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Original Article

Optimizing the Wire Electrical Discharge Machining (W-EDM) Technique for Al-l$_2$O$_3$/B4C Composite Materials

Ashwin G. Ghaysundar[1], Mahendra J. Sable[2], Dilip M. Patel[3]

[1,3]*Department of Mechanical Engineering, D.N. Patel College of Engineering, Maharashtra, India*
[2]*Department of Mechanical Engineering, COEP Technological University, Maharashtra, India,*

[1]*Corresponding Author : ashwinghaysundar@gmail.com*

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Abstract - *The rapid advancement of composite material manufacturing is essential in sustaining market growth across multiple industries. This study investigates the impact of Wire Electrical Discharge Machining (WEDM) of Al-Al_2O_3-B4C composites, which is affected by process variables such as wire feed rate, sample compositions, input current, and pulse time. The two reinforcement particles (wt% of alumina and boron carbide) and three input parameters, pulse-on time (P_{ON}), Wire Feed Rate (WFR), and Input current (I_p), were chosen to demonstrate the effect on the output response of Material Removal Rate (MRR) and Roughness Average (Ra). The Grey Relational Analysis (GRA) method determines hybrid composite materials' MRR and Ra. The Al-based MMC contains micro particles of alumina (45-micron mesh size, 99.90% purity) and Boron Carbide (50-micron mesh size, 99.95% purity). Al_2O_3 and B4C reinforce Al 6061 at weight percentages of 1, 3, 5%, and 1, 2, and 3%, respectively. The stir casting technique is used for composite preparation because it produces a homogeneous mixture. Based on the experimental findings, augmenting the PON and input current leads to a rise in the MRR, while decreasing the PON time and input current improves surface roughness; thus, PON and I_p are highly influencing parameters for MRR, while surface roughness and wire feed rate are fewer influencing parameters. Surface roughness and MRR were improved by using the parameters obtained by the GRA technique, which included a wire feed rate of 6 m/min, input current of 10 A, PON of 105 µs, and Al-MMC Aluminum 6061 with 1% and 5% by weight of boron carbide and alumina.*

Keywords - *Al+Al_2O_3+B4C, Multi-response optimization, Stir casting, WEDM, Grey relational analysis.*

1. Introduction

The rapid advancement in the manufacturing of composite materials has become one of the most essential factors in fostering industrial innovation and sustainable development. Industries are always searching for developing materials that may perform better than their traditional relatives; hence, manufacturing composite materials becomes pertinent. This realization has made aluminium-based composites such as Al-Al2O3-B4C popular due to their lightweight nature, corrosion resistance, high strength, and good wear properties.

These properties have made these composites worthwhile in the aerospace, automotive, and manufacturing sectors. Their adoption has skyrocketed, a clear testament to the pivotal role of these new materials in meeting the stringent demands of modern applications. Aluminum-based metal matrix composites are broadly utilized due to their exceptional strength and functional versatility. These composites, with their unparalleled combination of lightness and durability, not only boost the performance of industrial components but also prolong their lifespan, leaving us in awe of their immense potential. Another significant area of focus within the research community is the advancement of processing techniques for these materials. One of the most notable is the Electrical Discharge Machining (EDM) process.

This process facilitates the precision manufacturing of intricate geometries with a high-quality surface finish, particularly over electrically conductive material. This capability is essential for improving the characteristics of composites based on aluminum and allows for increased automation and efficiency in the material processing process. The continuous evolution of composite material technology is vital for meeting current industrial needs and shaping the future of manufacturing for sustainability and performance optimization [1].

One of the biggest challenges in realizing the potential of advanced composite materials is related to the complexities of their machining processes. Theoretically, conventional machining techniques need to be revised to address the unique needs of these materials; hence, it is advised to rely on other methodologies. Among others, WEDM is among the most crucial techniques developed, ensuring the needed accuracy to manufacture complex geometries and attain better surface finishes.

This capability makes WEDM a fundamental tool in machining electrically conductive composite materials. Strategic optimization of WEDM parameters is essential in enhancing machining efficiency and quality of outputs for MMCs. In industries that use advanced technological materials like aerospace, automotive, and manufacturing, proper and precise machining is critical to the performance and reliability of components. Advanced statistical and computational techniques are underpinned by pioneering work by Phate et al. [2] and Majumder et al. [3], who use techniques such as PCA and GRNN to fine-tune the parameters. These studies highlight that settings for POFF and Ip are critical since variables like current intensity and pulse-off time significantly impact the machining results, thus showing potential criticality in tapping MMCs to the maximum.

In another work, Phate et al. [2] applied Principal Component Analysis with Artificial Neural Network (PCA-ANN) to perform multi-parametric optimization on Aluminum/Silicon Carbide Metal Matrix Composite (Al/SiC MMC) during WEDM. This approach, which combines PCA-ANN and WEDM, is novel and has yet to be extensively explored in the literature. Employing an observed result using Taguchi L18 orthogonal arrays experimental design, it pointed out the excellent influence of the Silicon Carbide (SiC) composition in the material Pulse on Pulse Off Time (PON) and Current Intensity (Ip), among other things.

Following a similar trajectory, Majumder et al. [3] utilized both Multiple Regression Analysis and General Regression Neural Networks to predict and compare outcomes in surface roughness (Ra), material removal rate and kerf width in the Wire Electrical Discharge Machining of Titanium grade 6. Their findings demonstrated the superior accuracy of GRNN models, providing an error estimate of ±5%, compared to the ±10 % error estimate of MRA models. This underscores the high efficacy of neural networks in intricate machining processes.

Continuing the development of WEDM research, Kavimani et al. [4, 5] and Sonawane et al. [6] applied General Regression Analysis (GRA) with the Taguchi technique to further enhance the knowledge and optimization of process variables to accomplish maximum MRR and Ra. Kavimani et al. conducted a critical review and refined the application of GRA and response tuning for better utilization. They successfully machined a graphene-SiC magnesium composite, where the experimental results showed that MRR was enhanced with an increase in Pulse on Pulse Off Time (PON) and Wire Feed Rate (WFR).

In contrast, an increase in PON significantly enhanced Ra. Taguchi-Grey relational grade values were used to suggest the best levels for the input processing variables. These studies contribute to academic literature; however, they have significant practical implications for an industry where accurate component machining is critical to ensuring product performance and reliability. The work has emphasized the continued furtherance of the WEDM parameters that expand its practicality and accuracy in industry applications.

Sonawane et al. [6] utilized the PCA-based Taguchi technique to optimize WEDM machining parameters. P_{ON}, SV, P_{OFF}, IP, WFR, and cable tension are elected as input parameters to get the optimum variables for MRR, SR, and overcut. According to ANOVA results, pulse-on-time reflects a significant contribution to influencing the factors as per ANOVA results. When using PCA, engineers' judgment for allocating weights to quality characteristics becomes more transparent and more straightforward when using PCA compared to alternative methods.

Singh et al. [7] HMMCs have better qualities than single-reinforced composites and are being investigated in several sectors. Due to their superior resistance to wear, specific strength, and thermochemical qualities, they can be recommended for various engineering applications, including automotive, marine, and aviation, as well as those related to structure and mineral processing.

By optimizing the various parameters at different levels (i.e., wire feed velocity, wire tension, open voltage, servo voltage, P_{ON} Time, P_{OFF} -Time, and dielectric pressure by different thickness material) for tool steel D2, Ikram et al. [8] investigated the impacts of composites' kerf width, surface roughness, and MRR in WEDM. In the experimental design, Taguchi's L18 orthogonal array approach was applied. The control parameters and ideal values were found by statistical analysis using ANOVA and the S/N ratio. The findings show a significant relationship exists between Pulse Pulse on Time and the SR, kerf, and MRR.

Garg et al. [9] Prepared the novel composite of $Al/ZrO_2(p)$ MMC by applying the liquid stir casting process and mechanized by WEDM: machining input parameters, pulse width, Pulse Pulse off Time, dielectric conductivity, max. Feed rate, P_{ON}, WFR, wire tension, SV, and dielectric injection pressure are selected to find the performance of MRR and spark gap. The Taguchi technique was used to organize, carry out, and evaluate the trials to discover the ideal parameter setting. Prasad et al. [10] examined the Ti alloy's machining behavior using the WEDM technique.

Goyal et al. [11] The samples A75B25 and B100A0 exhibited a similar pattern. Because of the reduction in gap voltage or pulse current intensity, sample $A_{100}B_0$ exhibits a falling SR trend as a pulse on time increases (from 32 µs to 64 µs). By continuously stirring the reinforcing particles, sample $A_{100}B_0$ was determined to have minimal SR at machining settings of 3 A, 44 V, and 128 µs. Ravikumar et al. [12] explored the wear resistance and hardness properties of Al7075 enhanced with alumina and silicon carbide Hybrid Metal Matrix Composites (HMMC) produced through the stir casting method. They employed Taguchi's L27 orthogonal array to optimize process variables. Results show that increasing reinforcement improves hardness, and a wear test performed by applying a pin to a disc reflects that increased reinforcement increases wear resistance.

Despite the increasing interest in WEDM of composite materials, there remains a significant research gap in optimizing machining parameters, especially for Al-Al_2O_3-B4C composites. While several studies have been conducted on WEDM of various composite materials, including Metal Matrix Composites (MMCs), there is a lack of comprehensive research on the influence of process variables like wire feed rate, sample composition, input current, and pulse time on the machining performance of Al-Al_2O_3-B4C composites. This study investigates how WEDM of Al-Al_2O_3-B4C composites is affected by process variables such as wire feed rate, sample compositions, input current, and pulse time.

Al6061+ Alumina + Boron Carbide was prepared as matrix composite material by adding two or more materials and base matrix material. WEDM was applied to machining the prepared MMCs. Utilizing the Taguchi method and GRA, this research aimed to determine which WEDM process parameter combinations are most helpful in influencing output responses. The experimental setup followed the Taguchi method, employing an L27 orthogonal array for systematic testing. MRR and Ra were quantified by comparing initial and final weights over the machining duration.

2. Material Preparation

2.1. Fabrication of Composites

In this research, Al6061+Alumina+Boron Carbide composite material was chosen as the matrix due to its Commendable strength despite its lower machinability. Aluminum 6061 is a widely used matrix alloy for metal matrix composites, based on the chemical composition outlined in Table 1 [13-15]. The selection of materials was meticulously done considering their properties. The aluminum-based metal matrix composite incorporates microparticles of alumina, characterized by a 45-micron mesh size and 99.90% purity, along with boron carbide, featuring a 50-micron mesh size and 99.95% purity. A flow chart of the procedure used for composite preparation is shown in Figure 1. The photographs of MMCs can be depicted in Figure 2.

In Figure 1, The composite was meticulously prepared via the stir casting technique, wherein Al6061 served as the base metal, reinforced by B4C and Al_2O_3. During the composite preparation process, several critical steps were adhered to. Initially, ingots of the base metal, Al6061, were selected and cut into small pieces to fit the dimensions of the crucible. Subsequently, the crucible was heated to 750 °C to ensure proper melting.

Simultaneously, the reinforced particles and crucible were preheated to 400 °C, ensuring the optimal conditions for the subsequent mixing process. Once Al6061 was molten, the preheated reinforced particles were added to the base metal while stirring at 300 rpm for 10 minutes. This was crucial in ensuring the even dispersion of the reinforcing particles within the matrix material. This stirring procedure enabled the consistent dispersion of the reinforcing particles and guaranteed thorough wetting of the matrix material. Additionally, 1% magnesium was introduced to enhance wettability, while hexachloroethane was added for degasification of the molten metal, maintaining a constant temperature. The molten metal was transferred in a cast iron die in accordance with the requirements of the intended specimen when the stirring procedure was complete.

3. Experimental Methodology

The experimental approach employed a systematic method to optimize the process parameters of WEDM for the Al6061+Alumina+Boron Carbide composite material. The goal was to increase the MRR, lower the roughness of the surface, and narrow the kerf as much as possible. Following the stir casting process, the newly formed composite material underwent machining via WEDM. It was found that cutting using a 0.25 mm diameter brass wire coated with zinc worked better. Composite plates measuring 20×20×15 mm were used in the WEDM process for testing purposes. A piece of work and the WEDM test setup are shown in Figure 1. Table 2 shows the setup used for the WEDM experiments and lists the details of the experimental facility. The WEDM process parameters examined for improvement included Input current, Pulse on Time, and Wire feed rate. For consistency's sake, the Pulse Off time stayed the same during the experiment. A methodical design of the experiment's approach was used to run the experiments.

The orthogonal arrays and Taguchi method was used to identify the ideal settings and explore the parameter space. To minimize the number of trials required for complete testing, an L27 orthogonal array was utilized to organize the experiments. Table 3 also lists the specific input parameters that were thought about for the WEDM process, giving a complete picture of the variables that were being studied. P_{ON} (105, 108, and 110), WFR (4, 5, and 6 m/min), and Input current (10, 11, and 12A) are the different input parameters that were looked at for the machining and the Pulse Off time stayed the same.

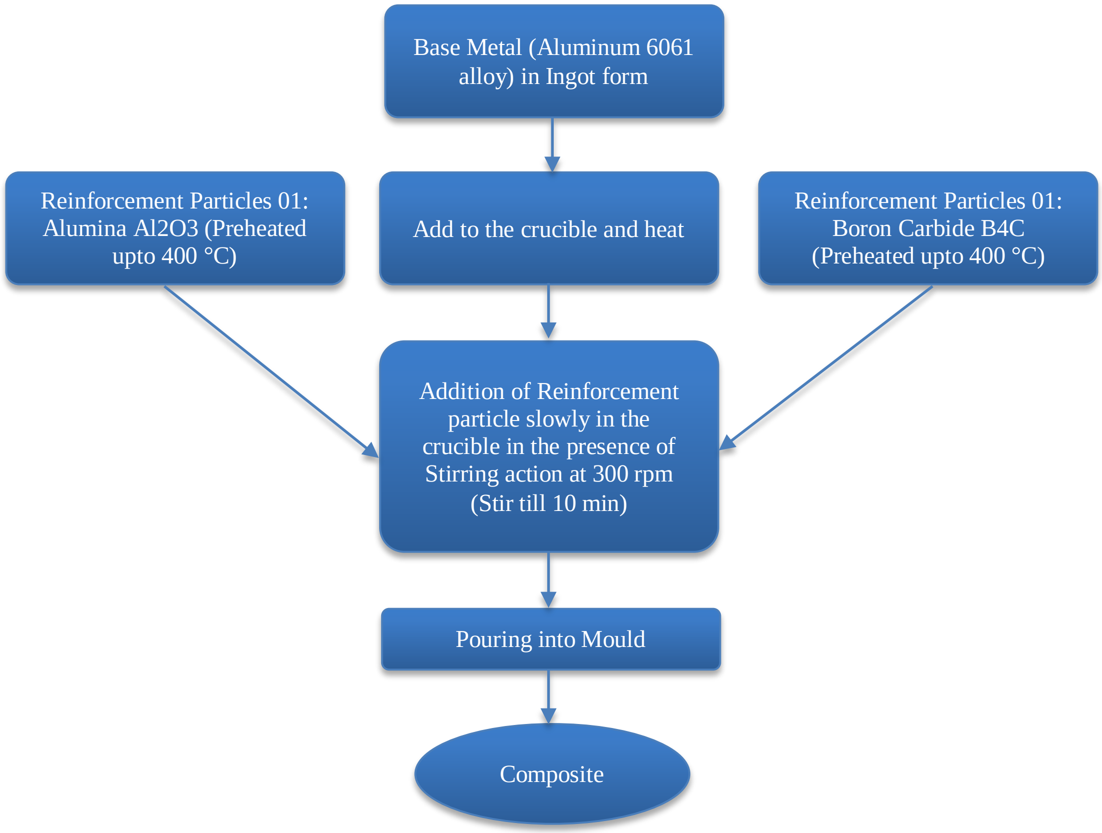

Fig. 1 Flow chart of procedure used for composite preparation

Table 1. Chemical composition of aluminum alloy 6061 [15]

Elements	Cu	Mg	Fe	Cr	Cu	Zn	Mn	Ti	Al
Composition in Percentage (%)	0.40	0.80	0.70	0.05	0.40	0.10	0.10	0.05	Balance

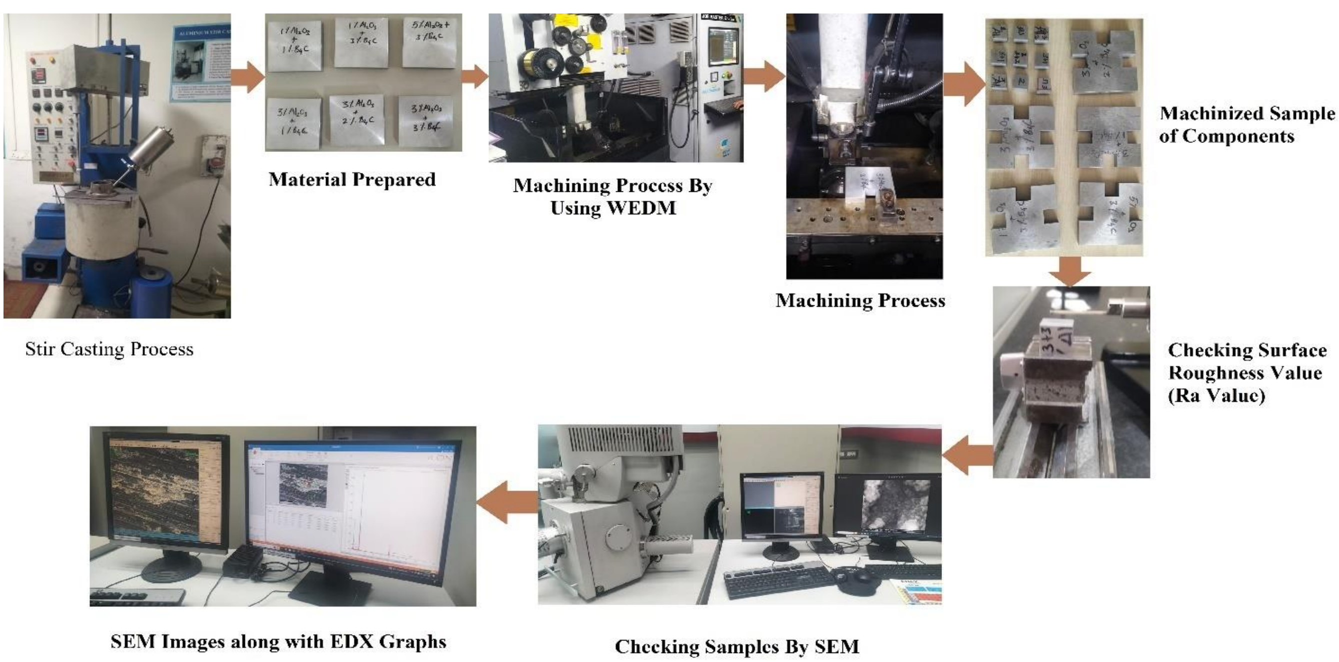

Fig. 2 Schematic of WEDM photograph of WEDM machine and workpiece

Table 2. Details of experimentation facility

Facility Used for Experimentation	Specifications
Material of Composite	Al6061, Boron Carbide, Alumina (Boron Carbide 1%, 2%, 3% by *wt*., Alumina 1%,3%,5% by *wt*.)
Specifications of Machine Used	Wire Electrical Discharge Machine
Machining Parameters Selection	Wire feed rate, Input current, Pulse on Time
Parameter for output	Material Removal Rate (MRR)
Surface Roughness, Ra	Mahr's Surface Tester in Techno-management

Table 3. The input process variables for WEDM machining of Al6061 composite

Input Parameters	Level		
	1	2	3
Alumina (% by weight)	1	3	5
Boron Carbide (% by weight)	1	2	3
Pulse On Time (μs)	105	108	110
Wire feed rate (m/min)	4	5	6
Input Current (A)	10	11	12

Table 4 presents the experimental outcomes for MMR (mm^3/min) and Ra and their corresponding input parameters. The experiments utilized the Design of Experiment (DOE) methodology. The objective of the experiment was to determine the optimal input parameters to enhance both the MRR and the weight difference before and after machining per unit of machining time, which was used to calculate the MRR, serving as a vital indicator of machining effectiveness and productivity.

Table 4. Experimental results data of MRR of Al6061-based MMC

Sr. No.	Alumina	B4C	Pulse On Time (μs)	WFR (m/min)	Ip (A)	Ra (μm)	MRR (mm^3/min)
1	1	1	105	4	10	1.876	11.55
2	1	1	105	4	11	2.097	14.235
3	1	1	105	4	12	2.138	17.872
4	1	2	108	5	10	2.687	16.478
5	1	2	108	5	11	2.736	20.003
6	1	2	108	5	12	3.012	23.376
7	1	3	110	6	10	3.264	20.476
8	1	3	110	6	11	3.056	23.658
9	1	3	110	6	12	3.843	26.895
10	3	1	108	6	10	2.142	17.362
11	3	1	108	6	11	2.016	20.448
12	3	1	108	6	12	2.072	23.847
13	3	2	110	4	10	4.874	19.496
14	3	2	110	4	11	3.983	23.082
15	3	2	110	4	12	3.598	26.683
16	3	3	105	5	10	1.651	9.241
17	3	3	105	5	11	2.021	12.189
18	3	3	105	5	12	2.874	15.768
19	5	1	110	5	10	3.882	20.769
20	5	1	110	5	11	2.587	23.717
21	5	1	110	5	12	2.047	26.909
22	5	2	105	6	10	1.65	9.507
23	5	2	105	6	11	2.157	13.289
24	5	2	105	6	12	2.784	15.989
25	5	3	108	4	10	2.046	14.323
26	5	3	108	4	11	3.859	17.204
27	5	3	108	4	12	4.564	20.988

Surface roughness was measured using Mahr's surface tester, which provided Ra, Rz, Rmr, and Rsm values for all species. Ra, measured in microns, represents the average deviation of the surface profile from the mean line, offering insights into surface quality and finish. By systematically adjusting process parameters such as P_{ON}, WFR, and Input Current and measuring MRR and surface roughness throughout each experimental iteration, the goal was to optimize machining outcomes. The MRR formula is provided below [17].

$$MRR(mm^3/min) = \frac{(Initial\ Weight\ of\ workpiece - Final\ weight\ of\ workpiece)(gram)}{Density * time\ taken\ ((\frac{gram}{mm3}) \times t)} \quad (1)$$

$$Density\ (g/mm^3) = \frac{mass\ of\ workpiece\ (gram)}{Volume\ of\ workpiece\ (mm3)} \quad (2)$$

4. Results & Discussion

4.1. Surface Topography of the Machined Surface

Figure 3(a) shows some of the surface features of a WEDM aluminum alloy specimen. The surface represents micro ridges and craters, which characterize the material removal mechanism in WEDM or wire electrical discharge machining.

Due to the aluminum alloy 6061's high thermal conductivity, the craters are more evident. These are the ones that are visible at the surface level and are probably caused by the liberation of gases that were trapped during machining. Further, the workpiece's electrochemical dissolution gives way to these micro voids' development.

Microcracks and black patches on the machined surface exhibit heavy thermal and mechanical stresses in a few places. Usually, micro-cracks are found near the particle-matrix interface, suggesting debonding between different material phases. The black patches are most probably the residue that is being left out by the machining process. Such patches are generally made because of their arcing nature, especially in composite materials like B75A25.

The EDS (Energy Dispersive Spectroscopy) analysis of the graph of the adjacent part shows the elemental composition of the machined surface: the main element is oxygen, at 46.5%; aluminum is 38.5%; iron is 11.8%; minor percentages of magnesium, silicon, manganese, copper, and zinc are present. Those are consistent with the phenomena that have been outlined in the given text and, in so doing, point out the typical surface features and defects that are observed in WEDM processes on aluminum alloys.

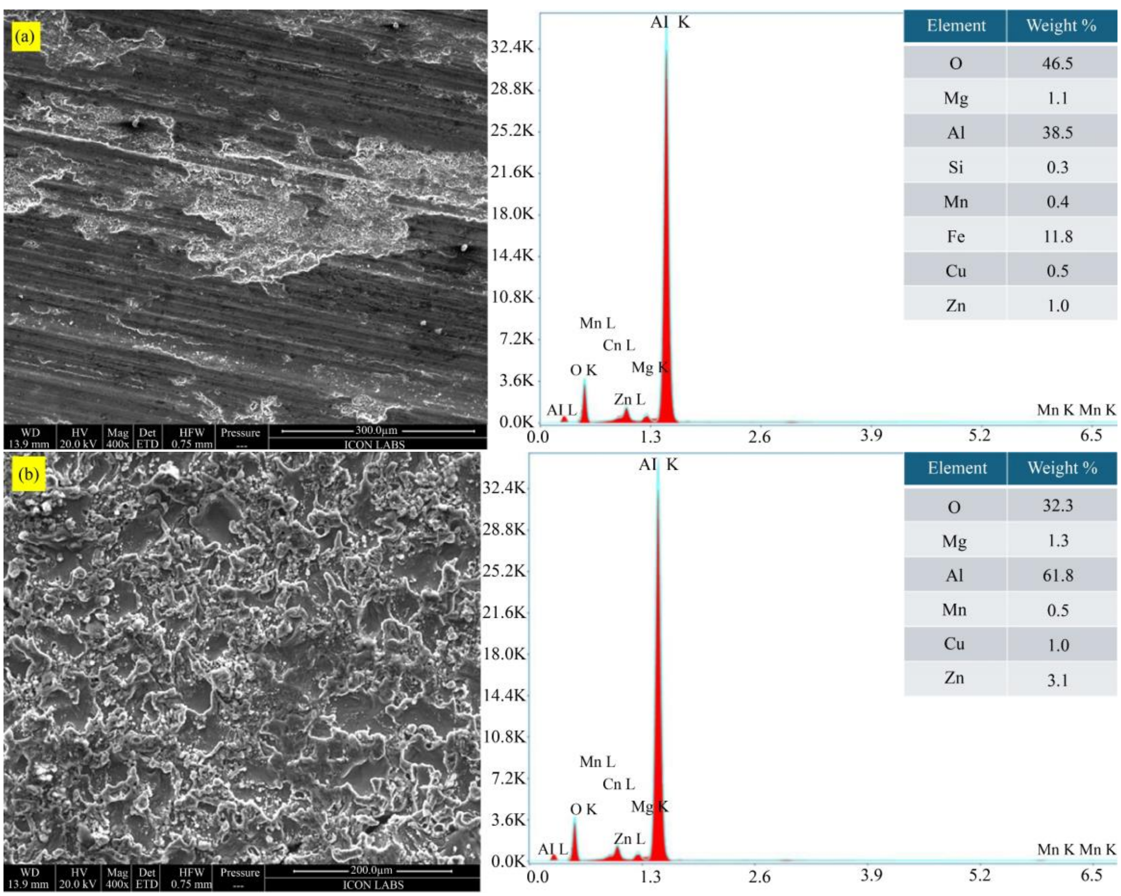

Fig. 3 Micrographs of the hybrid MMC machined surface (a) B1A1, and (b) B5A3.

In Figure 3(b), the surface texture is rough and uneven, having many micro-craters. Such a surface is characteristic of the material removal process in WEDM, where localized melting and vaporization of the composite material occur. Micro-cracks are located in the interfacial region between the particle and matrix.

The debonding of the reinforcement particles and matrix is indicated in those regions. Most likely, debonding occurs due to thermal stresses initiated during machining.

The right EDS spectrum depicts the machined surface's elementary composition. The major elements found are Aluminum (61.8%) and Oxygen (32.3%), with traces of Magnesium, Manganese, Copper, and Zinc.

The findings' surface features and defects agree with the phenomena described in the accompanying text, pointing to roughness in the machined composite material. This roughness is normally obtained when machined with WEDM. The surface texture and microcracks are effects of thermal and mechanical stresses developed during material removal.

4.2. Design of Experiment (DOE)

The experimental design is optimized to minimize the experiments conducted using the Taguchi method. These experimental findings offer significant insights into how P_{ON}, WFR, and Input Current alterations impact both MRR and Ra in WEDM of the Al6061+Alumina+Boron Carbide composite material l.

Using Minitab 17 software, the experimental trials were meticulously designed according to specified parameters. Five input variables were considered, with one variable having three levels, as depicted in Table 3.

To efficiently explore the parameter space and ensure comprehensive testing, a 27L orthogonal array was utilized for experimentation. Table 4 presents the results obtained from the experimental trials, detailing the MRR and Ra values for every set of input parameters. The analysis of the input variables of the output responses was conducted with a focus on the Signal-to-Noise Ratio (S/N).

This analysis chose The MRR to be maximized, as higher MRR levels indicate superior machining performance. By scrutinizing the S/N ratio across diverse input variables, it is possible to derive insightful information about how each parameter affects the responses that are produced. Hence, the S/N ratio was computed to maximize the MRR.

$$\frac{S}{N} = -10[\frac{1}{n}\sum\left(y_{ij}\ 2\right)], \quad (2)$$

Where, n- observations number, y_{ij}-observed response, i=1,2….n, j=1,2..k.

Table 5. S/N ratio and normalized values for Al 6061 MMC

S. No.	S/N Ratio MRR	S/N Ratio SR	Normalized MRR Value	Normalized SR Value
1	21.2516	-5.4647	0.1307	0.9299
2	23.0671	-6.4320	0.2827	0.8614
3	25.0435	-6.6002	0.4885	0.8486
4	24.3381	-8.5854	0.4096	0.6783
5	26.0219	-8.7423	0.6091	0.6632
6	27.3754	-9.5771	0.8000	0.5775
7	26.2249	-10.2750	0.6359	0.4994
8	27.4796	-9.7031	0.8160	0.5639
9	28.5934	-11.6934	0.9992	0.3198
10	24.7920	-6.6164	0.4596	0.8474
11	26.2130	-6.0898	0.6343	0.8865
12	27.5487	-6.3278	0.8267	0.8691
13	25.7989	-13.7577	0.5804	0.0000
14	27.2655	-12.0042	0.7834	0.2764
15	28.5247	-11.1212	0.9872	0.3958
16	19.3144	-4.3549	0.0000	0.9997
17	21.7194	-6.1113	0.1669	0.8849
18	23.9555	-9.1697	0.3694	0.6203
19	26.3483	-11.7811	0.6525	0.3077
20	27.5012	-8.2559	0.8193	0.7094
21	28.5980	-6.2224	1.0000	0.8769
22	19.5609	-4.3497	0.0151	1.0000
23	22.4698	-6.6770	0.2291	0.8427
24	24.0764	-8.8934	0.3819	0.6483
25	23.1207	-6.2181	0.2876	0.8772
26	24.7126	-11.7295	0.4507	0.3148
27	26.4394	-13.1869	0.6649	0.0962

4.3. Multi-Response Optimization Using Grey Relational Analysis

We are optimizing multiple responses utilizing the Taguchi method with GRA. A system where a certain quantity of data is known while some is uncertain is called a "grey system" [1]. Due to the constant uncertainty, grey systems will provide various potential answers. This theory's foundation, grey relational analysis, was modified to solve the intricate interactions between the specified performance indicators [1].

This analysis favorably defines the Grey Relational Grade (GRG) as an effective characteristic metric for assessment. Researchers are now focusing on Multi-Criteria Decision-Making (MCDM) strategies because of their unwavering ability to evaluate distinct alternatives based on various criteria to determine which is superior.

This writing suggested that MCDM concentrate upon GRA to examine the wire electrode discharge process optimization issue associated with Aluminum alloy (6061) composites [1]. GRA is a multi-response optimization technique that helps determine the best possible set of all process parameters and how every input parameter affects the answers. Below is a discussion of the process for figuring out the grey relationship grade.

Data is preprocessed to convert the initial sequence to a similar sequence. Data with numbers were normalized between 0 and 1. Several approaches to data preprocessing are offered, depending on the features of the data sequence. e. The smaller the surface roughness value, the better the performance features. This can be expressed as a normalized sequence of equations as follows:

$$X_{ij} = \frac{max(y_{ij}) - y_{ij}}{max\,(y_{ij}) - min\,(y_{ij})} \tag{3}$$

The performance feature, which benefits from larger values, is expressed as the normalized sequence of the original values.

$$X_{ij} = \frac{y_{ij} - min(y_{ij})}{max\,(y_{ij}) - min\,(y_{ij})} \tag{4}$$

Where, y_{ij} represents the original data.

The effectiveness of trial I for response j is determined based on the value x_{ij}, obtained through data preprocessing g. If x_i is equal to or closer to 1 than other experiments, then trial i is considered the most effective for response j. The primary objective of the reference sequence X_0 is to identify the experiment with the closest comparability sequence to the reference sequence e. This sequence is defined as (x_{01}, x_{02},..., x_{0j},..., x_{0n}) ¼ (1, 1,..., 1,.., 1), where x_{0j} represents the reference value for the j^{th} response.

Table 6 reflects the deviation sequences, Grey relational grade, and grey relational coefficient s. Next, the closeness between x_{ij} and x_{0j} is calculated using the grey relational coefficient t. The closer x_{ij} and x_{0j} are, the higher the grey relationship coefficient.

$$\gamma\left(x_{0j}, x_{ij}\right) = \frac{(\Delta_{min} + \xi\Delta_{max})}{(\Delta_{ij} + \xi\,\Delta_{max})}\; for\; i = 1,2,..., \; m\; and\; j = 1,2,\ldots,n \tag{5}$$

Where, y (x_{0j}, x_{ij}) is the grey relational coefficient between x_{ij} & x_{0j}

$$\Delta_{ij} = |x_{0j} - x_{ij}| \tag{6}$$

$\Delta_{min} = min\{\Delta_{ij},\; i = 1,2,\ldots.,m; j = 1,2,\ldots,n\}$ $\Delta_{max} = min\{\Delta_{ij},\; i = 1,2,\ldots.,m; j = 1,2,\ldots,n\}$, ξ is the constant coefficient, the range defined in $0 \le \xi \le 1$.

In this study, the characteristics coefficient $\xi = 0.5$ value is assumed d. For distinguishability, the index is the distinguishing coefficient (ξ). The value of ξ is smaller, which reflects that the distinguishability is high.

The grey relational grade is a measurement equation utilized for quantification within grey relational spa e. This equation can compute the grey relational grade, representing the weighted sum of the grey relational coefficients.

$$\Gamma(X_0\,, X_i) = \sum_{j=1}^{n} w_j \gamma\,(x_{0j}, x_{ij}) \quad for\; i = 1,2,\ldots m \tag{7}$$

Where, $\sum_{j=1}^{n} w_j\gamma = 1$ and $\Gamma(X_0, X_i)$ denoted as GRG between the reference sequence X_0 and the comparison sequence $_i$. Each response j carries a weight w_j, typically assigned based on the judgment of decision-makers.

The grey relational grade reflects the level of similarity between the reference sequence and the comparison sequence. Given that the comparison sequence most closely aligns with the reference sequence, the experiment with the highest grey relational grade represents the optimal choice. The order of 1 is the most prominent grey relational grade.

Experiment number 22, indicated in grey, represents the closest optimal combination of controllable factors: Composite combination Alumina 5%, Boron Carbide 1%, remaining Aluminum 6061 94% by weight and Machining parameters pulse-On Time 110 µm, wire feed rate 5 m/min, input current 12 A. Table 6 mentions the Deviation sequence, Coefficient of Grey Relation (GRC), Grade, and Ranks for the levels.

4.4. Optimization Techniques - Taguchi Method

Table 6 was used to calculate the means of the grey relational grade for every pair of configurable parameters, which were then compiled into Table 7.

The higher GRG, displayed in bold format in the following table, shows the better performance parameters. These are the ideal values for the regulated parameters PON-Time 110 µs (Level 3), WFR 5 m/min (Level 3), and Input Current 12 A (Level). Figure 2 reflects the WEDM machining parameters related to G and shows the WEDM parameters with a grey relational grade.

The grey relational grade's overall mean value = 0.6064.

Table 6. The values of the deviation sequence, Coefficient of Grey Relation (GRC), Grade, and ranks for the levels are calculated using the grey relational method

Sr. No.	Deviation Sequence (MRR)	Deviation Sequence (SR)	GRC (MRR)	GRC (SR)	Grade	Ranks
1	0.8693	0.0701	0.3651	0.8770	0.6211	13
2	0.7173	0.1386	0.4107	0.7829	0.5968	15
3	0.5115	0.1514	0.4943	0.7676	0.6310	10
4	0.5904	0.3217	0.4586	0.6085	0.5335	21
5	0.3909	0.3368	0.5612	0.5975	0.5794	17
6	0.2000	0.4225	0.7143	0.5420	0.6282	11
7	0.3641	0.5006	0.5786	0.4997	0.5392	20
8	0.1840	0.4361	0.7310	0.5341	0.6326	9
9	0.0008	0.6802	0.9984	0.4237	0.7110	4
10	0.5404	0.1526	0.4806	0.7662	0.6234	12
11	0.3657	0.1135	0.5776	0.8150	0.6963	5
12	0.1733	0.1309	0.7426	0.7925	0.7676	2
13	0.4196	1.0000	0.5437	0.3333	0.4385	27
14	0.2166	0.7236	0.6977	0.4086	0.5532	19
15	0.0128	0.6042	0.9751	0.4528	0.7139	3
16	1.0000	0.0003	0.3333	0.9994	0.6664	8
17	0.8331	0.1151	0.3751	0.8129	0.5940	16
18	0.6306	0.3797	0.4423	0.5684	0.5053	23
19	0.3475	0.6923	0.5900	0.4194	0.5047	24
20	0.1807	0.2906	0.7346	0.6324	0.6835	6
21	0.0000	0.1231	1.0000	0.8024	0.9012	1
22	0.9849	0.0000	0.3367	1.0000	0.6684	7
23	0.7709	0.1573	0.3934	0.7607	0.5771	18
24	0.6181	0.3517	0.4472	0.5870	0.5171	22
25	0.7124	0.1228	0.4124	0.8028	0.6076	14
26	0.5493	0.6852	0.4765	0.4219	0.4492	26
27	0.3351	0.9038	0.5987	0.3562	0.4774	25

Table 7. GRA grade response table

Parameters	1	2	3	Rank [max/min]
Alumina	0.6081	**0.6176**	0.5985	5 (0.0192)
B4C	**0.6695**	0.5788	0.5759	1 (0.0936)
Pulse On Time	0.5721	0.5958	**0.6309**	4 (0.0588)
Wire Feed Rate	0.5654	0.6218	**0.6369**	3 (0.0715)
Input Current	0.5781	0.5958	**0.6503**	2 (0.0722)

4.5. Analysis of Variance for the GRG

This study employs an ANOVA approach to ascertain the significance of controllable parameters on outcome characteristics. In order to achieve this, the contributions from each controllable parameter, as well as an error component, are divided into the overall variance of the grey relational grades. The squared deviations from the overall mean grade are added up to determine the total variance. The impact of changing a controllable parameter on the end characteristic was evaluated by calculating the percentage contribution of each procedural parameter to the overall sum of squared deviations.

According to the results, boron carbide, wire feed rate, input current, PulsePulse on Time, and alumina contributed 0.61%, 18%, 26%, 9%, and 28%, respectively. Among these, PulsePulse on Time, input current, and B4C reinforced particles are highly influential, while alumina and wire feed rate have comparatively lower influence. Table 8 presents the ANOVA results for each grey relational grade value.

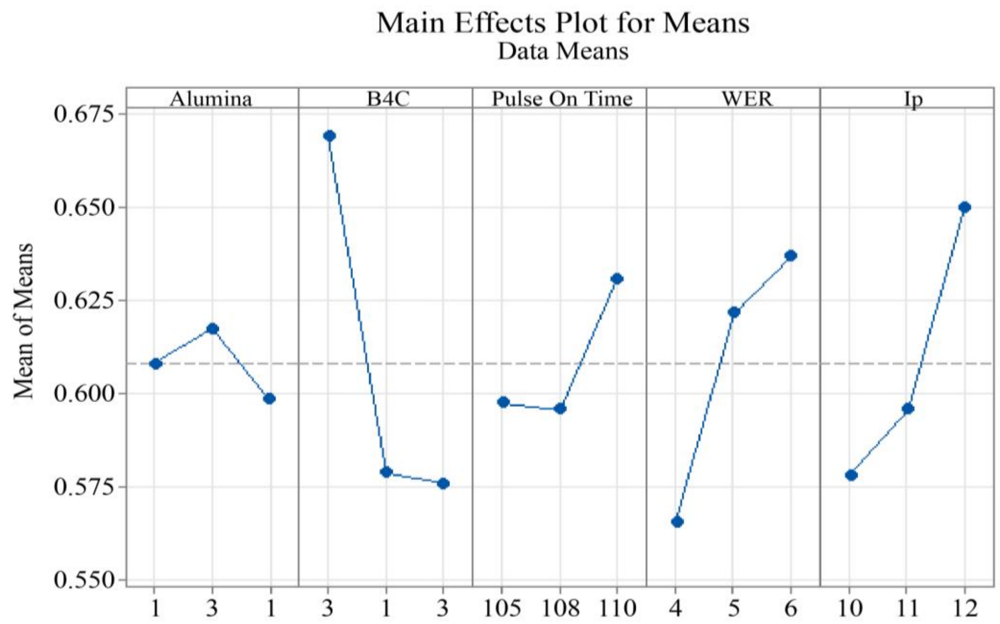

Fig. 4 GRD Graph

Table 8. Analysis of variance results

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
Alumina	2	0.001651	0.61%	0.001651	0.000826	0.08	0.922
B4C	2	0.051020	18.78%	0.051020	0.025510	2.54	0.110
Pulse On Time	2	0.077034	26.09%	0.077034	0.083517	3.05	0.089
WFR	2	0.025590	9.42%	0.025590	0.012795	1.27	0.307
Ip	2	0.095498	28.11%	0.095498	0.092749	3.77	0.078
Error	6	0.030842	16.99%	0.060842	0.003053		
Total	16	0.221635	100.00%				

5. Conclusion

WEDM was applied to machining the prepared MMCs. Through Taguchi and GRA, it was found to be the optimum way to process parameters that affect the output responses, such as MRR and Ra. By utilizing optimization approaches on the wire feed rate, sample compositions, pulse current, PulsePulse on time, and other input factors, we found an improved way of range.

This research optimizes the machining factors for MMCs, which are increasingly utilized in various industries due to their enhanced mechanical properties. By optimizing machining parameters, the study reduces material waste and energy consumption, aligning with sustainability goals in manufacturing processes. One may infer the following conclusions from the research work:

- It was discovered that when input current and PulsePulse on Time reduced, so did the Al-Al2O3+B4C composites' average MRR and SR values. Additionally, it was shown that up until a certain point, the MRR and SR increased with an increase in pulse current, after which they declined.
- An integrated GRA-Taguchi analysis was used to determine the ideal WEDM machining parameters, which were: sample composition of B4C = 1% and Al_2O_3 = 5%; pulse on time of 105 μs; input current of 10A; and wire feed rate of 6 m/min.

The percentage effects of the sample content (0.61% to 18.78%), PON (26.09%), input current (28.11%), and wire feed rate (9.52%) were all clearly displayed in the ANOVA findings.

References

[1] Nagender Kumar Chandla, Suman Kant, and M.M. Goud, "A Review on Mechanical Properties of Stir Cast Al-2024 Metal Matrix Composites," *Advances in Materials and Processing Technologies*, vol. 9, no. 3, pp. 948-969, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Mangesh R. Phate, Shraddha B. Toney, and Vikas R. Phate, “Multi-Parametric Optimization of WEDM Using Artificial Neural Network (ANN)-Based PCA for Al/SiCp MMC,” *Journal of the Institution of Engineers (India): Series C*, vol. 102, pp. 169-181, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] H. Majumder, and K.P. Maity, “Predictive Analysis on Responses in WEDM of Titanium Grade 6 Using General Regression Neural Network (GRNN) and Multiple Regression Analysis (MRA),” *Silicon*, vol. 10, pp. 1763-1776, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[4] V. Kavimani, K. Soorya Prakash, and Titus Thankachan, “Multi-Objective Optimization in WEDM Process of Graphene-SiC-Magnesium Composite Through Hybrid Techniques,” *Measurement*, vol. 145, pp. 335-349, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[5] V. Kavimani et al., “WEDM Parameter Optimization for Silicon@ r-GO/Magneisum Composite Using Taguchi Based GRA Coupled PCA,” *Silicon*, vol. 12, pp. 1161-1175, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] S.A. Sonawane, and M.L. Kulkarni, “Optimization of Machining Parameters of WEDM for Nimonic-75 Alloy Using Principal Component Analysis Integrated with Taguchi Method,” *Journal of King Saud University-Engineering Sciences*, vol. 30, no. 3, pp. 250-258, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[7] Lokesh Singh, Bharat Singh, and Kuldeep K. Saxena, “Manufacturing Techniques for Metal Matrix Composites (MMC): An Overview,” *Advances in Materials and Processing Technologies*, vol. 6, no. 2, pp. 441-457, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[8] Adeel Ikram et al., “Parametric Optimization for Surface Roughness, Kerf and MRR in Wire Electrical Discharge Machining (WEDM) Using Taguchi Design of Experiment,” *Journal of Mechanical Science and Technology*, vol. 27, pp. 2133-2141, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[9] Sanjeev Kr. Garg, Alakesh Manna, and Ajai Jain, “An Experimental Investigation for Optimization of WEDM Parameters during Machining of Fabricated Al/ZrO_2 (p)-MMC,” *Arabian Journal for Science and Engineering*, vol. 38, pp. 3471-3483, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[10] A.V.S. Ram Prasad, Koona Ramji, and G.L. Datta, “An Experimental Study of Wire EDM on Ti-6Al-4V Alloy,” *Procedia Materials Science*, vol. 5, pp. 2567-2576, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[11] Ashish Goyal, Huzef Ur Rahman, and S.A.C. Ghani, “Experimental Investigation & Optimisation of Wire Electrical Discharge Machining Process Parameters for Ni49Ti51 Shape Memory Alloy,” *Journal of King Saud University-Engineering Sciences*, vol. 33, no. 2, pp. 129-135, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] M. Ravikumar, H.N. Reddappa, and R. Suresh, “Study on Mechanical and Tribological Characterization of Al_2O_3/SiCp Reinforced Aluminum Metal Matrix Composite,” *Silicon*, vol. 10, pp. 2535-2545, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[13] Pankaj K. Gupta, and M.K. Gupta, “Mechanical and Microstructural Analysis of Al-Al_2O_3/B4C Hybrid Composites,” *Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications*, vol. 234, no. 12, pp. 1503-1514, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[14] A.G. Rao et al., “Fabrication and Characterization of Aluminum (6061)-Boron-Carbide Functionally Gradient Material,” *Materials and Manufacturing Processes*, vol. 25, no. 7, pp. 572-576, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[15] R. Venkata Rao, *Advanced Modeling and Optimization of Manufacturing Processes*, International Research and Development, 1st ed., Springer London, pp. 1-380, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[16] M. Manjaiah, S. Narendranath, and S. Basavarajappa, “Wire Electro Discharge Machining Performance of TiNiCu Shape Memory Alloy,” *Silicon*, vol. 8, pp. 467-475, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[17] P.M. Gopal, K. Soorya Prakash, and S. Jayaraj, “WEDM of Mg/CRT/BN Composites: Effect of Materials and Machining Parameters,” *Materials and Manufacturing Processes*, vol. 33, no. 1, pp. 77-84, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[18] Hargovind Soni, Narendranath Sannayellappa, and Ramesh Motagondanahalli Rangarasaiah, “An Experimental Study of Influence of Wire Electro Discharge Machining Parameters on Surface Integrity of TiNiCo Shape Memory Alloy,” *Journal of Material Research*, vol. 32, no. 16, pp. 3100-3108, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[19] T. Mythili, and R. Thanigaivelan, “Optimization of Wire EDM Process Parameters on Al6061/Al_2O_3 Composite and its Surface Integrity Studies,” *Bulletin of the Polish Academy of Sciences: Technical Sciences*, vol. 68, no. 6, pp. 1403-1412, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[20] R.V. Rao, V.J. Savsani, and D.P. Vakharia, “Teaching-Learning-Based Optimization: A Novel Method for Constrained Mechanical Design Optimization Problems,” *Computer-Aided Design*, vol. 43, no. 3, pp. 303-315, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[21] Shipra Verma, and P. Sudhakar Rao, “Study on Mechanical Behavior of Aluminum Alloy 6061 Based Composites A Review,” *IOSR Journal of Mechanical and Civil Engineering*, vol. 15, no. 4, pp. 16-20, 2018. [Google Scholar] [Publisher Link]

[22] Yunn-Shiuan Liao, Tzung-Jen Chuang, and Young-Ping Yu, “Study of Machining Parameters Optimization for Different Materials in WEDM,” *The International Journal of Advanced Manufacturing Technology*, vol. 70, pp. 2051-2058, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[23] Debabrata Rath et al., "WEDM Process Optimization for Machining Characteristics of AISI 52100 Grade Alloy Steel," *Advances in Materials Science and Engineering*, vol. 2022, pp. 1-12, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] Ravinder Kumar, and Santram Chauhan, "Study on Surface Roughness Measurement for Turning of Al 7075/10/SiCp and Al 7075 Hybrid Composites by Using Response Surface Methodology (RSM) and Artificial Neural Networking (ANN)," *Measurement*, vol. 65, pp. 166-180, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[25] Ayan Pramanick et al., "Optimization of Wire Electrical Discharge Machining Parameters for Cutting Electrically Conductive Boron Carbide," *Ceramics International*, vol. 42, no. 14, pp. 15671-15678, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[26] V. Suresh, A. Daniel Praneet, and J. Anoop, "Ingenious Analysis on Machining Parameters of Aluminium Alloy (LM25)/Graphite (Gr)/Boron Carbide (B4C) Hybrid Composites Using Wire Electrical Discharge Machining (WEDM)," *Materials Today: Proceedings*, vol. 37, pp. 3112-3117, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[27] J. Udaya Prakash et al., "Multi-objective Drilling Parameter Optimization of Hybrid Metal Matrix Composites Using Grey Relational Analysis," *Materials Today: Proceedings*, vol. 39, pp. 1345-1350, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[28] J. Udaya Prakash et al., "Multi-Objective Optimization Using Grey Relational Analysis for Wire EDM of Aluminium Matrix Composites," *Materials Today: Proceedings*, vol. 72, pp. 2395-2401, 2023. [CrossRef] [Google Scholar] [Publisher Link]