INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

OPEN ACCESS

**Received:** 22-07-2023

**Accepted:** 29-10-2023

**Published:** 06-12-2023

**Citation:** Bai BH, Kumar PN (2023) GRA & DFA Approach for Optimum Material Selection of Aluminium Metal Matrix Composites: A Comparative Study. Indian Journal of Science and Technology 16(45): 4244-4254. https://doi.org/10.17485/IJST/v16i45.1837

* **Corresponding author**.

haritha324@gmail.com

**Funding:** None

**Competing Interests:** None



Published By Indian Society for Education and Environment (iSee)

**ISSN**
Print: 0974-6846
Electronic: 0974-5645

# GRA & DFA Approach for Optimum Material Selection of Aluminium Metal Matrix Composites: A Comparative Study

**Banavath Haritha Bai[1]*, Podaralla Nanda Kumar[2]**

**1** Research Scholar, Department of Mechanical Engineering, JNT University Anantapur, Ananthapuramu, 515002, Andhra Pradesh, India
**2** Professor, Department of Mechanical Engineering, N.B.K.R.Institute of Science and Technology, Vidyanagar, 524413, Andhra Pradesh, India

## Abstract

**Objective:** To draw the best combination of material parameters which gives optimized tensile strength, hardness and density properties of the aluminium metal matrix composite. **Methods:** In this study, three parameters (i.e., base material: Al5083, Al6082 and Al7075, reinforcement material: Fly-ash, SiC, and $Al_2O_3$, and percent of reinforcement material: 2.5%, 5% and 7.5%) were chosen, each with three levels, for the fabrication of AMMC samples in accordance with the Taguchi experimental design $L_9$ in order to evaluate the tensile strength, hardness and density properties. With the considered set of material combinations, the AMMC samples are fabricated by using stir casting process. **Findings:** The optimum material combinations are chosen to get optimized properties of AMMC samples using GRA &DFA approach. Since, grey relational analysis is one of the foremost techniques applied when the nature of information is incomplete and uncertain. The experimental results are analyzed using GRA & DFA and drawn the optimum combination of material parameter such as Al6082 (base material), SiC (reinforcement material) and 7.5% (per cent of reinforcement material) with GRA and Al6082 (base material), SiC (reinforcement material) and 5% (per cent of reinforcement material) with DFA to get optimized properties of AMMC sample. It also found that the confirmation experiment results are adequate. **Novelty:** The use of fly-ash reinforcement as secondary reinforcement has widely increased due to their low cost and easily available as waste in thermal power plants. From the experimental results, it is observed that the tensile strength, hardness and density properties of aluminium alloy samples are improved due to the addition of reinforcement materials using stir casting process.

**Keywords:** DFA & GRA approach; Stir casting process; AMMC samples; Composite properties: Ultimate Tensile Strength; Brinel hardness; and Density

# 1 Introduction

Metal Matrix Composites (MMCs) refer to metallic materials that have been strengthened through the incorporation of various metals, ceramics, or natural compounds. Metal Matrix Composites (MMCs) are fabricated through the dispersion of reinforcement materials within the matrix metal. The process of reinforcement is commonly employed with the aim of enhancing the inherent properties of the base metal, including but not limited to strength, stiffness, conductivity, and other relevant characteristics. Aluminium and its alloys have emerged as highly constructive materials for use as base metals in metal matrix composites due to their advantageous characteristics, including reduced weight, increased strength, exceptional thermal and electrical properties, cost efficiency, improved resistance to corrosion, and heightened damping capacity. The automotive, aerospace, and sports industries requires a variety of aluminum-composite components for use in diverse conditions[(1)]. Consequently, extensive research has been conducted in recent years to investigate the combination of various aluminum alloys with different reinforcing elements[(2–4)]. The stability of the reinforcing elements at operating temperatures, as well as their non-reactivity, is important considerations[(5)]. Silicon Carbide (SiC) and Aluminium Oxide ($Al_2O_3$) are frequently employed as reinforcing agents. P. Chakrapani, T.S.A. Suryakumari concluded in their review of various researches as, Reinforcement particles play a significant role to alter the mechanical properties of AMMCs. Better results were obtained on tensile strength by using different reinforcement particles such as graphite, fly ash. Hardness of MMCs changes with the change in silicon carbide composition. Hardness of MMC increase with the addition of SiC weight fraction and Al2O3 weight fraction[(6)]. Additionally, there has been a growing trend in the use of fly-ash reinforcement, primarily due to its low cost and abundant availability as a waste product in thermal power plants[(7)]. The process of stir casting is a cost-effective method utilized for the production of aluminum based metal matrix composites[(8)]. On other hand, to achieve optimized combination of various parameters, extensive hundreds of trials have to be performed which costs high. The cost effective tool utilized for the optimization process is Design of Experiments (DoE), which involves the preparation of a series of tests to investigate the effects of specific changes in the input parameters of a system. This approach facilitates the aggregation of a substantial amount of resources and offers a meticulously structured strategy for addressing the research problem[(9,10)]. To explore the concept of multiple attributes decision-making, researchers often employ various techniques, including the Analytic Hierarchy Process (AHP)[(11)], data envelopment analysis (DEA), and grey relational analysis (GRA)[(12)]. Santonab Chakraborty proposed application of a newly developed multi-criteria decision-making tool, in the form of ordinal priority approach (OPA), for solving two parametric optimization problems for drilling operations of Al-MMCs[(13)]. One of the prominent techniques utilized in situations where information is incomplete and uncertain is grey relational analysis (GRA), which was introduced by Deng in 1989[(14)]. The authors[(15,16)] have utilized a combined approach involving the Taguchi $L_9$ orthogonal array and the Grey Relational Analysis (GRA) technique to optimize the injection molding parameters. Using grey relational analysis (GRA). Jebarose Juliyana, S et al.[(17)] derived the optimal cutting parameters for addressing the best thrust force (TF), surface roughness (SR), and burr height (BH) of drilled holes for the composite LM5/ZrO2. To validate the process output parameters, the Grey Relational Analysis (GRA) optimization approach was applied by Layatitdev Das et.al, and the effect of three process parameters, cutting speed, tool feed and cutting depth, is being studied on the machining responses[(18)]. A Taguchi coupled desirability function analysis was employed by S.V. Alagarsamy et.al,[(19)], to determine the optimal parameters with an objective to maximize the material removal rate (MRR) and minimize the surface roughness (SR)

## 1.1 Research Gap

After studying the previous research, extensive research has been made on AMMCs and the machining of AMMCs. No researcher fabricated AMMCs by using the optimization technique for the selection of constituent parameters but randomly taking parameter levels, which may lead to a defective combination of constituent levels. In this issue, to fill the gap, this research has been proposed with the assistance of GRA (Gray Relational Analysis) and DFA (Desirability Function Analysis).

# 2 Methodology

The effective tools utilized for the optimization process is Grey Relational Analysis and Desirability Function Analysis coupled with Taguchi Design of Experiments (DoE), which involves the preparation of a series of tests to reduce the number of experiments and hence the cost of experimentation.

## 2.1 Process parameters and design of experiments

In order to produce the AMMC samples, the materials and their contribution are tabulated in Table 1, which was selected from past research. The experimental design for conducting the experiments was developed using the Taguchi orthogonal array methodology, with the assistance of Mini-Tab software. The information presented in Table 2 provides a comprehensive overview of the material combinations utilized in the production of AMMC samples through the stir casting process.

**Table 1. Parameters and their levels**

| Sl. No. | Parameters | Levels | | |
|---|---|---|---|---|
| | | 1 | 2 | 3 |
| 1 | Base material (BM) | Al5083 | Al6082 | Al7075 |
| 2 | Reinforcement Material (RM) | FA | SIC | $Al_2O_3$ |
| 3 | Percentage of Reinforcement Material (PRM) | 2.5% | 5% | 7.5 |

**Table 2. $L_9$ orthogonal array design**

| AMMC Sample No. | Material Parameters | | |
|---|---|---|---|
| | BM | RM | PRM |
| 1 | Al5083 | FA | 2.5 |
| 2 | Al5083 | SiC | 5 |
| 3 | Al5083 | $Al_2O_3$ | 7.5 |
| 4 | Al6082 | FA | 5 |
| 5 | Al6082 | SiC | 7.5 |
| 6 | Al6082 | $Al_2O_3$ | 2.5 |
| 7 | Al7075 | FA | 7.5 |
| 8 | Al7075 | SiC | 2.5 |
| 9 | Al7075 | $Al_2O_3$ | 5 |

## 2.2 Sample Fabrication

Firstly, the necessary amount of matrix material is introduced into the crucible, and the temperature is elevated to 850 °C and maintained at this level until the base material is completely melted. After complete melting of the matrix material, a 1% concentration of the wetting agent magnesium (Mg) is introduced into the molten metal. The reinforcement particles are gradually introduced into the molten matrix material while undergoing stirring (Figure 1), and this process is sustained for duration of five minutes. Subsequently, the heterogeneous slurry was introduced into distinct steel dies that had been preheated, facilitating the production of samples intended for subsequent testing. In accordance with the experimental design, the AMMC samples are prepared as depicted in Figure 2. Subsequently, these samples are subjected to machining processes in adherence to ASTM standards, as illustrated in Figure 3. The purpose of employing a wire-cut EDM machine is to preserve the inherent properties of the AMMC samples, thereby facilitating the subsequent evaluation of their tensile strength, hardness, and density.

**Fig 1. Stir casting furnace**

**Fig 2. AMMC Sample with Die**

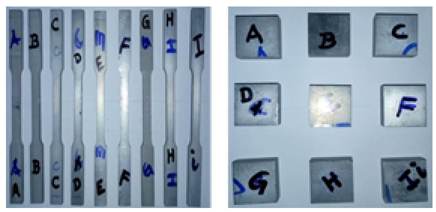

**Fig 3. AMMC test samples as per ASTM standards**

The surface of the fabricated AMMC sample, was examined through the utilization of scanning electron microscopy (SEM), as illustrated in Figure 4. The observable phenomenon of reinforcement particle dispersion within the aluminum matrix material is evident. Hence, the stir casting process is a highly suitable technique for achieving a homogeneous dispersion of reinforcement particles within metal matrix composites. The incorporation of SiC particles into the aluminum matrix resulted in enhanced properties of the aluminum alloy. Similarly, the brittleness of the AMMC sample was also found to be heightened due to the agglomeration of SiC particles.

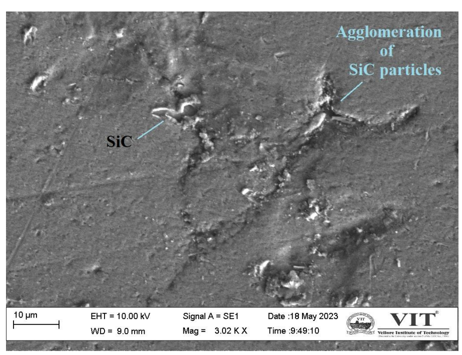


**Fig 4. SEM image of fabricated AMMC sample**

The prepared samples, in accordance with ASTM standards, undergo testing using a universal testing machine (Figure 5), a Brinell hardness tester (Figure 5), and a weighing method to evaluate their tensile strength, Brinell hardness number, and density. The obtained test results are organized in Table 3 and subsequently analyzed using gray relational analysis and Desirability Function Analysis.

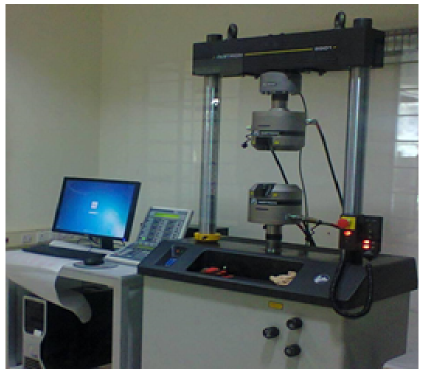

**Fig 5. Universal Testing Machine**

**Fig 6. Brinell Hardness Tester**

## 2.3 Optimization using GRA

Grey Relational Analysis (GRA) employs a distinct notion of information. The concept delineates scenarios devoid of information as black while contrasting them with situations characterized by complete information as white. Nevertheless, it is important to note that both of these hypothetical scenarios are rarely encountered in practical applications. Indeed, circumstances that fall between these two extremes are commonly characterized as being ambiguous or indeterminate. Hence, a gray system refers to a system characterized by a combination of known and unknown information. According to this definition, the quantity and quality of information can be understood as existing on a spectrum ranging from a complete absence of information to a state of comprehensive information, represented metaphorically as a continuum from black to white with varying shades of gray in between. Given the inherent presence of uncertainty, individuals consistently find themselves positioned within an intermediate realm, situated between opposing extremes, and residing within a nuanced and ambiguous domain. The experimental results were analyzed using gray relational analysis in order to determine the optimal combination of material factors for achieving optimized ultimate tensile strength (UTS), Brinell hardness number (BHN), and density. The procedural steps for the same are provided below.

### *2.3.1 Data pre-processing*

Data pre-processing, specifically data normalization, is typically necessary due to variations in range and unit among different data sequences. Different methodologies for data pre-processing in grey relational analysis are available depending on the characteristics of the data sequence.

If the target value of original sequence is infinite, then it has a characteristic of the "larger the better". The original sequence can be normalized as follows:

$$x^*{}_i(k) = \frac{x^o{}_i\,(k) - min\,x^o{}_i(k)}{max\,x^o{}_i\,(k) - min\,x^o{}_i\,(k)} \tag{1}$$

When the "smaller the better" is a characteristic of the original sequence, then the original sequence should be normalized as follows:

$$x^*{}_i(k) = \frac{max\,x^o{}_i\,(k) - x^o{}_i(k)}{max\,x^o{}_i\,(k) - min\,x^o{}_i\,(k)} \tag{2}$$

However, if there is a definite target value "nominal the best" to be achieved, the original sequence will be normalized in form:

$$x^*{}_i(k) = 1 - \frac{|\,x^o{}_i\,(k) - x^o|}{max\,x^o{}_i\,(k) - x^o} \tag{3}$$

Or, the original sequence can be simply normalized by the most basic methodology, i.e., let the values of original sequence are divided by the first value of the sequence:

$$x^*{}_i(k) = \frac{x^o{}_i(k)}{x^o{}_i(1)} \tag{4}$$

Where i = 1…, m; k = 1…, n. m is the number of experimental data items and n is the number of parameters. $x^o{}_i$(k) Denotes the original sequence, $x^*{}_i$(k) the sequence after the data pre-processing, max $x^o{}_i$(k) the largest value of $x^o{}_i$(k), min $x^o{}_i$(k) the smallest value of $x^o{}_i$(k), and $x^o$ is the desired value.

### *2.3.2 Grey relational coefficient and grey relational grade*

Grey relational analysis involves quantifying the degree of relevance between two systems or sequences, which is denoted as the Grey Relational Grade (GRG). Following the completion of data pre-processing, the grey relation coefficient $\xi_i$(k) pertaining to the $k^{th}$ performance characteristic in the $i^{th}$ experiment can be mathematically represented as:

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\,\Delta_{max}}{\Delta_{oi}\,(k) + \zeta\,\Delta_{max}} \tag{5}$$

Where, $\Delta_{oi}$ is the Deviation sequence

$$\begin{gathered} \Delta_{oi} = \|x^*{}_o(k) - x^*{}_i(k)\| \\ \Delta_{min} = i^{min}_{\forall j \varepsilon i} i^{min}_{\forall k} \left\|x^*{}_o(k) - x^*{}_j(k)\right\| \\ \Delta_{max} = i^{max}_{\forall j \varepsilon i} i^{max}_{\forall k} \left\|x^*{}_o(k) - x^*{}_j(k)\right\| \end{gathered} \tag{6}$$

$x^*{}_o$(k) Denotes the reference sequence and $x^*{}_i$(k) denotes the comparability sequence. $\zeta$ is distinguishing or identification coefficient: $\zeta$ [0, 1] (the value may be adjusted based on the actual system requirements). A value of $\zeta$ is the smaller and the distinguished ability is the larger. $\zeta$ = 0.5 is generally used. After the Grey Relational Coefficient (GRC) is derived, it is usual to take the average value of the grey relational coefficients as the grey relational grade. The grey relational grade is defined as:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \tag{7}$$

The grey relational grade $\gamma_i$ represents the level of correlation between the reference sequence and the comparability sequence. If the two sequences are identical, then the value of grey relational grade is equal to 1.

## 2.4 Optimization using desirability functional analysis

After analysing with GRA the experimental results were also analysed by using Desirability Function analysis(DFA), in order to determine the optimal combination of material factors for achieving optimized ultimate tensile strength (UTS), Brinell hardness number (BHN) and Density. The following are the steps for DFA.

#### 2.4.1 Calculate the individual desirability ($d_i$)

For the corresponding responses using the formula proposed by Derringer and Suich. There are three forms of the desirability functions according to the response characteristics.

**(a) The nominal-the-best:** The value of ŷ is required to achieve a particular target T, the desirability function can be written as

$$d_i = \begin{cases} \left(\dfrac{\widehat{y} - y_{min}}{T - y_{min}}\right)^s, & y_{min} \leq y \leq T, \quad s \geq 0 \\ \left(\dfrac{\widehat{y} - y_{min}}{T - y_{min}}\right)^t, & T \leq \widehat{y} \leq y_{min}, \quad t \geq 0 \\ 0 & \end{cases} \tag{8}$$

Where the $y_{max}$ and $y_{min}$ represent the upper and lower tolerance limits of ŷ and s and t represent the indices.

**(b) The larger-the-better:** The value of ŷ is expected to be the larger the better. The desirability function can be written as

$$d_i = \begin{cases} 0, & \widehat{y} \leq y_{min} \\ \left(\dfrac{\widehat{y} - y_{min}}{y_{max} - y_{min}}\right)^r, & y_{min} \leq \widehat{y} \leq y_{max}, \quad r \geq 0 \\ 1, & \widehat{y} \geq y_{max} \end{cases} \tag{9}$$

Where the $y_{min}$ represents the lower tolerance limit of ŷ, the $y_{max}$ represents the upper tolerance limit of ŷ and r represents index.

**(c) The smaller-the-better:** The value of ŷ is expected to be the smaller the better, the desirability function can be written as

$$d_i = \begin{cases} 1, & \widehat{y} \leq y_{min} \\ \left(\dfrac{\widehat{y} - y_{max}}{y_{min} - y_{max}}\right)^r, & y_{min} \leq \widehat{y} \leq y_{max}, \quad r \geq 0 \\ 0, & \widehat{y} \geq y_{min} \end{cases} \tag{10}$$

Where the $y_{min}$ represents the lower tolerance limit of ŷ, the $y_{max}$ represents the upper tolerance limit of ŷ and r represents the weight. The s, t and r indicate the weights and are defined according to the requirement of the user.

#### 2.4.2 Calculate the overall desirability (D)

The individual desirability values have been accumulated to calculate the overall desirability, using the following equation.

$$D = (d_1 * d_2 * d_2 \ldots\ldots\ldots\ldots d_n)^{1/n} \tag{11}$$

Here D is the overall or composite desirability value, $d_i$ is the individual desirability value of $i^{th}$ quality characteristic and n is the total number of responses.

## 3 Results and Discussion

The test results presented in Table 3 are utilized to assess the optimal mechanical and physical properties of AMMC through the application of the GRA approach. In the GRA approach, the initial step involves normalizing the experimental results through the utilization of equations in the data pre-processing stage, specifically from Equations (1), (2), (3) and (4). The utilization of Equations (1) and (2) is crucial in achieving optimal outcomes as they are employed to standardize the properties of tensile strength, hardness, and density. Typically, manufacturers prioritize materials with high tensile strength, high hardness, and low density. In order to meet the current demands of manufacturers, the experimental values, specifically tensile and hardness values, are normalized using Equation (1), while density values are normalized using Equation (2). The tabulated values in Table 4 represent the normalized values.

**Table 3. Experimental Results**

| Exp. No | Experimental Results | | |
|---|---|---|---|
| | Ultimate tensile strength (N/mm$^2$ ) | Brinel Hardness Number (BHN) | Density (D)Kg/m$^3$ |
| 1 | 115 | 55.84 | 2786.40 |
| 2 | 136 | 67.47 | 2816.90 |

*Continued on next page*

*Table 3 continued*

| | | | |
|---|---|---|---|
| 3 | 138 | 69.21 | 3097.30 |
| 4 | 131 | 63.11 | 2855.10 |
| 5 | 155 | 72.4 | 3007.50 |
| 6 | 125 | 58.34 | 2742.40 |
| 7 | 142 | 70.23 | 3132.30 |
| 8 | 129 | 60.73 | 2727.27 |
| 9 | 134 | 63.88 | 2828.30 |

The deviation sequence is evaluated from the normalized values by employing Equation (6) to determine the grey relation coefficient and grey relation grade values, after the experimental values have been normalized with respect to their characteristics. The GRC and GRG values are determined through the utilization of Equations (5) and (7). All of these values are dimensionless results obtained by normalizing the experimental results, and they are evaluated with respect to their respective characteristics. The tabulation of the deviation sequence (Delta), GRC, and GRG values can be found in Table 4.

**Table 4. NEVs, DVNEVs, GRCs and Grey Relational Grade**

| Sl. No | Normalized experimental values | | | Delta values of NEV | | | Grey Relational Coefficients | | | Grey Relational Grade (GRG) |
|---|---|---|---|---|---|---|---|---|---|---|
| | UTS | BHN | D | UTS | BHN | D | UTS | BHN | D | |
| 1 | 0 | 0.1 | 0.8540 | 1.000 | 1.0000 | 0.1460 | 0.3333 | 0.3333 | 0.7740 | 0.4802 |
| 2 | 0.525 | 0.7023 | 0.7787 | 0.475 | 0.2977 | 0.2213 | 0.5128 | 0.6268 | 0.6932 | 0.6109 |
| 3 | 0.575 | 0.8074 | 0.0864 | 0.425 | 0.1926 | 0.9136 | 0.5405 | 0.7219 | 0.3537 | 0.5387 |
| 4 | 0.400 | 0.4390 | 0.6844 | 0.600 | 0.5610 | 0.3156 | 0.4545 | 0.4713 | 0.6130 | 0.5129 |
| 5 | 1.000 | 1.0000 | 0.3081 | 0.000 | 0.0000 | 0.6919 | 1.0000 | 1.0000 | 0.4195 | 0.8065 |
| 6 | 0.250 | 0.1510 | 0.9626 | 0.750 | 0.8490 | 0.0374 | 0.4000 | 0.3706 | 0.9305 | 0.5670 |
| 7 | 0.675 | 0.8690 | 0.0000 | 0.325 | 0.1310 | 1.0000 | 0.6061 | 0.7923 | 0.3333 | 0.5772 |
| 8 | 0.350 | 0.2953 | 1.0000 | 0.650 | 0.7047 | 0.0000 | 0.4348 | 0.4150 | 1.0000 | 0.6166 |
| 9 | 0.475 | 0.4855 | 0.7506 | 0.525 | 0.5145 | 0.2494 | 0.4878 | 0.4929 | 0.6672 | 0.5493 |

After normalizing the experimental values with respect their characteristics, deviation sequence is assessed from the normalized values by using Equation (6) for grey relation coefficient and grey relation grade values. The GRC and GRG values are calculated by using the Equations (5) and (7). All these values are dimensionless results from normalized to grey relational grade values but are with respect their characteristics. The deviation sequence (Delta), GRC and GRG values are tabulated in Table 4.

**Table 5. Grey relational grade values for each factor at each level**

| Level | BM | RM | PRM |
|---|---|---|---|
| 1 | 0.5433 | 0.5234 | 0.5546 |
| 2 | 0.6288 | 0.6780 | 0.5577 |
| 3 | 0.5810 | 0.5517 | 0.6408 |
| Delta | 0.0855 | 0.1546 | 0.0862 |
| Rank | 3 | 1 | 2 |

Upon completion of the grey relational coefficient calculations for each response, the grey relational grade is subsequently determined for each factor at every level. This process enables the identification of the optimal level for each factor by considering their respective grey relational grade values. In the Grey Relational Analysis (GRA) approach, it is observed that the influential factor with the highest grey relational grade value among its considered levels represents the optimum level. The material factors are assessed and ranked based on their delta values in order to determine the most influential factor in achieving optimal properties. The ranking and mean values are presented in Table 5 and Figure 7, respectively.

From the Figure 7 and Table 5, it is observed the optimum material combination for getting the optimal properties in aluminium metal matrix composites through GRA are:

Base Material at 3$^{rd}$ Level i.e., Al 6082

Reinforcement Material is at 2$^{nd}$ Level i.e., SiC

Percentage of reinforcement Material is at Level 3 i.e., 7.5%

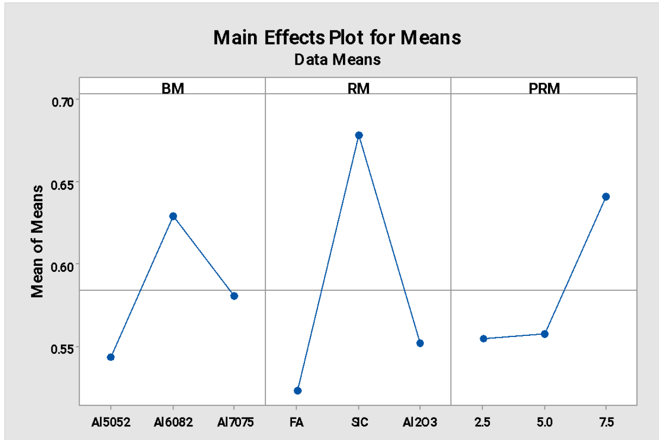


**Fig 7. Grey relational grade values for each factor at each level**

In the DFA approach the individual desirability values using equation 9 for UTS and BHN and Equation (10) for Density Composite Desirability values are calculated using Equation (10). Also, composite desirability values are calculated using Equation (11) and tabulated the values in the Table 6.

**Table 6. Individual desirability values**

| Sl No | Individual desirability values ($d_i$ ) | | | Composite desirability values ($D_c$ ) |
|---|---|---|---|---|
| | UTS | BHN | D | |
| 1 | 0.000 | 0.0000 | 0.8540 | 0.0000 |
| 2 | 0.525 | 0.7023 | 0.7787 | 0.6597 |
| 3 | 0.575 | 0.8074 | 0.0864 | 0.3423 |
| 4 | 0.400 | 0.4390 | 0.6844 | 0.4935 |
| 5 | 1.000 | 1.0000 | 0.3081 | 0.6754 |
| 6 | 0.250 | 0.1510 | 0.9626 | 0.3312 |
| 7 | 0.675 | 0.8690 | 0.0000 | 0.0000 |
| 8 | 0.350 | 0.2953 | 1.0000 | 0.4693 |
| 9 | 0.475 | 0.4855 | 0.7506 | 0.5573 |

After that the composite desirability values are calculated for each factor at each level (Table 7 & Figure 8) and the optimal level for each factor is identified based on their individual composite desirability values. The optimal level of any influential factor has the highest composite desirability value among their considered levels.

**Table 7. Composite desirability values for each factor at each level**

| Level | BM | RM | PRM |
|---|---|---|---|
| 1 | 0.3340 | 0.1645 | 0.2668 |
| 2 | 0.5000 | 0.6015 | 0.5702 |
| 3 | 0.3422 | 0.4103 | 0.3392 |
| Delta | 0.1660 | 0.4370 | 0.3033 |
| Rank | 3 | 1 | 2 |

From the Figure 8 and Table 7, it is observed the optimum material combination for getting the optimal properties in aluminium metal matrix composites through DFA are:

Base Material at 3$^{rd}$ Level i.e., Al 6082

Reinforcement Material is at 2$^{nd}$ Level i.e., SiC

Percentage of reinforcement Material is at Level 3 i.e., 5%

**Confirmation Experiment**

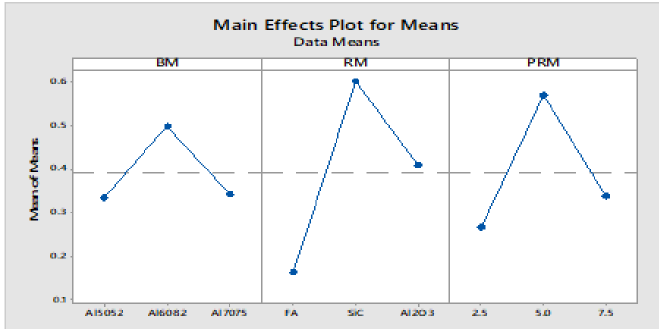


**Fig 8. Composite desirability values for each factor at each level**

Using the aforementioned combination of materials, the AMMC sample was manufactured and subsequently subjected to testing in order to validate the obtained results. Based on the data presented in Table 8, it can be observed that the results of GRA are better than that of DFA.

**Table 8. Confirmation test Results**

| GRA | | | | DFA | | | |
|---|---|---|---|---|---|---|---|
| **Optimum material combination** | **UTS** | **BHN** | **D** | **Optimum material combination** | **UTS** | **BHN** | **D** |
| Al6082/7.5% SiC MMC | 155 | 72.4 | 3007 | Al6082/5% SiC MMC | 147 | 69 | 3002 |

## 4 Conclusions

Based on the findings of this study, the following conclusions have been derived:

1. It can be inferred that the stir casting process is a highly suitable method for the production of aluminum metal matrix composite samples, and the incorporation of SiC particles leads to an enhancement in the properties of the aluminum alloy. The incorporation of SiC particles leads to an increase in the density of the aluminum alloy. Hence, it is recognized that the selection of optimal casting parameters is crucial to achieving a consistent and even distribution of reinforcement materials.
2. Based on the GRA analysis, it can be concluded that the combination of Al6082, SiC, and 7.5% material is determined to be the optimal combination for enhancing the properties of the aluminum alloy. And the hardness value and tensile strength of an aluminum alloy are increased due to the agglomeration of SiC particles.
3. Based on the DFA analysis, it can be concluded that the combination of Al6082, SiC, and 5% material is determined to be the optimal combination for enhancing the properties of the aluminum alloy. And the hardness value and tensile strength of an aluminum alloy are increased due to the agglomeration of SiC particles.
4. The confirmation experiment demonstrates that the GRA is effective when compared to DFA while addressing these specific research problems.
5. It can be concluded that the research gap has been filled by using the concept of taguchi-coupled GRA and DFA effectively by reducing the number of experiments.

## 5 Future scope of work

Several optimization techniques, such as dengs, vikor, and fuzzy logic, can be used to achieve a better combination of constituents for fabricating AMMCs.

## References

1) Fatchurrohman N, Iskandar I, Suraya S, Johan K. Sustainable Analysis in the Product Development of Al-Metal Matrix Composites Automotive Component. *Applied Mechanics and Materials*. 2015;695:32–35. Available from: https://doi.org/10.4028/www.scientific.net/AMM.695.32.
2) McDanels DL. Analysis of stress-strain, fracture and ductility behaviour of aluminium matrix composites containing discontinuous SiC reinforcement. *Metallurgical Transactions A*. 1985;16:1105–1115. Available from: https://doi.org/10.1007/BF02811679.

3) Madhukar P, Selvaraj N, Rao CSP. Manufacturing of aluminium nano hybrid composites: a state of review. In: International Conference on Advances in Materials and Manufacturing Applications (IConAMMA-2016) , 14–16 July 2016 , Bangalore, India;vol. 149 of IOP Conference Series: Materials Science and Engineering. IOP Publishing. 2016;p. 1–12. Available from: https://iopscience.iop.org/article/10.1088/1757-899X/149/1/012114.
4) Ozden S, Ekici R, Nair F. Investigation of impact behaviour of aluminium based SiC particle reinforced metal–matrix composites. *Composites Part A: Applied Science and Manufacturing*. 2007;38(2):484–494. Available from: https://doi.org/10.1016/j.compositesa.2006.02.026.
5) Babu KA, Jeyapaul R, Gugulothu B, Selvaraj S, Varatharajulu M. A Retrospective Investigation on Hybrid Metal Matrix Composites: Materials, Processing Methods, and Properties of Composites. *Iranian journal of chemistry & chemical engineering (IJCCE)*. 2023;42(6):1842–1870. Available from: https://doi.org//10.30492/IJCCE.2022.553499.5327.
6) Chakrapani P, Suryakumari TSA. Mechanical properties of aluminium metal matrix composites-A review. *Materials Today: Proceedings*. 2021;45(Part 7):5960–5964. Available from: https://doi.org/10.1016/j.matpr.2020.09.247.
7) Ramnath BV, Elanchezhian C, Annamalai RM, Aravind S, Atreya TSA, Vignesh V, et al. Aluminium metal matrix composites - a review" Rev. *Reviews on Advanced Materials Science*. 2014;38:55–60. Available from: https://www.ipme.ru/e-journals/RAMS/no_13814/06_13814_ramnath.pdf.
8) Soltani S, Khosroshahi RA, Mousavian RT, Jiang ZY, Boostani AF, Brabazon D. Stir casting process for manufacture of Al–SiC composites. *Rare Metals*. 2017;36(7):581–590. Available from: https://doi.org/10.1007/s12598-015-0565-7.
9) Montgomery DC. Design and Analysis of Experiments. Wiley. 2019. Available from: https://www.wiley.com/en-us/Design+and+Analysis+of+Experiments%2C+10th+Edition-p-9781119492443.
10) Selvaraj DP, Chandramohan P. Optimization of surface roughness of AISI 304 austenitic stainless steel in dry turning operation using Taguchi Design method. *Journal of Engineering Science and Technology*. 2010;5(3):293–301. Available from: https://jestec.taylors.edu.my/Vol%205%20Issue%203%20September%2010/Vol_5_3_293_301_DP_Selvaraj.pdf.
11) Babu KA, Venkataramaiah P, Yerrathota S. Material Selection for Preparation of Aluminium Hybrid Mmcs. *Materials Today: Proceedings*. 2018;5(5):12209–12222. Available from: https://doi.org/10.1016/j.matpr.2018.02.198.
12) Pervez MD, Shafiq F, Sarwar Z, Jilani MM, Cai Y. Multi-Response Optimization of Resin Finishing by Using a Taguchi-Based Grey Relational Analysis. *Materials*. 2018;11(3):1–19. Available from: https://doi.org/10.3390/ma11030426.
13) Chakraborty S, Raut RD, Rofin TM, Chakraborty S. Optimization of drilling processes of aluminium metal matrix composites using the robust ordinal priority approach. *Decision Analytics Journal*. 2023;7:1–8. Available from: https://doi.org/10.1016/j.dajour.2023.100258.
14) Deng J. Introduction to Grey System Theory. *Journal of Grey System*. 1989;1:1–24. Available from: https://uranos.ch/research/references/Julong_1989/10.1.1.678.3477.pdf.
15) Prayogo GS, Lusi N. Application of Taguchi technique coupled with grey relational analysis for multiple performance characteristics optimization of EDM parameters on ST 42 steel. In: THE 3RD INTERNATIONAL CONFERENCE ON ADVANCED MATERIALS SCIENCE AND TECHNOLOGY (ICAMST 2015), 6–7 October 2015, Semarang, Indonesia;vol. 1725, Issue 1 of AIP Conference Proceedings. 2016. Available from: https://doi.org/10.1063/1.4945515.
16) Pervez H, Mozumder MS, Mourad AHI. Optimization of Injection Molding Parameters for HDPE/TiO2 Nanocomposites Fabrication with Multiple Performance Characteristics Using the Taguchi Method and Grey Relational Analysis. *Materials*. 2016;9(8):1–12. Available from: https://doi.org/10.3390/ma9080710.
17) Juliyana SJ, Prakash JU, Čep R, Karthik K. Multi-Objective Optimization of Machining Parameters for Drilling LM5/ZrO2 Composites Using Grey Relational Analysis. *Materials*. 2023;16(10):1–13. Available from: https://doi.org/10.3390/ma16103615.
18) Das L, Nayak R, Saxena KK, Nanda J, Jena SP, Behera A, et al. Determination of Optimum Machining Parameters for Face Milling Process of Ti6A14V Metal Matrix Composite. *Materials*. 2022;15(14):1–13. Available from: https://doi.org/10.3390/ma15144765.
19) Alagarsamy SV, Ravichandran M, Kumar SD, Sakthivelu S, Meignanamoorthy M, Chanakyan C. A Taguchi coupled desirability function analysis of wire cut EDM behaviour of titanium dioxide filled aluminium matrix composite. *Materials Today: Proceedings*. 2020;27(Part 2):853–858. Available from: https://doi.org/10.1016/j.matpr.2020.01.021.