MULTI OBJECTIVE OPTIMIZATION OF MACHINING PARAMETERS OF EN-8 CARBON STEEL IN EDM PROCESS USING GRA METHOD

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Abstract: The selection of machining environment is one of the most important aspects in the majority of high end manufacturing process like EDM. Aiming to improve the machining performances of EN-8 steel during EDM process such as tool wear rate (TWR), material removal rate (MRR) and surface roughness (Ra), the influence of machining parameters were experimentally investigated using response surface methodology (RSM) based grey relational analysis (GRA) optimization technique in the present study. All three output responses are optimized individually and then argument came to select most optimum result. To overcome this situation, a GRA based multi optimization technique was implemented to get the optimized result. Furthermore the ANOVA study provides that the discharge current (Ip) has greatest impact over the spark on time (Ton) followed by spark off time (Toff) and flushing pressure (Fp). From the confirmatory test, 15.08% of overall improvement occurs in the machining performance after following GRA.

Key words: EDM, Grey Relations Analysis, TWR, MRR, Ra.

1. INTRODUCTION

In EDM a series of spark is produced to erode a conductive material. Harder metals can be removed by using softer metals as tools. So EDM is an excellent process used in mould making and tool & die making industry and also used a common method for making prototypes and production parts made of difficult to machine materials (Drozda, 1983; Ho & Newman, 2003). The versatility in EDM made it a process that can access the intricate shaped machine parts. Various types of operations can be done as cutting in EDM, sinking by EDM, grinding by EDM. EDM is very much skilled for machining of hard material such as heat treated tool steels, composites, super alloys, ceramics, carbides, heat resistant steels etc. and also been used for precision machining. The higher carbon grades are mostly used for stamping dies, metal cutting tools, etc.

As EDM is a very effective machining process for industrial point of view, many researchers are working for it. Yue et al. described about the influence of the metal vapour jet erode from tool on MRR of steel. Selected electrode materials for this study were copper, brass and zinc (Yue et al., 2018). Zinc plays greater result compared to copper followed by brass. Hourmarnd et al. described the influence of EDM parameter for Al-Mg_2Si metal matrix composite by considering RSM approach (Hourmarnd et al., 2015). Copper was used as electrode for machining purpose. Zhao et al. studied about the improvement the performance of EDM cutting for silicon carbide. Higher MRR and lower TWR was observed in this machining process compared to others (Zhao et al., 2014).

A multi optimization technique i.e. GRA is a highly used for many machining processes and shows a significant improvement in output result (Maniyar & Ingole, 2018; Dewangan & Biswas, 2013; Aravindan et al., 2018; Mishra & Routara, 2017). EN8 and EN24 grades of steel are used to form axles, shaft, bolts, studs etc. but they possess low corrosion resistance. Authors concluded by different heat treatments, such as annealing, normalizing and hardening with different quenching agents (water and oil) the corrosion behaviour of selected EN8 and EN24 grades of steels (Aparna et al., 2015). Rao et al. had taken Titanium alloys (Ti_6Al_4V) and EN-8 Steel as workpiece material to study the material removal and surface roughness characters. They found how input process parameters like processing time, electrolyte composition, electrolyte concentration and electrolyte temperature has a significant role in the minimization of roughness in ECH (Rao et al., 2015). Balasubramanian and Senthilvelan described the machining characteristics of EN-8 and D3 steel material via EDM with Cast Copper and Sintered Powder Metallurgy Copper (P/M Copper) as tool material (Balasubramanian and Senthilvelan, 2014).

Koteswararao et al. were considered EN 31 carbon alloy steel as workpiece material to study the machining characteristics through EDM process. Discharge current was the most influencing factor on MRR, TWR and over cut compared to other parameters such as pulse on time and diameter of tool

(Koteswararao et al., 2017). Kishan et al. studied the MRR of EN-8 steel on EDM by using different electrode materials such as copper and brass. They concluded that the copper electrode has greater effect on MRR compared to brass (Kishan et al., 2018).
By extensive literature study, EN-8 steel and copper are selected for the workpiece and tool material respectively for machining by EDM process. Machining characteristics has been analysing through RSM and GRA as multi optimization technique.

2. EXPERIMENTAL DETAILS AND METHODOLOGY

All experiments for this current research work were conducted by die-sinking EDM machine (Model: ECOWIN MIC-432CS PNC) considering positive polarity of the electrode with internal flushing pressure 0.2kgf/cm^2 as shown in Figure 1. Here the commercial grade Kerosene oil (specific gravity = 0.820, flash point = 65^{0}C) was used as dielectric fluid.

(a) Die-sinking EDM set-up

(b) Tool holder with Workpiece and tool

Fig. 1. Die-sinking EDM set-up (Model: ECOWIN MIC-432CS PNC)

Table 1. Chemical composition of workpiece material "EN-8 tool steel" (mass fraction, %)

Element	C	Mn	Si	P	S	Fe
mass fraction, %	0.40	1.00	0.30	0.05	0.05	Balance

The workpiece material selected for this experiment was EN8 carbon steel. As it is a pre hardened high tensile steel, which offers ready to machining ability in the hardened and tempered condition, so no further heat treatment was conducted. It shows good machinability and better polish ability, compared to other alloy steel. The chemical composition of the workpiece material is given in Table 1.
For the current research purpose, the cylindrical shape pure copper is considered as electrode material to perform the machining operation on medium carbon steel EN-8 in a die sinking EDM process. In this experiment spark gap, voltage, duty cycle and polarity is kept constant with varying input current (Ip), pulse on time (Ton), pulse off time (Toff) and flushing pressure (Fp). When an optimum spark gap (0.01-0.5)mm is maintained metal removal starts. Peak voltage around (30-250)V is maintained. The voltage is kept constant with 50V. Peak current increases the high energy and remove the material from the workpiece. When discharge takes place between two points of anode and cathode intensive heat is generated near the cutting zone that melts and evaporates the small quantities of the workpiece material. Finally plasma channel collapses and the removed particles are flushed away by flushing by the dielectric fluid flow between the tool and the workpiece. The final product so produced in EDM is exactly replica of the shape of the electrode.
All experiments were conducted based upon design matrix. After successful machining of the EN-8 steel, three important machining features such as TWR, MRR and Ra were examined individually. Furthermore multi performance characteristics technique i.e. GRA was implemented for ease in optimization.

2.1 Design of Experiment

From the numerous literatures, it is observed that the Response Surface Methodology (RSM) is one of the most successful DOE compared to others (Hourmarnd et al., 2015; Moharana & Sahoo, 2014; Subramonian et al., 2010; Majhi et al., 2013). It is a pragmatic monetization technique dedicated to the valuation of relations existing between a group of controlled experimental factors and the observed results of one or more selected criteria.

Table 2. Process parameters and experimental design levels

Process parameters	Symbols	Levels		
		(1)	(2)	(3)
Discharge current [A]	(Ip)	4	14	24
Spark on time [μs]	(Ton)	10	105	200
Spark off time [μs]	(Toff)	10	30	50
Flushing pressure [Kgf/cm^2]	(Fp)	0.25	0.50	0.75

Four input process parameters such as Discharge current (Ip), Spark on Time (Ton), Spark off Time (Toff) and Flushing Pressure (Fp) were taken into consideration with three levels of variations as shown in Table 2. Here the Box-Bhenken design (3 center points and 3 blocks) was considered for the formation of RSM design matrix with 27 experimental trials as shown in Table 3.

Table 3. Experimental design matrix with results

Run	I_p	T_{on}	T_{off}	F_p	TWR	MRR	R_a
1	4	10	30	0.5	0.00003	0.0169	3.437
2	24	10	30	0.5	0.00308	0.2146	12.419
3	4	200	30	0.5	0.00001	0.0046	2.168
4	24	200	30	0.5	0.00153	0.4294	15.940
5	14	105	10	0.25	0.00513	0.3263	7.379
6	14	105	50	0.25	0.00036	0.0416	11.050
7	14	105	10	0.75	0.00115	0.2471	9.743
8	14	105	50	0.75	0.00424	0.2124	10.369
9	4	105	10	0.25	0.00015	0.0117	2.364
10	24	105	10	0.25	0.00431	0.2361	13.210
11	4	105	50	0.25	0.00024	0.0254	2.872
12	24	105	50	0.25	0.00752	0.4281	14.014
13	14	10	30	0.25	0.00020	0.1960	9.796
14	14	200	30	0.25	0.00054	0.2181	10.408
15	14	10	30	0.75	0.00364	0.1686	10.200
16	14	200	30	0.75	0.00028	0.1803	13.934
17	4	105	30	0.25	0.00001	0.0202	1.202
18	24	105	30	0.25	0.00041	0.2309	10.133
19	4	105	30	0.75	0.00011	0.0120	2.596
20	24	105	30	0.75	0.00518	0.3254	11.836
21	14	10	10	0.5	0.00049	0.2443	12.774
22	14	200	10	0.5	0.00382	0.1987	12.608
23	14	10	50	0.5	0.00418	0.2250	13.071
24	14	200	50	0.5	0.00194	0.1798	12.501
25	14	105	30	0.5	0.00160	0.2073	13.725
26	14	105	30	0.5	0.00370	0.2086	13.759
27	14	105	30	0.5	0.00204	0.2061	13.638

The sample photographs of electrode and workpiece after machining and measurement of surface roughness are shown in Figure 2. From three output responses, TWR and Ra should be minimum whereas MRR to be maximum. So these scenarios fall under multi objective optimization. For the present work, GRA is considered to convert the multiple responses to a single response.

(a) Cu Electrodes (b) Workpiece after machining (c) During "Ra" measurement

Fig. 2. Electrodes and workpiece after EDM process

2.2 Grey relational analysis and data processing

Grey Relational Analysis (GRA) is a mathematical model based upon grey system theory that converts multiple responses to a single response. In this process, the experimental results were first normalized on the basis of the response characteristics i.e. "higher the better" or "lower the better" as given in equation (1) and (2) respectively.

$$\mathrm{x_i}(k) = \frac{\max\ \mathrm{y_i}(k) - y_i(k)}{\max\ \mathrm{y_i}(k) - \min\ \mathrm{y_i}(k)} \tag{1}$$

$$\mathrm{x_i}(k) = \frac{\mathrm{y_i}(k) - \min\ y_i(k)}{\max\ \mathrm{y_i}(k) - \min\ \mathrm{y_i}(k)} \tag{2}$$

Where, $x_i(k)$ and $y_i(k)$ are the normalized and experimental value for ith experiment using kth response respectively, min $y_i(k)$ and max $y_i(k)$ are the minimum and maximum value of $y_i(k)$ for the kth response respectively.

After successful calculation of normalized value, the Grey Relation Coefficient (GRC) "$\zeta i(k)$" for the kth response characteristics in the ith experiment was calculated following the equation (3).

$$\zeta_i(k) = \frac{\Delta\min + \zeta\Delta\max}{\Delta i(k) + \zeta\Delta\max} \tag{3}$$

Where $\Delta i(k)$ is the deviation sequence of the reference sequence and ζ is the identification coefficient whose value lies between 0 and 1, usually taken on the basis of weights of the output responces. For the present study, all the output responces are given equal weightage. Δmax and Δmin are the global maximum and minimum values of each sequence respectively.

After calculating the GRCs, for n number of responses, the Grey Relational Grade (GRG) "γ" can be calculated using equation (4).

$$\gamma = \frac{1}{n}\sum_{i=1}^{n}\zeta_i(k) \tag{4}$$

3. RESULT AND DISCUSSIONS

Experiments were conducted according to RSM design matrix as explained earlier. After successful machining operation, the weights of the workpiece and tool followed by the dimensional measurements of the machined surface were taken for calculation of TWR, MRR and Ra. At first the individual influence of output responses are considered for analysis and then multi objective optimization technique i.e. GRA is used to optimize by considering all three output responses i.e. TWR, MRR and Ra simultaneously.

3.1 Influence of EDM parameters on TWR

The influence of input parameters of EDM on TWR is shown in the Figure 3. The figure elucidates that the Ip is directly proportional to TWR i.e. TWR increases with respect to Ip. As Ip follows increase of pulse energy tends to production of more heat energy, which results increase in melting as well as evaporation of the electrode. It can be recommended that the Ip has a significant impact on TWR (Dhar et al., 2007). When higher Ton was considered, more energy released in between inter electrode gap which results dissociation of dielectric fluid followed by release of carbon particle and deposition over surface of the tool as a protective layer. This results a reduced TWR at higher Ton (Habib, 2009). The graph also represents that the increasing flushing pressure and Toff result more TWR value. As TWR should as minimum as possible, so optimum parameter for TWR will be Ip = 4A, Ton = 200s, Toff = 10s and Fp= 0.5kgf.

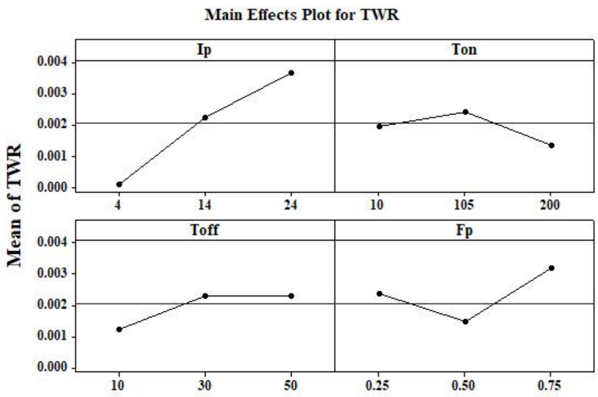

Fig. 3. Main effect plot for TWR

3.2 Influence of EDM parameters on MRR

The main effect plot of all four process parameters such as Ip, Ton, Toff and Fp on the MRR are shown in Figure 4. This figure shows that the discharge current (Ip) is directly proportional to MRR as with increase in discharge current from 4A to 14A, the MRR value also in increasing pattern. This is predictable as stronger spark occurs with increase in pulse current, which produces the higher temperature, causing more material to melt and erode from the workpiece (Ghoreishi & Tabari, 2007).

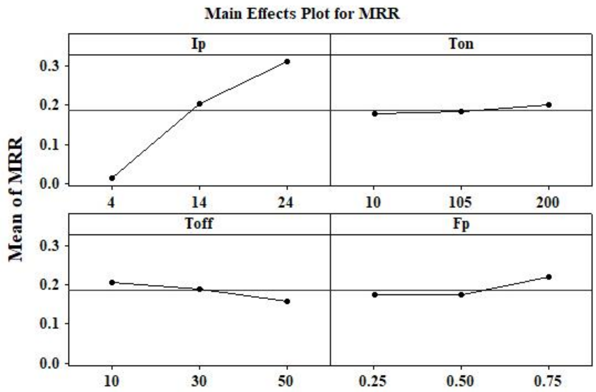

Fig. 4. Main effect plot for MRR

Considering pulse-on-time for observing the effect on output response i.e. MRR value increases with respect to Ton. Theoretically, the total energy supply to the workpiece increases with increases of Ton, so more material may erode from workpiece. In addition to that, there is some limitation for higher Ton value as the plasma formed in between inter electrode gap restrict the energy transfer results decreasing in MRR. But, with higher Ton value, the plasma formed between the inter electrode gap actually hampers the energy transfer and it results the reduction in MRR value (Saha & Choudhuri, 2009; Kung et al., 2009). The graph also represents that the increasing flushing pressure results more MRR value. The rate of MRR is quite higher at Fp = 0.75kgf/cm^2 compare to 0.25kgf/cm^2 and 0.5kgf/cm^2. As MRR should be as maximum as possible, so optimum parameter for MRR will be Ip = 24A, Ton = 200s, Toff = 10s and Fp = 0.75kgf/cm^2.

3.3 Influences of EDM parameters on Ra

The main effect plots for surface roughness (Ra) with respect to various input parameters are shown in Figure 5. As higher pulse current refers to formation of high energy for material removal leading to crack formation on machined surface and subsequent poor surface finish achieved (Guu et al., 2003).

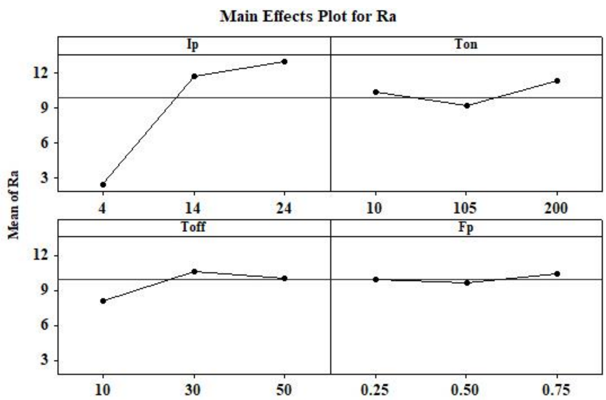

Fig. 5. Main effect plot for Ra

When pulse on time is increasing, Ra value falls up to a certain level then higher roughness value attained. At higher pulse on time, higher surface roughness achieved as creation of plasma refers to the formation of many cracks followed by higher Ra. Initially with increase in Toff, surface roughness increases to a maximum level and later it starts decreasing. Flushing pressure has no significant effect on surface roughness. As Ra should be as minimum as possible, so optimum parameter for Ra should be Ip = 4A, Ton = 105s, Toff=10s and Fp = 0.50kgf/cm^2.

3.4 Implementation of Grey Relational Analysis

From the individual analysis of all output responses over each and every input parameter, it is very difficult to draw the common ultimate result for all responses. To avoid such ambiguity a multi optimization technique i.e. GRA was implemented to get the optimized result. In such analysis, multiple performances are incorporated to a single response i.e. Grey Relational Grade (GRG), for ease in optimization (Lin & Wang, 2010). The respective steps for getting GRG values are explained in section 2.2. At first the normalised value for MRR is calculated by using equation (1) where as TWR and Ra by using equation (2). These normalised values are utilized to calculate grey relational co-efficient for respective responses using equation (3). Consequently GRG is evaluated from GRC's for individual experimental run by using equation (4) and tabulated in Table 4. According to GRG rules, "Higher is better" policy was considered for all the experimentations (Tosun & Pihtili, 2010).

Table 4. Grey relational analysis response table

Run	Normalized Results			Grey Relational Coefficient (GRC)			GRG
	TWR	MRR	Ra	TWR	MRR	Ra	
1	0.9970	0.0290	0.8484	0.9941	0.3399	0.7673	0.7004
2	0.5914	0.4944	0.2389	0.5503	0.4972	0.3965	0.4813
3	1.0000	0.0000	0.9345	1.0000	0.3333	0.8841	0.7391
4	0.7967	1.0000	0.0000	0.7109	1.0000	0.3333	0.6814
5	0.3184	0.7573	0.5809	0.4232	0.6732	0.5440	0.5468
6	0.9527	0.0871	0.3318	0.9136	0.3539	0.4280	0.5652
7	0.8473	0.5709	0.4205	0.7661	0.5381	0.4632	0.5891
8	0.4365	0.4892	0.3780	0.4701	0.4946	0.4456	0.4701
9	0.9809	0.0167	0.9212	0.9632	0.3371	0.8638	0.7213
10	0.4279	0.5450	0.1852	0.4664	0.5235	0.3803	0.4567
11	0.9692	0.0490	0.8867	0.9420	0.3446	0.8152	0.7006
12	0.0000	0.9969	0.1307	0.3333	0.9939	0.3651	0.5641
13	0.9747	0.4506	0.4169	0.9518	0.4764	0.4616	0.6300
14	0.9282	0.5026	0.3754	0.8744	0.5013	0.4446	0.6068
15	0.5169	0.3861	0.3895	0.5086	0.4489	0.4502	0.4692
16	0.9639	0.4136	0.1361	0.9326	0.4602	0.3666	0.5865
17	0.9991	0.0367	1.0000	0.9982	0.3417	1.0000	0.7800
18	0.9465	0.5327	0.3940	0.9034	0.5169	0.4521	0.6241
19	0.9860	0.0174	0.9054	0.9727	0.3372	0.8409	0.7170
20	0.3119	0.7552	0.2785	0.4208	0.6713	0.4093	0.5005
21	0.9358	0.5643	0.2148	0.8861	0.5343	0.3891	0.6032
22	0.4921	0.4569	0.2261	0.4961	0.4794	0.3925	0.4560
23	0.4446	0.5188	0.1947	0.4737	0.5096	0.3830	0.4555
24	0.7431	0.4124	0.2333	0.6606	0.4597	0.3947	0.5050
25	0.7886	0.4772	0.1503	0.7028	0.4888	0.3705	0.5207
26	0.5080	0.4802	0.1480	0.5040	0.4903	0.3698	0.4547
27	0.7288	0.4743	0.1562	0.6483	0.4875	0.3721	0.5026

The Pareto graph of GRGs is shown in Figure 6 and three highest GRG values are observed for the run numbers 17, 3 and 9 in descending order. The main effect plot for GRG is shown in Figure 7. The graph concludes about the optimal process parameter for EDM as Ip = 4A, Ton = 200μs, Toff = 10μs and Fp=0.50kgf/cm^2.

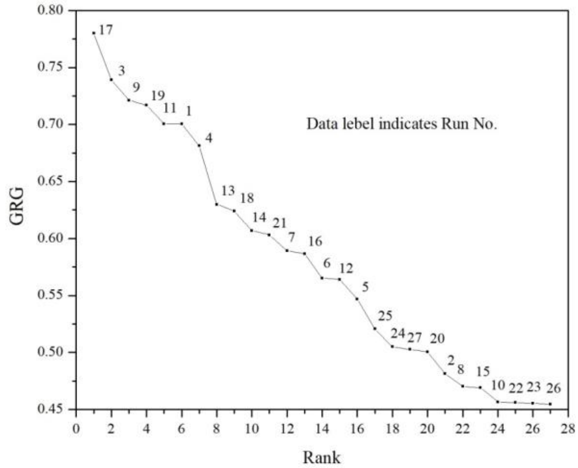

Fig. 6. Grey relation grades for the multi performance

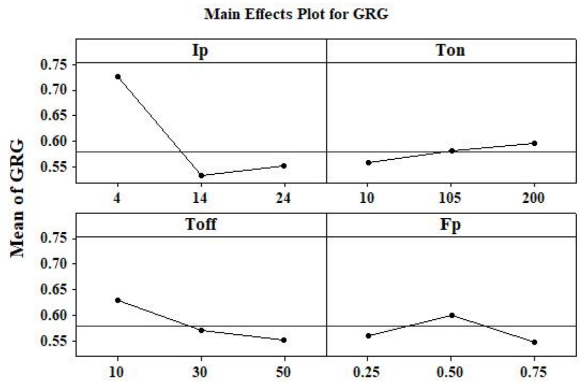

Fig. 7. Main effect plot for GRG

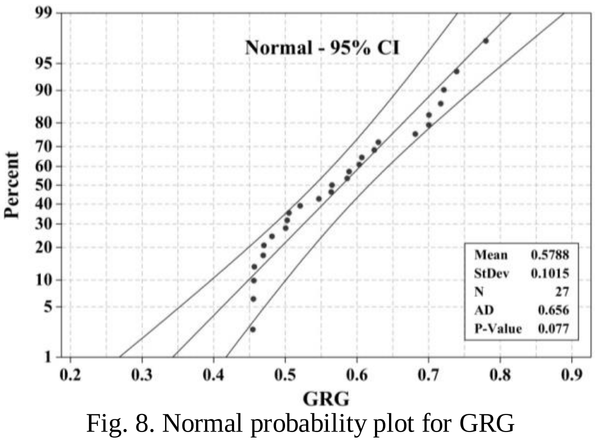

Fig. 8. Normal probability plot for GRG

Table 5. Analysis of Variance for GRG

Source	DF	Seq. SS	Adj. SS	Adj. MS	F	P
Regression	4	0.1151	0.0975	0.0243	11.41	0.000
Linear	4	0.1151	0.0975	0.0243	11.41	0.000
Ip	1	0.0919	0.0778	0.0778	36.43	0.000
Ton	1	0.0046	0.0205	0.0205	9.63	0.009
Toff	1	0.0182	0.0052	0.0052	2.47	0.142

Fp	1	0.0003	0.0001	0.0001	0.07	0.792
Residual Error	22	0.0256	0.0256	0.0021		
Lack-of-Fit	20	0.0233	0.0233	0.0023	2.01	0.378
Pure Error	2	0.0023	0.0023			
Total	26	0.2680				
S = 0.0462392 R^2 = 90.43 % R^2 (adj) = 79.26 %						

The normal probability plot for GRG describes the fitness of the model as shown in the Figure 8. The effectiveness of the each process parameters on the enhancement of multi-performance characteristics i.e. for minimize TWR, maximize MRR and minimize Ra are described in Table 5 i.e. analysis of variance (ANOVA) for GRG. In addition to that the table also represents the suitability of the developed numerical model by describe the significance of the all the input process parameters on overall quality characteristics of the EDM process quantitatively. Based on numerous literatures, the confidence level for the design is taken 95%. The ANOVA indicates that the Ip and Ton are the most significant factors among all four process paramters and Ip having utmost effect on the output response follow by Ton, Toff and Fp. The R^2 and adj. R^2 value obtained from the ANOVA table i.e. 90.43% and 79.26% respectively concludes the greatest adequacy of the designed model with respect to output response.

3.5 Confirmatory experiment

The confirmatory experiment was conducted based upon the optimal parameter setting, which was getting through GRA analysis as given in Table 6 and then compared with the previous results. The optimal result is showing a very good agreement compared to previous result. The GRG value obtained from optimal setting is 0.9185, which is almost 15.08% of overall improvement in GRG value. Thus, it can be concluded that the quality characteristics may greatly improve through this statistical study.

Table 6. Results of confirmatory experiment

Responses	Optimal machining parameter (Ip = 4A, Ton = 200μs, Toff = 10μs and Fp = 0.50kgf/cm^2)
TWR [mm^3/min]	0.0005945
MRR [mm^3/min]	0.4703
Ra [μm]	2.1029
GRG	0.9185
Earlier highest GRG value	0.7800
% of improvement	**15.08 %**

4. CONCLUSIONS

In this present research work, the influence of various EDM process parameters has been studied for TWR, MRR and Ra on the basis of productivity, quality characteristics surface integrity etc. during the machining of EN-8 tool steel and multi optimization technique i.e. GRA is applied for getting optimal process parameters for improvisation of output responses. The following conclusions are listed below. Such conclusions are the following:

- RSM based L27 design matrix was taken for study the influence of TWR, MRR and Ra of EDM machining on EN-8 tool steel using Cu electrode and kerosene di-electric environment.
- During individual analysis, it was observed that the TWR value increases with Ton to an optimal level and then starts decrease. The Ip shows directly proportional to TWR. Toff has no any significant effect on TWR value.
- MRR was strongly affected by Ip followed by Fp and Ton. It shows an increasing behaviour with all three process parameters except Toff.
- Ra was influenced by Ip and Fp. Minimum surface roughness is recorded at low Ip.
- GRA was successfully implemented to enhance the machining creditability of EDM process with multi-performance characteristics, i. e., TWR, MRR and Ra. The optimum parameter setting of EDM process was found to be Ip = 8A, Ton = 200μs, Toff = 10μs, and Fp = 0.50kgf/cm^2 for minimum TWR & Ra and maximum MRR value simultaneously. A confirmatory test was also been performed to support the findings and a significant improvement of 15.08% in GRG value was observed.

5. REFERENCES

1. Aparna, I., Sudhakar, I., Ramana, V. S. N. V., (2015). *An Experimental Study on Corrosion Behavior of En8 and En24 Grade Steels*, Materials Today: Proceedings, **2**, 1251–1256.
2. Aravindan, N., Ashok, U. K., Laxminarayana, P., (2018). *Multi response optimisation of EDM parameters for Micro channels machining of SS 316 with Taguchi – GRA*, Materials Today: Proceedings, **5**(13), 27028-27035.
3. Balasubramanian, P., Senthilvelan, T., (2014). *Optimization of Machining Parameters in EDM Process Using Cast and Sintered Copper Electrodes*, Procedia Material Science, **6**, 1292–1302.
4. Dewangan, S., Biswas, C. K., (2013). *Optimisation of machining parameters using grey relation analysis for EDM with impulse flushing*, International Journal of Mechatronics and Manufacturing Systems, **6**(2), 144-158.
5. Dhar, S., Purohit, R., Saini, N., Sharma, A., Kumar, G. H., (2007). *Mathematical modeling of electric discharge machining of cast Al–4Cu–6Si alloy–10wt.% SiCP composites*, Journal of Materials Processing Technology, **194**(1-3), 24-29.

6. Drozda, T. J., (1983). *Tool and manufacturing engineers handbook: Machining*. Society of Manufacturing Engineers, USA.
7. Ghoreishi, M., Tabari, C., (2007). *Investigation into the effect of voltage excitation of pre-ignition spark pulse on the electro-discharge machining (EDM) process*, Materials and Manufacturing Processes, **22**(7-8), 833–841.
8. Guu, Y. H., Hocheng, H., Chou, C. Y., Deng, C.S., (2003). *Effect of electrical discharge machining on surface characteristics and machining damage of AISI D2 tool steel*, Materials Science and Engineering: A, **358**(1–2), 37-43.
9. Habib, S. S., (2009). *Study of the parameters in electrical discharge machining through response surface methodology approach*, Applied Mathematical Modelling, **33**(12), 4397-4407.
10. Ho, K. H., Newman, S. T., (2003). *State of the art electrical discharge machining (EDM)*, International Journal of Machine Tools and Manufacture, **43**(13), 1287-1300.
11. Hourmand, M., Farahany, S., Sarhan, A. A. D., Noordin, M. Y., (2015). *Investigating the electrical discharge machining (EDM) parameter effects on Al-Mg2Si metal matrix composite (MMC) for high material removal rate (MRR) and less EWR--RSM approach*, The International Journal of Advanced Manufacturing Technology, **77**(5-8), 831–838.
12. Kishan, B., Premkumar, B. S., Gajanana, S., (2018). *Development of Mathematical Model for Metal Removal Rate on EDM using Copper & Brass Electrodes*, Materials Today: Proceedings, **5**, 4345–4352.
13. Koteswararao, B., Babu, K. S., Ravi, D., Kumar, K. K., Chandra, P., (2017). *Investigation of Machining Parameter in EDM of High Carbon Steel Alloy (EN31)*, Materials Today: Proceedings, **4**, 1375–1384.
14. Kung, K. Y., Horng, J. T., Chiang, K. T., (2009). *Material removal rate and electrode wear ratio study on the powder mixed electrical discharge machining of cobalt-bonded tungsten carbide*, The International Journal of Advanced Manufacturing Technology, **40**(1-2), 95–104.
15. Lin, K. W., Wang, C. C., (2010). *Optimizing multiple quality characteristics of wire electrical discharge machining via Taguchi method-based gray analysis for magnesium alloy*, Journal of Chung Cheng Institute of Technology, **39**, 23–34.
16. Majhi, S. K., Pradhan, M. K., Soni, H., (2013). *Optimization of EDM parameters using integrated approach of RSM, GRA and ENTROPY method*, International Journal of Applied Research in Mechanical Engineering, **3**(1), 82-87.
17. Maniyar, K. G., Ingole, D. S., (2018). *Multi response Optimization of EDM Process Parameters for Aluminium Hybrid Composites by GRA*, Materials Today: Proceedings, **5**(9), 19836-19843.
18. Mishra, B. P., Routara, B. C., (2017). *An experimental investigation and optimisation of performance characteristics in EDM of EN-24 alloy steel using Taguchi Method and Grey Relational Analysis*, Materials Today: Proceedings, **4**, 7438–7447.
19. Moharana, B. R., Sahoo, S. K., (2014). *An ANN and RSM Integrated Approach for Predict the Response in Welding of Dissimilar Metal by Pulsed Nd: YAG Laser*, Universal Journal of Mechanial Engineering, **2**, 169–173.
20. Rao, P. S., Jain, P. K., Dwivedi, D. K., (2016). *Precision Finishing of External Cylindrical Surfaces of EN8 Steel by Electro Chemical Honing (ECH) Process using OFAT Technique*, Materials Today: Proceedings, **2**, 3220–3229.
21. Saha, S. K., Choudhury, S. K., (2009). *Experimental investigation and empirical modeling of the dry electric discharge machining process*, International Journal of Machine Tools and Manufacture, **49**(3–4), 297-308.
22. Subramonia, S., Anand, T. J. S., Rahman, A. A., Salleh, M. S., (2010). *RSM based modeling for surface roughness prediction in laser machinin*, International Journal of Engineering & Technology, **10**(4), 26–32.
23. Tosun, N., Pihtili, H., (2010). *Gray relational analysis of performance characteristics in MQL milling of 7075 Al alloy*, The International Journal of Advanced Manufacturing Technology, **46**(5-8), 509–515.
24. Yue, X., Yang, X., Kunieda, M., (2018). *Influence of metal vapor jets from tool electrode on material removal of workpiece in EDM*, Precision Engineering, **53**, 278-288.
25. Zhao, Y., Kunieda, M., Abe, K., (2014). *Study of EDM cutting of single crystal silicon carbide*, Precision Engineering, **38**(1), 92-99.

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