OPTIMIZING DRILLING OPERATION OF HYBRID ALUMINIUM COMPOSITES USING MEREC AND ENTROPY-BASED WEIGHTING STRATEGIES—AN MCDM BASED COMPARATIVE STUDY

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ABSTRACT

Hybrid Aluminium Metal Matrix Composites have gained a lot of attention in the industrial sphere due to their excellent mechanical properties and lightweight nature. However, machining these composites presents substantial challenges because of the variable mechanical properties across the bulk. Traditional machining, like drilling, calls for optimization of drilling parameters for ensuring high material removal rates (MRR), minimal surface roughness (Ra), and enhanced hole quality. This study employs Multi-Criteria Decision-Making (MCDM) techniques—MARCOS, MABAC, MOORA, WASPAS, and ARAS—combined with two distinct weighting strategies: Entropy and the Method of Removal Effects of Criteria (MEREC). Drilling of stir-cast hybrid aluminium composites (Al 7075 + SiC + fly ash + bagasse ash) was performed using Taguchi's design of experiments. The MCDM techniques were then employed to obtain ranks of all the 27 experimental runs to choose the optimum. The results reveal that drill diameter and feed rate significantly influence optimal machining conditions. The study highlights that the 15th experimental run (10 mm drill diameter, 170 RPM spindle speed, 41 mm/min feed rate) yielded the best compromise across performance criteria. Furthermore, a strong correlation among rankings from different MCDM techniques demonstrates their robustness and reliability for machining optimization.

KEYWORDS

MCDM, Aluminium Composites, Drilling, Machining, Optimization

1 INTRODUCTION

New age composite materials, particularly Hybrid Aluminum Metal Matrix Composites (H-AMMC), have recently attracted more attention from materials scientists(Rana and Lata 2018). Since these composites combine lightweight qualities with enhanced mechanical capabilities, they are a topic of interest in many industries, particularly aerospace, automotive, marine, and defence. Pure aluminium, on the other hand, lacks the necessary rigidity for industrial applications despite having a strong strength-to-weight ratio and corrosion resistance (Alem et al. 2020). To solve this problem, researchers have investigated reinforcing aluminium using fibres, ceramic particles, particulates, and nanoparticles(Bakshi et al. 2010; Divakar et al. 2018; Akinwande et al. 2023). Even while ceramic reinforcements like SiC, B4C, TiC, and WC can enhance mechanical properties, they present difficulties during machining, increasing tool wear and resulting in subpar surface finishing(Bhaskar and Karuppusamy 2022; Bui et al. 2023). This problem can be reduced by combining harder ceramic particles with softer particles like fly ash, rice husk, or coconut shell ash(Moosa and Awad 2016; Kumar and Singh 2024). Better mechanical qualities, such as greater stiffness and wear resistance, are achieved by the resulting H-AMMCs without sacrificing aluminium's lightweight nature(Aziz et al. 2021; Althahban et al. 2022). Continuous fibre reinforcing, stir casting, liquid metal infiltration, in-situ synthesis, powder metallurgy, and friction stir processing are some of the techniques utilized to create AMMC. However, the stir casting technique is the most preferred method for this investigation. Since stir casting produces H-AMMC with improved mechanical qualities and at a lower cost than previous methods.

One of the most important subtractive machining methods used in the industry is drilling(Abbas et al. 2020). However, because H-AMMCs are diverse, conducting drilling operations on them poses several special difficulties(Babu et al. 2022). The interaction between the cutting tools and these composites frequently results in problems such surface roughness, burr formation, tool wear, and delamination factor. These difficulties have a major effect on the machined components' performance, dependability, and hole quality(Baraily et al. 2024; Ghadai et al. 2024). Furthermore, several input parameters, such as tool diameter, feed rate, depth of cut, spindle speed, and lubrication, affect crucial response parameters such as material removal rate and surface roughness(Ghadai et al. 2023). Furthermore, objective weights in MCDM techniques also ensure that the process of decision making is free from biases from the decision maker(Chatterjee and Chakraborty 2024).

A precise balance of these factors is necessary to maximize the material removal rate, minimize tool wear, and provide a high-quality surface finish(Ragavendran et al. 2019; Kalita et al. 2023). Optimizing the machining conditions for H-AMMCs is crucial to improving component quality, production efficiency, and cost-effectiveness. To overcome the difficulties involved in drilling these sophisticated composites, it is essential to determine the best set of parameters that will guarantee efficient material removal, structural integrity, and desired surface finishes(Deosant et al. 2021). Applying particular methodologies known as optimization techniques is crucial to achieving ideal machining characteristics, such as a high material removal rate, low surface roughness, high-quality holes, and little delamination(Kayaroganam et al. 2021). In EDM of hybrid AMMC (Al7075 + 6% SiC + 6% B4C), Mohankumar et al. 2024) investigated how machining parameters affect Surface Roughness (SR), Tool Wear Rate (TWR), and Material Removal Rate (MRR). For single responses, optimization using RSM; for multi-responses, a hybrid approach (EWM, Taguchi, TOPSIS, GRA) was employed. Significant values were determined by ANOVA, which produced an adequate SR (9.1924–10.3877 µm), a minimum EWR (0.0068–0.0103 mm^3/min), and a high MRR (0.4172–0.5240 mm^3/min). The proximity coefficient and Grey relationship grade improved by 15% and 16%, respectively, according to confirmation tests. EDM efficiency for AMMC machining was improved by SEM analysis, which verified low flaws and excellent surface integrity.

Using 27 tests and Taguchi's orthogonal array, Baraily et al.(Baraily et al. 2024) examined and optimized the drilling of hybrid Al-MMCs (Al 7075 + 2% SiC + 2.5% fly ash & bagasse ash). The effects of drill diameter, spindle speed, and feed rate on conicity, delamination, and MRR are investigated. While lower spindle speed and feed rate reduce delamination and conicity, higher drilling parameters enhance MRR. The ideal settings (170 rpm, 41 mm/min, 10 mm drill) are found through multi-objective optimization using RAMS and RATMI, which results in MRR = 7.473 g/min, delamination = 1.0416, and conicity = 0.00002. Strong matrix-reinforcement bonding is confirmed by SEM examination, and hardness rises with reinforcement. RAMS and RATMI for drilling optimization are validated by a comparative study. Through stir casting, AA8011 reinforced with 1-3% boron carbide and 1-2% aloe Vera Kumar et al.(Kumar et al. 2024) developed H-AMMC, which is essential for applications in electronics, automotive, and aerospace. A tubular copper electrode was used for electrical discharge drilling, and the roundness error, drilling rate, electrode wear rate, and taper angle were all measured. A hybrid multi-criteria decision-making approach was used to optimize process parameters. In comparison to initial settings, optimal conditions (9A current, 25µs pulse-on, 12µs pulse-off, 60 kg/cm² pressure, 1.5mm electrode) caused improvements in drilling rate of 25%, roundness of 23%, taper angle of 14%, and electrode wear rate of 7%.

In order to improve surface integrity during machining, Gowtham and Senthilkumar (Gowtham and Senthilkumar 2022) added solid lubricant MoS2 to H-AMMCs made by stir casting. According to their research, adding MoS2 decreased friction, which in turn enhanced the hybrid composite's surface roughness. The study contrasted a hybrid AMMC (AA5052 + 3% MoS2 + 9% Si3N4) with a conventional AMMC (AA5052 + 9% Si3N4) and showed that the solid lubricant in the hybrid composite produced better surface properties. Jebarose Juliyana et al. (2023) used the stir casting method to create LM5/ZrO2 composites and used Grey Relational Analysis (GRA) to optimize the surface roughness, burr height and thrust force of the composite holes. GRA validated their study's findings that certain parameters, including feed rate, spindle speed, and 6% reinforcement, were ideal for reducing thrust force and surface roughness. In the experimental investigation of LM6/B4C composites made by stir casting, Rubi et al.(Rubi et al. 2022) found that adding more B4C improved both the density and hardness of the composite. According to Grey Relational Analysis (GRA), burr height, surface roughness, and thrust force could all be effectively decreased with faster spindle speeds and lower feed rates. LM24 alloy, SiC, and coconut shell ash were combined to create a hybrid AMMC by Arulraj et al.(Arulraj et al. 2021) via squeeze casting. They found the ideal parameters by using the Taguchi L16 experimental design, and they found that the impact strength of the composite was significantly influenced by the percentage of reinforcement, squeeze time, and squeeze pressure.

Although MCDM techniques have been extensively employed in various engineering fields for decision-making involving conflicting criteria and alternatives, their application to drilling operations on hybrid aluminium metal matrix composites (HAMMC) fabricated via stir casting remains unexplored. Furthermore, to the best of the author's knowledge, no published studies to date have utilized the Entropy and MEREC approach for criteria weight determination in this context. Unlike standard deviation-based weight allocation, which emphasizes variability, Entropy captures data diversity, while MEREC assesses the impact of excluding each criterion, offering a more comprehensive evaluation. This study introduces a novel integration of MARCOS, MABAC, and MOORA MCDM methods—alongside Entropy and MEREC weighting schemes—to rank input parameters for maximizing material removal rate (MRR) while minimizing surface roughness (Ra). The approach provides a unique framework for identifying optimal drilling parameters in HAMMCs, representing a significant contribution to the current body of composite machining research

2 MATERIALS AND METHOD

2.1 *Experimental Details*

The experimental data used in the present work has been taken from a published literature presented by Baraily et al. (2024). and Ghadai et al. (2024). The input parameters in these literatures are identical, therefore, it becomes possible to compile the responses to obtain a 4-response decision matrix for MCDM application. Here, the development of Al-MMC was carried out using the stir casting technique. Prior to the casting process, the preheating of silicon carbide (SiC) (mesh size ~ 150 µm), bagasse ash (particle mesh size ~ 150 µm), and fly ash (particle mesh size ~ 150 µm) reinforcements was carried out using a muffle furnace at 200 °C. The base alloy used is Al-7075. Machining of the developed composite was done using a vertical milling machine to puncture 27 holes through them by varying Feed rate, Spindle speed, and drill bit radius. Characterization of the developed composite was also done to ensure that the composite was developed as intended, which is elaborated upon in Baraily et al. (2024)

2.2 *Weight Allocation Strategies*

2.2.1 *Entropy Method*

A vast number of studies have explored the use of entropy-based weight calculation in MCDM techniques(Chodha et al. 2022). This method assigns weights to criteria based on the information embedded within the dataset. The procedural steps for calculating weights using the entropy method are as follows:

Step 1: The Decision matrix is formulated as $X = [x_{ij}]_{mxn}$ where m is the number of alternatives and n is the number of criteria. A decision matrix consists of performance value of each alternative corresponding to different criteria arranged in a matrix form.

Step 2: In the present work, normalization of the decision matrix is done using following equation

$$P = [p_{ij}]_{mxn}; p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}^2} \quad (1)$$

Step 3: Entropy of each criteria is calculated using the following equation

$$e_j = \frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} . \ln p_{ij} \quad (2)$$

$$w_{ij} = \frac{|1 - e_{ij}|}{\sum_{j=1}^{n} |1 - e_{ij}|} \quad (3)$$

Step 4: Finally, the weight of the criteria is calculated following

Table 1. Experimental Data

Sr. No.	Drill Dia	Speed	Feed	MRR	Delamination	Conicity	Ra
1	7.8	90	15	2.054	1.027692	0.00172	8.784
2	7.8	90	25	1.834	1.025128	0.00006	8.448
3	7.8	90	41	3.159	1.049103	0.00562	7.954
4	7.8	170	15	2.721	1.076795	0.00784	6.901
5	7.8	170	25	2.803	1.046026	0.00086	8.346
6	7.8	170	41	4.761	1.035897	0.0043	7.224
7	7.8	225	15	2.054	1.023077	0.00272	5.547
8	7.8	225	25	2.752	1.074744	0.00736	6.77
9	7.8	225	41	4.871	1.04	0.00324	7.689
10	10	90	15	2.013	1.0091	0.00036	5.431
11	10	90	25	5.454	1.0269	0.00284	6.118
12	10	90	41	7.507	1.018	0.00156	5.179
13	10	170	15	3.378	1.0649	0.01002	4.693
14	10	170	25	4.545	1.0303	0.00312	4.856
15	10	170	41	7.473	1.0416	0.00002	7.772
16	10	225	15	4.081	1.0464	0.00492	6.084
17	10	225	25	4.629	1.0665	0.00968	4.271
18	10	225	41	9.216	1.0233	0.00196	10.44
19	11.8	90	15	4	1.028898	0.00226	3.265
20	11.8	90	25	3.33	1.040932	0.00422	4.015
21	11.8	90	41	9.74	1.101441	0.01692	5.515
22	11.8	170	15	4.79	1.034661	0.00294	2.603
23	11.8	170	25	4.62	1.025	0.00152	3.691
24	11.8	170	41	9.478	1.042627	0.00646	3.342
25	11.8	225	15	4.28	1.021949	0.00486	2.716
26	11.8	225	25	6.481	1.023898	0.00332	2.974
27	11.8	225	41	10.059	1.031271	0.00608	2.924

2.2.2 MEthod on Removal Effects of Criteria (MEREC) Method

A weight determination method based on the removal effects of criteria was introduced by Mehdi Keshavarz-Ghorabaee et al.(Keshavarz-Ghorabaee et al. 2021) on 2019. Unlike most of the conventional weighting methods, which assess the variance in alternatives' performance concerning each criterion, MEREC determines criterion weights by evaluating the impact of their removal. The procedure for determining weights using the MEREC method, as detailed by the original author, comprises the following steps:

Step 1: Construction of decision matrix. A matrix X=[xij] of size n x m; where m represents the no. of criteria and n is no. of alternatives is formulated based on the problem.

Step 2: Decision matrix is normalized using the as under

$$n_{ij}^{x} = \begin{cases} \dfrac{\min_k x_{kj}}{x_{ij}} & if\ j\ \in B \\ \dfrac{x_{ij}}{\max_k x_{kj}} & if\ j\ \in C \end{cases} \quad (4)$$

Where B is the set of beneficial criteria and C is the set of non-beneficial (cost) criteria

Step 3: Calculation of overall performance of the alternatives (S_i) is done as

$$S_i = \ln\left(1 + \left(\frac{1}{m} \sum_j |ln(n_{ij}^{x})|\right)\right) \quad (5)$$

Step 4: Performance of the alternatives by removing each criterion (S'_{ij}) is calculated as under

$$S'_{ij} = \ln\left(1 + \left(\frac{1}{m} \sum_{k,k \neq j} |ln(n_{ik}^{x})|\right)\right) \quad (6)$$

Step 5: E_j is calculated by summing up the absolute deviation as under

$$E_j = \sum_i |\ S'_{ij} - S_i\ | \quad (7)$$

Step 6: Weight of the criteria is determined using the following formula

$$w_j = \frac{E_j}{\sum_k E_k} \tag{8}$$

This w_j is the weight assigned to each criterion for all the MCDM techniques used in this paper.

2.3 Multi-Criteria Decision-Making Techniques

2.3.1 Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS)

Introduced by Stević et al.(Stević et al. 2020) in 2019 to solve a supplier selection problem in the healthcare sector, the MARCOS method has since found broad application in various multi-criteria decision-making (MCDM) scenarios. This technique ranks alternatives by analysing their relative distances fro ideal and anti-ideal solutions, employing a utility function to establish their order. The most favourable alternative is the one positioned closest to the ideal solution while being farthest from the anti-ideal. The key procedural steps of this approach are as follows:

Step 1: Both ideal and anti-ideal solutions are within the decision matrix to formulate an extended decision matrix

$$X = \begin{bmatrix} x_{aa1} & x_{aa2} & \cdots & x_n \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{22} & \cdots & x_{mn} \\ x_{a1} & x_{a2} & \cdots & x_{an} \end{bmatrix} \tag{9}$$

Here, x_{aai} represents the worst alternative, while x_{ai} denotes the best alternative for a given criterion.

Step 2: Calculation of the weighted normalized decision matrix is done using the formula shown below:

$$\begin{aligned} n_{ij} &= w_j \times \frac{x_{ai}}{x_{ij}} \text{ if } a \text{ cost criteria} \\ n_{ij} &= w_j \times \frac{x_{ij}}{x_{ai}} \text{ if a benefit criteria} \end{aligned} \tag{10}$$

Step 3: The Degree of utility of all the alternatives is calculated as follows

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{11}$$

$$K_i^- = \frac{S_i}{S_{aai}} \tag{12}$$

Where $S_i = \sum_{i=1}^{n} v_{ij}$

Step 4: The degree of compromise with the ideal and anti-ideal solutions is quantified using the following equation

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}} \tag{13}$$

Where $f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-}$ and $f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-}$ represent the utility functions concerning the ideal and anti-ideal functions respectively.

Step 5: The alternatives are ranked in descending order of their utility functions.

2.3.2 Multi-Attributive Border Approximation Area Comparison (MABAC)

Pamucar et al.(Pamučar and Ćirović 2015) introduced the Multi-Attributive Border Approximation Area Comparison (MABAC) method to address MCDM problems, initially applying it to forklift selection. In this approach, ranking of alternatives is done based on the distance of the border approximation area from the criterion function. The key advantages of MABAC lie in its stability, accuracy, and the ease of its mathematical framework. The steps involved in MABAC are outlined below:

Step 1: Formulation of the decision matrix, similar to other MCDM techniques.

Step 2: Decision matrix is normalized using equations mentioned below

$$t_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}; j \in B \tag{14}$$

$$t_{ij} = \frac{x_{ij} - x_i^+}{x_i^+ - x_i^-}; j \in H \tag{15}$$

Where $x_i^+ \, and \, x_i^+$ are maximum and minimum values of the observed criterion in the decision matrix.

Step 3: Weighted normalized matrix is determined as

$$V = [v_{ij}]_{mxn} \,; v_{ij} = w_j.t_{ij} + w_j \tag{16}$$

Step 4: Border approximation area matrix is determined as

$$G = [g_i]_{1xn} \,; g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{1/m} \tag{17}$$

Step 5: Distance of the alternatives from the border approximation area is calculated as

$$Q = V - G \tag{18}$$

$Where\ V\ and\ G\ are\ matrices\ defined\ in\ Step\ 3\ and\ 4$

Step 6: Criterion function is calculated as:

$$Si = \sum_{j=1}^{n} q_{ij} \tag{19}$$

Alternatives are ranked in the descending order of the criterion function. That is, highest value of criterion function is to be ranked as 1.

2.3.3 Multi-Objective Optimization by Ratio Analysis (MOORA)

MOORA was used by Chakraborty(Chakraborty 2011) in a decision making problem for optimizing machining characteristics. MOORA method was further strengthened when Brauers et al.(Brauers et al. 2008) did a comparative analysis of various normalization techniques to arrive at the normalization technique discussed below. The steps involved in MOORA are highlighted below as follows

Step 1: To normalize the decision matrix, the equation given below is used:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{20}$$

Step 2: Weighted normalized matrix is calculated as under

$$r_{ij} = n_{ij} \times w_j \tag{21}$$

Step 1: Performance score is calculated from the weighted normalized decision matrix using the formula given as

$$y_i = \sum_{j=1}^{g} r_{ij} - \sum_{j=g+1}^{n} r_{ij} \tag{22}$$

where criteria 1 to criteria 'g' are the beneficial criteria

Step 2: Ranks are allotted to criteria based on performance scores. The highest performance score is ranked first, second highest the second and so on.

2.3.4 Weighted Aggregated Sum Product Assessment (WASPAS)

WASPAS method used by Zavadskas and Chakraborty(Chakraborty and Zavadskas 2014) integrates two widely recognized MCDM approaches — the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). WASPAS had better accuracy in comparison with both of its parent methods, making it more desirable. This method evaluates a composite index by integrating the effects of the weighted sum and product, which is then used to prioritize the alternatives. The sequence of steps involved is outlined below:

Step 1: The decision matrix is normalized with the help of the following equations:

$$n_{ij} = \frac{x_{ij}}{\max_i(x_{ij})} \; for\ benificial\ criteria \tag{23}$$

$$n_{ij} = \frac{\min_i(x_{ij})}{x_{ij}} \; for\ cost\ criteria \tag{24}$$

Step 2: Importance of alternative relative to other alternatives is calculated using the weighted sums as follows

$$Q_{WAS} = \sum_{i=1}^{n} x_{ij} \times w_j \tag{25}$$

Step 3: Calculation of the relative significance of the alternatives through the product-based method was done using the equation given below.

$$Q_{WAP} = \prod_{i=1}^{n} x_{ij}^{w_j} \tag{26}$$

Step 4: Cumulative importance score using the WASPAS technique is calculated as follows

$$Q_{WASPAS} = \alpha \times Q_{WAS} + (1-\alpha) \times Q_{WAP} \tag{27}$$

α is the factor that decides the weightage of each index. It is chosen as 0.5 commonly.

2.3.5 Additive Ratio Assessment

Zavadskas and Turskis(Zavadskas and Turskis 2010) introduced the ARAS method in 2010 as a practical and efficient approach to multi-criteria decision-making (MCDM). The method is founded on the principle that an alternative's effectiveness is directly influenced by its performance value for a given criterion and the corresponding criterion weight. This concept serves as the foundation for its application. The procedural steps of the ARAS method are as follows:

Step 1: decision matrix is normalized using one of the two equations based on whether the criteria is beneficial or cost

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}; for\ benificial\ criteria \tag{28}$$

$$n_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m} \frac{1}{x_{ij}}}; for\ cost\ criteria \tag{29}$$

Step 2: Weighted normalized decision matrix is calculated using equation presented below.

$$r_{ij} = n_{ij} \times w_j \tag{30}$$

Step 3: The following equation is used to determine the optimality function.

$$S_i = \sum_{j=1}^{n} r_{ij} \tag{31}$$

Step 4: Quantification of utility is done using the equation below and alternatives are ranked in the descending order of the obtained value.

$$K_i = \frac{S_i}{S_0} \tag{32}$$

3 RESULTS AND DISCUSSION

The responses from the experimental data was used to formulate a decision matrix in the considered MCDM problem. For the allocation of weights to each criterion, Weights obtained for the four criteria using Entropy weights and MEREC method is shown in table 2 below.

Criteria	MRR	Delamination	Conicity	Ra	Criteria
Entropy	0.24996	0.249453	0.250838	0.249749	Entropy
MEREC	0.284795	0.010636	0.482278	0.222291	MEREC

Table 2. Weights of criteria

The obtained weights are used MABAC, MOORA, WASPAS, MARCOS and ARAS methods to rank the 27 experimental runs based to obtain an optimal compromise between one beneficial and three cost criteria.

3.1 Selection using MCDM techniques

Ranking of 27 experimental trials was done using five different MCDM techniques discussed in earlier sections. Steps involved in the ranking of alternatives is religiously followed as discussed in section 2. The ranks obtained show a clear compromise between conflicting criteria to assign ranks to the alternatives. The better ranked alternatives are concentrated towards the bottom of the table, suggesting that the larger drill diameter results in better compromise between criteria. This also shows a slight dominance of MRR and Conicity criteria in the ranks obtained using all the methods considered. MOORA method considers the first alternative to be the best alternative which is a peculiar case as it is ranked among the bottom by other MCDM techniques. MOORA method compares across criteria but does not consider the ideal and anti-ideal solutions within a given criterion and this is reflected in the ranks thus obtained. Methods like MARCOS and MABAC show more fluctuation indicating that they are more responsive to entropy-weighted criteria changes. Similar trends are also observed with the ranks obtained using MEREC weights. The 15th experimental run wherein drill bit of 10mm diameter with spindle speed of 170 RPM and feed rate of 41 mm/rev was used to do the machining was ranked as the most suitable compromise by six of the 10 weight-MCDM combinations used in this study. Further analysis of the ranking also suggests that experimental trials with higher feed rate is more likely to have better ranks with other parameters kept constant.

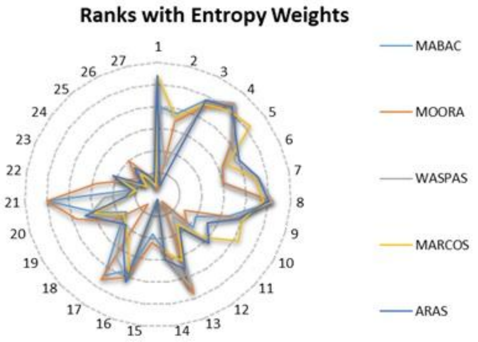

Figure 1. Ranks of Experimental trials based on Entropy Weights

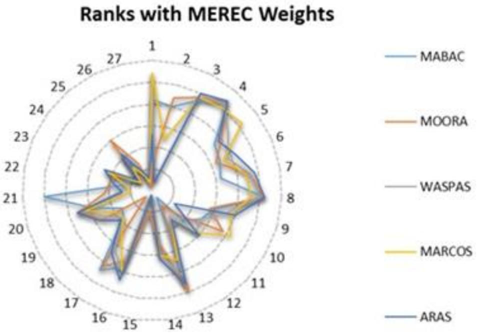

Figure 2. Ranks of Experimental trials based on MEREC Weights

3.2 Correlation Studies

The Pearson correlation coefficient reveals a moderate to high degree of correlation between the ranks obtained using different MCDM methods. The difference in finding the compromise of each MCDM technique could be the reason behind the moderate correlation observed between certain techniques.

Entropy Weights					
	MABAC	MOORA	WASPAS	MARCOS	ARAS
MABAC	1	0.81	0.82	0.73	0.67
MOORA		1.00	0.59	0.44	0.45
WASPAS			1.00	0.90	0.97
MARCOS				1.00	0.88
ARAS					1
MEREC Weights					
MABAC	1.00	0.80	0.73	0.71	0.66
MOORA		1.00	0.65	0.69	0.71
WASPAS			1.00	0.93	0.91
MARCOS				1.00	0.78
ARAS					1.00

Table 2. Correlation Table

Since there is over 80% correlation between ranks obtained in an inter-weight comparison in all of the MCDM techniques considered, it is safe to suggest that the MCDM techniques considered in this study are robust against fluctuations in the weights arising from the biases in the decision maker.

4 CONCLUSION

This work presents a comparative analysis of some of the most prominently used MCDM techniques namely MARCOS, MABAC, MOORA WASPAS and ARAS coupled with two different weight allocation strategies namely Entropy weights and MEREC method. The problem considered in this study is drilling operation in hybrid aluminium composite using SiC, fly-ash and bagasse ash as reinforcements. Experiments were done following full factorial taguchi design of experiments to record four responses namely MRR, Ra, Delamination and Conicity. MRR was treated was the beneficial criteria and the other three responses were treated as cost criteria. Ranks obtained using different MCDM techniques suggest the following:

- The 15th and 27th experimental runs are ranked among the best by most of the MCDM techniques. This result suggest that drill bit radius is a significant factor along with feed rate for the optimal compromise.
- There is a significant overlap between the ranks obtained using different weights in this study suggesting very little influence of weight allocation strategy.
- MOORA ranks was seen to have the least overlap with other methods in this decision making problem. It highlights the one dimensional approach that MOORA adopts for the decision making while other methods considered in this study are more complex in the decision-making process.
- Good correlation among the ranks obtained using the majority of the techniques also further validates the study.

This work can be further extended to compare other subjective weight allocation strategies, such as AHP and SWARA, with domain-specific experts to get a clearer picture of the optimum in this scenario.

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