning analysis

In this paper, three inputs and one output fuzzy-logic system are used. The inference engine (Mamdani fuzzy inference system) performs fuzzy reasoning with fuzzy rules to generate a fuzzy value. These fuzzy rules are presented in the form of 'if-then' control rule. For each rule, the three inputs are assigned in the fuzzy

Table 3
Computing GRC and grey fuzzy reasoning grade (GFRG).

Run no.	Normalized			Grey relation coefficient (GRC)			GFRG	Rank
	N WLT	N SCD	N SR	WLT	SCD	SR		
1	0.6514	0.7163	0.4150	0.5892	0.6380	0.4608	0.5612	29
2	0.0548	0.8981	0.0000	0.3460	0.8307	0.3333	0.5948	18
3	0.9772	0.0937	0.9872	0.9564	0.3555	0.9750	0.7776	02
4	0.8377	0.0372	0.9872	0.7549	0.3418	0.9750	0.6891	08
5	0.5323	0.7163	0.6819	0.5167	0.6380	0.6112	0.5835	24
6	0.5481	0.9146	0.3528	0.5253	0.8541	0.4359	0.5931	22
7	0.1109	0.9146	0.2322	0.3599	0.8541	0.3944	0.5943	20
8	0.7331	0.1722	0.9378	0.6520	0.3766	0.8894	0.6828	10
9	0.4635	1.0000	0.6344	0.4824	1.0000	0.5776	0.7250	06
10	0.8574	0.7273	0.9269	0.7780	0.6471	0.8724	0.7731	4
11	0.4345	0.8774	0.4516	0.4693	0.8031	0.4769	0.6298	14
12	0.6040	0.8540	0.3419	0.5581	0.7740	0.4317	0.5711	25
13	0.8444	0.9904	0.7185	0.7627	0.9811	0.6398	0.7741	03
14	0.2501	0.9931	0.1956	0.4000	0.9864	0.3833	0.5937	21
15	0.5687	0.8733	0.3784	0.5369	0.7978	0.4458	0.5930	23
16	0.4697	0.7493	0.3784	0.4853	0.6661	0.4458	0.5562	30
17	0.9316	0.1281	0.7751	0.8797	0.3645	0.6898	0.6495	12
18	0.4438	0.8209	0.3163	0.4734	0.7363	0.4224	0.5625	26
19	0.5071	0.9628	0.4516	0.5036	0.9308	0.4769	0.6339	13
20	0.6308	0.7906	0.4260	0.5753	0.7049	0.4655	0.5614	28
21	0.7584	0.0551	0.9872	0.6742	0.3460	0.9750	0.6829	09
22	0.0000	0.8788	0.2925	0.3333	0.8049	0.4141	0.5955	17
23	0.4978	0.4959	0.7075	0.4989	0.4979	0.6309	0.5619	27
24	0.5022	0.9683	0.4260	0.5011	0.9404	0.4655	0.6241	15
25	1.0000	0.0000	1.0000	1.0000	0.3333	1.0000	0.7781	01
26	0.4333	0.9077	0.3967	0.4687	0.8442	0.4532	0.6071	16
27	0.7707	0.1102	0.9634	0.6856	0.3598	0.9319	0.6828	11
28	0.1958	0.9105	0.0969	0.3834	0.8481	0.3564	0.5944	19
29	0.3839	0.9917	0.7550	0.4480	0.9837	0.6712	0.7189	07
30	0.8675	0.6887	0.9707	0.7905	0.6163	0.9447	0.7723	05

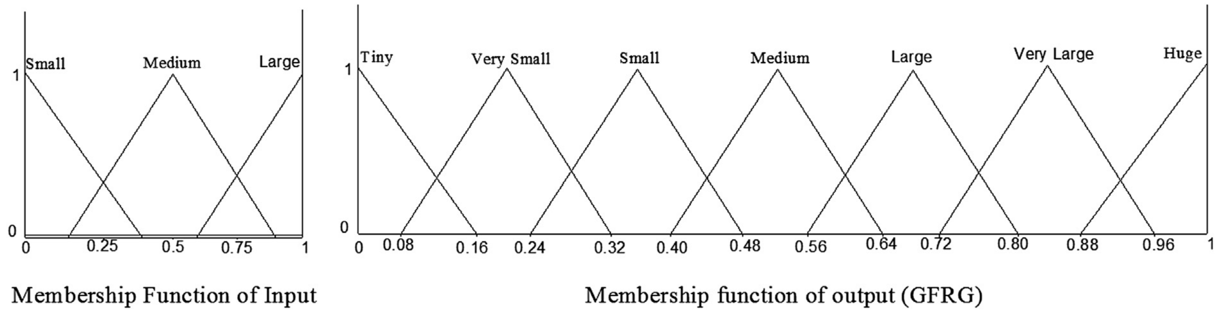

Fig. 5. Membership function of input and output.

subsets of small, medium and large and the corresponding membership functions $\mu x1$, $\mu x2$ and $\mu x3$ respectively. The output is assigned to any of the seven fuzzy subsets (tiny, very small, small, medium, large, very large) membership functions μY. The membership functions of the input and output are indicated in Fig. 5. The relationship between three inputs and the output is represented in the form of 'if-then' control rules that are:

Rules 1: if $x1$ is Large and $x2$ is Large and $x3$ is Large then Y is Very Large else
Rules 2: if $x1$ is Small and $x2$ is Medium and $x3$ is Medium then Y is Medium else
…..
…..
Rules n: if $x1$ is Small and $x2$ is Small and $x3$ is Very Small then Y is Very Small else

Fuzzy rules are directly derived based on the fact that 'larger-the-better' characteristic. The rule based fuzzy-logic reasoning procedure is shown in Fig. 6. By tracking maximum–minimum compositional operation, the fuzzy reasoning of these rules yields a fuzzy output. Finally, the defuzzifier converts fuzzy predicted value into a GFRG by using MATLAB tool box [20]. This GFRG values are provided in Table 3.

The higher value of GFRG means comparability sequence has a stronger correlation to the reference sequence. Based on Table 4 and Fig. 7, the optimal setting of the EDM process parameters is found to correspond to experimental run no. 10 i.e. with discharge current at level one (1 A), pulse on time at level one (10 µs), tool work time at level one (0.2 s), and tool lift time also at level one (0.0 s). This has been indicated in bold font in Table 2. The difference between maximum and minimum value of GFRG of EDM parameters is also calculated and provided in Table 4.

The response equation of GFRG is shown in Eq. (5). The most influencing factor for multi-performance is the maximum of this value (i.e. rank 1) which is the pulse on time (T_{on}). The same information can also be obtained from Fig. 7 by finding out the response graph with the steepest slope. The rank versus GFRG plot (paerto graph) is shown in Fig. 8 which indicates the ranking of the experimental run with multi-performance characteristics.

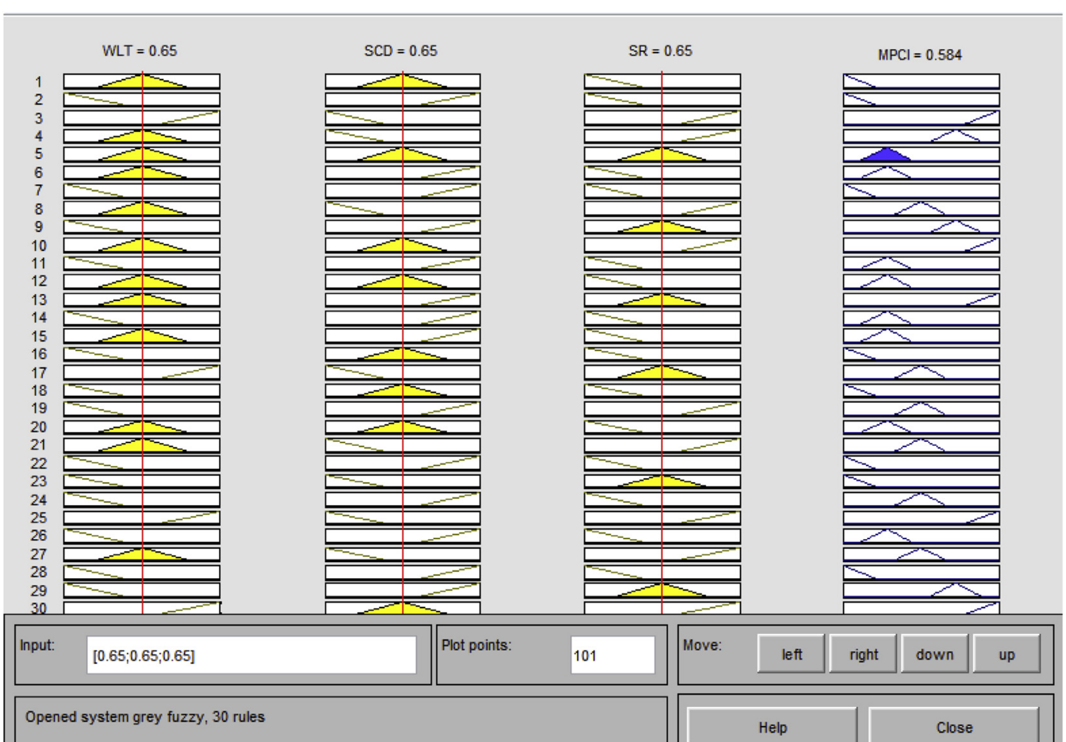

Fig. 6. Fuzzy logic reasoning procedure.

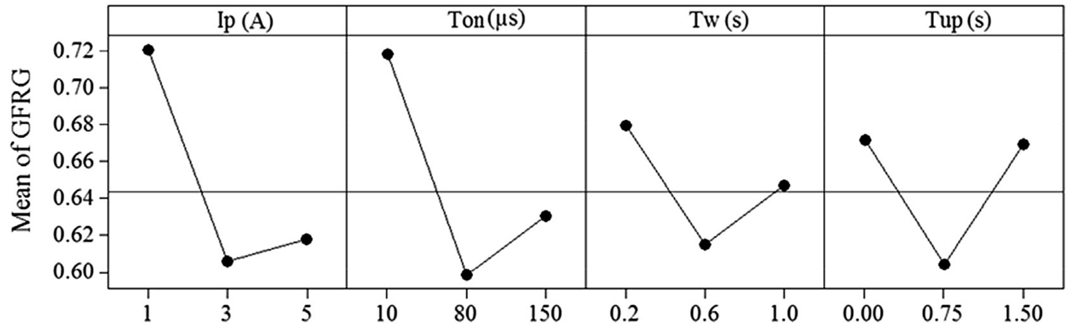

Fig. 7. Main effect plots for GFRG.

Table 4
Response table for the grey-fuzzy reasoning grade.

Level	Ip	T_{on}	T_w	T_{up}
1	0.7209	0.7183	0.6794	0.6717
2	0.6167	0.6042	0.6325	0.6137
3	0.6180	0.6303	0.6472	0.6695
Max–min	0.1042	0.1141	0.0469	0.0579
Rank	2	1	4	3

$$\begin{aligned}\mathrm{GFRG} = {} & 0.850229 - 0.0257278 \times \mathrm{Ip} - 0.00310761 \times T_{on} \\ & - 0.0402639 \times T_w - 0.00144444 \times T_{up} + 1.54955 \\ & \times 10^{-05} \times T_{on}^2\end{aligned} \tag{5}$$

The results of analysis of variance (ANOVA) of GFRG are shown in Table 5. This examination is done at a significance confidence level of 95%. Fisher's F-test is further applied to find out the EDM parameters with prominent effect on multiple performance characteristics of surface integrity. Similar information is also provided by % contribution which is indicated in the last column in same table. In this table insignificant terms obtained from the P values have been eliminated and the remaining terms are provided. This table represents that Ip is the most significant factor followed by T_{on}.

The obtained results are verified by the confirmatory experiment. Table 6 shows confirmation results of surface integrity aspects corresponding to initial and optimal machining conditions. It is evident that machining with the optimal parametric combination would minimize WLT form 12.452 to 6.954 μm, SCD from 0.0210 to 0.0202 μm/μm^2 and decrease SR from 4.8600 to 2.06 μm. The estimated or predicted GFRG ($\widehat{Y}$) at the optimum level of the machining parameters can be calculated by Eq. (6).

$$\widehat{Y} = Y_m + \sum_{i=1}^{q} \left(\overline{Y}_i - Y_m\right) \tag{6}$$

where Y_m is the mean of GFRGs for all experimental runs and $\overline{Y}_i$ is the mean of GFRG at the optimum level of ith parameter, and q is the number of machining parameters that significantly affect GFRG. Table 6 also indicates that the machining with optimal setting would result in an improvement of GFRG of 0.2119 and 0.2341 for experimental and predicted values respectively. Therefore, the current study clearly demonstrates that grey-fuzzy-logic method combined with RSM-based design of experiment is a useful technique with smaller number of experimental trials and for ease in optimizing multi-performance characteristics of EDMed surface integrity.

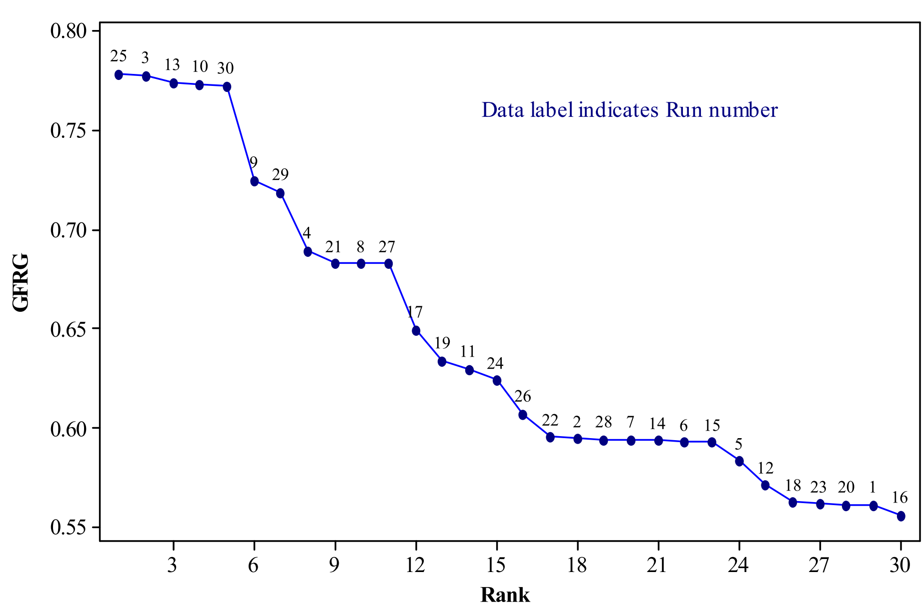

Fig. 8. GFRG for multi-performance.

Table 5
Analysis of variance for GFRG.

Source	DOF	SS	MS	F	P	% Contribution
Regression	3	0.12399	0.041329	24.48	0.000	73.86
Linear	2	0.08248	0.041240	24.43	0.000	49.13
Ip	1	0.04766	0.047658	28.23	0.000	28.39
T_{on}	1	0.03482	0.034822	20.63	0.000	20.74
Square	1	0.04151	0.041508	24.59	0.000	24.73
T_{on}*T_{on}	1	0.04151	0.041508	24.59	0.000	24.73
Residual error	26	0.04389	0.001688			26.14
Lack-of-fit	5	0.01370	0.002739	1.91	0.136	8.16
Pure error	21	0.03019	0.001438			17.98
Total	29	0.16788				100.00

Table 6
Comparison of results obtained under initial and optimal machining condition.

Levels	Initial machining parameters level	Optimum machining parameters level	
	Ip = 3 A, T_{on} = 80 µs, T_w = 0.6 s, T_{up} = 0.75 s	Ip = 1 A, T_{on} = 10 µs, T_w = 0.2 s, T_{up} = 0.0 s	
		Predicted	Experimental
WLT (µm)	12.452		6.954
SCD (µm/µm^2)	0.0210		0.0202
SR (µm)	4.8600		2.06
GFRG	0.5612	0.7953	0.7731
Improvement in the GFRG		0.2341	0.2119

5. Conclusions

The current research work utilizes hybrid optimization technique using GRA and fuzzy-logic method for simultaneously optimizing multiple performance characteristics of surface integrity (WLT, SCD and SR) in EDM. Based on the above experimental investigation as well as analysis, the following conclusions are presented:

1) The optimal EDM parametric combination of Ip = 1 A, T_{on} = 10 µs, T_w = 0.2 s and T_{up} = 0.0 s has been determined using grey-fuzzy logic with an aim to achieve minimum EDMed surface integrity of AISI P20 tool steel.
2) ANOVA results demonstrated that the pulse-on time is the most significant parameter followed by discharge current, whereas tool work time and tool lift time do not significantly affect the multi-performance characteristics of surface integrity.
3) Comparison of machining performance obtained under initial and optimal condition of machining indicated an improvement of GFRG of 0.2119 and 0.2341 for experimental and predicted values respectively.
4) The hybrid technique of grey-fuzzy logic method combined with RSM-based experimental design has a good potential to do away with the arduous task of multiple criteria optimization by converting the data into a single GFRG and hence can be effectively used in optimising the process parameters in EDM in order to achieve minimum aspects of surface integrity.

References

[1] R. Snoeys, F. Staelens, W. Dekeyser, Current trends in nonconventional material removal processes, CIRP Ann. Manufact. Technol. 35 (2) (1986) 467–480.
[2] B. Bhattacharyya, S. Gangopadhyay, B.R. Sarkar, Modelling and analysis of EDMed job surface integrity, J. Mater. Process. Technol. 189 (2007) 169–177.
[3] M.K. Pradhan, Estimating the effect of process parameters on surface integrity of EDMed AISI D2 tool steel by response surface methodology coupled with grey relational analysis, Int. J. Adv. Manufact. Technol. (2013) 1–12.
[4] J.H. Jung, W.T. Kwon, Optimization of EDM process for multiple performance characteristics using Taguchi method and grey relational analysis, J. Mech. Sci. Technol. 24 (5) (2010) 1083–1090.
[5] P.N. Singh, K. Raghukandan, B.C. Pai, Optimization by Grey relational analysis of EDM parameters on machining Al-10%SiCp composite, J. Mater. Process. Technol. 155–156 (1–3) (2004) 1658–1661.
[6] S. Dewangan, C.K. Biswas, Optimisation of machining parameters using grey relation analysis for EDM with impulse flushing, Int. J. Mechatron. Manufact. Syst. 6 (2) (2013) 144–158.
[7] P. Rupajati, B.O.P. Soepangkat, B. Pramujati, H.C.K. Agustin, Optimization of recast layer thickness and surface roughness in the wire EDM process of AISI H13 tool steel using taguchi and fuzzy logic, Appl. Mech. Mater. 493 (2014) 529–534.
[8] M.R. Shabgarda, M.A. Badamchizadehb, G. Ranjbarya, K. Aminic, Fuzzy approach to select machining parameters in electrical discharge machining (EDM) and ultrasonic-assisted EDM processes, J. Manufact. Syst. 32 (2013) 32–39.
[9] M.M. Barzani, E. Zalnezhad, A.A.D. Sarhan, S. Farahany, S. Ramesh, Fuzzy logic based model for predicting surface roughness of machined Al-Si-Cu-Fe die casting alloy using different additives turning, Meas. J. Int. Meas. Confeder. 61 (2015) 150–161.
[10] A.K. Pandey, A.K. Dubey, Taguchi based fuzzy logic optimization of multiple quality characteristics in laser cutting of Duralumin sheet, Opt. Lasers. Eng. 50 (2012) 328–335.
[11] A.M. Acilar, A. Arslan, Optimization of multiple input–output fuzzy membership functions using clonal selection algorithm, Exp. Syst. Appl. 38 (2011) 1374–1381.
[12] P. Sengottuvel, S. Satishkumar, D. Dinakaran, Optimization of multiple characteristics of EDM parameters based on desirability approach and fuzzy modeling, in: International Conference on Design and Manufacturing, IConDM, 64, 2013, pp. 1069–1078.
[13] S. Dewangan, S. Gangopadhyay, C.K. Biswas, Study of surface integrity and dimensional accuracy in EDM using fuzzy TOPSIS and sensitivity analysis, Measurement 63 (2015) 364–376.
[14] J.L. Lin, C.L. Lin, The use of the grey-fuzzy logic for the optimization of the manufacturing process, J. Manuf. Process Technol. 160 (2005) 9–14.
[15] B.O.P. Soepangkat, B. Pramujati, Optimization of surface roughness and recast thickness in the wire-EDM process of AISI D2 tool steel using Taguchi-grey-fuzzy, Appl. Mech. Mater. 393 (2013) 21–28.
[16] T. Rajmohan, K. Palanikumar, S. Prakash, Grey-fuzzy algorithm to optimise machining parameters in drilling of hybrid metal matrix composites, Composites: Part B 50 (2013) 297–308.
[17] R.K. Pandey, S.S. Panda, Optimization of bone drilling parameters using grey-based fuzzy algorithm, Measurement 47 (2014) 386–392.
[18] S. Pattnaik, D.B. Karunakar, P.K. Jha, Multi-characteristic optimization of wax patterns in the investment casting process using grey-fuzzy logic, Int. J. Adv. Manuf. Technol. 67 (5–8) (2013) 1577–1587.
[19] A. Krishnamoorthy, S.R. Boopathy, K. Palanikumar, J.P. Davim, Application of grey fuzzy logic for the optimization of drilling parameters for CFRP composites with multiple performance characteristics, J. Int. Meas. Confeder. 45 (5) (2012) 1286–1296.
[20] Y.S. Yang, W. Huang, A grey-fuzzy Taguchi approach for optimizing multi-objective properties of zirconium-containing diamond-like carbon coatings, Exp. Syst. Appl. 39 (1) (2012) 743–750.
[21] D.C. Montgomery, Design & Analysis of Experiments, Wiley, New York (, 2001.
[22] S. Rajendran, K. Marimuthu, M. Sakthivel, Study of crack formation and resolidified layer in EDM process on T90Mn2W50Cr45 tool steel, Mater. Manuf. Process. 28 (6) (2013) 664–669.
[23] J.L. Deng, Introduction to grey system theory, J. Grey Syst. 1 (1989) 1–24.
[24] Y. Tzeng, F. Chen, Multi-objective optimisation of high-speed electrical discharge machining process using a Taguchi fuzzy-based approach, Mater. Design 28 (4) (2007) 11.