

Multi-Objective Optimization of Electrochemical Discharge Machining (ECDM) of Inconel 625 for Aerospace Applications

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Abstract

The present study focuses on the multi-objective optimization of electrochemical discharge machining (ECDM) of Inconel 625 using a Taguchi-based Entropy-TOPSIS approach. Unlike conventional studies primarily considering MRR and surface roughness (R_a), this investigation additionally incorporates overcut, form error, and orientation tolerance error to comprehensively evaluate machining performance. The optimal parameter combination was identified as feed rate (F) of 0.20 mm/min, flow rate (Q) of 0.75 L/min, and electrolyte concentration (C) of 10%. Taguchi analysis revealed non-monotonic effects of F and Q, while C exhibited a decreasing trend in the closeness coefficient (C_i). ANOVA identified F, Q, and their interaction (F $\times$ Q) as the most influential factors, whereas C was individually insignificant but showed a meaningful interaction with Q. The regression model demonstrated good predictive capability with $R^2 = 94.23\%$ and adjusted $R^2 = 91.18\%$. Overall, the Taguchi-Entropy-TOPSIS methodology proved effective for optimizing multiple machining responses and improving the overall ECDM performance of Inconel 625.

Keywords: Electrochemical Drilling Machining (ECDM), TOPSIS, Material Removal Rate (MRR), Surface Roughness (R_a), Overcut (OC), Circularity Error (CE) and Perpendicularity Error (PE)

1. Introduction

Inconel is a nickel-based superalloys widely recognized for their excellent high-temperature strength, corrosion resistance, oxidation resistance, and mechanical stability under severe service conditions. These properties make Inconel materials particularly suitable for demanding applications in aerospace, gas turbines, nuclear power plants, chemical processing, marine systems, automotive components, and oil and gas industries, where components are exposed to elevated temperatures, corrosive environments, and high mechanical loads. However, the same properties that provide superior service performance also make Inconel alloys extremely difficult to machine using conventional processes. Their high strength, low thermal conductivity, pronounced work hardening, and tendency to generate high cutting temperatures and tool wear can result in poor surface quality, dimensional inaccuracies, and reduced tool life. Therefore, non-conventional machining processes are increasingly employed for the precision machining of Inconel components. Among these, Electrochemical Discharge Machining (ECDM) offers the potential to machine

complex geometries and difficult-to-machine materials by combining electrochemical dissolution and thermal discharge mechanisms, thereby reducing reliance on direct mechanical cutting forces and tool contact. ECDM can be particularly advantageous for producing micro-holes, slots, intricate profiles, and other precision features in Inconel components used in turbine blades, combustion chambers, aerospace engine parts, heat exchangers, fuel-system components, and nuclear and chemical processing equipment. Thus, the development and optimisation of ECDM parameters for Inconel machining are important for improving material removal rate, dimensional accuracy, surface quality, and machining efficiency.

2. Literature Review

Electrochemical Machining (ECM) is a non-traditional machining process based on anodic dissolution and is particularly suitable for hard-to-machine, electrically conductive materials with complex geometries. Depending on the process conditions, ECM can provide good dimensional accuracy and surface finishes in the range of approximately 0.2–12.5 μm R_a . Advanced variants such as Wire Electrochemical Machining (WECM), Jet-ECM, and hybrid ECM have further improved machining precision, productivity, and applicability to micro-scale and biomedical components. Chavan et al. (2025) reviewed hybrid ECM technologies and highlighted their potential to improve machining efficiency through auxiliary energy sources and advanced monitoring systems, while identifying equipment cost, process control, scalability, and electrolyte sustainability as major challenges. Singh et al. (2023) reported that electrochemical micromachining (ECMM) is effective for producing micro-holes, micro-channels, and complex structures in difficult-to-machine materials without the thermal and mechanical damage associated with conventional machining.

Several investigations have focused on improving ECM efficiency through electrolyte management and process optimization. Schupp et al. (2021) demonstrated that the surface chemistry and microstructure of 42CrMO_4 significantly influence electrochemical dissolution efficiency. Ozerkan et al. (2020) developed a hybrid electrochemical drilling system incorporating tool rotation and internal electrolyte flushing, achieving improved material removal and dimensional accuracy. Kendall et al. (2022) established that nozzle geometry and electrolyte flow characteristics significantly affect Jet-ECM depth of cut and machining profiles. Ge et al. (2024) further demonstrated that appropriate management of electrolyte pressure and flow energy can improve material removal, surface quality, and energy utilization. Similarly, Sharma et al. (2023) emphasized that electrolyte feeding strategies and electrolyte composition play critical roles in discharge stability and machining precision. Electrochemical and electrochemical-discharge-based micromachining have also been extensively investigated for precision hole and microfeature fabrication. Rashedul et al. (2021) reported that electrode electrical and thermal conductivities strongly influence MRR and electrode wear during ECDM, with W70Cu30 providing favourable machining performance. Sivashankar et al. (2022, 2023) demonstrated that minimum-quantity electrolyte supply can reduce overcut and improve machining accuracy compared with conventional flooding. Chandrasekhar and Prasad (2020) successfully applied an Entropy-VIKOR approach for multi-response optimization of ECM drilling of AA6061-TiB₂ composites, considering MRR, overcut, and delamination. Preethi et al. (2024) employed Entropy-COPRAS for optimizing electrochemical machining of magnesium/graphene/Si₃N₄ composites and demonstrated the effectiveness of integrated MCDM techniques for simultaneous response optimization. Zou et al. (2023) reported that non-Newtonian electrolytes can stabilize the gas film and substantially reduce overcut and heat-affected-zone dimensions during ECDM micro-hole fabrication. Wang et al. (2023) further showed that ultrasonic assistance can

enhance material removal, surface precision, and surface integrity through cavitation-induced micro-jet effects.

The selection of machining parameters and optimization methodology has been a major focus of recent ECM research. Jayaganthan and Prakash (2018) used Taguchi and ANOVA techniques to identify applied voltage as the dominant parameter during ECMM of Mg-based hybrid composites. Deepak and Hariharan (2022) found that voltage and electrolyte concentration significantly affect radial overcut, taper angle, and MRR during micro-ECM of SS304. Chourasiya and Krishna (2023) integrated TOPSIS-JAYA with RSM for multi-objective optimization of ECM, demonstrating the effectiveness of hybrid optimization approaches. Nagarajan et al. (2022) employed TOPSIS with metaheuristic algorithms for simultaneous optimization of MRR and environmental impact during ECM of Monel 400. Kavimani et al. (2024) combined Taguchi, CRITIC-based optimization, and ANFIS for ECM of Mg-Li-Sr alloy, confirming the capability of hybrid data-driven approaches for process optimization. Tosun et al. (2024) introduced a Hole Performance Index incorporating hole geometry and drilling time, demonstrating the importance of integrated performance measures in electrochemical drilling. Particular attention has been given to nickel-based superalloys because of their high strength, corrosion resistance, thermal stability, and poor conventional machinability. Singh et al. (2023) investigated ECM of Inconel 625 using voltage, tool feed rate, and electrolyte flow rate as process variables and optimized MRR and surface roughness through RSM and desirability-based optimization. The optimum conditions produced an MRR of 0.1928 g/min and surface roughness of 0.99 μm , confirming the suitability of ECM for Inconel 625. For Inconel 718, Saha (2024) demonstrated that electrolyte concentration, feed rate, and voltage significantly affect MRR, surface roughness, and radial overcut, while MOGA-ANN provided an effective multi-objective optimization framework. Zhu et al. (2018) established that the heat-treatment condition and metallurgical phases of Inconel 718 substantially influence electrochemical dissolution and surface roughness. Wang et al. (2019) further showed that mixed NaNO_3 - NaOH electrolytes can suppress stray corrosion and improve machining localization and surface quality.

Although substantial research has been conducted on ECM, ECMM, and ECDM of various difficult-to-machine materials, studies specifically addressing ECDM of Inconel 625 remain limited. In particular, the combined effects of electrode feed rate, electrolyte flow rate, and electrolyte concentration on multiple machining responses have not been adequately explored. Most existing studies predominantly consider MRR and surface roughness, while geometric characteristics such as overcut, form error, and orientation tolerance error receive comparatively less attention. Therefore, a systematic investigation incorporating these multiple performance characteristics and employing an appropriate MCDM/MADM-based optimization framework is required to identify the optimum ECDM conditions for Inconel 625 and provide improved machining accuracy and overall process performance.

3. Methodology

Entropy-TOPSIS MCDM Technique

The Entropy-TOPSIS methodology integrates two powerful tools:

- **Entropy Method** → Determines the objective weights of criteria based on information entropy.
- **TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)** Ranks alternatives by calculating their closeness to the positive ideal solution.

3.1 Step-by-Step Procedure of Entropy-TOPSIS

Step 1: Formulation of the Decision Matrix

A decision matrix is constructed with m alternatives and n criteria:

$$Y_{ij} = \begin{bmatrix} Y_{11} & Y_{12} & \cdots & \cdots & Y_{1n} \\ Y_{21} & Y_{22} & \cdots & \cdots & Y_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ Y_{m1} & Y_{m2} & \cdots & \cdots & Y_{mn} \end{bmatrix} \quad \text{Eq. (1)}$$

Where 'm' and 'n' represent the alternatives and attributes, respectively.

Step 2: Normalization of the Decision Matrix

Since criteria may have different measurement units, normalization is applied

$$r_{ij} = \frac{Y_{ij}}{\sqrt{\sum_{i=1}^m Y_{ij}^2}} \quad (1 \leq i \leq m, 1 \leq j \leq n) \quad \text{Eq. (2)}$$

Step 3: Entropy Calculation

The entropy of each criterion is calculated as:

Entropy measures the degree of uncertainty or disorder associated with a criterion.

$$\dot{\epsilon}_j = -\varsigma \sum_{i=1}^m \rho_{ij} \ln(\rho_{ij}) \quad (1 \leq i \leq m, 1 \leq j \leq n) \quad \text{Eq. (3)}$$

Where, $\varsigma = \frac{1}{\ln(p)}$, and p is the number of alternatives

$$\rho_{ij} = \frac{Y_{ij}}{\sum_{i=1}^m Y_{ij}} \quad \text{Eq. (4)}$$

Step 4: Determination of Objective Weights

The degree of diversification is calculated as:

$$\varphi_j = 1 - \dot{\epsilon}_j \quad \text{Eq. (5)}$$

Where, φ_j represents the degree of diversity.

$$\omega_j = \frac{\varphi_j}{\sum_{j=1}^n \varphi_j} \quad \text{Eq. (6)}$$

Thus, criteria with higher variability (information richness) receive greater weights.

Step 5: Weighted Normalized Decision Matrix

The weighted normalized values are computed as:

$$V_{ij} = \omega_j * r_{ij} \quad \text{Eq. (7)}$$

This incorporates the relative importance of each criterion.

Step 6: Identification of Positive and Negative Ideal Solutions

$$\begin{aligned} v_i^+ &= \{(max_i V_{ij} | j \in J), (min_i V_{ij} | j \in J') \mid i = 1, 2, \dots, m\} \\ &= \{v_1^+, v_2^+, \dots, v_j^+, \dots, v_n^+\} \end{aligned} \quad \text{Eq. (8)}$$

$$\begin{aligned} v_i^- &= \{(min_i V_{ij} | j \in J), (max_i V_{ij} | j \in J') \mid i = 1, 2, \dots, m\} \\ &= \{v_1^-, v_2^-, \dots, v_j^-, \dots, v_n^-\} \end{aligned} \quad \text{Eq. (9)}$$

Step 7: Separation Measures

The Euclidean distance of each alternative from PIS and NIS is calculated:

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_i^+ - v_{ij})^2} \quad \text{Eq. (10)}$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_i^- - v_{ij})^2} \quad \text{Eq. (11)}$$

Step 8: Closeness Coefficient and Ranking

The relative closeness coefficient is calculated as:

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-}; 0 \leq C_i^+ \leq 1 \quad \text{Eq. (12)}$$

Step 9: Rank the experimental runs in descending order of C_i^+ values.

4. Experimentation

The experiments were designed using the Taguchi method and conducted on an ELECHEM TECHNIK electrochemical machining system, as shown in Figure 1.



Figure 1. Experimental Setup for Electrochemical Drilling

The setup consists of a machining chamber, control panel, and electrolyte circulation pump, operating at a constant 24 V. The workpiece is securely clamped in a vice, while the hollow tool electrode is mounted to a screw-driven stepper motor. A current-sensing circuit prevents tool-workpiece short circuits by restricting tool movement when the current exceeds the preset limit. Sodium chloride (NaCl) solution was used as the electrolyte and supplied through the hollow electrode to facilitate material removal during electrochemical drilling.

4.1 Work material

Inconel 625 was selected as the workpiece material due to its excellent resistance to aggressive corrosive environments. Its high strength, outstanding corrosion resistance, and resistance to stress-corrosion cracking make it suitable for demanding applications, particularly in chemical processing and nuclear reactor components. The chemical composition of Inconel 625 is presented in Table 1.

Table 1. Chemical Composition of INCONEL 625

Element	Fe	Cr	Si	Mo	Mn	C	Ni
Wt.%	5	20-23	0.50	8-10	0.50	0.10	balance

4.2 Design of Experiments

The independent machining parameters considered for Inconel 625 were electrode feed rate, electrolyte flow rate, and electrolyte concentration. Their respective levels and ranges are presented in Table 2. The experiments were designed using Taguchi's L27 orthogonal array, as listed in Table 3, to produce 6 mm diameter through-holes using the electrochemical drilling process, as shown in Fig. 2.



Figure 2. Electrochemical drill Hole on INCONEL 625

Table 2. Input Process Parameters with their Levels for ECD of Inconel 625

Factor	Process Parameter	Level 1	Level 2	Level 3
F	Feed rate of electrode (mm/min)	0.15	0.2	0.25
Q	Discharge rate of Electrolyte (lit/min)	0.5	0.75	1
C	Concentration of Electrolyte (%)	10	15	20

Table 3. L27 Orthogonal Array

Exp No.	F	Q	C
1	0.15	0.5	10
2	0.15	0.5	15
3	0.15	0.5	20
4	0.15	0.75	10
5	0.15	0.75	15
6	0.15	0.75	20
7	0.15	1	10
8	0.15	1	15
9	0.15	1	20
10	0.2	0.5	10
11	0.2	0.5	15
12	0.2	0.5	20
13	0.2	0.75	10
14	0.2	0.75	15
15	0.2	0.75	20
16	0.2	1	10
17	0.2	1	15
18	0.2	1	20
19	0.25	0.5	10

20	0.25	0.5	15
21	0.25	0.5	20
22	0.25	0.75	10
23	0.25	0.75	15
24	0.25	0.75	20
25	0.25	1	10
26	0.25	1	15
27	0.25	1	20

5. Results and Discussions

The present study investigates the electrochemical machining (ECM) of Inconel 625, a nickel-based superalloy, by examining the effects of electrode feed rate (F), electrolyte flow rate (Q), and electrolyte concentration (C) on machining performance. The process was evaluated using material removal rate (MRR), surface roughness (Ra), overcut (OC), circularity error (CE), and Perpendicularity error (PE). The experimental results were organized into a vector decision matrix, as presented in Table 4.

Table 4. Decision Matrix of the Experimental Results

S.No.	MRR (g/min)	R _a (μm)	OC (mm)	CE (mm)	PE (mm)
1	0.063	0.45	0.37	0.19	0.13
2	0.070	0.39	0.35	0.13	0.12
3	0.080	0.36	0.36	0.09	0.14
4	0.072	0.48	0.35	0.27	0.13
5	0.085	0.46	0.39	0.25	0.12
6	0.103	0.44	0.43	0.26	0.13
7	0.064	0.57	0.53	0.25	0.22
8	0.084	0.58	0.61	0.28	0.21
9	0.106	0.59	0.69	0.34	0.22
10	0.090	0.36	0.25	0.04	0.09
11	0.099	0.33	0.23	0.08	0.06
12	0.109	0.32	0.21	0.09	0.07
13	0.099	0.43	0.14	0.08	0.06
14	0.114	0.44	0.17	0.07	0.05
15	0.131	0.36	0.19	0.12	0.05
16	0.092	0.54	0.23	0.08	0.12
17	0.112	0.52	0.29	0.13	0.11
18	0.136	0.53	0.36	0.21	0.12
19	0.123	0.34	0.26	0.24	0.21
20	0.131	0.26	0.23	0.26	0.19
21	0.143	0.22	0.19	0.26	0.19
22	0.129	0.36	0.06	0.11	0.16
23	0.146	0.37	0.07	0.08	0.14
24	0.165	0.32	0.08	0.03	0.13

25	0.121	0.46	0.05	0.07	0.19
26	0.144	0.45	0.11	0.02	0.18
27	0.168	0.43	0.17	0.09	0.17

5.1 Entropy Weights Measurement for the Responses

The entropy weight method objectively determines the relative importance of evaluation criteria by quantifying the information content of the decision matrix. In this study, the experimental data in Table 4 were used to calculate the entropy weights of the selected performance criteria based on their evaluation values. The decision matrix responses were first normalized using Eq. (2). Subsequently, the entropy and evaluation indices were calculated using Eqs. (3) and (4), followed by the determination of the final weights using Eqs. (5) and (6). The resulting entropy indices are presented in Table 5.2. The weights assigned to the ECM responses were $W_{MRR} = 0.0749$, $W_{Ra} = 0.0475$, $W_{OC} = 0.3451$, $W_{CE} = 0.3859$, and $W_{PE} = 0.1515$, respectively.

Table 5. Entropy Indices for ECM Responses

S.No.	MRR	R _a	OC	CE	PE
1	-0.0823	-0.1228	-0.1488	-0.1409	-0.1171
2	-0.0890	-0.1145	-0.1463	-0.1069	-0.1126
3	-0.0975	-0.1080	-0.1452	-0.0856	-0.1152
4	-0.0900	-0.1366	-0.1452	-0.1786	-0.1145
5	-0.1022	-0.1308	-0.1550	-0.1717	-0.1119
6	-0.1156	-0.1269	-0.1655	-0.1769	-0.1158
7	-0.0822	-0.1547	-0.1895	-0.1695	-0.1660
8	-0.1008	-0.1512	-0.2066	-0.1824	-0.1650
9	-0.1197	-0.1494	-0.2230	-0.2047	-0.1684
10	-0.1059	-0.1124	-0.1144	-0.0409	-0.0882
11	-0.1127	-0.1036	-0.1075	-0.0736	-0.0791
12	-0.1214	-0.0967	-0.1017	-0.0829	-0.0775
13	-0.1127	-0.1248	-0.0765	-0.0736	-0.0643
14	-0.1245	-0.1208	-0.0858	-0.0757	-0.0555
15	-0.1375	-0.1145	-0.0961	-0.0982	-0.0555
16	-0.1057	-0.1440	-0.1078	-0.0793	-0.1119
17	-0.1232	-0.1403	-0.1297	-0.1111	-0.1066
18	-0.1410	-0.1385	-0.1502	-0.1524	-0.1080
19	-0.1302	-0.1013	-0.1167	-0.1673	-0.1640
20	-0.1373	-0.0920	-0.1055	-0.1765	-0.1547
21	-0.1458	-0.0821	-0.0954	-0.1735	-0.1504
22	-0.1362	-0.1124	-0.0376	-0.0937	-0.1330
23	-0.1476	-0.1080	-0.0432	-0.0765	-0.1228
24	-0.1601	-0.1013	-0.0510	-0.0333	-0.1196
25	-0.1301	-0.1308	-0.0333	-0.0683	-0.1536
26	-0.1465	-0.1288	-0.0606	-0.0195	-0.1455

27	-0.1632	-0.1248	-0.0854	-0.0897	-0.1433
e_j	0.9894	0.9928	0.9477	0.9415	0.9771
d_j	0.0106	0.0072	0.0523	0.0585	0.0229
W_j	0.0749	0.0475	0.3451	0.3859	0.1515

5.2 TOPSIS Optimization

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is an MCDM technique used to identify the most preferable alternative based on its shortest distance from the positive ideal solution and greatest distance from the negative ideal solution. In the TOPSIS procedure, the decision matrix is first normalized to eliminate differences in units and magnitudes among the criteria. The normalized ECM drilling responses calculated using Eq. (2) are presented in Table 6.

Table 6. Normalization (r_{ij}) Values of the Responses

S.No.	MRR	R_a	OC	CE	PE
1	0.1076	0.1898	0.2215	0.2029	0.1697
2	0.1196	0.1717	0.2160	0.1364	0.1605
3	0.1356	0.1581	0.2136	0.1004	0.1657
4	0.1215	0.2214	0.2136	0.2913	0.1644
5	0.1448	0.2078	0.2354	0.2738	0.1592
6	0.1723	0.1988	0.2603	0.2869	0.1671
7	0.1075	0.2666	0.3222	0.2684	0.2841
8	0.1421	0.2575	0.3714	0.3011	0.2815
9	0.1809	0.2530	0.4230	0.3633	0.2907
10	0.1522	0.1672	0.1511	0.0382	0.1144
11	0.1662	0.1491	0.1384	0.0818	0.0987
12	0.1846	0.1355	0.1280	0.0960	0.0960
13	0.1660	0.1943	0.0868	0.0818	0.0750
14	0.1915	0.1852	0.1013	0.0851	0.0618
15	0.2212	0.1717	0.1183	0.1211	0.0618
16	0.1518	0.2395	0.1390	0.0905	0.1592
17	0.1886	0.2304	0.1808	0.1440	0.1486
18	0.2296	0.2259	0.2245	0.2280	0.1513
19	0.2043	0.1446	0.1553	0.2629	0.2789
20	0.2207	0.1265	0.1347	0.2858	0.2552
21	0.2413	0.1084	0.1171	0.2782	0.2447
22	0.2181	0.1672	0.0346	0.1135	0.2039
23	0.2458	0.1581	0.0413	0.0862	0.1815
24	0.2779	0.1446	0.0510	0.0295	0.1749
25	0.2040	0.2078	0.0297	0.0742	0.2526
26	0.2431	0.2033	0.0637	0.0153	0.2328
27	0.2863	0.1943	0.1007	0.1069	0.2276

The weighted normalization step incorporates the relative importance of each criterion into the normalized decision matrix. Each normalized response is multiplied by its corresponding weight to reflect its significance in the decision-making process. The resulting weighted normalized decision matrix, calculated using Eq. (7), is presented in Table 7. Following weighted normalization, the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) are determined in the TOPSIS procedure. The PIS represents the best performance, while the NIS corresponds to the worst performance for each criterion based on its benefit or cost nature. The PIS and NIS values calculated using Eqs. (8) and (9) are presented in Table 8.

Table 7. Weighted Normalized (V_{ij}) Decision Matrix

S.No.	MRR	R_a	OC	CE	PE
1	0.0081	0.0090	0.0764	0.0783	0.0257
2	0.0090	0.0082	0.0746	0.0526	0.0243
3	0.0102	0.0075	0.0737	0.0387	0.0251
4	0.0091	0.0105	0.0737	0.1124	0.0249
5	0.0108	0.0099	0.0813	0.1057	0.0241
6	0.0129	0.0094	0.0898	0.1107	0.0253
7	0.0080	0.0127	0.1112	0.1036	0.0430
8	0.0106	0.0122	0.1282	0.1162	0.0426
9	0.0135	0.0120	0.1460	0.1402	0.0440
10	0.0114	0.0079	0.0521	0.0147	0.0173
11	0.0124	0.0071	0.0477	0.0316	0.0149
12	0.0138	0.0064	0.0442	0.0370	0.0145
13	0.0124	0.0092	0.0299	0.0316	0.0114
14	0.0143	0.0088	0.0350	0.0328	0.0094
15	0.0166	0.0082	0.0408	0.0467	0.0094
16	0.0114	0.0114	0.0480	0.0349	0.0241
17	0.0141	0.0109	0.0624	0.0556	0.0225
18	0.0172	0.0107	0.0775	0.0880	0.0229
19	0.0153	0.0069	0.0536	0.1015	0.0422
20	0.0165	0.0060	0.0465	0.1103	0.0387
21	0.0181	0.0052	0.0404	0.1073	0.0371
22	0.0163	0.0079	0.0119	0.0438	0.0309
23	0.0184	0.0075	0.0142	0.0333	0.0275
24	0.0208	0.0069	0.0176	0.0114	0.0265
25	0.0153	0.0099	0.0103	0.0286	0.0383
26	0.0182	0.0097	0.0220	0.0059	0.0353
27	0.0214	0.0092	0.0348	0.0413	0.0345

Table 8. PIS and NIS Values for the Responses

	MRR	R_a	OC	CE	PE
PIS	0.0214	0.0052	0.0103	0.0059	0.0094

NIS	0.008	0.0127	0.146	0.1402	0.044
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After identifying the PIS and NIS, the Euclidean separation measures of each alternative from the PIS and NIS are calculated using Eqs. (10) and (11), respectively. The closeness coefficient (CC) is then determined using Eq. (12), representing the relative proximity of each alternative to the ideal solution. A higher CC value indicates better overall performance and is therefore preferred for ranking the alternatives. The calculated separation measures and CC (C_i^+) values are presented in Table 9.

Table 9. Separation Measures (S_i^+ , S_i^-) and Closeness Coefficient (C_i^+) Values for the Alternatives

S.No.	S_i^+	S_i^-	C_i^+
1	0.1004	0.0950	0.4862
2	0.0818	0.1148	0.5839
3	0.0740	0.1261	0.6302
4	0.1256	0.0798	0.3885
5	0.1238	0.0761	0.3807
6	0.1329	0.0664	0.3332
7	0.1452	0.0505	0.2582
8	0.1653	0.0301	0.1539
9	0.1943	0.0056	0.0280
10	0.0447	0.1590	0.7805
11	0.0466	0.1495	0.7622
12	0.0469	0.1481	0.7594
13	0.0338	0.1624	0.8275
14	0.0374	0.1585	0.8091
15	0.0513	0.1452	0.7390
16	0.0512	0.1453	0.7396
17	0.0738	0.1210	0.6214
18	0.1072	0.0892	0.4542
19	0.1101	0.1006	0.4775
20	0.1144	0.1046	0.4776
21	0.1094	0.1115	0.5047
22	0.0440	0.1659	0.7906
23	0.0333	0.1709	0.8371
24	0.0195	0.1833	0.9040
25	0.0375	0.1760	0.8242
26	0.0289	0.1833	0.8638
27	0.0499	0.1498	0.7500

Table 10. Response Table for S/N Ratios for Closeness Coefficient (C_i^+)

Level	F	Q	C
1	-11.131	-4.514	-4.755
2	-2.958	-4.080	-5.209
3	-3.188	-8.683	-7.313

Delta	8.174	4.602	2.557
Rank	1	2	3

The response table in Table 10 shows the effects of electrode feed rate (F), electrolyte flow rate (Q), and electrolyte concentration (C) on the TOPSIS closeness coefficient (C_i^+). Among the parameters, F has the highest Delta value (8.174), indicating the strongest influence on C_i^+ , followed by Q (4.602) and C (2.557). Thus, electrode feed rate is the most influential parameter for optimizing overall machining performance, whereas electrolyte concentration has the least effect.

Figure 3 presents the main-effect plots of the S/N ratios for the TOPSIS closeness coefficient (C_i^+) at different levels of F, Q, and C. The electrode feed rate (F) shows a sharp increase in S/N ratio up to 0.20 mm/min, followed by a slight decrease at 0.25 mm/min, indicating a strong non-linear effect. Similarly, the electrolyte flow rate (Q) exhibits maximum S/N at 0.75 L/min, while a significant decline occurs at 1.0 L/min. In contrast, electrolyte concentration (C) shows a continuous decrease in S/N ratio with increasing concentration, with 10% providing the highest value. Therefore, the optimum parameter combination for maximizing the S/N ratio of C_i^+ is F = 0.20 mm/min, Q = 0.75 L/min, and C = 10%. Overall, F and Q exhibit non-monotonic effects, whereas C shows a monotonic decreasing trend, highlighting the importance of maintaining moderate F and Q levels and a lower electrolyte concentration for improved machining performance.

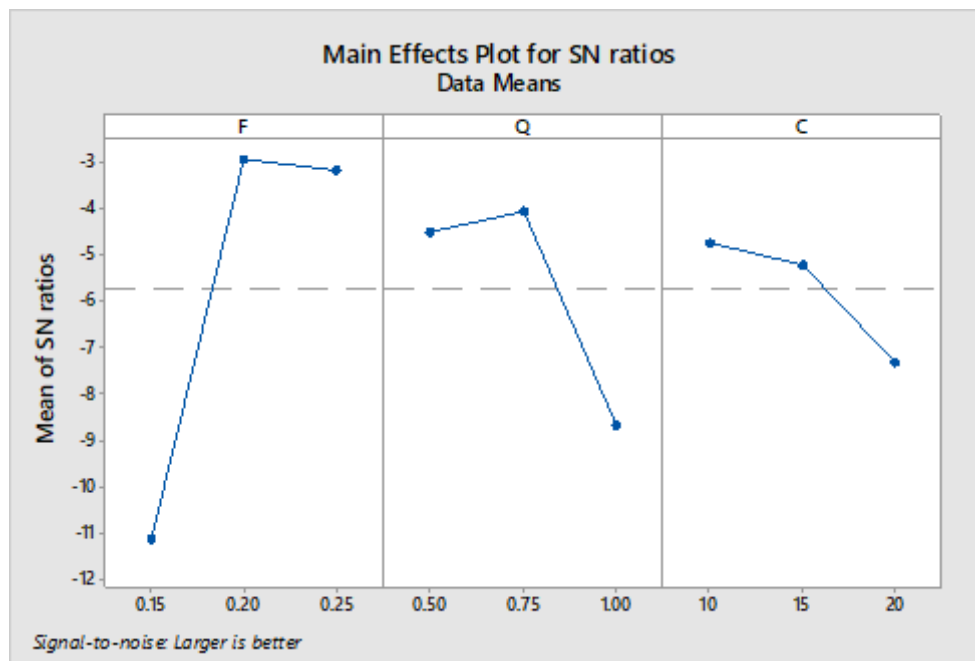


Figure 3. Main effect Plots for S/N Ratios of Closeness Coefficient (C_i^+)

Table 11 presents the ANOVA results for the Closeness Coefficient (C_i^+) based on electrode feed rate (F), electrolyte flow rate (Q), and electrolyte concentration (C). The model is statistically significant ($P = 0.000$), with F being the most influential factor ($F\text{-value} = 116.44$, $P = 0.000$), followed by Q ($F\text{-value} = 6.78$, $P = 0.019$). Significant quadratic effects are observed for F^2 (41.96 , $P = 0.000$) and Q^2 (13.28 , $P = 0.002$), confirming their non-linear influence on C_i^+ . Significant interaction effects are also observed for $F \times Q$ (86.16 , $P = 0.000$) and $Q \times C$ (9.41 , $P = 0.007$), indicating that the effect of one parameter depends on

the level of another. In contrast, C is statistically insignificant as an individual factor (F-value = 2.53, P = 0.130).

Table 11 ANOVA Results for Closeness Coefficient (C_i^+)

Source	DF	Adj SS	Adj MS	F	P
Model	9	1.34549	0.149499	30.85	0.000
Linear	3	0.60936	0.203120	41.92	0.000
F	1	0.56423	0.564233	116.44	0.000
Q	1	0.03285	0.032850	6.78	0.019
C	1	0.01228	0.012276	2.53	0.130
Square	3	0.26939	0.089797	18.53	0.000
FxF	1	0.20335	0.203346	41.96	0.000
QxQ	1	0.06433	0.064333	13.28	0.002
CxC	1	0.00171	0.001711	0.35	0.560
2-way Interaction	3	0.46674	0.155580	32.11	0.000
FxQ	1	0.41753	0.417527	86.16	0.000
FxC	1	0.00360	0.003603	0.74	0.401
QxC	1	0.04561	0.045610	9.41	0.007
Error	17	0.08238	0.004846		
Total	26	1.42787			

S = 0.0696125, $R^2 = 94.23\%$, $R^2(\text{Adj}) = 91.18\%$, $R^2(\text{Pred}) = 84.09\%$

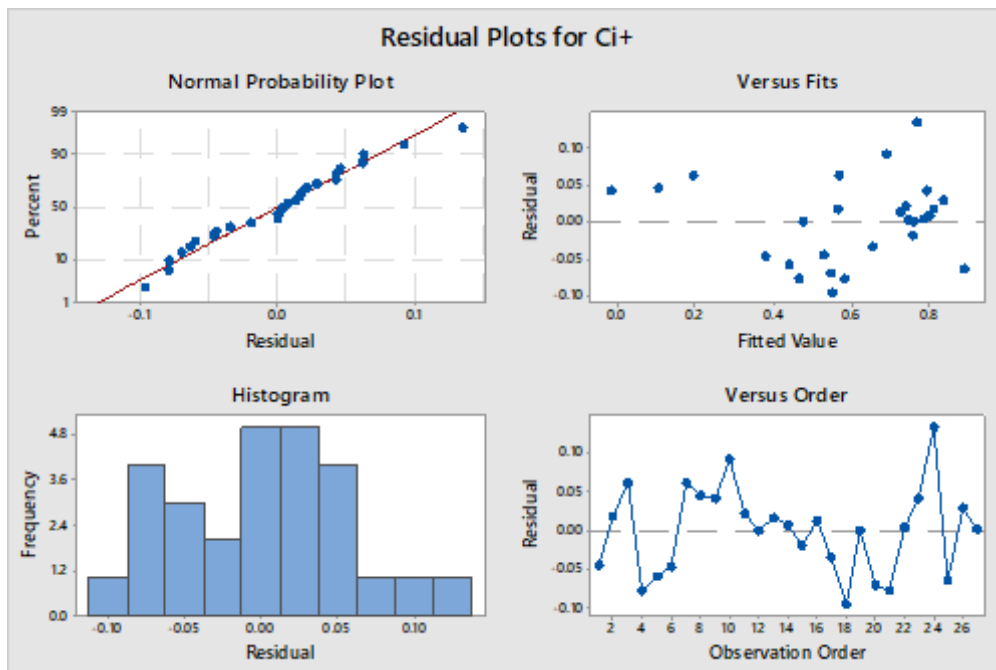


Figure 4. Residual plots for Closeness Coefficient (C_i^+)

Figure 4 presents the residual diagnostic plots used to assess the adequacy of the model developed for the Closeness Coefficient (C_i^+). The Normal Probability Plot and Histogram indicate approximately normally

distributed residuals, while the Residuals versus Fits plot shows random scattering around zero, confirming constant variance. The Residuals versus Order plot also exhibits no systematic pattern, indicating residual independence. Overall, the diagnostic plots confirm that the model satisfies the major statistical assumptions and is adequate and reliable for predicting C_i^+ .

6. Conclusions

The present study focused on the multi-objective optimization of ECDM of Inconel 625 using a Taguchi-based Entropy-TOPSIS approach, considering MRR, surface roughness, overcut, form error, and orientation tolerance error for comprehensive machining performance evaluation. The major findings are as follows:

- The proposed multi-response optimization framework identified a single optimal parameter combination of feed rate (F) = 0.20 mm/min, flow rate (Q) = 0.75 L/min, and electrolyte concentration (C) = 10%, resulting in improved overall machining performance.
- Taguchi analysis revealed that F and Q exhibit non-monotonic effects, whereas C demonstrates a distinct decreasing trend in the closeness coefficient (C_i^+). Hence, moderate levels of F and Q , together with a lower electrolyte concentration, are favourable for achieving improved multi-response performance.
- The ANOVA results confirmed the statistical significance and adequacy of the developed model for predicting the closeness coefficient, with a highly significant p -value of 0.000.
- Feed rate and flow rate were identified as the most influential individual parameters, with $F = 116.44$ ($p = 0.000$) and $Q = 6.78$ ($p = 0.019$), respectively, indicating their significant contribution to machining performance.
- The $F \times Q$ interaction exhibited a highly significant effect ($F = 86.16$, $p = 0.000$), while the $Q \times C$ interaction was also statistically significant ($F = 9.41$, $p = 0.007$), demonstrating the importance of parameter interactions in ECDM performance optimization.
- Electrolyte concentration, considered independently, was statistically insignificant ($F = 2.53$, $p = 0.130$); however, its interaction with flow rate significantly influenced the overall machining performance.
- The regression model exhibited good predictive capability, with $R^2 = 94.23\%$ and adjusted $R^2 = 91.18\%$, confirming its satisfactory adequacy for predicting the closeness coefficient.
- Overall, the Taguchi-Entropy-TOPSIS methodology proved to be an effective and robust decision-making framework for simultaneously optimizing multiple machining characteristics of Inconel 625 during ECDM.

Future Scope

Future studies may investigate other difficult-to-machine alloys, alternative optimization techniques, and detailed surface integrity and microstructural characteristics. Additional responses such as tool wear, dimensional accuracy, energy consumption, and sustainability can also be considered for improved industrial applicability.

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