OPTIMIZATION OF LANTHANUM OXIDE (LA_2O_3), ALUMINIUM OXIDE (AL_2O_3) INCORPORATED ALUMINIUM METAL MATRIX COMPOSITES DEVELOPED USING STIR CASTING MACHINE

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DOI: 10.17973/MMSJ.2025_11_2025124

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ABSTRACT

As lightweight materials with enhanced mechanical and tribological properties, aluminum metal matrix composites, or AMMCs, are attracting more and more attention. This work used the stir-casting process to reinforce Al 6063 alloy with rare earth oxide (LaO_3) and alumina (AlO_3) to create a hybrid AMMC. A consistent distribution of reinforcements inside the matrix was verified by SEM and EDS investigation. The composite's machinability was further examined using electro discharge machining (EDM), in which the rate of material removal (MRR) and wear rate of the cutting tool (TWR) were maximized by optimizing the input parameters of current, trigger on (Ton), and trigger off (Toff). Box-Behnken Design (BBD) was used to arrange the experimental trials, and mean effect and signal-to-noise ratio (S/N) diagrams were used to assess the data. Subjective weight allocation techniques were combined with multi-criteria decision-making (MCDM) techniques, specifically MABAC and MOORA, to attain a balanced trade-off between MRR and TWR. 9 A current, Ton of 5, and Toff of 4 were found to be the ideal parameter settings, guaranteeing increased machining efficiency with no tool deterioration. The results demonstrate the potential of hybrid AMMCs supplemented with rare earth elements in applications that demand enhanced machinability and structural dependability.

Keywords: MCDM, ALUMINIUM COMPOSITES, DRILLING, MACHINING, OPTIMIZATION

1 INTRODUCTION

Polymer composites, such as glass-fibre reinforced composites and phenolic-resin asbestos, garnered a lot of attention from researchers at the turn of the 20th century. However, because of their poor strength and extreme heat sensitivity, their application in the aerospace and defence industries was restricted. The creation of metal matrix composites (MMCs), which had the benefit of being stronger than polymer composites and lighter than basic metals or alloys, was prompted by the space race between superpowers in the 1970s [1]. In the age of globalization, engineers are constantly looking for stronger, lighter, and more affordable materials, which is driving up demand for cutting-edge technologies and materials. Superior mechanical, thermal, and electrical qualities, along with increased resistance to radiation, moisture, severe temperatures, and vacuum outgassing, are how MMCs satisfy these demands. MMCs consist of a minimum of one metal serving as the matrix, with a ceramic, an organic or inorganic compound, or another metal serving as the secondary component [1]. The automotive industry is increasingly using these composite materials for lightweight components since they are stronger and lighter than conventional materials like steel [2]. Higher physical strength with reduced thermal expansion and notable resistance to thermal forces, remarkable wear resistance, specific stiffness, and robust corrosion resistance are what make MMCs unique [3. 4]. Light metals like titanium (Ti), magnesium (Mg), and aluminum (Al) are examples of common matrix materials. The uniqueness of high strength-to-weight ratio, affordability, ease of processing, corrosion resistance, and lightweight nature, aluminum and its alloys are especially preferred. Because of their increased hardness with decreased ductility when ceramic particles are added to the base metal matrix—aluminum matrix composites, or AMCs, are gradually taking the place of cast iron in automotive parts [5]. Particle-reinforced composites are the subject of current research, particularly those that contain rare earth elements and oxides (REEs/REOs), which are well-known for their accessibility, affordability, and ease of dispersion, leading to uniform distribution throughout the matrix. The composite's intended purpose determines which reinforcement materials are used. Lightweight metal reinforcement creates new opportunities for applications where weight reduction is essential.

Aluminum matrices are frequently reinforced with Al_2O_3 [6, 7], ZrO2 [8], SiO2/TiO2, Si3N4 [9], TiC [10], SiC [11], B4C [12, 13], TiB, carbon nanotubes (CNTs), and diamond to improve their mechanical and tribological qualities. Interest in hybrid MMCs has increased in recent years. The 15 lanthanides (atomic numbers 57–71), yttrium (39) and scandium (21), are examples of rare earth elements that are widely utilized in the chemical, metallurgical, pharmaceutical, and oil refining sectors. Their use has grown to include permanent magnets, glass polishing, and electronic devices, frequently including aluminum oxide (Al_2O_3). A nonconventional machining technique called electrical discharge machining (EDM) can be used to produce intricate profiles on hard conductive materials. In EDM, a succession of distinct discharges between a workpiece (anode) and a wire tool (cathode), separated by a dielectric fluid, are used to accomplish machining [14]. Because of their mechanical qualities and tolerance to high temperatures, aluminum alloys reinforced with TiC and SiC particles are extensively utilized in the automotive and aerospace industries. However, the high cost of manufacture, which is mostly caused by severe tool wear during machining due to the abrasive character of the workpiece, frequently limits the full potential of MMCs. According to Velusamy et al., EDM is a better technique for accurate material removal because traditional machining of MMCs is difficult because of the abrasive particles that wear out the tool [15].

Finding the ideal parameter combinations to enhance results like quality and efficiency is referred to as optimization in this context [16]. The correlations between input and output parameters are evaluated using various statistical analytic techniques such as Response Surface Methodology (RSM), and many more. the Taguchi method is a popular technique for designing experiments (DoE) that effectively tests different factor levels while reducing the number of experiments. Multiple response parameters are converted into single-response values for prioritization using multi-response optimization techniques such as Weighted-Grey Relational Analysis (WGRA) and various other techniques. Using a variety of factors, these tools assist in determining the optimal solutions [14].

According to Mohan et al., a larger volume % of SiC has a negative influence on MRR but a good impact on TWR and surface roughness (SR), but a higher discharge current increases the material removal rate (MRR) [17]. The results of Sivasankar et al. showed that employing entropy-based GRA during the EDM of hot-pressed ZrB2 increased machining performance measures, such as weight-to-wear ratio, TWR, MRR, and taper angle [18]. The effects of input parameters on SR, TWR, and MRR in AISI D2 tool steel during EDM were investigated by Majhi et al [19]. using entropy and GRA approaches. Kumar et al. discovered that while longer T_{on} and greater pulse duty factor have a detrimental effect on EWR but improve surface roughness, increasing current increases spark energy and electrode wear rate (EWR). When milling Al–Cu-TiB2, the TOPSIS approach was employed for multi-objective optimization in order to determine the best parameter values.

ANOVA and GRA were coupled in other research, such as one on microwire EDM, to improve multi-performance metrics [20, 21]. In order to optimize input and output parameters in Al/SiC/Gr hybrid composites, GRA as well as TOPSIS were also utilized for EDM of powder-mixed H-11 die steel [22]. It was determined that feed rate, cutting speed, and depth of cut had the greatest effects on SR Using GRA, TOPSIS, and RSA models, titanium alloy milling under low lubrication circumstances demonstrated how cutting parameters affected flank wear and SR [23]. While another study used a combined Taguchi-GRA-weight method to optimize wear rate chractarestics in AA6063/SiCp material, identifying SiCp weight percentage, load, and sliding distance as critical factors [24]. Gopal et al. used Taguchi's equiped with GRA for determining critical factors effecting Sr and MRR in a hybrid Mg MMC. Taguchi-based PCA in conjunction with GRA was used to maximize MRR and minimize SR. For multi-objective optimization, where the conventional Taguchi method by itself was inadequate, the Taguchi-GRA approach proved to be successful [25]. In order to enhance output quality, this method was utilized to optimize WEDM input parameters such as Ton, Toff, WF, SV, WT, and IP. The ideal kerf width (229 mm) and SR (2.187 mm) for hybrid MMC machining by wire EDM were determined. Ghadai used various MCDM techques for the parametric optimization of end milling process of Al1070. [20].

A survey of the literature shows that although a number of research teams have created AMMCs with reinforcements like LaO_3 and AlO_3, less focus has been placed on employing MCDM approaches to assess their machining performance.

Therefore, in the present research work the below mentioned points were addressed:

1. Hybrid AMMCs is developed with base Aluminium alloy Al 6063 incorporated with rare earth elements (La_2O_3) and Al_2O_3 using stir casting process
2. The developed hybrid AMMC composite were further analysed at nano level using morphological tests.
3. The machining of developed Hybrid AMMCs were carried out using Electro Discharge machine (EDM).
4. Optimization of EDM parameters using MABAC and MOORA MCDM technique.

2 DEVELOPMENT AND CHARACTERIZATION OF RARE EARTH REINFORCED AMMC:

2.1 *AMMC Development details*

The AMMC is developed using Al 6063 (Zn- 0.005, Si- 0.525, Mn- 0.07, Cr- 0.01, Mg- 0.466, Al- 98.627, Cu- 0.27, Ti- 0.025, Fe- 0.161) mixed with Al_2O_3 and La_2O_3. Two distinct furnaces are used in the development of the hybrid AMMC: (i) stir casting apparatus for converting to liquid form and (ii) and a muffle furnace for pre-heating. In the furnace, a predetermined weight percentage of reinforcement is heated for one to two hours at temperatures between 150 and 300 ℃. To eliminate any moisture content, the reinforcements are preheated within a muffle furnace. Al_2O_3 and La_2O_3 were the reinforcements that were utilized. The AMMC was created using weight percentages of 1.5% for La_2O_3 and 5% for AL_2O_3. The reinforcement particle size (average) were in the range of 5 to 25 µm with 99.5% purity. At the same time, the mold is heated to about 350 ℃ while the crucible placed in stir casting equipment is heated above solidofication temperature of aluminum, which is 780 ℃. The aluminum specimen is put into the crucible and left there until it liquefies, at which point the reinforcement is added gradually with a spoon once the base metal is converted to liquid form. To ensure homogeneous mixing of the reinforcement, the mixture was agitated for eight minutes within the crucible using an HSS stirrer set to 650 rpm after the reinforcement was added to the molten Al 6061. After stirring process, the AMMC was sent to the heated mold, where solidification took palce and was recovered after roughly seven to eight hours.

2.2. Characterization of Developed AMMC.

Scanning Electron Microscope (SEM) with model id as EVO MA18 fitted with Oxford Energy-dispersive X-ray spectroscopy (EDS) for elemental composition investigation, the morphology of a cut slice of rare earth reinforced AMMC was assessed. Similarly, Oxford Instrument's MFP 3D Origin model was used to assess the morphology corresponding to cut section of the generated matrix composite through Atomic Force Microscopy (Asylum Research). The projected image surface size varied between 9.00 and 9.52 µm2, and images were taken with a scanning rate of 1.00 Hz and a scanning range of 3 3 μm^2.

Figure 1. Stir Casting Apparatus

Figure 2. Muffle Furnace

2.3. Non-conventional Electro discharge machining of AMMC

Using pulsating electrical sparks driven by a D.C. input, the cutting tool and workplate serve as electrodes in the unconventional process termed as EDM, which removes material. The workpiece material is melted and vaporized for removal by the extreme heat produced by these sparks. In the hybrid aluminum metal matrix composites (HAMMC) EDM experiment, the workpiece was made of Al6063 as the base metal and reinforced with 2% La_2O_3 and 5% Al_2O_3. Kerosene as dielectric fluid during machining along with the tool (copper made), and the workpiece were immersed in it. EDM has benefits include hardness insensitivity, the ability to manufacture intricate structures without causing damage, and non-contact material removal. Its drawbacks, however, include crater-marked surfaces and slow machining speeds. The goal of research is to better understand the physics of EDM to increase its stability and efficiency. Three phases are identified by Erden et al. for the removal of EDM material: surface erosion, the development of strong electrostatic forces, and dielectric breakdown.

2.4 Weight Allocation Strategies

2.4.1 Standard Deviation Method (SDM)

An established technique for allocating weights to evaluate criteria is the SDM, which uses the standard deviation between performance values across various alternatives to do so. The steps involved under SDM are as follows:

Normalization of the decision matrix using the formula: -

$$n_{ij} = \frac{a_{ij} - b_j}{b_j - w_j} \ldots\ldots\ldots (1)$$

where b_j : best alternative and w_j : worst alternative.

The standard deviation for weight allocations is evaluated:

$$q_j = \mathrm{std}\,(N) = \sqrt{\frac{1}{m-1} \cdot \sum_{i=1}^{n} \left(n_{ij} - \bar{n}_j\right)^2} \ldots\ldots\ldots (2)$$

Weights are evaluated through eq. 3 mentioned below:

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k}, j = 1, \ldots, n \ldots\ldots\ldots\ldots\ldots (3)$$

2.4.2 Criteria Importance Through Inter-criteria Correlation (CRITIC) method

The CRITIC approach is basically a weight allocation driven technique which assigns weights to criteria based on the correlation between various criteria. The following are the steps in this procedure. [17]. In order to compute a normalized deviation matrix N, the best and worst performnce value of b_j and w_j respectively under all criterion are determined using the formula below.

$$n_{ij} = \frac{a_{ij} - b_j}{b_j - w_j} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Column wise Standard deviation calculated as

$$s_j = \mathrm{std}\,(N) = \sqrt{\frac{1}{m-1} \cdot \sum_{i=1}^{n} \left(n_{ij} - \bar{n}_j\right)^2} \ldots\ldots\ldots\ldots\ldots (5)$$

Pearson correlation coefficient (equation mentioned below) is used to evaluate Linear correlation between columns of N is given by

$$c_{jk} = \mathrm{corr}(N) = \frac{\sum_{i=1}^{mm} \left(n_{ij} - \bar{n}_j\right)\left(n_{ik} - \bar{n}_k\right)}{\sqrt{\sum_{i=1}^{m} \left(n_{ij} - \bar{n}_j\right)^2 \sum_{i=1}^{m} \left(n_{ik} - \bar{n}_k\right)^2}}, j, k = 1, \ldots, n \ldots\ldots (6)$$

The criteria j (q_j) which creates conflict is evaluated and is considered to be the key indicator to assign weights to evaluation criteria.

$$q_j = s_j \cdot \sum_{k=1}^{n} \left(1 - |c_{jk}|\right), j = 1, \ldots, n \ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Weights are determined as

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k}, j = 1, \ldots, n \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

2.5. MABAC

MABAC, was developed by, D Pamucar & G. Cirovic [26] and has subsequently been applied extensively to address a variety of real-world issues. MABAC offers a number of important benefits that make it dependable and efficient. Even when the qualifying values' units of measurement change, the MABAC approach consistently produces reliable findings. This implies that regardless of the units chosen, the results remain consistent and trustworthy. When criteria changes, such as when a criterion shifts from a benefit to a cost, the MABAC approach stays constant. For MCDM processes with numerous criteria and alternatives, the MABAC approach has an algorithm that works well and maintains the integrity of the findings [27]. It can be applied to various domains of MCDM situations and has extensive applicability. It is an effective and useful instrument to apply in MCDM procedures because its mathematical formulas are straightforward and controllable regardless of the quantity of options and criteria [27].

Step 1: Determining the decision matrix like all other MCDM techniques.

Step 2: Normalization of the decision matrix is done using the following equations

$$t_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}; j \in B \ldots\ldots\ldots\ldots\ldots (9)$$

$$t_{ij} = \frac{x_{ij} - x_i^+}{x_i^+ - x_i^-}; j \in H \ldots\ldots\ldots\ldots\ldots (10)$$

Where $x_i^+ and\ x_i^+$ are highest and lowest values of observed criterion in decision matrix.

Step 3: Weighted normalized matrix is evaluated :

$$V = [v_{ij}]_{mxn}; v_{ij} = w_j.t_{ij} + w_j \ldots\ldots\ldots\ldots\ldots (11)$$

Step 4: determination of Border approximation area matrix :

$$G = [g_i]_{1xn}; g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{1/m} \ldots\ldots\ldots\ldots\ldots (12)$$

Step 5: calculation of distance of all alternatives from border approximation area :

$$Q = V - G \ldots\ldots\ldots\ldots (13)$$

Here, matrix V and G already defined in Step 3 and 4.

Step 6: detremination of Criterion function using the equation mentioned below :

$$Si = \sum_{j=1}^{n} q_{ij} \ldots\ldots\ldots\ldots\ldots (14)$$

Ranking of alternatives are carried out in descending order of the criterion function. i.e criterion function with maximum value is to be ranked 1.

2.6 MOORA Method

MOORA is a successful MCDM/MODM technique that was first presented by Brauers and Zavadskas [28]. It is intended to address complicated, multi-objective, and frequently contradictory issues. In MOORA method, the normalized values of the benefit criterion are added, and the normalized values of the cost criteria are subtracted, to determine the ratio system. With the highest score indicating the top ranking, and so forth, this mathematical solution provides us with the score for each choice [29]. The MOORA method is a straightforward, but efficient MCDM procedure that can be employed in different domains. By normalizing the results, it guarantees consistency and makes comparing and evaluating each criterion simple [30, 31].

The process for making decisions using the MOORA method is mentioned in steps discussed below:

Step 1: Creation of decision matrix during this step, the criteria values are transformed into a decision matrix.

$$[X] = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} \\ x_{21} & x_{22} & \cdots & x_{2j} \\ \vdots & \vdots & \vdots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} \end{bmatrix} \ldots\ldots\ldots\ldots\ldots (15)$$

Step 2: decision matrix normalization in the MOORA method aims to standardize all element values within the matrix. The formula used for normalization is as follows:

$$x_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \ldots\ldots\ldots\ldots\ldots (16)$$

Step 3: Calculating the optimized attribute values involves multiplying the corresponding elements from the decision matrix. This optimization process is computed based on equation:

$$Z_i = \sum_{i=1}^{g} W_i x_{ij}^* - \sum_{i=g+1}^{n} W_i x_{ij}^* \ldots\ldots\ldots\ldots\ldots (17)$$

Step 4: Ranking is accomplished by sorting the y_i values, where y_i represents the optimized values of alternatives, allowing identification of the best alternative.

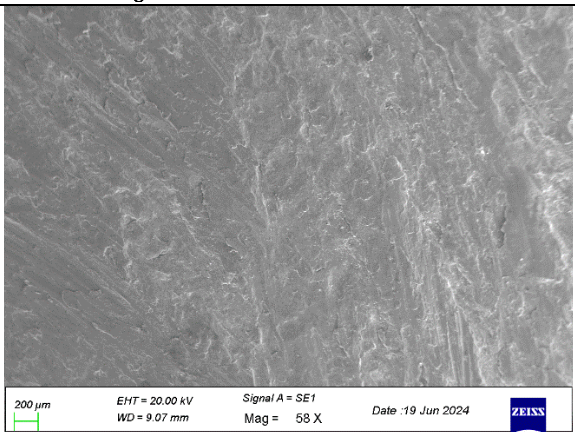
Table 1. Experimental Data

Sl. No	Current (A)	Trigger on	Trigger off	Tool-wear rate (gm/s)	Material-Removal rate (gm/s)
1	12	5	3	0.0003567	0.0004167
2	12	9	3	0.0000367	0.0002900
3	12	5	5	0.0000533	0.0000967
4	12	9	5	0.0000333	0.0003267
5	15	7	5	0.0000267	0.0002600
6	9	7	5	0.0000167	0.0002900
7	15	7	3	0.0000200	0.0003967
8	15	9	4	0.0000133	0.0003400
9	9	7	3	0.0000267	0.0002300
10	12	7	4	0.0000133	0.0003933
11	12	7	4	0.0000133	0.0001267
12	15	5	4	0.0000167	0.0000400
13	9	9	4	0.0000400	0.0003133
14	12	7	4	0.0000067	0.0003800
15	9	5	4	0.0000467	0.0001033

3 RESULTS AND DISCUSSION

3.1 Morphology and Composition of Developed AMMC

Figures 2-4 (5% Al_2O_3 1.5% La_2O_3) respectively, display the morphology of La_2O_3 and Al_2O_3 intigrated AMMC. Figures 5 display the findings of the EDS analysis and SEM images. Tables 2, show the equivalent weight percentage of additional reinforcement in the Al 6063 base alloy. SEM micrographs make it evident that tiny reinforcing particles are dispersed haphazardly across the Al 6063 alloy's surface. However, it is to nate that the mixing of reinforcements have been carried out in powder form after succesful preheating in the furnace. From the SEM images it can be seen that the structure of the reinforcements is close to globular form and the same is evident from the EDS data which shows the presence of La_2O_3 and Al_2O_3 present in weight percentage, which is consistent with the SEM findings.



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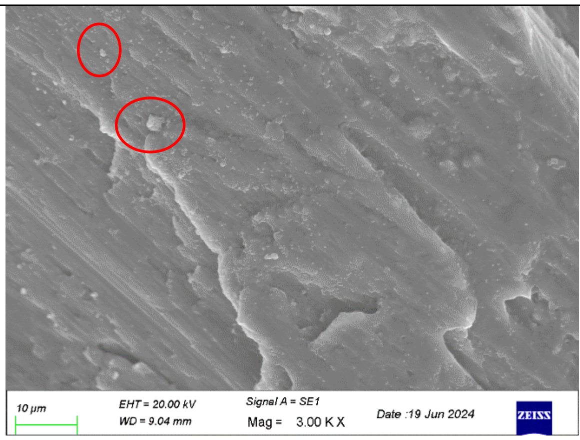

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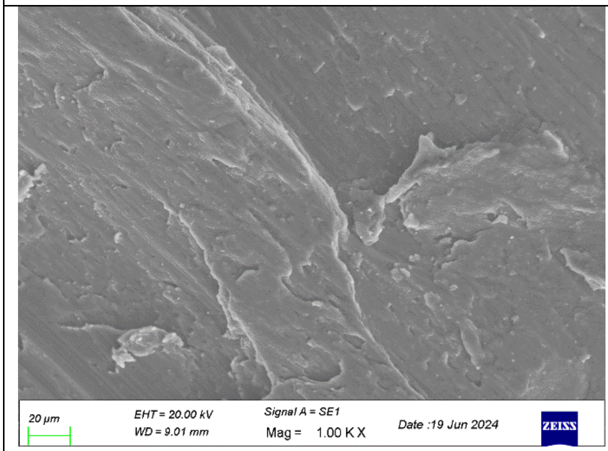

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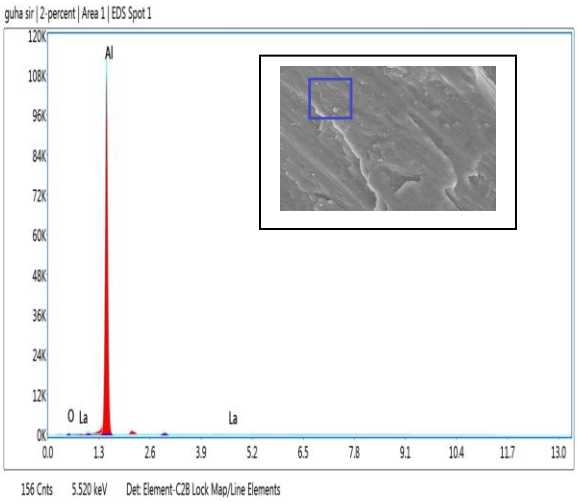


(5)

Figure 2-4. SEM images of Al6063 (5% Al_2O_3 1.5% La_2O_3) Figure 5: EDS graph

Element	Weight %	Atomic %	Net Int.
O K	1.21	2.02	126.10
Al K	98.33	97.89	34345.18
La L	0.46	0.09	22.56

Table 2. Al 6063 (5% Al_2O_3 2 % La_2O_3)

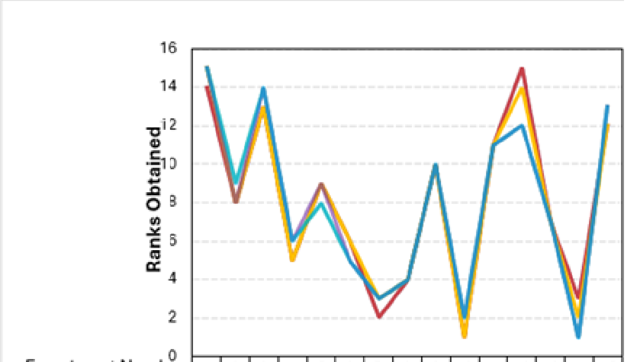
3.2 Optimization of Machining Parameters.

A border approximation approach as discussed in an earlier section is adopted to rank the alternatives from best to worst using MABAC method. Normalization of the decision matrix is done using eq. 9 and eq. 10. Three different weight allocations are adopted to minimize the decision maker's biases in weight allocation process. The weights as per standard deviation were 0.5673 and 0.4327 and CRITIC allocates 0.461 and 0.539 to MRR and TWR respectively. These weights along with Mean Weights were introduced into the rank calculating process using MABAC method to calculate three different weighted normalized decision matrixes using eq. 11. Border approximation area is calculated for each criterion from the weighted normalized matrix using eq. 12 and the distance from this area is calculated for each alternative. These distances are summed up across all criteria to arrive at a performance score for each alternative. This is used to rank alternatives in descending order of the performance score. The ranks are plotted against experiment no. to arrive at the graph shown in fig.6 below.

Similarly, the MOORA method was also used to rank the alternatives and cross-validate the MCDM ranks obtained using MOORA method. The normalization of the decision matrix is done using eq. 16 and the difference between beneficial and cost criteria is calculated as the performance score using eq. 17 which is used to rank the alternatives. A significant degree of overlap in ranks obtained using both the techniques can be seen from fig. 6. Pearson correlation coefficients were calculated using the formula shown in equation 18 to obtain the correlation plot shown in fig. 7.

$$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}} \ldots\ldots\ldots (18)$$

It can be seen from the figure that there is very little deviation among different techniques used. This suggests that the ranks obtained are reliable and consistent across different techniques used. This validates the ranks obtained using MCDM techniques. It is also interesting to note
that intermediate values of Current on time, current off time and current intensity results in the best compromise between MRR and TWR while high input values of current on time resulted in the most significant deterioration in the optimal compromise between the two output responses considered.



Experiment Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
MABAC	14	8	13	5	9	6	2	4	10	1	11	15	7	3	12
MABAC STDEV	14	8	13	5	9	6	2	4	10	1	11	15	7	3	12
MABAC CRITIC	15	8	13	5	9	6	3	4	10	1	11	14	7	2	12
MOORA	15	9	14	6	8	5	3	4	10	2	11	12	7	1	13
MOORA STDEV	15	8	14	6	9	5	3	4	10	2	11	12	7	1	13
MOORA CRITIC	15	9	14	6	8	5	3	4	10	2	11	12	7	1	13

Figure 6. Ranks Matrix depicting variation of ranks for different experimantal runs.

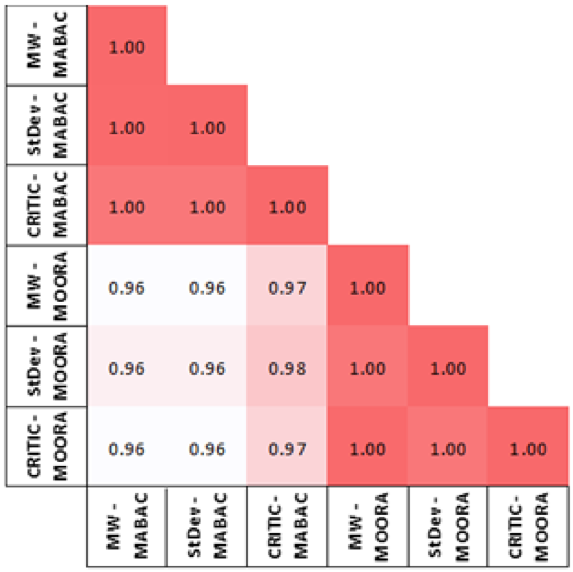


Figure 7. Correlation plot between ranks obtained using all MCDM techniques.

4 CONCLUSION

Using Al6063 as the matrix material and La_2O_3 and Al_2O_3 as reinforcements, the current study primarily focuses on the development and machining optimization of hybrid AMMC. Stir casting was used for development, and the metal matrix composite's morphological and structural analysis utilizing SEM, showed that reinforcements had been successfully included. In order to optimize MRR and surface roughness, the created composite was machined using a Electro discharge machining that followed the BBD design of experiments. To determine the best compromise between tool wear rate and MRR, experimental trails were ranked using two distinct MCDM techniques. One can infer the following conclusion through present work: SEM results indicated small size particles of reinforcement randomly distributed over the surface of Al 6063 alloy and EDS results indicated lower wt.% of La_2O_3 and Al_2O_3.
Strong consistency amongst the used MCDM approaches was found through statistical evaluation of ranking patterns. A high degree of agreement was indicated by the Spearman rank correlation coefficients between MABAC and MOORA across various weighting techniques, which were determined to be between 0.96 and 1.00. The robustness of the optimization framework was further demonstrated by the heatmap (Fig. 2), which further proved that the correlation between approaches was over 0.95. Additionally, rank stability study revealed that CRITIC offered more precise alternative discrimination while Standard Deviation-based weighting reduced variations among experiments. These findings support the validity of utilizing a variety of MCDM approaches as opposed to depending just on one.
Using mean weights, SDM weights, and CRITIC weights, MABAC and MOORA MCDM strategies indicated that the best compromise in tool wear and MRR could be achieved by selecting a machining condition of 9 A current, 5 trigger on, and 4 trigger off. This was a dominant optimal solution consistently across all six combinations of weight allocation methods and MCDM methods examined in the current work.

ACKNOWLEDGMENTS

The authors extend their acknowledgement to the financial support of the European Union under the REFRESH-Research Excellence For REgion Sustainability and High-tech Industries project number CZ.10.03.01/00/22_003/0000048 via the Operational Programme Just Transition.

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