

Article

A Hybrid Design of Experiment Approach in Analyzing the Electrical Discharge Machining Influence on Stir Cast Al7075/B₄C Metal Matrix Composites

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Abstract: The present work centers on aluminum-based metal matrix composites (AMCs), synthesized via stir casting and then processed by electrical discharge machining (EDM) in the case of Al7075 as a matrix and 6 wt.% boron carbide (B₄C) as reinforcement. A design of experiment (DoE) approach, powered by hybrid optimization techniques (such as the entropy weight method (EWM), grey relational analysis (GRA) incorporated Taguchi method) was used to investigate the relationship between current (I), pulse ON time (Ton), pulse OFF time (Toff), and electrode gap (Gap) as input parameters and the material removal rate (MRR), tool wear rate (TWR), and surface roughness (SR) as response parameters. The results showed that an I = 140 A, Ton = 120 ms, Toff = 50 ms, and Gap = 0.4 mm combination gives the best response parameters of MRR = 0.5628 mm³/min, TWR = 0.0048 mm³/min, and SR = 4.4034 μs.

Keywords: aluminum matrix composites (AMCs); aluminum 7075; boron carbide (B₄C); electrical discharge machining (EDM); design of experiment (DoE); grey relational analysis (GRA)



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1. Introduction

1.1. Metal Matrix Composites

The metal matrix composites (MMCs) represent an advanced class of materials, capable of amalgamating the desirable properties of metals with the enhanced performance offered by reinforcements [1]. MMCs typically consist of two phases: a metal alloy serving as the matrix phase, with ceramic particles dispersed within it. The objective behind developing MMCs is to achieve a blend of properties unattainable by either the metal matrix or the reinforcement phase alone. Consequently, MMCs often exhibit superior mechanical, thermal, and physical characteristics compared to conventional metal. The selection of the reinforcement material for MMCs is contingent upon the desired properties of the resulting composite material. Various types of reinforcements are commonly used, including ceramic, metal-based, and polymer reinforcements. On the other hand, MMCs employ several major matrix phases, such as aluminum, magnesium, titanium, and copper matrix composites. These matrix phases serve as the foundation into which the reinforcements are incorporated, contributing to the diverse range of properties exhibited by MMCs.

Aluminum is frequently chosen as the matrix phase in MMCs due to its advantageous attributes, including low density, high strength-to-weight ratio, excellent corrosion resistance, and efficient thermal conductivity [2]. The selection of the reinforcement phase depends on specific performance requirements and desired properties. Common reinforcements used in aluminum-based metal matrix composites (AMCs) encompass silicon carbide (SiC), aluminum oxide (Al_2O_3), boron carbide (B_4C), titanium diboride (TiB_2), and titanium carbide (TiC) [3].

The fabrication of MMCs involves manufacturing processes like (i) powder metallurgy, (ii) liquid metallurgy, (iii) solid-state processing, and (iv) in situ processing. Liquid state fabrication processes allow for the amalgamation of the distributed phase (reinforcement material) into a liquefied metal (matrix material) followed by its solidification. Among the various manufacturing techniques, the stir casting process is the most popular and economical method due to its simplicity of process, easy control of composite structures, and capability of mass production. In stir casting fabrication, the dispersed phase materials are mixed with a molten matrix material using continuous mechanical stirring.

Following the production of MMCs, such as through the stir casting process as in the present case, there frequently arises a requirement for further processing or machining, and various manufacturing technologies can be employed for this purpose.

Electrical discharge machining (EDM) is a non-traditional machining process used to shape metal parts by employing electrical discharges or sparks [4]. This method is highly effective for machining intricate shapes and hard materials that are otherwise challenging to process using conventional machining techniques [5]. During the EDM process, material removal occurs due to the electrical discharges between the tool and the workpiece. Both the tool (electrode) and the workpiece, submerged in dielectric fluid—commonly deionized water or oils—serve as a medium for electrical conduction and help in flushing away debris [6]. Figures 1 and 2 show the EDM machining setup and process.

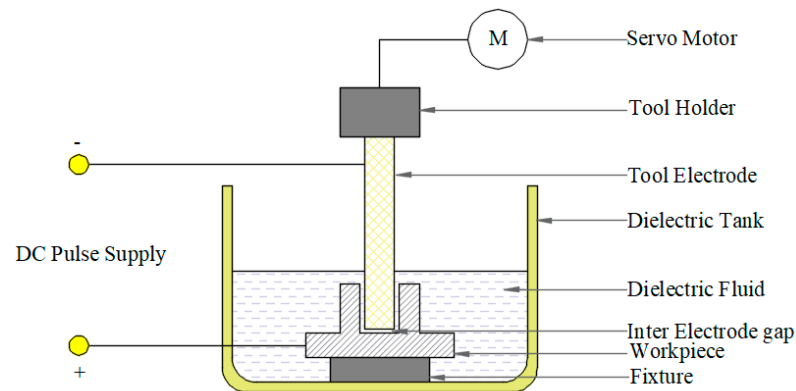


Figure 1. Arrangement and components of an electrical discharge machining (EDM) setup.

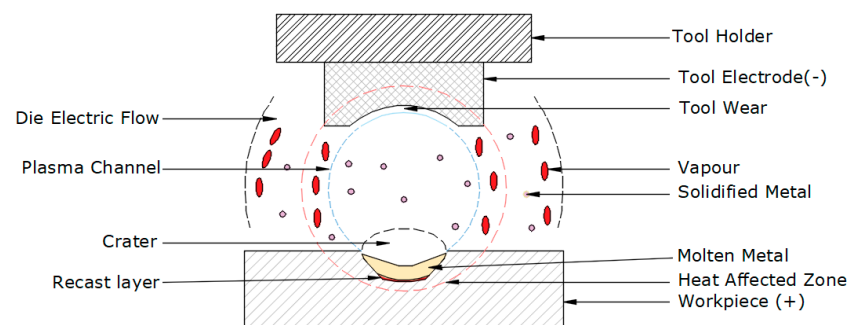


Figure 2. The operational stages of the electrical discharge machining (EDM) process.

1.2. Design of Experiments

The machining of MMCs using EDM can pose considerable challenges, primarily due to the presence of nonconductive particles and their impact on the EDM process [3]. Achieving improved machining results requires meticulous parameter optimization and the selection of suitable electrodes.

The data collected from experiments conducted on an EDM process can be analyzed to establish correlations between process parameters and performance metrics. For the scope, the optimization of a process involves identifying the ideal settings for controllable factors, aiming to maximize the desired process outcome. This pursuit of optimal settings enhances overall performance, leading to improved quality and efficiency [5].

The efficiency of the EDM process is commonly identified by the following performance parameters [7]: (i) material removal rate (MRR) (ii) electrode or tool wear rate (EWR/TWR), and (iii) surface toughness (SR).

Various statistical analysis techniques, including analysis of variance (ANOVA), regression analysis (RA), response surface methodology (RSM), and optimization algorithms, can be employed for this purpose. These methods aid in defining the optimal parameter settings necessary to achieve favorable results in the process.

Between other procedures, the Taguchi method stands as one of the most widely accepted and popular design of experiment (DoE) approaches [5]. Developed by Genichi Taguchi, this statistical methodology aims to enhance the quality and performance of products or processes. The key components in the Taguchi analysis are orthogonal array (OA) and the signal-to-noise ratio (SNR):

- OA is applied with the scope to ensure an efficient and balanced testing combination of different levels of factors. The signal-to-noise ratio (SNR) defines the ratio of deviation of the target value to the variability of the experimental values.
- SNR is used to analyze the performance of the processes. There are three objectives of SNR used for the analysis depending upon the nature of response variables [8,9], named as: (i) the smaller the better, (ii) the larger the better, and (iii) the nominal the better. OA and SNR are used in efficient experimentation and analysis of data to assist in decision-making and cost-effective improvements.

By providing a systematic framework, the Taguchi method facilitates the identification of optimal factor settings, the reduction of variability, and the overall improvement of process performance [10].

In the multi-objective optimization process, Grey relational analysis (GRA), the weighted Grey relational analysis (WGRA) technique for order of preference by similarity to ideal solution (TOPSIS), desirability function (DF), entropy weight method (EWM), and many other techniques are applied for optimize the process parameters [11,12]. GRA and TOPSIS are not specific optimization tools, yet they can be used as part of an optimization process to rank and select the most efficient solution based on multiple criteria. EWM is applied to prioritize alternatives or evaluate the relative importance of different response parameters. It is based on the concept of entropy from information theory, and it measures the degree of uncertainty or randomness in the system. Multi-objective optimization techniques exploit response parameter weights in the process of converting multiple responses into a single response value. The inclusion of weights of response parameters in the optimization process is a crucial phase. The weight of response parameters can be assigned in different ways, like equal, subjective, objective, or a combination of subjective and objective weights [13]. EWM is one of the methods to assign the weightage of the response parameter. This method was proposed by Shannon and Weavers in 1947 and again further developed by Zeleny in 1982. Explained the application of the Taguchi method to optimize the wire EDM process parameters [14,15] for powder mixed electrical discharge machining (PMEDM) of silicon-reinforced aluminum metal matrix composite. MRR, TWR, and SR were optimized by a hybrid Taguchi method coupled with DF, PSO, and RSM approaches and the validation test showed the close relationship between predicted and experimental results [16]. The optimal input parameter values for maximum MRR and minimum EWR for EDM of AISI

316LN stainless steel were predicted using a desirability-based PSO approach [17]. The Grey relational analysis (GRA) proposed by Deng (1989) has been proven to effectively resolve the complicated interrelationships among multiple performance characteristics of the EDM process [18–20]. Lin and Lin [21] proposed a new approach for the optimization of multiple performance characteristics of the EDM process based on the OA with GRA. To employ OA combined with GRA to optimize the multiple objective process parameters for wire EDM of Inconel 825 material [22]. Many researchers have applied the Taguchi-based GRA method to optimize the process parameters for high-speed turning operation of Inconel 718 material [23], micro EDM of SS 304 material [24], turning operations of Ti-6Al-4V alloy [25,26], turning S45C carbon steel [27], plasma arc welding of materials [28], end mill of glass fiber-reinforced polymers (GFRP) [29], and on tool-specific Caldie steel [23–25,27–30] to obtain the improved response results. EDM machining was carried out for EN-31 materials and optimized MRR through the GRA-based ANOVA method [31]. MRR, TWR, and SR of the EDM process for Inconel-600 material were optimized by the RSM and the GRA-based ANOVA method [32]. This worked also on titanium alloys, MRR and SR of Grade 5 (Ti-6Al-4V) titanium alloy was optimized through a Taguchi-coupled GRA and ANOVA method, e.g., by [33–36]. The EDM process was carried out in cemented carbide material and the response parameters MRR, TWR, and SR were optimized by the Taguchi GRA with the ANOVA method [37]. Optimized EDM process parameters for cutting a B₄C (boron carbide)-reinforced Al7075 metal matrix composite using RSM were elicited, in the sense that current and pulse ON time greatly affected response parameter performance [38].

Finally, some investigations have proposed a hybrid method of Taguchi-based PCA and WGRA to optimize the process parameters of EDM of RENE80 nickel supper alloy and concluded that the hybrid method is effective in determining optimal process parameters [39,40]. EDM of pure titanium alloy process parameters was optimized by the hybrid method of Taguchi-based GRA with RSM approach and the significance of process factors was studied by ANOVA [9]. More in general, the benefits of EWM for multiple objective optimizations in EDM, wire EDM, electric discharge drilling (EDD), electric discharge diamond grinding (EDDG), electrochemical spark machining (ECSM) processes, laser-based machining process, and CNC-based machining process were also reviewed [41]. The entropy weight method was also used to measure the weightage of performance parameters for the site selection of water sources [42].

Stir casting process parameters, reinforcement percentage, grain size, and blade angle value are optimized to obtain optimal tensile strength and micro-hardness casting by the application of the hybrid optimization technique Taguchi coupled with the entropy-weighted method and GRA. The influence of process parameters was analyzed by ANOVA in an Al2024/red mud composite [43,44]. Taguchi-integrated TOPSIS and GRA multiple objective hybrid optimization techniques were employed to optimize of magnesium alloy EDM process and the output results were analyzed by ANOVA to identify the process parameter contributions [45]. The laser cutting process of AL6061/SiC/Al₂O₃ materials parameters was also optimized by the application of Taguchi integrated-based GRA [46].

Applications of aluminum alloys in friction load environments have been restricted because of their poor wear resistance. Therefore, analysis of tribological and machining properties of aluminum-based materials is becoming of paramount interest. Many researchers have analyzed and concluded the incorporation of hard ceramic materials into soft materials improves tribological properties. SiC-reinforced Al7050 MMC [47], graphene-incorporated Al7075 MMC [48,49], Al₂O₃-reinforced Al7075 MMC [50], SiC-reinforced Al7075 [51,52], 7.5% SiC-reinforced Al6061 MMC [53], and TiC-reinforced Al6070 MMC [54] were subjected to wear analysis using the Taguchi method and the results concluded that particles addition improved the wear resistance of the composite materials compared to the base metal, and also the sliding distance mostly influenced the wear property.

As per the literature survey, many researchers have analyzed the effect of EDM input process parameters like current, voltage, pulse time, gap voltage, polarization, wire speed, and spark gap on output parameters MRR, TWR, SR, and overcut of Al-MMC reinforced

with Al_2O_3 , SiC, TiC, and graphene using the Taguchi method and multi-objective optimization techniques GRA and TOPSIS incorporated with ANOVA. Most of the researchers have focused on the B_4C -reinforced 7XXX series of aluminum alloys, and, in multi-objective optimization process, many researchers did not include the weightage of output process parameters in their experimental analysis to optimize EDM process parameters. In this experimental analysis, a B_4C -reinforced aluminum metal matrix composite (Al7075) was subjected to the EDM process, and the input parameters current, Ton, Toff, and electrode gap were optimized to obtain the best response parameter MRR, TWR, and SR result using a hybrid optimization technique (entropy method coupled with GRA and ANOVA). SEM analysis was included in the experimental study of the machined surface.

2. Materials and Methodology

The current investigation opted for Al7075 as the matrix material and B_4C as the reinforcing element. Al7075 represents a high-strength aluminum alloy that is widely employed in various industrial applications due to its exceptional mechanical properties, corrosion resistance, and light-weight nature [55]. In the automotive sector, Al7075 is utilized for manufacturing components such as engine blocks, suspension parts, and drive train components [56]. Moreover, it finds application in the production of sports goods, contributing to items like bicycle frames and tennis rackets. In aerospace industries, Al7075 is employed for structural purposes, while also serving in tooling and cutting applications [57]. By reinforcing Al7075 with B_4C , the resulting composite amalgamates the corrosion resistance and light-weight characteristics of Al7075 with the heightened wear resistance and hardness properties offered by B_4C . The chemical composition of the Al7075 matrix material is shown in Table 1.

Table 1. Chemical composition of Al7075.

Constituents	Si	Fe	Cu	Mn	Mg	Cr	Zi	Ti	Others	Al
%	0.4	0.5	1.2–2	0.3	2.1–2.9	0.18–2	5.1–6.1	0.2	0.15	Balance

According to the Taguchi design of experiment (DoE), four EDM input parameters were chosen, namely: (i) current (I), (ii) pulse ON time (Ton), (iii) pulse OFF time (Poff), and (iv) electrode gap (Gap). Each input parameter was set at three levels, which count into two degrees of freedom for each factor. Based on degrees of freedom, L27 OA was selected in the present assessment. The experimental process parameters and their levels are exposed in Table 2. Taguchi analysis included the concept of SNR and ANOVA to identify the optimum level of each process parameter. In SNR, as said, Taguchi defines three objectives, such as smaller the better, larger the better, and nominal the better [9]. The highest value of SNR in the experimental region is considered as the optimum level for the particular process parameter [58]. The Taguchi method, as usual, was planned here to optimize the single objective response characteristic [59,60]. The experimental setup and the EDM machine specifications are presented in Tables 3 and 4.

Table 2. Control factors and level values.

Parameter	Parameter Values		
	1	2	3
Current (I)	60	100	140
Pulse ON Time (Ton)	100	110	120
Pulse OFF time (Toff)	50	60	70
Electrode Gap (Gap)	0.2	0.4	0.6

Table 3. Experimental setup.

Workpiece	A17075 MMC-Thickness 10 mm
Electrode	Brass-Diameter 0.3 mm
Dielectric Fluid	Kerosene
Polarity	Workpiece: Negative; Electrode: Positive
Electrode Rotation Speed	120 RPM

Table 4. EDM machine specifications.

Machine	SODICK AQ300L
Max. travel of X, Y, Z axes (mm)	300 × 200 × 200
Max. travel of U, V axes (mm)	80 × 80
Max. Machining size (mm)	500 × 300 × 180
Machine tool dimension (mm)	1300 × 2400 × 2210

The ratio between the difference of weight of the work piece before and after the machining and the machining time is called material removal rate (MRR) and evaluated by [61]:

$$\text{MRR} = \frac{W_b - W_a}{t} \quad (1)$$

where:

W_b = Weight of work piece before machining

W_a = Weight of work piece after machining

t = Machining time.

The ratio between the difference in weight of the electrode before and after the machining and the machining time is called tool wear rate (TWR) and is evaluated by:

$$\text{TWR} = \frac{E_b - E_a}{t} \quad (2)$$

where:

E_b = Weight of electrode before machining

E_a = Weight of electrode after machining

t = Machining time.

2.1. Taguchi Method

In the Taguchi method, the performance parameter characteristics were presented by SNR and the process parameter contribution on the response parameters was accessed by ANOVA. In this experimental analysis the larger the better (LB) objective was selected for MRR because the higher MRR reduced the production time. The smaller the better (SB) objective was selected for TWR and SR because of minimum electrode wear was preferred during the machining process and a minimum value of SR results in a good surface finish. Equations (3) and (4) showcase the SNR calculation for MRR, TWR, and SR [58].

$$\text{SNR}(LB) = -10 \log_{10} \frac{1}{n} \sum_{i=1}^n X_{ij}^2 \quad (3)$$

$$\text{SNR}(SB) = -10 \log_{10} \frac{1}{n} \sum_{i=1}^n \frac{1}{X_{ij}^2} \quad (4)$$

where:

n = Number of replications of experiments

X_{ij} = Experimental response value in i column j row

$i = 1, 2, 3, \dots, n$ and $j = 1, 2, 3, \dots, k$.

2.2. Multiple Response Optimization

In a multi-objective performance process, enhancing one performance parameter may lead to the deterioration of another. To address such challenges, Grey relational analysis (GRA) proves effective by transforming multi-objective problems into single-objective ones, simplifying the optimization process [58]. This paper delves into an experimental study aiming to optimize multiple objectives—material removal rate (MRR), tool wear rate (TWR), and surface roughness (SR)—within the electrical discharge machining (EDM) process for B₄C-reinforced Al7075 metal matrix composite. The study employed hybrid optimization techniques, specifically, the integration of entropy coupled with GRA and ANOVA. The primary objective of GRA is to optimize multi-objective response characteristics [18].

2.3. Entropy Weight Method Procedure

In EWM, m indicators and n samples are set in the evaluation and the measured value of the i indicator in the j sample is recorded as X_{ij} . The first step in this process is the normalization of the measured value i index in the j sample indicated by P_{ij} . The value of the P_{ij} is calculated by Equation (5) [42,53].

$$P_{ij} = \frac{X_{ij}}{\sum_{j=1}^n X_{ij}} \quad (5)$$

The entropy value (E_i) of the i index is determined by Equation (6) [43].

$$E_i = \frac{\sum_{j=1}^n P_{ij}}{\ln n} \quad (6)$$

The range of entropy values is zero to one. The larger the value of the entropy, is the superior the differentiation degree of index i . The weightage of the response parameter is calculated by Equation (7) [43].

$$W_i = \frac{1 - E_i}{\sum_{i=1}^m (1 - E_i)} \quad (7)$$

2.4. Grey Relational Analysis Procedure

The process involves converting a single data input into a distributed and scaled form, ensuring that the data are evenly distributed and fall within the acceptable range of 0 to 1 [62–64]. This transformation is necessary to facilitate further analysis of the data. In the EDM process, it is common for data to exist at various levels and in different units [3,65,66]. As a result, it is necessary to normalize all experimental response data. Normalization can be achieved by employing the following Equations (8) and (9) [59,67,68]:

1. Lower the better criterion:

$$Z_{ij} = \frac{\text{Max}(X_{ij}) - X_{ij}}{\text{Max}(X_{ij}) - \text{Min}(X_{ij})} \quad (8)$$

2. Higher the better criterion

$$Z_{ij} = \frac{X_{ij} - \text{Min}(X_{ij})}{\text{Max}(X_{ij}) - \text{Min}(X_{ij})} \quad (9)$$

where:

Z_{ij} = Normalized value

X_{ij} = Experimental response value in i column j row

$\text{Max}(X_{ij})$ = Maximum response value

$\text{Min}(X_{ij})$ = Minimum response value

The deviation sequence is calculated after the normalization of the data process, using Equation (10) [69–71]:

$$\Delta_{ij} = \text{Max}(Z_{ij}) - Z_{ij} \quad (10)$$

where:

Δ_{ij} = Deviation sequence value in i column j row

Z_{ij} = Normalized value of i column j row

$\text{Max}(Z_{ij})$ = Maximum normalized value

The Grey relational coefficient (GRC) is computed to quantify bonding between the ideal and actual responses [72–74]. This calculation is performed to determine the GRC value. Multi-objective problems are converted into a single objective problem in GRA process [75,76]. The calculation of GRC is determined through the utilisation of Equation (11) provided in references [58,59].

$$Y_{ij} = \frac{\text{Min}(\Delta_{ij}) - \Psi(\text{Max}(\Delta_{ij}))}{\Delta_{ij} - \Psi(\text{Max}(\Delta_{ij}))} \quad (11)$$

where:

Y_{ij} = Grey relational coefficient value in i column j row

Δ_{ij} = Deviation sequence value in i column j row

Ψ = Distinguishing coefficient

$\text{Max}(\Delta_{ij})$ = Maximum deviation value

$\text{Min}(\Delta_{ij})$ = Minimum deviation value

The assumed value for Ψ is within the range of zero to one. Adoption of both “the larger the better” and “the lower the better” criteria for the multi-objective response characteristics has led to significant advancements. In this study, the value of Ψ is considered to be equal to 0.5. The Grey relational grade (GRG) is defined based on the converted single objective problem and the GRC value [22]. According to the rule, higher GRG values are used to evaluate multiple characteristics, and the corresponding parameters are chosen to achieve the normalized optimum level of combination. GRG is determined through Equation (12) provided in references [59].

$$G_j = \frac{1}{k} \sum_{i=1}^k Y_{ij} \quad (12)$$

where:

G_{ij} = Grey relational grade value in j row

Y_{ij} = Grey relational coefficient value in i column j row

k = Number of response parameters.

3. Results and Discussion

To achieve the maximum output response values, each input processing parameter's contribution to the response parameters was investigated. A Taguchi-based GRA coupled EWM with the RSM technique opted for this experimental investigation of response parameters against the input parameters. In this experimental analysis, MRR, TWR, and SR were considered as response parameters, and I, Ton, Toff, and Gap were considered as input process parameters. As per DoE experiments, the results are listed in Table 5. The determined SNR of the same for experimentally validated results is also listed in Table 5.

Taguchi-based analysis was incorporated to optimize process parameters MRR, based on the SNR to find the combination to maximize the response MRR parameter and is shown in Figure 3. Figure 3 explains that the initial increase in current reduces the MRR value, yet a further increase in current allows the MRR to grow. This can be attributed to the fact that the MRR is directly proportional to the current. The increase in current develops more energetic sparks that lead to an increase in the erosion of the material and MRR [77]. The increase in pulse ON time increases the MRR due to the increased discharge time of

high-frequency sparks in the work zone. The shorter pulse duration reduces the spark energy, and the minimum discharge time leads to lower MRR. Increased pulse ON time produces longer spark durations, and the heat energy produced is sufficient to cause larger craters to form on the work piece's material, increasing the rate of material removal. The increased pulse OFF time reduces the contact time of spark energy with the workpiece and subsequent spark development will decrease with the increase of Toff time which leads to a drop in MRR. The increase of Toff time increases the dielectric fluid flow which leads to a hardened working zone, and this hardening effect will reduce the MRR. High thermal energy is developed during the smaller gap between the tool and the workpiece due to the high thermal energy, and the workpiece material is liquefied and evaporated quickly, leading to increase in the MRR.

Table 5. DoE, experimental values, and calculated SNR.

I	Ton	Toff	Gap	MRR	TWR	SR	SNR-MRR	SNR-TWR	SNR-SR
60	100	50	0.2	0.5165	0.0015	3.9271	−5.7386	56.4782	−11.8814
60	100	60	0.2	0.5117	0.0013	3.9189	−5.8197	57.7211	−11.8633
60	100	70	0.2	0.5084	0.0012	3.9126	−5.8759	58.4164	−11.8493
100	110	50	0.4	0.5231	0.0032	4.1352	−5.6283	49.8970	−12.3299
100	110	60	0.4	0.5198	0.0029	4.1328	−5.6833	50.7520	−12.3249
100	110	70	0.4	0.5169	0.0029	4.1302	−5.7319	50.7520	−12.3194
140	120	50	0.6	0.5571	0.0042	4.3968	−5.0813	47.5350	−12.8627
140	120	60	0.6	0.5559	0.0039	4.3942	−5.1001	48.1787	−12.8576
140	120	70	0.6	0.5538	0.0039	4.3908	−5.1329	48.1787	−12.8509
100	120	50	0.2	0.5288	0.0046	4.1376	−5.5342	46.7448	−12.3350
100	120	60	0.2	0.5263	0.0042	4.1237	−5.5753	47.5350	−12.3057
100	120	70	0.2	0.5236	0.004	4.1182	−5.6200	47.9588	−12.2941
140	100	50	0.4	0.5626	0.0047	4.4032	−4.9960	46.5580	−12.8754
140	100	60	0.4	0.5598	0.0046	4.3982	−5.0393	46.7448	−12.8655
140	100	70	0.4	0.5563	0.0046	4.3956	−5.0938	46.7448	−12.8604
60	110	50	0.6	0.5376	0.0032	4.5228	−5.3908	49.8970	−13.1081
60	110	60	0.6	0.5351	0.0032	4.5192	−5.4313	49.8970	−13.1012
60	110	70	0.6	0.5332	0.0031	4.5146	−5.4622	50.1728	−13.0924
140	110	50	0.2	0.5651	0.0057	4.4134	−4.9575	44.8825	−12.8955
140	110	60	0.2	0.5623	0.0057	4.3875	−5.0006	44.8825	−12.8443
140	110	70	0.2	0.5601	0.0053	4.3826	−5.0347	45.5145	−12.8346
60	120	50	0.4	0.5456	0.0048	4.5323	−5.2625	46.3752	−13.1264
60	120	60	0.4	0.5424	0.0042	4.5284	−5.3136	47.5350	−13.1189
60	120	70	0.4	0.5383	0.0041	4.5192	−5.3795	47.7443	−13.1012
100	100	50	0.6	0.5205	0.0028	4.1321	−5.6716	51.0568	−12.3234
100	100	60	0.6	0.5186	0.0026	4.1293	−5.7033	51.7005	−12.3175
100	100	70	0.6	0.5162	0.0027	4.1278	−5.7436	51.3727	−12.3144

An extremely small gap can lead to unstable sparking where the discharge may not form reliably, and an extremely large gap can also lead to instability and unpredictable sparking behavior, which leads to a reduction in the MRR. The response table for SNR of MRR rank input parameters in the order of current, pulse ON time, electrode gap, and pulse OFF time is shown in Table 6. ANOVA analyses of the Taguchi results studied the influence of each parameter and their percentage of contribution [78] on MRR as portrayed in Table 7.

Table 6. Response table for signal to noise ratios for MRR (i.e., larger is better).

Level	I	Ton	Toff	Gap
1	−5.519	−5.52	−5.362	−5.462
2	−5.655	−5.369	−5.407	−5.348
3	−5.048	−5.333	−5.453	−5.413
Delta	0.606	0.187	0.09	0.114
Rank	1	2	4	3

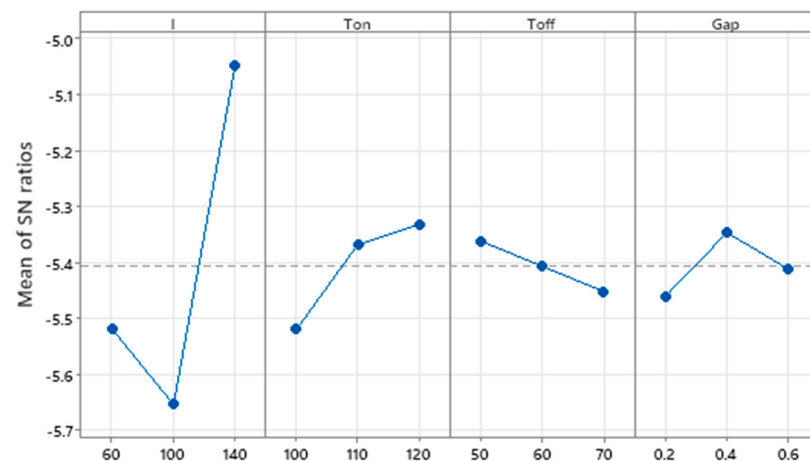


Figure 3. Main effects plot for SN ratios of MRR (i.e., signal to noise: larger is better).

Table 7. Analysis of variance for MRR.

Source	DF	Adj SS	Adj MS	F-Value	p-Value	Contribution %
I	2	0.049088	0.024544	22.05	0	72.06%
T _{on}	2	0.014016	0.007008	6.3	0.008	20.59%
T _{off}	2	0.001032	0.000516	0.46	0.636	1.50%
Gap	2	0.003987	0.001994	1.79	0.195	5.85%
Error	18	0.020033	0.001113			
Total	26	0.088157				

Table 7 results show all the input parameters that contributed to MRR, and the value of current affects the MRR in maxima at 72.06% followed by Ton 20.59%. Gap and Toff values have a minimum contribution of the MRR values at a percentage of 5.85% and 1.50%, respectively. Figure 4 shows the contribution percentage of input parameters against the MRR.

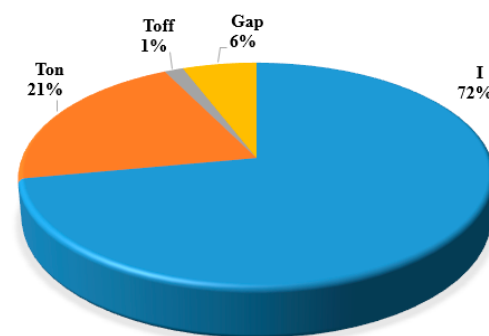


Figure 4. Parameter contribution for MRR.

One of the significant factors that affects the performance of the EDM process is electrode wear or tool wear and it disturbs the machining accuracy, surface finish, and efficiency of the process. In the EDM process, tool wear or electrode wear is a natural occurrence, and it has an impact on the machined surface geometric corrections. TWR is influenced by the melting point of the workpiece material. The carbon accumulation on the surface of the electrode during the sparking has an impact on the tool wear. Figure 5 shows the main effect plot for SNR of TWR. It explains the increase in current will result in an increase in TWR due to the development of high-strength, long lasting successive sparks with high thermal energy. The high thermal energy accelerates the electrode material degradation [79].

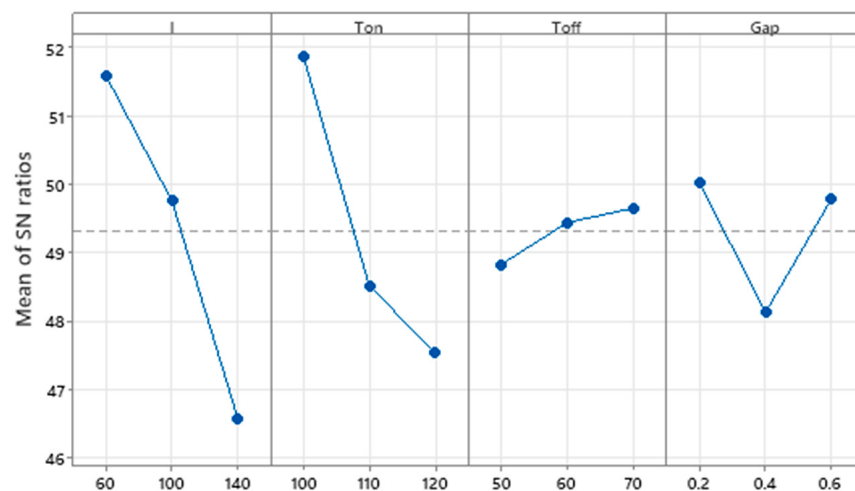


Figure 5. Main effects plot for SN ratios of TWR (i.e., signal to noise: smaller is better).

A shorter duration of the Ton decreases the TWR, and lower Ton reduces the spark energy and reduces the TWR. The excessive Ton increased the high-frequency discharge sparks at high strength to erode the workpiece material and electrode material. The workpiece will melt and evaporate for longer if the Ton is increased, which will increase the time it takes for thermal energy to be produced and increase the pace at which tools wear out. The shorter duration of Toff is not enough to flush debris between the electrode and the workpiece, which leads to an increase in the TWR. Increased Toff slows down tool wear because it gives time to flush debris between the electrode and workpiece and increases the cooling time of the electrode to reduce the TWR.

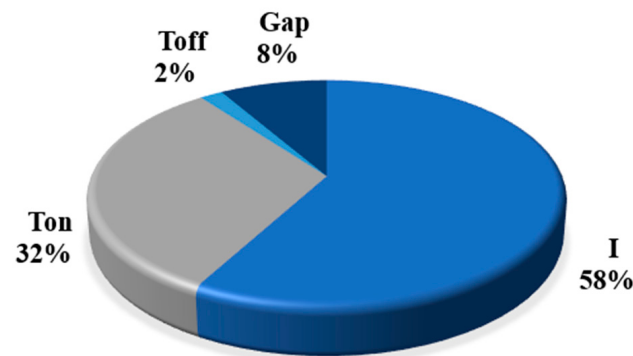
When the gap between the electrode and the workpiece is larger, it can lead to increased TWR. The relationship between the electrode gap and TWR is directly proportional. The larger gap results in longer spark discharge, which will increase the material erosion from the electrode material [78]. The larger electrode gap increases the electrical resistance between the electrode and the workpiece. A smaller gap between the electrode and workpiece creates high current density and produces unstable sparking which causes uneven erosion of the electrode. The electrode wear is not uniform across the electrode surface. The wear can be more pronounced in a specific area depending on the electrode gap and spark distribution. The response table for SNR of TWR ranks the input parameters in the order of current, pulse ON time, electrode gap, and pulse OFF time; shown in Table 8. The influence of the input process parameter on the response parameter TWR was analyzed by the ANOVA method and the percentage of contribution [80] on TWR is portrayed in Table 9. The results clearly show that all the input parameters contributed to TWR, and a maximum 58.06% contribution of current affects the TWR followed Ton 31.65%. The Gap and Toff values have a minimum contribution to the TWR values at a percentage of 8.47% and 1.82%, respectively. Figure 6 shows the contribution percentage of input parameters against the TWR.

Table 8. Response table for signal to noise ratios for TWR (i.e., smaller is better).

Level	I	Ton	Toff	Gap
1	51.58	51.87	48.82	50.01
2	49.75	48.52	49.44	48.12
3	46.58	47.53	49.65	49.78
Delta	5	4.33	0.83	1.89
Rank	1	2	4	3

Table 9. Analysis of variance for TWR.

Source	DF	Adj SS	Adj MS	F-Value	p-Value	Contribution %
I	2	0.000016	0.000008	12.75	0	58.06%
T _{on}	2	0.000009	0.000004	6.95	0.006	31.65%
T _{off}	2	0	0	0.4	0.676	1.82%
Gap	2	0.000002	0.000001	1.86	0.185	8.47%
Error	18	0.000011	0.000001			
Total	26	0.000039				

**Figure 6.** Parameter contribution for TWR.

The small irregularity on a machined surface is termed surface roughness. The surface roughness is made up of three elements: roughness, wavering, and form. The machined surface has many irregularities in the surface due to the effects of input parameters. The lower surface roughness indicates a fine surface and high surface roughness indicates more irregularities in the surface. As the current increases, an increase in the thermal energy is developed in the machining region. In the EDM process, random discharge between the electrode and the workpiece is connected by many tinny craters. The size of the craters formed on the machined surface is defined by the magnitude of discharge energy [5].

The magnitude of discharge energy is increased by the increase of current the result of high energy increases the MRR at the same time it creates deeper and wider craters increasing the surface roughness. Due to high thermal energy, wider and deeper dimensions of the crater were developed on the work piece surface, and crater development increased the surface roughness. The size of the craters also depends upon the Ton; smaller craters are developed by short sparks with minimum heat, while larger craters are produced by the longer Ton due to the longer sparks with high heat [5]. The longer Ton results in higher MRR due to the high energy sparks discharged to each spark discharge. It leads to an increase in the MRR, due to the aggressive MRR developing a rough surface finish and also due to high localized temperature on the spark region, creating more intense sparking and developing a rough machined surface. The thick recast layer was developed due to the longer Ton. Recast layers are re-solidified materials formed after each spark discharge. These thick recast layers form a rough machined surface. A shorter Ton generates smaller and more controlled sparks, resulting in a smoother surface finish.

Longer Toff allows more time for dielectric fluid to flow into the spark gap to flush away debris and cool the electrode and workpiece. Efficient cooling and debris removal can contribute to the smooth apparent finish. The effective cooling of the electrode and workpiece reduces the thermal effects associated with sparking, recast layering, and surface irregularities. The longer Toff allows more complete re-solidification of the molten metal created during spark discharge. The lower Toff time does not allow the complete flushing of debris and re-solidification of the recast material. This causes poor surface roughness. The electrode gap has an inverse square relationship with the surface finish. A smaller electrode gap leads to concentrated energy in the discharge sparks, causing more intense

sparking and high localized temperature. More energetic sparks develop a smooth surface and fine surface texture.

High focused energy spark due to the smaller gap results in deeper material removal and it leads to significant crater formation and smooth surface finish. The dielectric breakdown occurs in the smaller gap, and leads to good surface finish and machining stability. A greater electrode gap develops randomized craters and an uneven surface finish [5]. The effects of input parameters on response parameter SR are shown in Figure 7. The rank of the influencing parameters is portrayed in Table 10, and is ranked the order of current, electrode gap, pulse ON time, and pulse OFF time. The ANOVA analysis results are revealed in Table 11, and it shows that the maximum contribution for SR was current at 41% followed by 30% and 28% for electrode gap and pulse ON time, respectively. The contribution of Toff was minimal in the surface roughness. Figure 8 shows the contribution of input parameters on the surface roughness of the machined surface.

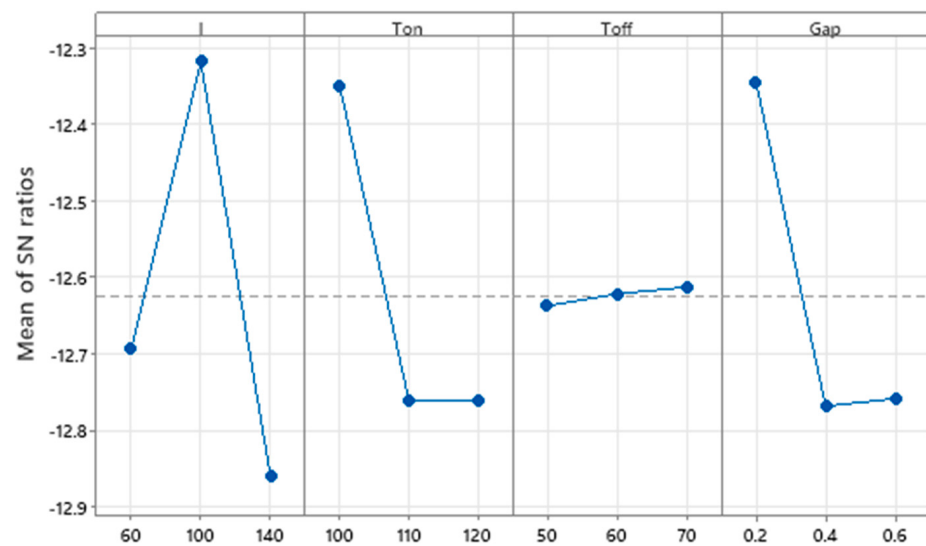


Figure 7. Main effects plot for SN ratios of SR (i.e., signal to noise: smaller is better).

Table 10. Response table for signal to noise ratios for SR (i.e., smaller is better).

Level	I	Ton	Toff	Gap
1	−12.69	−12.35	−12.64	−12.34
2	−12.32	−12.76	−12.62	−12.77
3	−12.86	−12.76	−12.61	−12.76
Delta	0.54	0.41	0.02	0.42
Rank	1	3	4	2

Table 11. Analysis of variance for SR.

Source	DF	Adj SS	Adj MS	F-Value	p-Value	Contribution %
I	2	0.33962	0.169811	12.66	0	41.06%
Ton	2	0.23866	0.119328	8.89	0.002	28.84%
Toff	2	0.00067	0.000337	0.03	0.975	0.10%
Gap	2	0.24812	0.124062	9.25	0.002	30.00%
Error	18	0.24153	0.013418			
Total	26	1.0686				

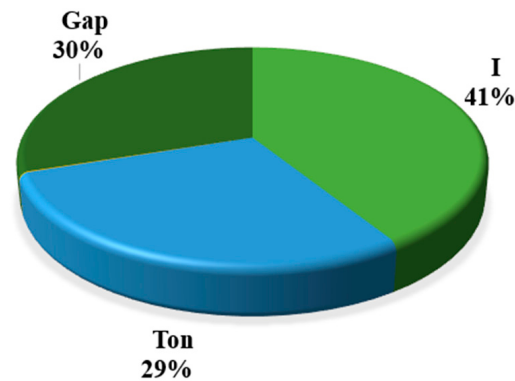


Figure 8. Parameter contribution for SR.

3.1. Entropy Weight Method

Weightage of the response parameter was assigned through EWM. In this process, the results of the experimental values were normalized using Equation (5) to convert the different scale values into the same scale value for comparison. The normalized value of the EWM is shown in Table 12. From the normalized values, the weightage of the response parameter was determined using Equation (7) and tabulated in Table 13. The weightage of each response parameter value was utilized in the multiple response optimization process.

Table 12. Normalization and entropy measure values of response parameters-EWM.

Normalization Values			Entropy Measure		
MRR	TWR	SR	MRR	TWR	SR
0.0356	0.0151	0.0340	−0.1188	−0.0634	−0.1149
0.0353	0.0131	0.0339	−0.1180	−0.0569	−0.1147
0.0351	0.0121	0.0338	−0.1175	−0.0534	−0.1146
0.0361	0.0323	0.0358	−0.1199	−0.1109	−0.1191
0.0359	0.0293	0.0357	−0.1193	−0.1033	−0.1191
0.0357	0.0293	0.0357	−0.1189	−0.1033	−0.1190
0.0384	0.0424	0.0380	−0.1252	−0.1340	−0.1243
0.0383	0.0394	0.0380	−0.1251	−0.1273	−0.1243
0.0382	0.0394	0.0380	−0.1247	−0.1273	−0.1242
0.0365	0.0464	0.0358	−0.1208	−0.1425	−0.1192
0.0363	0.0424	0.0357	−0.1204	−0.1340	−0.1189
0.0361	0.0404	0.0356	−0.1200	−0.1296	−0.1188
0.0388	0.0474	0.0381	−0.1261	−0.1446	−0.1245
0.0386	0.0464	0.0380	−0.1257	−0.1425	−0.1244
0.0384	0.0464	0.0380	−0.1251	−0.1425	−0.1243
0.0371	0.0323	0.0391	−0.1222	−0.1109	−0.1268
0.0369	0.0323	0.0391	−0.1218	−0.1109	−0.1267
0.0368	0.0313	0.0390	−0.1215	−0.1084	−0.1266
0.0390	0.0575	0.0382	−0.1265	−0.1643	−0.1247
0.0388	0.0575	0.0379	−0.1261	−0.1643	−0.1241
0.0386	0.0535	0.0379	−0.1257	−0.1566	−0.1240
0.0376	0.0484	0.0392	−0.1234	−0.1466	−0.1270
0.0374	0.0424	0.0392	−0.1229	−0.1340	−0.1269
0.0371	0.0414	0.0391	−0.1223	−0.1318	−0.1267
0.0359	0.0283	0.0357	−0.1195	−0.1008	−0.1191
0.0358	0.0262	0.0357	−0.1192	−0.0955	−0.1190
0.0356	0.0272	0.0357	−0.1188	−0.0982	−0.1190

Table 13. Weightage of response parameters.

	MRR	TWR	SR
W_i	0.3343	0.3314	0.3343

3.2. Grey Relational Analysis

The results of each parameter have different scales or units. For a fair comparison, it is necessary to convert the results into a common scale [62]. In Grey relational analysis (GRA), normalization is converting the experimental data into a common scale of zero to one. The normalized value of MRR, TWR, and SR were calculated based on the criteria that larger is better for MRR, smaller is better for TWR and SR [76] using Equations (8) and (9), and the same as shown in Table 14. The deviation of each normalized value from the maximum value was identified. The GRC of each experiment was determined from a normalized value. The weighted GRG was calculated from GRC and the weightage of the response parameter was calculated from EWM and shown in Table 14. Thus, the multi-objective problem was converted into a single-objective problem. The maximum value of the GRG with processing parameters was ranked as ‘one’ and the same parameter combination was considered as the optimal combination which provided better MRR, TWR, and SR values [58]. The results of the GRA, GRG, and rank is enumerated in Table 14.

Table 14. Grey relational response variables and rank.

Normalization Values			Deviation Sequence			Grey Relational Coefficient			GRG	Rank
MRR	TWR	SR	MRR	TWR	SR	MRR	TWR	SR		
0.1495	0.1432	0.0252	0.8505	0.8568	0.9748	0.3702	0.3685	0.3390	0.1197	25
0.0612	0.0514	0.0109	0.9388	0.9486	0.9891	0.3475	0.3452	0.3358	0.1143	26
0.0000	0.0000	0.0000	1.0000	1.0000	1.0000	0.3333	0.3333	0.3333	0.1111	27
0.2696	0.6295	0.3763	0.7304	0.3705	0.6237	0.4064	0.5744	0.4450	0.1583	19
0.2097	0.5663	0.3724	0.7903	0.4337	0.6276	0.3875	0.5355	0.4434	0.1517	20
0.1568	0.5663	0.3681	0.8432	0.4337	0.6319	0.3723	0.5355	0.4417	0.1499	22
0.8652	0.8040	0.7936	0.1348	0.1960	0.2064	0.7876	0.7184	0.7078	0.2460	9
0.8448	0.7564	0.7895	0.1552	0.2436	0.2105	0.7631	0.6724	0.7038	0.2377	11
0.8090	0.7564	0.7843	0.1910	0.2436	0.2157	0.7236	0.6724	0.6986	0.2328	12
0.3721	0.8624	0.3803	0.6279	0.1376	0.6197	0.4433	0.7842	0.4465	0.1858	16
0.3273	0.8040	0.3574	0.6727	0.1960	0.6426	0.4264	0.7184	0.4376	0.1756	17
0.2786	0.7727	0.3483	0.7214	0.2273	0.6517	0.4094	0.6875	0.4342	0.1699	18
0.9581	0.8762	0.8035	0.0419	0.1238	0.1965	0.9226	0.8015	0.7178	0.2713	4
0.9109	0.8624	0.7957	0.0891	0.1376	0.2043	0.8487	0.7842	0.7099	0.2603	6
0.8516	0.8624	0.7917	0.1484	0.1376	0.2083	0.7711	0.7842	0.7059	0.2512	8
0.5282	0.6295	0.9857	0.4718	0.3705	0.0143	0.5145	0.5744	0.9722	0.2291	13
0.4841	0.6295	0.9803	0.5159	0.3705	0.0197	0.4922	0.5744	0.9621	0.2255	14
0.4505	0.6091	0.9734	0.5495	0.3909	0.0266	0.4764	0.5612	0.9495	0.2209	15
1.0000	1.0000	0.8192	0.0000	0.0000	0.1808	1.0000	1.0000	0.7344	0.3037	1
0.9530	1.0000	0.7792	0.0470	0.0000	0.2208	0.9141	1.0000	0.6936	0.2896	2
0.9159	0.9533	0.7716	0.0841	0.0467	0.2284	0.8561	0.9146	0.6864	0.2729	3
0.6679	0.8897	1.0000	0.3321	0.1103	0.0000	0.6009	0.8193	1.0000	0.2689	5
0.6122	0.8040	0.9941	0.3878	0.1960	0.0059	0.5632	0.7184	0.9884	0.2523	7
0.5405	0.7885	0.9803	0.4595	0.2115	0.0197	0.5211	0.7028	0.9621	0.2429	10
0.2225	0.5438	0.3712	0.7775	0.4562	0.6288	0.3914	0.5229	0.4430	0.1507	21
0.1879	0.4962	0.3666	0.8121	0.5038	0.6334	0.3811	0.4981	0.4412	0.1466	23
0.1440	0.5204	0.3642	0.8560	0.4796	0.6358	0.3687	0.5104	0.4402	0.1465	24

The influence of input parameters on GRG is shown in the main effect plot in Figure 9. The Figure explains that the increase in current and Ton improves the GRG value and the decrease in the Toff value increases the GRG. The initial increment of the electrode gap improves the GRG but further increment of the electrode gap reduces the GRC. The contribution of the input parameter on the GRG was analyzed by ANOVA and the results are

presented in Table 15. The model summary listed in Table 16 shows a 99% confidence level. The findings indicate that current and Ton play significant roles in the GRG, contributing 60.47%, and 34.67%, respectively. In contrast, Toff and Gap parameters exhibit minimal contributions to the GRG, accounting for 3.24% and 1.59%, respectively. Figure 10 shows the parameter contribution in the GRG. The interaction of the input parameter with GRG is shown in Figure 11.

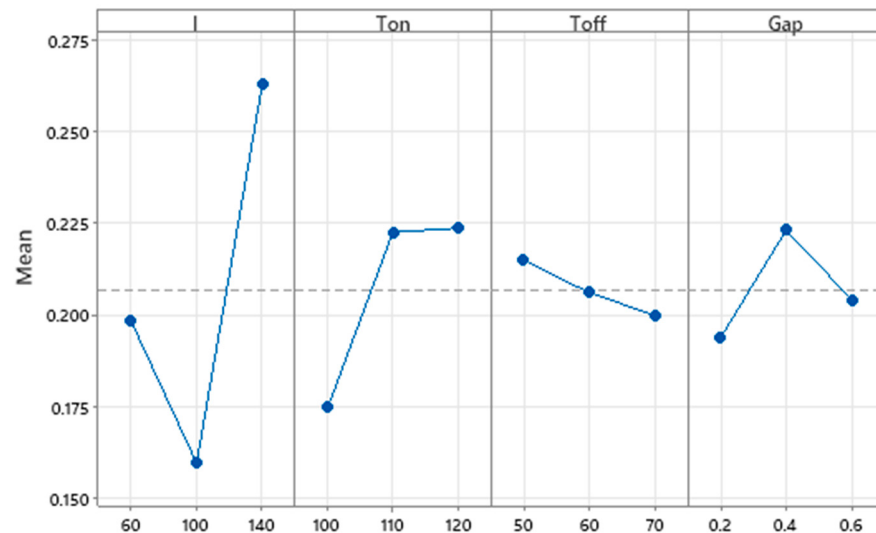


Figure 9. Main effects plot for GRG.

Table 15. Analysis of variance for GRG.

Source	DF	Adj SS	Adj MS	F-Value	p-Value	Contribution %
Linear	4	0.031008	0.007752	2.98	0.041	
I	1	0.01875	0.01875	7.22	0.013	60.47%
T _{on}	1	0.010756	0.010756	4.14	0.054	34.67%
T _{off}	1	0.001021	0.001021	0.39	0.537	3.27%
Gap	1	0.000482	0.000482	0.19	0.671	1.59%
Error	22	0.057149	0.002598			
Total	26	0.088157				

Table 16. Model summary.

S	R-sq	R-sq(adj)	R-sq(pred)
0.00644	99.34%	98.78%	97.40%

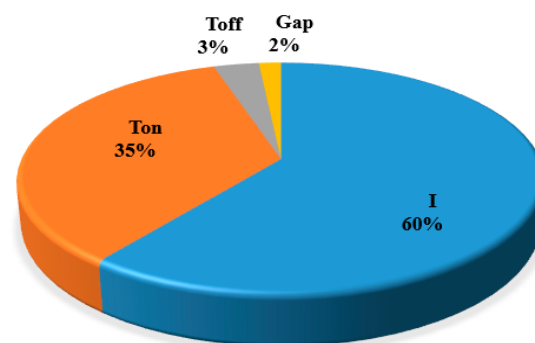


Figure 10. Parameter contribution for GRG.

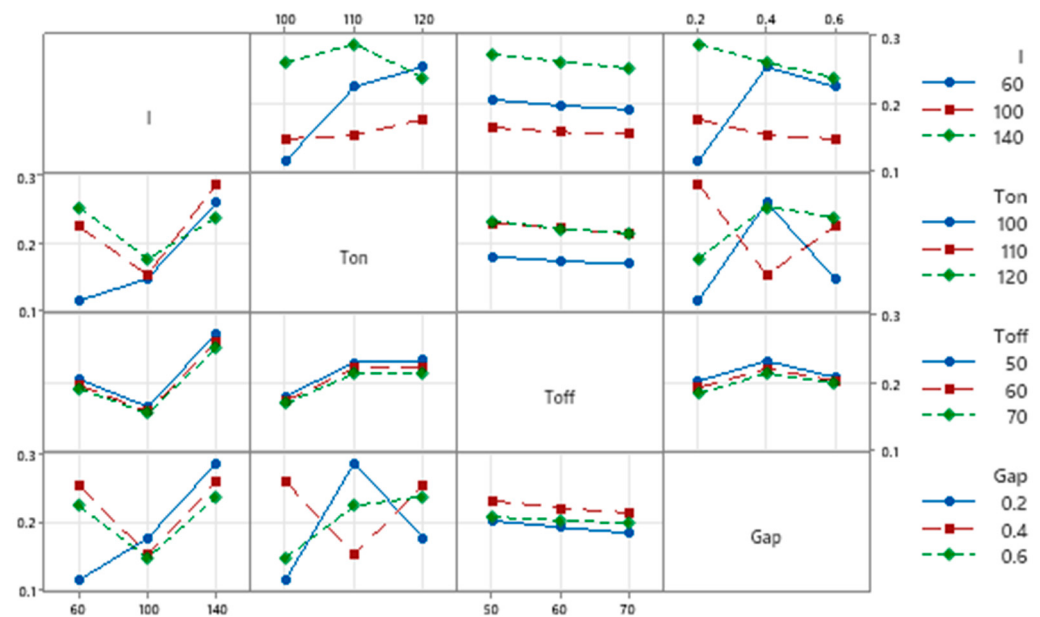


Figure 11. Interaction plot of GRG.

The optimum parametric condition for the optimum value of MRR, TWR, and SR were obtained through the response in Table 17, and the optimum levels are highlighted for easy identification. As per Table 17, the optimum value of the MRR, TWR, and SR were obtained from levels of input parameters $I = 140$ A, $T_{on} = 120$ ms, $T_{off} = 50$ ms, and $Gap = 0.4$ mm. Thus, the multiple objective problem was solved, and the best combination of parameters to give maximum results was identified. Based on the optimal process parameters, a conformational test was conducted and the results show 0.5628 MRR, 0.0048 TWR 4.4034 SR, and 0.2746 of GRG values and a 118% improvement in GRG compared to the initial parameter results GRG value, as mentioned in Table 18.

Table 17. Response table for Grey relation grade.

Parameter	Level 1	Level 2	Level 3	Deviation	Rank
I	0.0661	0.0532	0.0876	0.0345	1
T_{on}	0.0582	0.0741	0.0745	0.0163	2
T_{off}	0.0716	0.0687	0.0666	0.0050	4
Gap	0.0645	0.0743	0.0680	0.0098	3
Total mean value of Grey relational grade					0.0690

Table 18. Confirmation test values.

Test Condition	Levels	C	Ton	Toff	Gap	MRR	TWR	SR	GRG
Initial parameters	$A_3B_3C_3D_3$	140	120	70	0.6	0.5538	0.0039	4.3908	0.2328
Optimum parameters	$A_3B_3C_1D_2$	140	120	50	0.4	0.5628	0.0048	4.4034	0.2746
% of Improvement:									118%

3.3. SEM Analysis

The SEM image Figure 12a shows the electrical discharge machined surface condition when using initial parameter values $A_3B_3C_3D_3$. The image indicates some of the recast layer is formed on the surface due to long pulse-off time. Long pulse-off time allows more time to re-solidify the liquid debris (5). Craters and cracks are formed on the surface due to the high energy sparks that developed from longer duration due to high current and high

pulse on time (5, 38, 31). Some of the partially solidified debris presented on the surface escaped from the dielectric fluid (24).

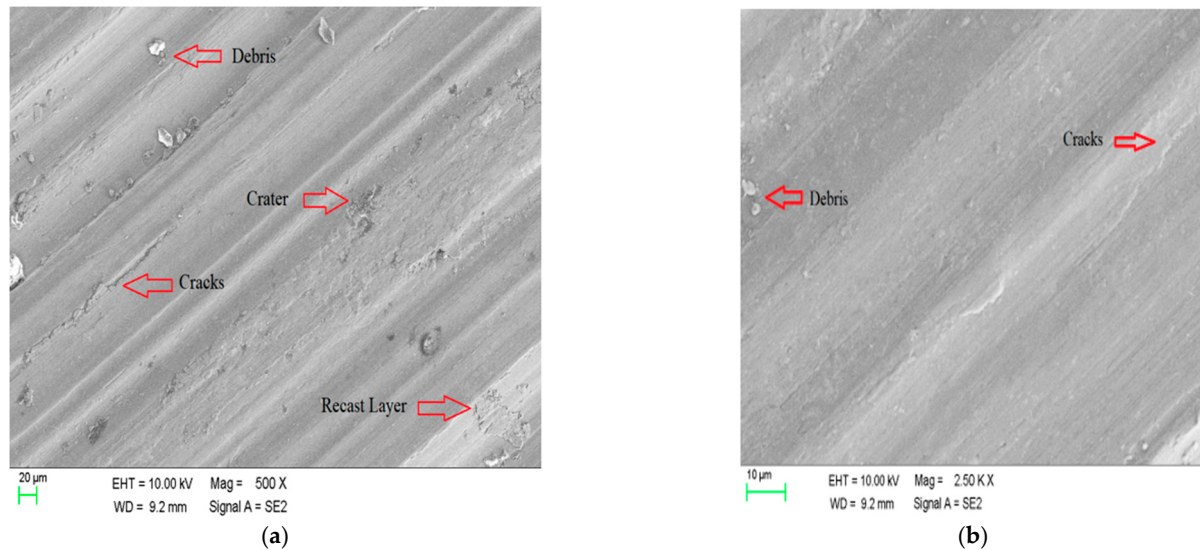


Figure 12. (a) SEM image of initial parameters. (b) SEM image of optimum parameters.

The SEM image in Figure 12b shows the condition of the machined surface at the optimal level of process parameter value obtained from the analysis A3B3C1D2. This image shows the formation of the recast layer is mostly negligible and the formation of craters and cracks are presented due to the high current and high pulse on time (11, 20). Due to the small electrode gap, most of the debris is melted and removed through pressurized dielectric fluid (10).

4. Conclusions and Recommendations

This experimental analysis involved the utilization of design of experiments (DoE) to plan and conduct experiments aiming to explore the impact of input parameters on the response parameters—material removal rate (MRR), tool wear rate (TWR), and surface roughness (SR)—within the electrical discharge machining (EDM) process. The investigation centered on the machining of B₄C-reinforced aluminum metal matrix composite (MMC) samples, fabricated via the stir casting method.

The collected experimental data underwent thorough analysis, employing various optimization techniques. A combination of process parameters was determined through the Taguchi approach for single response optimization, while the entropy weight method (EWM), Grey relational analysis (GRA), along with analysis of variance (ANOVA), were used for multiple response optimization. From this comprehensive investigation, several significant conclusions were drawn.

Single Response Optimization:

- **MRR:** All the selected process parameters played a significant role in MRR. The maximum MRR can be achieved at the higher setting of current and pulse ON time, lower setting of pulse OFF time, and electrode gap values. The optimum parameter combination of values for maximum MRR was current = 140 A, Ton = 120 ms, Toff = 50 ms, and Gap = 0.4 mm.
- **TWR:** The input process parameters current, pulse ON time, pulse off time, and electrode gap contributed to the TWR. The minimum TWR obtained at the combination parameter values was 140 A, 120 ms, 40 ms, and 0.4 mm, respectively.
- **SR:** The current, pulse ON time, and electrode gap were the most significant factors affecting the surface roughness of the machined materials. The optimum surface roughness obtained at the process parameter values were current = 140 A, Ton = 120 ms, Toff = 50 ms, and Gap = 0.6 mm.

- The results showed that an increase in current and pulse ON time increased MRR, TWR, and SR values. An increase in pulse OFF time and electrode gap reduced MRR, TWR, and SR values.

Multi-Response Optimization:

- The weightage of the response parameters, calculated through EWM, had a significant role in the multi-response optimization process. The weightage of the response parameters was MRR = 0.3343, TWR = 0.3314, and SR = 0.3343.
- Grey relational analysis was utilized for the optimization process. The optimum value of the response parameters was MRR=0.5628 mm³/min, TWR = 0.0048 mm³/min, and SR = 4.4034. The optimum process parameter values to obtain better results were current = 140 A, pulse ON time = 120 ms, pulse OFF time = 50 ms, and electrode gap = 0.4 mm.
- The confirmation experiment was conducted based on the optimized process parameter values and the results were compared to the initial parameter values results. The comparison showed the improvement of the Grey response grade of 81%.
- Hybrid multi-objective optimization of the EWM, GRA incorporated with ANOVA technique was applied to analyze the results to determine the optimum parameter combination values to obtain better output results.
- SEM analysis showed optimum parameter level machined surface condition of minimum debris and cracks without recast layer formation.

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Nomenclature

Al7075	Aluminum 7075
AMCs	Aluminum-based metal matrix composites
AlSi	Silicon-reinforced aluminum metal matrix composite
ANOVA	Analysis of variance
B ₄ C	Boron carbide
CNC	Computer numerical controlled
DF	Desirability function
DoE	Design of experiment
ECSM	Electrochemical spark machining
EDD	Electric discharge drilling
EDDG	Electric discharge diamond grinding
EDM	Electrical discharge machining
EWR	Electrode or tool wear rate
EWM	Entropy weight method
Gap	Electrode gap
GRA	Grey relational analysis
GRG	Grey relational grade
I	Current intensity
LB	The larger the better (objective)
MMCs	Metal matrix composites
MRR	Material removal rate

OA	Orthogonal array
PMEDM	Powder mixed electrical discharge machining
RA	Regression analysis
RSM	Response surface methodology
SB	The smaller the better (objective)
SEM	Scanning electron microscope
SNR	Signal-to-noise ratio
SR	Surface roughness
TiC	Titanium carbide
Ton	Pulse ON time
Toff	Pulse OFF time
TOPSIS	Technique for order of preference by similarity to ideal solution
TWR	Tool wear rate
WGRA	Weighted Grey relational analysis

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