International Journal of Basic and Applied Sciences, 14 (1) (2025) 23-31

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/rgh5jx90
Research paper

Analysis of ECM performance using critic GRA method

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Received: February 19, 2025, Accepted: March 6, 2025, Published: March 21, 2025

Abstract

A hybrid CRITIC-GRA method is adopted to determine the best possible parameter combinations for the ECM drilling process. The input process parameters considered were voltage, duty cycle, and electrolyte concentration. The performance measures considered are machining rate (MR), overcut (OC), and surface corrosion factor (SCF). CRITIC evaluates the standard deviations as 0.33, 0.29, and 0.29 for MR, OC, and SCF respectively. The weights were calculated as 0.327, 0.238, and 0.435 for MR, OC, and SCF respectively. It was evaluated that voltage at level 3 (9V), duty cycle at level 3 (90%), and electrolyte concentration at level 2 (30gm/l), were the ideal combination for the ECM drilling process. Duty cycle and electrolyte concentration were shown to be the most important parameters influencing quality features based on the ANOVA results. The confirmation results have improved the GRG by 0.1309 from the initial value.

Keywords: *Standard Deviations; ECM, Metal Matrix Composites; Duty Cycle; Voltage; Surface Corrosion Factor.*

1. Introduction

Electrochemical machining (ECM) is an unconventional machining process that finds application in the aerospace, biomedical, and automobile industries. By carefully adjusting important parameters like electrode materials, electrolyte composition, current density, temperature, and pH, electrochemical process optimization is essential to maximizing efficiency, minimizing energy consumption, and achieving desired product quality. This ultimately leads to more cost-effective and sustainable applications in a variety of industries. The ECM parameters on Hastelloy C276 have been optimized by Siva et al. Circularity, taper angle, and metal removal rate (MRR) were among the machining quality metrics that were considered, along with the electrolyte (mmol L^{-1}), feed rate (mm/rev), and duty ratio. The Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) multi-criteria decision-making (MCDM) process assigns a weight to each response using an Analytic Hierarchy Process (AHP). The results show that the metal removal rate of sodium nitrate ($NaNO_3$) is higher than that of sodium chloride (NaCl) and sodium bromide (NaBr). However, it will result in a hole of poor quality. The feed rate has an inverse relationship with the taper angle. The ECM parameters on Al/15%SiC composites were investigated by Waghmare et al. in 2024. The process parameters were optimized using an L_{27} orthogonal array (OA). The best machining settings are found using the TOPSIS. Choosing the optimal combination level means the minimum surface roughness is 20 V, feed rate (f) 0.4 mm/min, and electrolyte concentration (c) 30 g/lit. By choosing the optimal combination level, a maximum MRR of 25V, a feed rate of 0.4 mm/min, and an electrolyte concentration of 30 g/lit can be attained. Maniraj and Thanigaivelan (2019) investigated the MRR and radial overcut (ROC) of aluminum 6061 metal matrix composites (MMCs) augmented with ground-granulated blast furnace slag (GGBS) using ECM. After analyzing variance (ANOVA), the percentage (%) composition of GGBS is determined to be the most significant factor. Additionally, the best machining settings for better MRR and lower ROC have been found using the MCDM technique. Higher MRR and lower ROC are best achieved with 10 V, 50%, 35 g/l, and 12% of GGBS composition. ECM was used by Annamalai and Dhavamani (2023) to create holes in scrap aluminum alloy wheels (SAAW) with reinforcement in the form of alumina. By adjusting variables including voltage, duty cycle, electrolyte concentration, and stirrer speed using an L_{18} OA experimental design, the manufactured material is machined utilizing ECM for micro-holes. The Preference Ranking Organization Method of Enrichment Evaluation (PROMETHEE-2) is an MCDM technique that is used to maximize the factors. The optimal factor levels are 10 V, 90% duty cycle, 25 g/l, and 140 rpm. ANOVA shows that the stirrer rpm contributes 31.91% to the ECM process, which is a dominant role. Preethi et al. (2024) investigated the ECM machinability tests of graphene-reinforced magnesium composite and silicon nitride (Si_3N_4). According to the study, the main parameters influencing MRR and surface roughness are feed rate and electrolyte concentration. The influence of Si_3N_4% on MRR was 8.1%, whereas the influence on Ra was 14.9%. The unique optimal solution for MRR and Ra is obtained by using the Integrated Entropy-COmplex Proportional ASsessment (COPRAS) approach. According to COPRAS, the ideal conditions produced a surface roughness of 6.18 µm and an MRR of 0.11285 g/min. Using the TOPSIS, Geethapriyan et al. (2019) examined the ECM performance on 718 Inconel. The ideal process parameter setting was determined to be voltage 10 V, electrolyte concentration 30 g/l, microtool feed rate 0.1µm/s, duty ratio 33% for sodium chloride: voltage 10 V, electrolyte concentration 25 g/l, microtool feed rate 1 µm/s, duty ratio 33% for sodium nitrate. Using sodium nitrate as the electrolyte solution, Pradeep et al. (2019) examined the effects of ECM process parameters on SS304 alloy using a polymer graphite electrode (PGE). According to the experimental results, the best conditions for accessing the multi-response characteristics in the ECM process with a hole within the aspect ratio of 0.8 micron meters are 23 g/l of electrolyte concentration, 9 V of machining voltage, and 55% duty cycle. The best-contributing factor in the selected limited parameters is determined by analyzing the process parameters using ANOVA. The findings showed that, with a 52.29% contribution, voltage is the most important element. Saranya et al. used a 30 vol% ethylene glycol mixed $NaNO_3$ electrolyte in their L_{18} OA ECM studies. A workpiece made of Al7075 + 10 vol%B_4C metal matrix composites with a thickness of 500 µm and a ceramic coating with a diameter of 360 µm is applied to the tool electrode. The ideal combination, according to Grey Relational Analysis (GRA), is 35 g/L of electrolyte, 9 V of voltage, 70% duty cycle, and 30% ethylene glycol. The electrolyte concentration, which is 46.36%, is the most promising factor according to the ANOVA. The prediction value of the Artificial Neural Network (ANN) model is 0.1675 and 1.1400, which are quite near to the machining rate and surface corrosion factors GRA optimum values of 0.1667 and 1.1395, respectively. For machinability experiments using electrochemical machining (ECM), Rajan et al. (2025) have taken into consideration metal additive produced 316L stainless steel. Performance analysis based on the ratio analysis approach is conducted using the MCDM method, specifically entropy-based multi-objective optimization. According to the study, for the best machining performance, 14 V, 35 g l-1 $NaNO_3$ electrolyte concentration, and 90% duty cycle are advised. The optimal combination is 16 V, 35 g l^{-1} electrolyte concentration, and 60% duty cycle, per the major effect table. According to the results of the ANOVA, the duty cycle contributes around 27.06 percent of the machining performance, voltage contributes 24.015 percent, and electrolyte content contributes about 15.58 percent. In the current investigation, Geethapriyan et al. (2022) used a heat-treated copper tool electrode on aluminium 8011 alloy to carry out the ECM procedure. The impact of a heat-treated electrode on MRR, overcut, conicity, and circularity was examined by varying process parameters, including voltage, duty factor, frequency, and electrolyte concentration. The ideal parameters were found using the artificial bee colony (ABC) technique. Voltage (14 V), electrolyte concentration (30 gL^{-1}), frequency (60 Hz), and duty cycle (33%) for the annealed tool electrode and voltage (14 V), electrolyte concentration (20 g/L), frequency (70 Hz), and duty cycle (33%) for the quenched tool electrode are the ideal combinations of input process parameters determined by the ABC algorithm. It is evident from the literature, that ECM process optimization is pursued by researchers on copper, aluminum alloy and stainless steel. The MCDM application on difficult-to-cut materials especially on metal matrix composites is sparse. In this research the fabricated scrap alloy wheel matrix reinforced with 5% aluminum oxide (Al_2O_3) is machined using ECM, considering the L_{18} OA and CRITIC-GRA techniques were used for process parameter optimization.

2. Criteria importance through intercriteria correlation -GRG method

The CRITIC-GRA technique is a hybrid strategy that ranks the alternatives through the Grey Relational Analysis (GRA) method after generating criteria weights using the Criteria Importance through Intercriteria Correlation (CRITIC) method.

2.1. Critic method

Diakoulaki et al. (1995) initially proposed the CRITIC technique, which mines all the data provided in the evaluation criteria by analyzing the assessment matrix. By taking into account a criterion's association with other criteria and standard deviation, this method assesses criterion weights.

In an initial decision matrix, $B = (\phi_{ij})_{x\times y}$, φ_{ij}, where "x" represents the number of alternatives, "y" indicates the number of criteria, and φ_{ij} is the i^{th} alternative's performance measure in relation to the j^{th} criterion.

Equation (1) is used to normalize the initial decision matrix (table 1) using the CRITIC technique and values are presented in Table 2.

$$D_{ij} = \frac{\phi_{ij}-\phi_j^{min}}{\phi_j^{max_j^{min}}} \quad (1)$$

Where ϕ_j^{max}= max (φ_{ij},i=1…., a), and ϕ_j^{min}= min (φ_{ij},i=1…., a).

The weights allocated to each criterion are determined by taking into account its standard deviation as well as its association with other criteria. Accordingly, the weight of the j^{th} criterion W_j can be ascertained using the subsequent method (Alinezhad et al. 2019 & Krishnan et al. 2021):

$$\delta_j = \frac{W_j}{\sum_{i=1}^{m} W_i} \quad (2)$$

Where W_j is the amount of information present in the j^{th} criterion, can be acquired in the manner described below:

$$W_j = \sigma_j \sum_{i=1}^{m}(1-\rho_{ij}) \quad (3)$$

ρ_{ij} denotes the correlation coefficient between the j^{th} and i^{th} criteria, σ_j denotes the standard deviation of the j^{th} criterion.

The weights for each response were then determined using CRITIC analysis to represent its respective GRA relative relevance. Equation 3, which computes the correlation coefficient and standard deviation, was applied to the array of GRC. Tables 3 and 4 provide the correlation coefficient and standard deviation values for each quality indicator, respectively.

Next, using Equation 3, the matching weights for every quality attribute were determined. This is displayed in Table 2. The GRG was also computed using these weights.

Table 1: L_{18} OA

Expt No	Voltage in volts	Duty cycle in %	Electrolyte concentration in gm/l	MR in µm/s	OC in µm	SCF
1	7	50	20	0.179	212	2.3
2	7	70	30	0.200	160	2
3	7	90	40	0.227	120	2.16
4	8	50	20	0.185	180	2.03
5	8	70	30	0.208	140	2.016
6	8	90	40	0.250	100	2.28
7	9	50	30	0.217	110	2.42
8	9	70	40	0.192	130	1.851
9	9	90	20	0.179	150	1.758
10	7	50	40	0.238	90	2.112
11	7	70	20	0.217	112	2.307
12	7	90	30	0.200	135	2
13	8	50	30	0.185	192	2.166
14	8	70	40	0.179	170	2.031
15	8	90	20	0.200	144	2.017
16	9	50	40	0.227	105	2.289
17	9	70	20	0.208	155	2.254
18	9	90	30	0.250	90	2.222

Table 2: Normalized Output Performance by CRITIC Method

Normalized output performance Experiment Run	MR in µm/s	Overcut in µm	SCF
1	0.000	0.181	0.00
2	0.426	0.634	0.30
3	0.754	0.393	0.68
4	0.262	0.589	0.09
5	0.590	0.610	0.42
6	0.918	0.211	1.00
7	0.836	0.000	0.54
8	0.672	0.860	0.19
9	0.508	1.000	0.00
10	1.000	0.465	0.83
11	0.820	0.171	0.54
12	0.631	0.634	0.30
13	0.164	0.384	0.09
14	0.344	0.588	0.00
15	0.557	0.609	0.30
16	0.877	0.198	0.68
17	0.467	0.251	0.42
18	1.000	0.299	1.00

Table 3: Correlation Coefficient of Output Performance

	MR	OC	SCF
MR	1	0.8697	-0.5077
OC	0.8697	1	-0.2307
SCF	-0.5077	-0.2307	1

Table 4: Standard Deviation and Overall Weights of Output Performance

	MR	OC	SCF
STD.DEV.	0.33	0.29	0.26
W_i	0.327	0.238	0.435

3. Multi-response optimization using CRITIC +GRA

The recommended approach is multi-response optimization applying GRA when there are double or extra responses with varying quality attributes. Grey analysis is another tool that can be used to compare finite data that appears to be irregular (Kuo et al. 2008). Therefore, the following GRA procedures are used in this study to achieve multi-response optimization of EDM parameters.

3.1. Grey system model

Deng (1982) proposed the Grey System Model (GSM) based on the random uncertainty of tiny samples (Chan et al. 2007 & Rajesh & Ravi 2015). Since its beginnings, GST has gradually evolved into an estimation method to address certain complex and multivariate system challenges. These kinds of systems are frequently described as having "grey" or ambiguous information. According to control theory, a system is referred to as "white" if all relevant information about it is known, and "black" if all relevant information about it is unknown. A "grey" system with inadequate and limited information is any system that falls between these bounds.

The GRA method is used to solve such issues. The GRA technique is used in this study to optimize the process parameters while accounting for the correlation between several performance metrics. The GRA for choosing the best machining parameters is presented in detail in the next section. Additionally, the best machining parameters are determined and verified while taking into account various performance attributes.

3.2. Pre-processing of data

Data pre-processing is necessary for gray relational analysis because different data sequences may have different ranges and units. When the target's orientations in the sequence differ or the sequence's scatter range is very wide, data pre-processing is also required. Transforming the original sequence into a similar sequence is known as data pre-processing. The experimental records are normalized in the range of 0 to 1 for this purpose. There are several approaches to data pre-processing accessible for GRA, reliant on the features of the data sequence. The steps are listed below.

1) Determine the process factors and performance traits that need to be assessed.
2) Ascertain how many levels the process parameters have.
3) Allocate the process factors to the suitable OA after choosing it.
4) Based on the orthogonal array's configuration, carry out the experiments.
5) Normalize the MR.OC, and SCF experimental results.
6) Compute the gray relational coefficient.
7) By averaging the GRC, determine the GRG.
8) Apply statistical ANOVA and the GRG to the study of the experimental outcomes.
9) Decide which process parameter levels are ideal.
10) Use the confirmation experiment to confirm the ideal process parameters.

MR is the main phenomenon in ECM which chooses the machinability of the material under concern. For the "larger-the-better" characteristic like MR, the original sequence can be normalized as follows:

$$x_i^*(k)=\frac{x_i(k)-\min x_i(k)}{\max x_i(k)-\min x_i(k)} \tag{4}$$

Where, $x_i^*(k)$and $x_i(k)$ are the order next to the data preprocessing and comparability order respectively, k=1 for MR; i=1, 2, 3…, 18 for experiments 1 to 18.

The OC and SCF are too significant measures of ECM performance. Assortment of best process factors for ECM of SAW-AMMC at the development phase and their influence on OC and SCF have up till now to be explained. To get the best cutting performance, the “smaller-the-better” quality characteristic has been used for lessening together the OC and SCF. When the “smaller-the-better” is a characteristic of the unique order, then the unique order should be normalized as below:

$$x_i^*(k)=\frac{\max x_i(k)-x_i(k)}{\max x_i(k)-\min x_i(k)} \tag{5}$$

Where, $x_i^*(k)$ and $x_i(k)$ are the order next to the data preprocessing and comparability order correspondingly, k = 2 and 3 for OC and SCF; i=1, 2, 3…, 18 for experiments 1 to 18 . Table 5 shows the values for normalizing the MR. Table 6-7 shows the values for normalizing the OC and SCF.

Table 5: Shows the Values for Normalizing the MR

Experimental Run	$x_i(k) - \min x_i(k)$	$\max x_i(k) - \min x_i(k)$
1	0.0000	0.0714
2	0.0214	0.0714
3	0.0487	0.0714
4	0.0066	0.0714
5	0.0298	0.0714
6	0.0714	0.0714
7	0.0388	0.0714
8	0.0137	0.0714
9	0.0000	0.0714
10	0.0595	0.0714
11	0.0388	0.0714
12	0.0214	0.0714
13	0.0066	0.0714
14	0.0000	0.0714
15	0.0214	0.0714
16	0.0487	0.0714
17	0.0298	0.0714
18	0.0714	0.0714

Table 6: Shows the Values for Normalizing the OC

Experimental Run	$\max x_i(k) - x_i(k)$	$\max x_i(k) - \min x_i(k)$
1	0.00	122.00
2	52.00	122.00
3	92.00	122.00
4	32.00	122.00
5	72.00	122.00
6	112.00	122.00
7	102.00	122.00
8	82.00	122.00
9	62.00	122.00
10	122.00	122.00
11	100.00	122.00
12	77.00	122.00
13	20.00	122.00
14	42.00	122.00
15	68.00	122.00
16	107.00	122.00
17	57.00	122.00
18	122.00	122.00

Table 7: Shows the Values for Normalizing the SCF

Experimental Run	$\max x_i(k) - x_i(k)$	$\max x_i(k) - \min x_i(k)$
1	0.120	0.662
2	0.420	0.662
3	0.260	0.662
4	0.390	0.662
5	0.404	0.662
6	0.140	0.662
7	0.000	0.662
8	0.569	0.662
9	0.662	0.662
10	0.308	0.662
11	0.113	0.662
12	0.420	0.662
13	0.254	0.662
14	0.389	0.662
15	0.403	0.662
16	0.131	0.662
17	0.166	0.662
18	0.198	0.662

Entire sequences are listed in Tables 8 and 9 after data preprocessing using Equations 4 and 5.
The GRG offered in Table 10 is estimated by averaging the GRC and complete calculation of the several objective optimizations resolution using Equation 6.

$$\mu_j = \frac{1}{m}\sum_{n=1}^{m} \xi_i(n) \tag{6}$$

Where μ_j is the GRG of the jth experiment and m is the no. of performance characteristics.
The multi-response performance index given in Table 11 shows the average value of the GRG for each level. Figure 1 shows the effects plot for GRG. The maximum value of GRG specifies the top conceivable level of the process parameters. The estimated maximum GRG value designates the nearness to the optimal value. The whole mean of the GRG for the 18 runs is assessed and given in Table 11. The optimal machining factors grouping for improved MR and smaller OC and SCF is found to be (9V,90%, and 30gm/l) as given in Table 11.

Table 8: Performance Characteristics After Data Processing

Expt. Run.	MR	OC	SCF
1	0.0000	0.0000	0.1813
2	0.3000	0.4262	0.6344
3	0.6818	0.7541	0.3927
4	0.0926	0.2623	0.5891
5	0.4167	0.5902	0.6103
6	1.0000	0.9180	0.2115
7	0.5435	0.8361	0.0000
8	0.1923	0.6721	0.8595
9	0.0000	0.5082	1.0000
10	0.8333	1.0000	0.4653
11	0.5435	0.8197	0.1707
12	0.3000	0.6311	0.6344
13	0.0926	0.1639	0.3837
14	0.0000	0.3443	0.5876
15	0.3000	0.5574	0.6088
16	0.6818	0.8770	0.1979
17	0.4167	0.4672	0.2508
18	1.0000	1.0000	0.2991

Table 9: Deviation Sequences

Expt. Run.	MR	OC	SCF
1	1.0000	1.0000	0.8187
2	0.7000	0.5738	0.3656
3	0.3182	0.2459	0.6073
4	0.9074	0.7377	0.4109
5	0.5833	0.4098	0.3897
6	0.0000	0.0820	0.7885
7	0.4565	0.1639	1.0000
8	0.8077	0.3279	0.1405
9	1.0000	0.4918	0.0000
10	0.1667	0.0000	0.5347
11	0.4565	0.1803	0.8293
12	0.7000	0.3689	0.3656
13	0.9074	0.8361	0.6163
14	1.0000	0.6557	0.4124
15	0.7000	0.4426	0.3912
16	0.3182	0.1230	0.8021
17	0.5833	0.5328	0.7492
18	0.0000	0.0000	0.7009

Table 10: Computed Grey Relational Grade

Exp. No.	Grey relational coefficient			GRG
	MR	OC	SCF	
1	0.3333	0.3333	0.3792	0.1178
2	0.4167	0.4656	0.5777	0.1661
3	0.6111	0.6703	0.4516	0.1853
4	0.3553	0.4040	0.5489	0.1504
5	0.4615	0.5495	0.5620	0.1754
6	1.0000	0.8592	0.3880	0.2334
7	0.5227	0.7531	0.3333	0.1651
8	0.3824	0.6040	0.7807	0.2028
9	0.3333	0.5041	1.0000	0.2213
10	0.7500	1.0000	0.4832	0.2311
11	0.5227	0.7349	0.3761	0.1698
12	0.4167	0.5755	0.5777	0.1748
13	0.3553	0.3742	0.4479	0.1334
14	0.3333	0.4326	0.5480	0.1501
15	0.4167	0.5304	0.5610	0.1688
16	0.6111	0.8026	0.3840	0.1860
17	0.4615	0.4841	0.4002	0.1468
18	1.0000	1.0000	0.4164	0.2487

4. Effect of process variables

Figure 1 displays the mean effect plot for GRG and rise in voltage level displays the declining output performance. The rise in duty cycle decrease the output performance and further rise in duty cycle improve the output responses. The rise in electrolyte concentration improves the output performance.

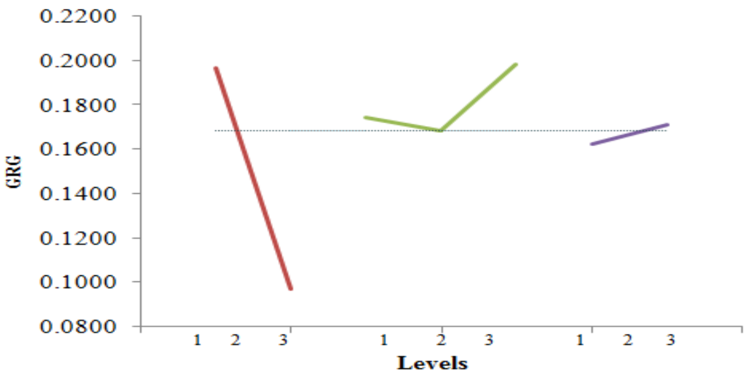

Fig. 1: Mean Effect Plot for GRG.

Table 11: Multi Response Performance Index

Notations	Level 1	Level 2	Level 3	Main effect (Maximum -Minimum)
MR	0.1764	0.1969	0.0969	0.1000
OC	0.1742	0.1685	0.1981	0.0296
SCF	0.1625	0.1772	0.1643	0.0148
μ_j=0.1683				

4.1. ANOVA

To examine how a process parameter affects a performance attribute, an ANOVA is performed [18]. The total of the squared deviations is used to calculate the impact of process parameters. It forecasts the critical process variable that affects output quality. One can compute the sum of the squared deviations from the total mean of the GRG.

$$SS_d = \sum_{j=1}^{p} (\mu_j - \mu_i)^2 \quad (7)$$

Where μ_j is the mean of the GRG for the j^{th} experiment and p is the number of experiments in the OA. The mean square of a factor is obtained by dividing the computed sum of squares by the degrees of freedom. Using Equation 8, the percentage contribution (φ) of each design parameter is found.

$$\alpha_j = \frac{ss_j}{ss_T} \quad (8)$$

Furthermore, the Fisher's F test is too did to form machining factors that effect the performance characteristic. ANOVA for GRG is presented in Table 12. As per the ANOVA table duty cycle and electrolyte concentration display an elevated percentage contribution, hence duty cycle and electrolyte concentration are leading parameters that influence the MR, OC, and SCF.

Table 12: ANOVA Table

Symbol	Factors	Degree of freedom	Sum of squares	Mean squares	F ratio	Percentage contribution (φ)
A	Voltage	2	0.0023	0.0012	1.331	0.52
B	Duty cycle	2	0.0062	0.0031	3.519	56.80
C	Electrolyte Concentration	2	0.0038	0.0019	2.183	20.57
E	Error	11	0.0097	0.0009		22.12
	Total	17	0.0221	0.0013		100

5. Confirmation test

A confirmation test was run to demonstrate how the performance characteristics had improved[19]. Using the best level of machining parameters, the computed GRG(η) can be found as

$$\eta = \eta_m + \sum_{i=1}^{q} (\eta_i - \eta_m) \tag{9}$$

Where η_i is the GRG mean at the ideal level, q is the no. of important parameters, and η_m is the GRG's overall mean. Using Equation (9), the expected MR, OC, SCF, and GRG for the optimal machining factors are determined and shown in Table 13. The comparison between the GRG and empirically obtained values is also displayed in Table 13. The ECM method has performed better overall since the GRG has improved by 0.1309 from the starting point.

Table 13: Confirmation Test

	Primary levels of machining parameters	Optimal combination levels of machining parameters	
		Prediction	Experiment
	$A_1B_1C_1$	$A_3B_3C_2$	$A_3B_3C_2$
Observed MR (mm/min) value	0.000	-	1.000
Observed OC(mm) value	0.000	-	1.000
Observed SCF value	0.181		0.2991
Grey relational grade	0.1178	0.3663	0.2487

6. SEM analysis of hole

The hole analysis is performed using the SEM Figure 2 machined at ideal mixture of process variables. It is evident that the circumference of the hole is filled with delaminated surfaces. The hole is found to be circular and stray current effect is noticed on the surfaces. Figure 3 shows the over etched surfaces near the hole area machined at 7V,90% and 40gm/l electrolyte concentration.

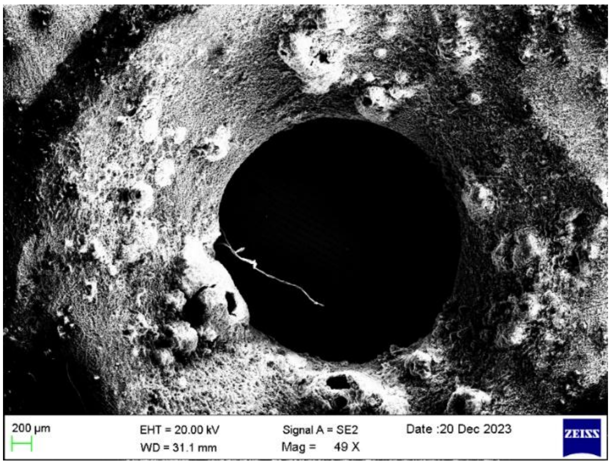

Fig. 2: SEM of the Hole Surface with Stray Current Effect.

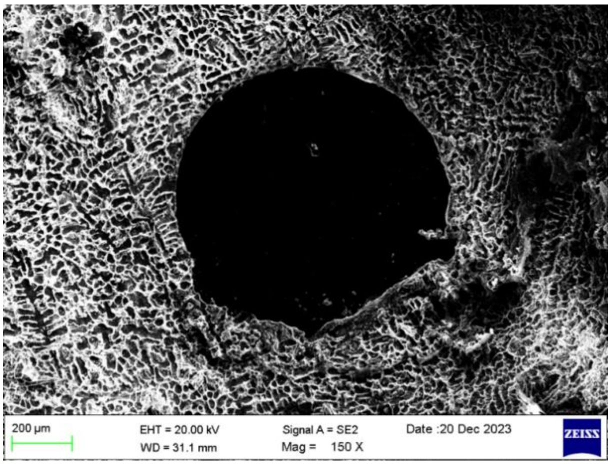

Fig. 3: Microhole with Delaminated Surfaces.

7. Conclusion

A hybrid CRITIC-GRA method looked at the best possible parameter combinations for the ECM drilling process. The input process parameters considered were voltage (V), duty cycle, and electrolyte concentration. Several trials were conducted in series using the L_{18} Taguchi orthogonal array (OA), considering all elements at three levels. Next, for each experimental run, the following values were determined: MR, OC, and SCF. Moreover, the ECM drilling process was optimized by CRITIC analysis and grey relational analysis. Grey relational analysis was used in conjunction with the CRITIC analysis to establish the relative importance of each performance attribute. CRITIC evaluates the standard deviations as 0.33, 0.29, and 0.29 for MR, OC, and SCF respectively. The weights were calculated as 0.327, 0.238, and 0.435 for MR, OC and SCF respectively. It was discovered that A3B3C2voltage at level 3 (9V), duty cycle at level 3 (90%), and electrolyte concentration at level 2 (30gm/l), were the ideal combination for the ECM drilling process. Duty cycle and electrolyte concentration were shown to be the most important parameters influencing quality features based on the ANOVA results. The confirmation results have improved the GRG by 0.1309 from the initial value.

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