

Experimental Investigation and Multi-Response Optimization of Wire-Edm Performance Characteristics

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Abstract

Hastelloy is a nickel-based superalloy widely used in demanding marine, nuclear, energy, and aerospace applications because of its high strength and excellent corrosion resistance. Its high hardness and thermal stability, however, make conventional machining difficult. This study investigates the effects of pulse-on time (T_{ON}), pulse-off time (T_{OFF}), flushing pressure (FP), and wire feed rate (WF) on material removal rate (MRR) and surface roughness parameters during Wire Electrical Discharge Machining (WEDM) of Hastelloy. An L16 orthogonal array was employed, and the multiple responses were optimized using an integrated Entropy-TOPSIS approach. Entropy was used to determine the objective weights of the responses, while TOPSIS identified the best-performing parameter combination. The optimum condition was obtained at $T_{ON} = 118 \mu s$, $T_{OFF} = 55 \mu s$, $FP = 7 \text{ bar}$, and $WF = 7 \text{ m/min}$. ANOVA identified T_{ON} as the most influential parameter, followed by T_{OFF} , WF, and FP. Residual analysis confirmed the adequacy of the developed model, with normally distributed errors and no significant systematic trends. The findings demonstrate the effectiveness of the Entropy-TOPSIS framework for achieving a balanced combination of machining productivity and surface quality in WEDM of Hastelloy.

Keywords: Hastelloy, WEDM, MRR, Surface Roughness, Flushing Pressure, Wire Feed, Entropy-TOPSIS.

1. Introduction

Hastelloy is a nickel-based superalloy widely employed in demanding engineering applications, including marine, chemical processing, nuclear, energy, aerospace, pressure-vessel, and high-temperature systems, owing to its excellent combination of mechanical strength, thermal stability, oxidation resistance, and superior resistance to corrosive environments. In particular, its ability to withstand aggressive chemical media and elevated temperatures makes it suitable for components exposed to severe operating conditions. However, these desirable properties are also responsible for its poor machinability. High hardness, toughness, work-hardening tendency, and low thermal conductivity increase cutting forces and heat generation during conventional machining, resulting in accelerated tool wear, higher machining costs, dimensional inaccuracies, and difficulties in obtaining the desired surface integrity. Hence, the selection of an appropriate advanced machining process is essential for the efficient and precise manufacturing of

Hastelloy components. Wire Electrical Discharge Machining (WEDM) is an advanced non-traditional machining process that is particularly suitable for machining hard, tough, and electrically conductive materials such as Hastelloy. Unlike conventional machining, WEDM removes material through a series of controlled, rapid electrical discharges generated between a continuously travelling wire electrode and the workpiece in the presence of a dielectric fluid. Since there is no direct physical contact between the cutting tool and the workpiece, mechanical cutting forces and conventional tool-wear-related limitations can be substantially reduced. WEDM also offers high dimensional accuracy, the ability to produce intricate profiles, and effective machining of complex geometries that are difficult to achieve using conventional processes.

Wire electrical discharge machining (WEDM) is an advanced non-traditional manufacturing technique in which a computer-numerically-controlled (CNC)-guided conductive wire removes material through controlled electrical discharges, enabling the processing of electrically conductive alloys and composite materials [1]. Its capability to produce intricate profiles and complex three-dimensional features with high precision has made it an important manufacturing process for dies, turbine elements, aerospace structures, precision transmission components, and biomedical applications [2]. Jaya Kishore Sunkara et al. [3] examined the WEDM behaviour of Ti-6Al-4V alloy, particularly the effects of machining conditions on geometric errors and dimensional variations. Thia Paul et al. [4] presented a comprehensive assessment of WEDM applications in superalloys and other advanced engineering materials, emphasizing the relationship between operating conditions and machining outcomes. Nevertheless, maintaining dimensional and angular precision during taper machining remains difficult because thermal stresses and discharge-induced forces can cause wire bending, thereby affecting kerf dimensions and taper accuracy. Machining quality is also governed by factors such as electrode diameter, cutting velocity, discharge voltage, dielectric flushing conditions, and workpiece characteristics. Bhatti H. A. [5] evaluated different dielectric environments during EDM of D2 tool steel and observed a 6.52% decrease in specific energy consumption and an 18.75% enhancement in dimensional precision. Joshua Adjei-Yeboah and Muhammad Pervej Jahan [6] investigated geometric precision during WEDM of fin-shaped and gear-shaped profiles, including tapered geometries, demonstrating the importance of accurate profile generation for machining complex components.

To manage the competing requirements associated with multiple machining responses, researchers have increasingly adopted multi-objective optimization strategies in WEDM. Manoj Mythili T. et al. [7] examined the suitability of multi-criteria decision-making (MCDM) methods for identifying favourable combinations of machining parameters. Ezhilan M. et al. [8] combined the Taguchi technique with TOPSIS to enhance the machining performance of zirconia-reinforced Al7050 alloy. Jagdale et al. [9] investigated the WEDM of Ti-6Al-4V using a Taguchi L9 experimental design and established that pulse-on time and peak current substantially influence material removal rate and surface roughness. Saif Ahmad Afridi et al. [10] applied grey relational analysis and analysis of variance (ANOVA) to assess the machining behaviour of D2 tool steel, identifying pulse-on time as the principal contributor to variations in multiple responses. Jayavelu Udaya Prakash et al. [11] studied LM6/B₄C/fly-ash composites and reported that gap voltage and reinforcement content play important roles in determining machining performance. Vi Hong Nguyen et al. [12] optimized WEDM conditions for Al6061 alloy through ANOVA and genetic algorithms, finding that an increase in feed rate improves material removal rate but adversely affects surface finish and wire wear ratio. Mithilesh K. Dikshit and Vimal Kumar Pathak [13] employed advanced optimization techniques, including MOAVOA and MOGA, to investigate cryogenically

processed Ti-6Al-4V and identified discharge current as the most influential machining variable. Lokesh Kumar et al. [14] developed an integrated ANFIS-PSO framework for predicting and optimizing the WEDM performance of NiTi shape-memory alloys, whereas Soni Kumari et al. [15] used grey-based analysis to improve productivity and surface quality during EDM of P20 tool steel.

The growing requirement for dependable estimation of machining outcomes has encouraged the adoption of machine learning (ML) approaches in WEDM investigations [16-17]. Kapil Surani et al. [18] employed Taguchi experimental design and regression modelling to examine WEDM of X37CrMoV5-1 tool steel, establishing peak current and pulse-on time as the major factors affecting material removal and tool wear rates. Gehlot N. et al. [19] integrated response surface methodology (RSM) with grey relational analysis to optimize multiple machining responses, including surface roughness and material removal rate, during the machining of C632 bronze. Samson Jerold Samuel Chelladurai et al. [20] applied RSM and desirability-based optimization to LM24/TiB₂/fly-ash composites and identified pulse duration as the most influential process variable. Jorge M. Cortes Mendoza et al. [21] showed that artificial neural networks (ANN) and random forest (RF) models can outperform conventional regression techniques in machining-response prediction, obtaining coefficients of determination (R^2) of up to 0.9956. Can Cogun and Ece Ayli [22] proposed an ANN-based strategy for controlling electrode wear in EDM and achieved a 66.7% reduction in tool wear. Shunmugesh K. et al. [23] highlighted the potential of ensemble learning algorithms, particularly Extra Trees and XGBoost, for regression-based modelling of machining processes. Zhou Q. et al. [24] combined ANN with the NSGA-II algorithm to optimize multiple objectives in multi-pass WEDM, demonstrating reliable predictive and optimization performance. Jeet I. et al. [25] assessed hybrid RSM-ANN modelling and established the effectiveness of ANN in representing nonlinear relationships between process variables and machining responses. Kumar P. et al. [26] compared support vector machines (SVM), XGBoost, and k-nearest neighbours (KNN) for predicting EDM outcomes; SVM performed best for tool wear rate and recast-layer thickness, whereas KNN provided better predictions of material removal rate.

Although substantial progress has been made in WEDM technology, important research opportunities remain. Previous investigations have largely addressed conventional workpiece materials, while the machining characteristics of cryogenically treated materials, particularly during taper cutting, have received comparatively limited attention. Furthermore, comprehensive optimization frameworks that jointly evaluate productivity-related measures and geometric precision under competing process requirements remain insufficiently explored. Despite the availability of several optimization and prediction techniques, the combined application of advanced hybrid MCDM procedures and machine learning models requires further investigation, especially for accurately representing complex nonlinear interactions among machining variables. The reviewed studies demonstrate extensive use of Taguchi methods, regression analysis, ANN, RSM, and multi-criteria decision-making techniques for optimizing EDM/WEDM performance. However, based on the supplied literature, the present study focuses specifically on WEDM of AISI 1040 steel, considering MRR, average surface roughness (R_a), and ten-point mean roughness (R_z) simultaneously.

2. Methodology

TOPSIS decision making method is a technique introduced by Yoon and Hwang. It is a worldwide accepted approach to finding the best alternative that is closest to the ideal solution. The basic principle in this method is that chosen alternative should have the shortest distance from the positive ideal solution

(PIS) and the farthest distance from the negative ideal solution (NIS). The procedural steps involved are as follows.

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:

$$Y_{ij} = \begin{bmatrix} Y_{11} & Y_{12} & \cdots & \cdots & Y_{1n} \\ Y_{21} & Y_{22} & \cdots & \cdots & Y_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ Y_{m1} & Y_{m2} & \cdots & \cdots & Y_{mn} \end{bmatrix} \quad \text{Eq. (3.1)}$$

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

$$r_{ij} = \frac{Y_{ij}}{\sqrt{\sum_{i=1}^m Y_{ij}^2}} \quad (1 \leq i \leq m, 1 \leq j \leq n) \quad \text{Eq. (3.2)}$$

Step 3: Entropy Calculation

The entropy of each criterion is calculated as:

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

$$\epsilon_j = -\sum_{i=1}^m \rho_{ij} \ln(\rho_{ij}) \quad (1 \leq i \leq m, 1 \leq j \leq n) \quad \text{Eq. (3.3)}$$

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

$$\rho_{ij} = \frac{Y_{ij}}{\sum_{i=1}^m Y_{ij}} \quad \text{Eq. (3.4)}$$

Step 4: Determination of Objective Weights

The degree of diversification is calculated as:

$$\varphi_j = 1 - \epsilon_j \quad \text{Eq. (3.5)}$$

Where, φ_j represents the degree of diversity.

$$\omega_j = \frac{\varphi_j}{\sum_{j=1}^n \varphi_j} \quad \text{Eq. (3.6)}$$

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

Step 5: Weighted Normalized Decision Matrix

The weighted normalized values are computed as:

$$V_{ij} = \omega_j * r_{ij} \quad \text{Eq. (3.7)}$$

This incorporates the relative importance of each criterion.

Step 6: Identification of Positive and Negative Ideal Solutions

$$\begin{aligned} v_i^+ &= \{(max_i V_{ij} | j \in J), (min_i V_{ij} | j \in J') \mid i = 1, 2, \dots, m\} \\ &= \{v_1^+, v_2^+, \dots, v_j^+, \dots, v_n^+\} \\ v_i^- &= \{(min_i V_{ij} | j \in J), (max_i V_{ij} | j \in J') \mid i = 1, 2, \dots, m\} \end{aligned} \quad \text{Eq. (3.8)}$$

$$= \{v_1^-, v_2^-, \dots, v_j^-, \dots, v_n^-\} \quad \text{Eq. (3.9)}$$

Step 7: Separation Measures

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

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_i^+ - v_{ij}^+)^2} \quad \text{Eq. (3.10)}$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_i^- - v_{ij}^-)^2} \quad \text{Eq. (3.11)}$$

Step 8: Closeness Coefficient and Ranking

The relative closeness coefficient is calculated as:

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-}; 0 \leq C_i^+ \leq 1 \quad \text{Eq. (3.12)}$$

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

3. Experimentation

In the present investigation, HASTELLOY specimens were machined using Wire Electrical Discharge Machining (WEDM) with a 0.25 mm diameter brass wire electrode, as shown in Fig. 1. HASTELLOY is a nickel-based superalloy widely used in automotive and engineering applications such as gears, axles, bolts, spindles, shafts, and studs, particularly where high tensile strength, wear resistance, and corrosion resistance are required. The selected WEDM process parameters and their levels are presented in Table 1. A Taguchi L16 orthogonal array was employed to design the experimental trials, and the corresponding experimental combinations are presented in Table 2. Surface roughness was measured using an SJ-301 surface roughness tester at three different locations on each machined surface. The average of the three measurements was considered as the final surface roughness (R_a) value for each experimental trial.

The L16 orthogonal array design is a type of experimental design used in statistical analysis. It is a specific type of Taguchi design that consists of 16 runs or experiments with different combinations of factors. The L16 design is an efficient way to study the effects of a relatively small number of factors on a particular response. It is named after the fact that it is based on an orthogonal array with 16 rows. An orthogonal array is a mathematical construct that ensures that each combination of factors appears the same number of times in the design, which helps to reduce the effects of confounding variables and improve the efficiency of the analysis. To use the L16 orthogonal array design, the experimenter selects the factors that are believed to influence the response and assigns each factor to a specific level. The design is then used to run 16 experiments, each with a different combination of factor levels. The results of these experiments are analysed using statistical methods to determine the effects of each factor on the response. The L16 orthogonal array design is particularly useful in industries such as manufacturing, where it can be used to optimize production processes and reduce the variability of output. It is also commonly used in quality control, product design, and other fields where statistical analysis is important for understanding and improving complex systems.



Fig 1: WEDM Experimental Setup

Table 1: Fixed Parameters and Corresponding Levels

Process Parameters	L1	L2	L3	L4
Pulse-On-Time	112	114	116	118
Pulse-Off-Time	51	53	55	57
Flushing Pressure	7	8	9	10
Wire Feed	5	6	7	8

Table 2: L16 Orthogonal Array

S.NO	TON	TOFF	WP	WF
1	112	51	7	5
2	112	53	8	6
3	112	55	9	7
4	112	57	10	8
5	114	51	8	7
6	114	53	7	8
7	114	55	10	5
8	114	57	9	6
9	116	51	9	8
10	116	53	10	7
11	116	55	7	6
12	116	57	8	5
13	118	51	10	6
14	118	53	9	5
15	118	55	8	8

16	118	57	7	7
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4. Results and Discussion

The experimentally measured MRR and surface roughness parameters (R_a), (R_q), (R_y), and (R_z) were optimized using the Entropy-TOPSIS method. Entropy determined the objective weights, while TOPSIS ranked the 16 experimental trials according to their relative closeness to the ideal solution. Table 3 presents the experimental results, with MRR ranging from 2.9375 to 6.6125 mm³/mm. Experiment 16 achieved the highest MRR, whereas Experiment 8 recorded the lowest. Experiment 1 exhibited the minimum (R_a), (R_q), and (R_y), while Experiment 8 had the lowest (R_z). These results indicate a trade-off between material removal rate and surface quality, necessitating multi-response optimization. Table 4 presents the normalized decision matrix, converting the experimental responses into dimensionless values for comparison. The normalized MRR ranges from 0.1589 for Experiment 8 to 0.3576 for Experiment 16, providing a common basis for the Entropy-TOPSIS analysis.

Table 3. Experimental Responses (Y_{ij})

S.NO	MRR	R_a	R_q	R_y	R_z
1	3.725	2.76	3.4	16.28	13.12
2	4.175	2.84	3.61	19.21	13.34
3	5.1	3.01	3.72	18.34	13.82
4	5.3	2.9	3.61	17.94	13.12
5	4.725	3.13	3.92	19.47	14.15
6	5	3.26	4.08	18.87	15.12
7	4.95	3.18	3.96	21.29	14.67
8	2.9375	2.98	3.74	18.38	12.98
9	3.5	3.19	3.89	17.13	13.53
10	4.025	2.85	3.58	18.8	13.84
11	4.6875	3.14	3.81	17.54	13.62
12	3.3575	3.3	4.06	18.76	14.34
13	4.1425	2.84	3.57	17.75	13.56
14	4.85	3.21	4.03	20.21	13.88
15	5.4675	3.13	3.87	19.52	14.17
16	6.6125	3.21	4.01	19.73	14.26

Table 4. Normalized Values (r_{ij})

S.NO	MRR	R_a	R_q	R_y	R_z
1	0.2015	0.2253	0.2232	0.2181	0.2367
2	0.2258	0.2318	0.2369	0.2574	0.2407
3	0.2758	0.2457	0.2442	0.2457	0.2493
4	0.2866	0.2367	0.2369	0.2404	0.2367
5	0.2556	0.2555	0.2573	0.2609	0.2553
6	0.2704	0.2661	0.2678	0.2528	0.2728

7	0.2677	0.2596	0.2599	0.2719	0.2647
8	0.1589	0.2432	0.2455	0.2463	0.2342
9	0.1893	0.2604	0.2553	0.2295	0.2441
10	0.2177	0.2326	0.235	0.2519	0.2497
11	0.2535	0.2563	0.2501	0.235	0.2457
12	0.1816	0.2694	0.2665	0.2514	0.2587
13	0.224	0.2318	0.2343	0.2351	0.2446
14	0.2623	0.262	0.2645	0.2708	0.2504
15	0.2957	0.2555	0.255	0.2615	0.2557
16	0.3576	0.262	0.2632	0.2644	0.2573

Entropy analysis was used to calculate the objective weights of the five performance characteristics. The entropy values for MRR, Ra, Rq, Ry, and Rz were 0.993, 0.993, 0.9994, 0.9995, and 0.9994, respectively. The corresponding weights were 0.7801, 0.0612, 0.0555, 0.0695, and 0.0337. MRR received the highest weight, indicating its dominant influence on the decision-making process, while Rz received the lowest weight. These weights were subsequently used in the TOPSIS analysis. Table 5 presents the weighted normalized decision matrix obtained by multiplying the normalized responses by their respective entropy weights. The weighted MRR values range from 0.1239 to 0.2790, with the maximum recorded in Experiment 16. The resulting matrix was used to determine the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) for TOPSIS ranking.

Table 5. Weighted Normalized Values (r_{ij})

S.NO	MRR	Ra	Rq	Ry	Rz
1	0.1572	0.0138	0.0124	0.0152	0.008
2	0.1761	0.0142	0.0132	0.0179	0.0081
3	0.2152	0.015	0.0136	0.0171	0.0084
4	0.2236	0.0145	0.0132	0.0167	0.008
5	0.1994	0.0156	0.0143	0.0181	0.0086
6	0.211	0.0163	0.0149	0.0176	0.0092
7	0.2088	0.0159	0.0144	0.0189	0.0089
8	0.1239	0.0149	0.0136	0.0176	0.0079
9	0.1477	0.0159	0.0142	0.016	0.0082
10	0.1698	0.0142	0.013	0.0175	0.0084
11	0.1978	0.0157	0.0139	0.0163	0.0083
12	0.1417	0.0165	0.0148	0.0175	0.0087
13	0.1748	0.0142	0.013	0.0163	0.0082
14	0.2046	0.016	0.0147	0.0188	0.0084
15	0.2307	0.0156	0.0141	0.0182	0.0086
16	0.279	0.016	0.0146	0.0184	0.0087

Table 6 presents the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) for the five performance characteristics. For MRR, the highest weighted value (0.2790) is considered the PIS and the

lowest value (0.1239) as the NIS. For R_a , R_q , R_y , and R_z , the minimum values represent the PIS, while the maximum values represent the NIS because these are lower-the-better characteristics. These PIS and NIS values are subsequently used to calculate the separation measures (S^+ and S^-) and the closeness coefficient (C^+) in the TOPSIS method.

Table 6. PIS and NIS Values

	MRR	R_a	R_q	R_y	R_z
PIS	0.279	0.0138	0.0124	0.0152	0.0079
NIS	0.1239	0.0165	0.0149	0.0189	0.0092

Table 7. S_i^+ and S_i^- , C_i^+ Values

S.NO	S_i^+	S_i^-	C_i^+
1	0.1218	0.0337	0.2167
2	0.1029	0.0524	0.3372
3	0.0639	0.0913	0.5884
4	0.0554	0.0998	0.6429
5	0.0797	0.0755	0.4862
6	0.0682	0.0871	0.5608
7	0.0703	0.085	0.5471
8	0.1551	0.003	0.0191
9	0.1314	0.024	0.1544
10	0.1092	0.046	0.2966
11	0.0813	0.0739	0.4764
12	0.1374	0.0178	0.1148
13	0.1042	0.051	0.3287
14	0.0745	0.0807	0.52
15	0.0485	0.1068	0.6878
16	0.0045	0.1551	0.9716

Table 7 presents the separation measures (S_i^+ and S_i^-), closeness coefficient (C_i^+), and signal-to-noise ratio (SNRA1) obtained from the TOPSIS analysis. The C_i^+ values range from 0.0191 to 0.9716, where a higher value indicates closer proximity to the positive ideal solution. Experiment 16 has the highest C_i^+ value of 0.9716, followed by Experiment 15 with 0.6878, indicating better overall machining performance. In contrast, Experiment 8 has the lowest C_i^+ value of 0.0191, indicating the least desirable overall performance. The corresponding SNRA1 values further reflect the relative performance of the experimental trials, with Experiment 16 achieving the highest value of -0.2501.

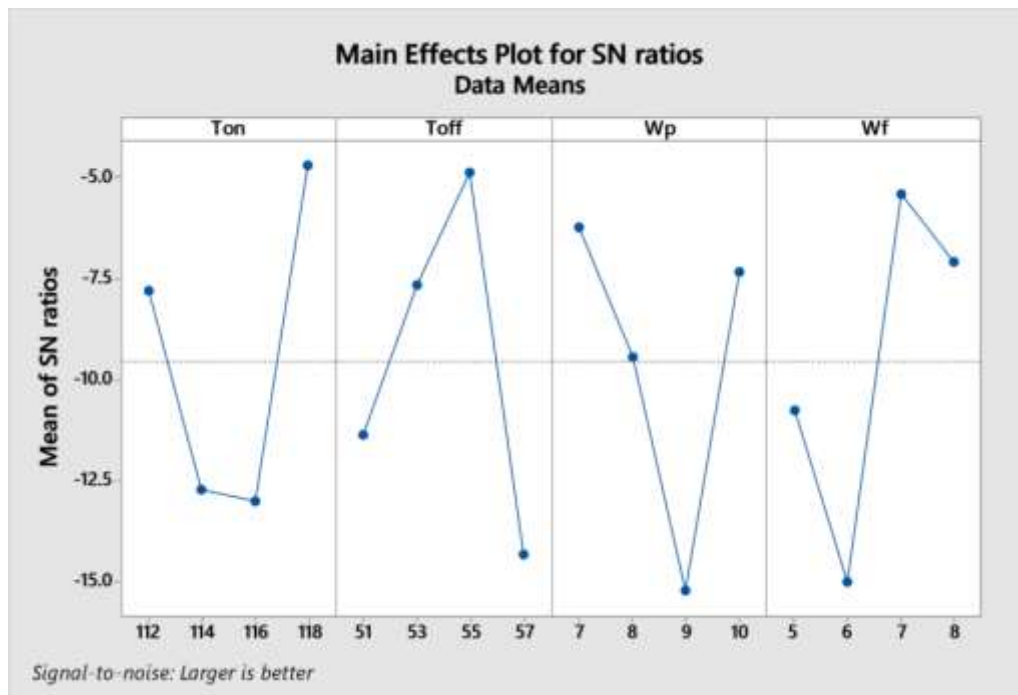


Fig.2 Main Effect Plot for SN ratio

The main effects plot for SN ratios (Figure 2) illustrates the influence of Ton, Toff, WP, and WF on machining performance. Based on the larger-is-better criterion, higher SN ratios indicate better and more robust performance. The highest SN ratios are obtained at Ton = 118, Toff = 55, WP = 7, and WF = 7. Ton and WF exhibit pronounced variations, indicating their considerable influence on machining performance. Therefore, the optimum parameter combination is Ton = 118, Toff = 55, WP = 7, and WF = 7.

Table 8. Analysis of Variance

Source	DF	AdjSS	AdjMS	F-Value	P-Value
Model	13	0.883403	0.067954	7.96	0.117
Linear	4	0.204401	0.0511	5.99	0.148
Ton	1	0.090797	0.90797	10.63	0.083
Toff	1	0.051709	0.51709	6.06	0.133
FP	1	0.000216	0.000216	0.03	0.88
WF	1	0.006576	0.006576	0.77	0.473
Square	4	0.187414	0.046853	5.49	0.16
Ton*Ton	1	0.099274	0.99274	11.63	0.076

Toff*Toff	1	0.07287	0.07287	8.54	0.1
Fp*Fp	1	0.106282	0.106282	12.45	0.072
Wf*Wf	1	0.076509	0.076509	8.96	0.096
2-way Interaction	5	0.313048	0.6261	7.33	0.124
Ton*Toff	1	0.20801	0.020801	2.44	0.259
Ton*WP	1	0.134343	0.134343	15.74	0.058
Ton*WF	1	0.028966	0.028966	3.39	0.207
Toff*WP	1	0.078319	0.078319	9.17	0.094
Toff*WF	1	0.075582	0.075582	8.85	0.097
Error	2	0.017075	0.008538		
Total	15	0.900479			

Table 8 presents the ANOVA results for the SN ratio. The overall model has 13 degrees of freedom, an F-value of 7.96, and a P-value of 0.117, indicating that it is not statistically significant at the 5% level. Among the linear terms, Ton shows the highest F-value (10.63), followed by Toff (6.06). The quadratic terms Fp^2 ($F = 12.45$) and Ton^2 ($F = 11.63$) also exhibit relatively strong effects. The $Ton \times W$ interaction has the highest F-value (15.74) among the interaction terms, with $P = 0.058$, approaching statistical significance. However, none of the terms satisfies the conventional significance criterion of $P < 0.05$.

Figure 3 presents the residual plots used to evaluate the adequacy of the developed model for the closeness coefficient (C_i^+). The normal probability plot shows that the residuals approximately follow a normal distribution. The residuals versus fits plot indicates random scattering around zero without a clear pattern or funnel shape, suggesting constant variance. The histogram of residuals shows a relatively balanced distribution of positive and negative residuals with small prediction errors. Finally, the residuals versus observation order plot exhibits fluctuations around zero without a systematic trend, indicating no obvious sequential effect. Overall, the residual plots suggest that the model assumptions are reasonably satisfied.

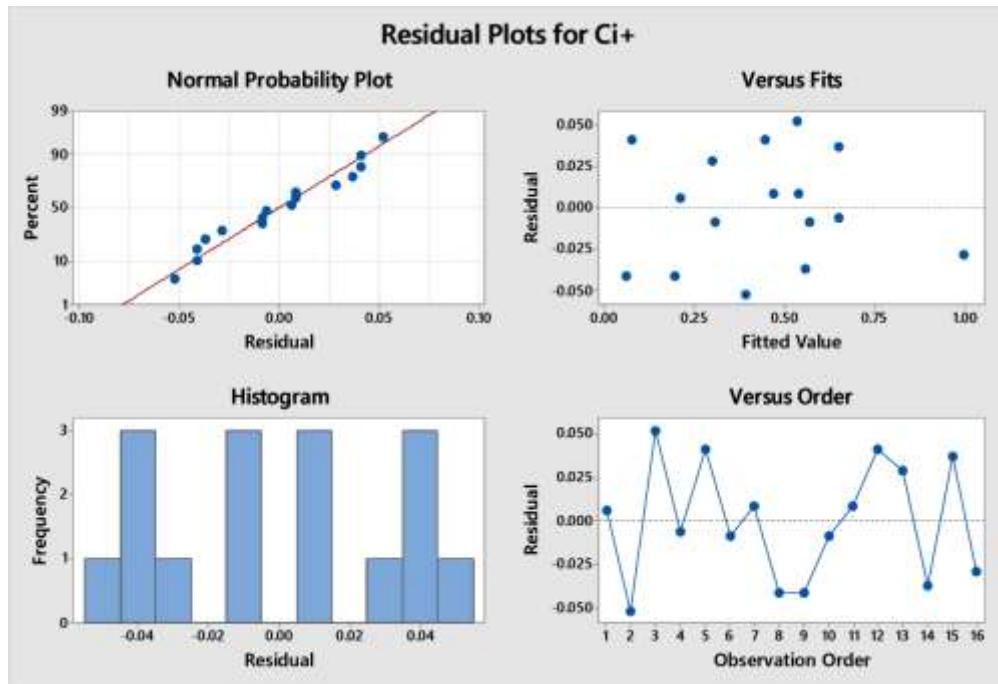


Fig. 3 Residual plots for Ci^+

Conclusions

The major conclusions drawn from the present investigation are summarized as follows:

- The Entropy-TOPSIS analysis identified the optimal WEDM parameter combination as a pulse-on time (T_{on}) of 118 μs , pulse-off time (T_{off}) of 55 μs , flushing pressure (F_p) of 7 bar, and wire feed rate (WF) of 7 m/min.
- The ANOVA results indicated that pulse-on time (T_{on}) was the most influential parameter, followed by pulse-off time (T_{off}), wire feed rate (WF), and flushing pressure (F_p).
- The residual plots showed an approximately normal distribution of errors without systematic patterns, indicating that the model assumptions were reasonably satisfied and supporting the model's suitability for predicting the overall utility and multiple response characteristics.

Future Scope of the Study

Future studies can explore different electrode wire materials, shapes, and coatings, along with previously fixed parameters such as dielectric type, flushing pressure, peak current, workpiece material and thickness, duty cycle, frequency, and wire diameter to further improve WEDM performance.

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