Optimal Selection of Materials for Aluminum Metal Matrix Composites Utilizing the GRA Approach

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Abstract:

In this work, three parameters (i.e., base material: Al5083, Al6082 and Al7075, reinforcement material: Fly-ash, SiC, and Al2O3, 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 L9 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. To identify the optimal combination of material parameters that results in optimized tensile strength, hardness, and density properties for the aluminum metal matrix composite. The utilization of the GRA approach facilitates the selection of material combinations that yield optimized properties in AMMC samples. Grey relational analysis proves particularly useful in cases of incomplete and uncertain information. Employing GRA, the experimental results are assessed to determine the most effective combination of material parameters. This includes Al6082 as the base material, SiC as the reinforcement material, and a reinforcement percentage of 7.5%, all contributing to the attainment of optimized properties in the AMMC sample.

Keywords: GRA approach, Stir casting process, AMMC samples, Composite properties.

I. Introduction

Aluminum and its alloys are widely recognized as suitable materials for industries such as aerospace, marine, and automotive due to their lightweight nature and remarkable thermal properties [1]. These qualities make them highly attractive for crafting high-performance components for various applications. Metal Matrix Composites (MMCs) refer to metallic substances strengthened by incorporating diverse metals, ceramics, or natural compounds. The process of creating Metal Matrix Composites (MMCs) involves integrating reinforcement materials into the matrix metal, resulting in improved properties. 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 favorable 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 require a range of aluminum-composite components for use in diverse conditions. 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, are important considerations [5]. Silicon Carbide (SiC) and Aluminium Oxide (Al_2O_3) are frequently employed as reinforcing agents. The utilization of SiC reinforcement has been observed to enhance the tensile strength, hardness, density, and wear resistance of aluminum (Al) and its alloys in recent years [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]. The primary 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 [9-11]. To explore the concept of multiple attributes decision-making, researchers often employ various techniques, including the Analytic Hierarchy Process (AHP)[12], data envelopment analysis (DEA), and grey relational analysis (GRA)[13]. One of the prominent strategies employed in situations characterized by incomplete and uncertain information is the grey relational analysis (GRA), which was introduced by Deng in 1989 [14]. In their work, the authors applied the Grey Relational Analysis (GRA) technique alongside a Taguchi Orthogonal Array (OA) to identify the most optimal combination of process parameters for the Electrical Discharge Machining (EDM) process. The outcomes of their investigation showcased a significant elevation in grey relational grade, thereby confirming GRA's efficacy in enhancing the performance attributes of EDM [15]. Similarly, in the present study, a combined approach employing the Taguchi L9 orthogonal array and the Grey Relational Analysis (GRA) technique has been employed to optimize injection molding parameters [16]. Another study, carried out by Zou, S.Y. et al. [17], employed a blend of the Taguchi method and Grey Relational Analysis (GRA) to identify the critical factors impacting the surface treatment of concrete structures. Furthermore, Uthaya Kumar et al. [18] conducted an investigation involving multi-factor dry sliding wear experiments on AA6531 metal matrix composites (MMCs). The researchers employed the Grey Relational Analysis (GRA) method and a Taguchi L9 orthogonal array to analyse the data obtained from the experiments. Several other researchers have employed the Taguchi experimental design methodology, specifically utilizing the color grey, in order to identify the most optimal performing variables across a range of research problems. These researchers have achieved successful outcomes in their respective studies [19-23]. The objective of this research is to identify the material combination that yields the highest tensile strength, elevated hardness, and reduced density in the aluminum metal matrix composite.

II. Methodology

2.1 Process parameters and design of experiments

In order to produce the AMMC samples, the materials and its contribution are tabulated in Table 1, was selected from the past research. The experimental design for conducting the experiments was developed using the Taguchi orthogonal array methodology, with the assistance of MiniTab 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

Initially, the required quantity of matrix material is placed into the crucible, and the temperature is raised to 850°C, maintaining it at this level until the base material completely liquefies. Upon complete melting of the matrix material, a 1% concentration of the wetting agent magnesium (Mg) is introduced into the molten metal. Simultaneously, the reinforcement particles are gradually incorporated into the molten matrix material while undergoing stirring (refer to Figure 1), a process continued for five minutes. Following this, the resulting heterogeneous slurry is poured into separate preheated steel dies, allowing the creation of samples designated for subsequent testing. Conforming to the experimental design, the AMMC samples are fashioned as illustrated in Figure 2. These samples are then subjected to machining procedures in accordance with ASTM standards, as demonstrated in Figure 3. The use of a wire-cut EDM machine serves to preserve the intrinsic 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

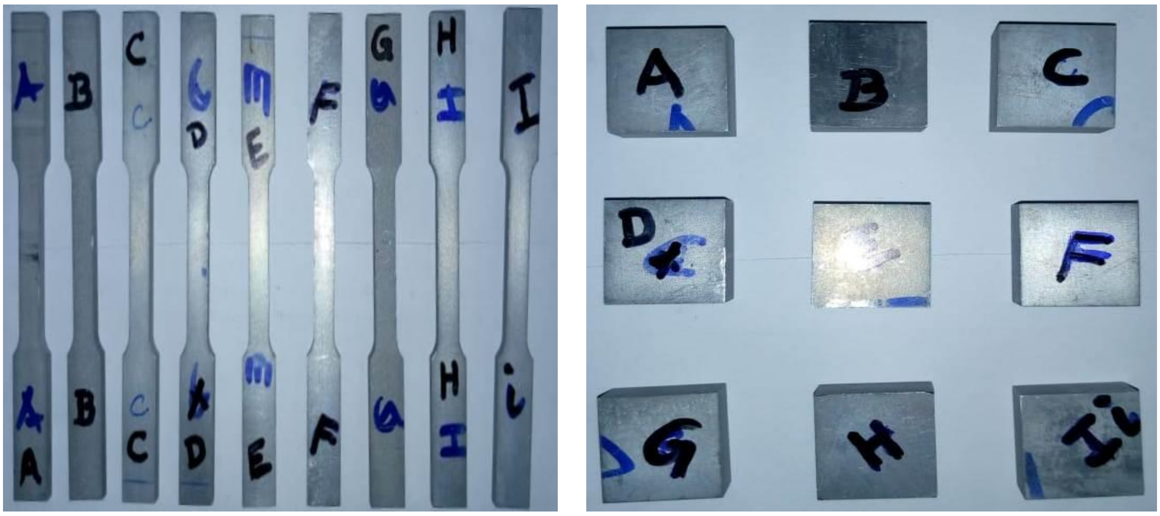

Fig 3. AMMC test samples as per ASTM standards

The prepared samples, in accordance with ASTM standards, endure testing using a universal testing machine (Fig 4), a Brinell hardness tester (Fig 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 analysed using grey relational analysis [24-25].

Fig 5. Universal Testing Machine

Fig 6. Brinell Hardness Tester

2.3 Optimization using GRA

Grey Relational Analysis (GRA) operates on a unique concept of information, categorizing situations without information as black and contrasting them with fully informed scenarios as white [26]. However, it's important to recognize that these theoretical extremes are seldom encountered in practical situations. More often, situations lie in between, labeled as ambiguous or indeterminate. Thus, a grey system denotes a system where both known and unknown information coexist. Within this framework, the quantity and quality of information span a spectrum from complete absence to comprehensive knowledge, symbolized as a continuum from black to white, with diverse shades of grey 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 grey 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:

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

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

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

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

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

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:

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

Where $i = 1\ldots, m; k = 1\ldots, n$. 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:

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

Where, Δ_{oi} is the Deviation sequence

$$\left.\begin{aligned} \Delta_{oi} &= \| x^*{}_o(k) - x^*{}_i(k) \| \\ \Delta_{\min} &= i^{min}_{\forall j \epsilon i} i^{min}_{\forall k} \| x^*{}_o(k) - x^*{}_j(k) \| \\ \Delta_{\max} &= i^{max}_{\forall j \epsilon i} i^{max}_{\forall k} \| x^*{}_o(k) - x^*{}_j(k) \| \end{aligned}\right\} \quad (6)$$

$x^*{}_o(k)$ Denotes the reference sequence and $x^*{}_i(k)$ denotes the comparability sequence. ζ is distinguishing or identification coefficient: ζ [0, 1] (the value may be adjusted based on the actual system requirements). A value of ζ *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:

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

The grey relational grade γ_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.

III. Results and Discussion

The results obtained from the conducted tests, as shown in Table 3, are utilized to assess the optimal mechanical and physical characteristics of AMMC through the GRA method. The GRA approach initiates by normalizing the experimental outcomes, incorporating equations from the data pre-processing stage, specifically Equations (1) to (4). Equations (1) and (2) hold a critical role in achieving optimal outcomes, standardizing properties such as tensile strength, hardness, and density. Manufacturers commonly prioritize materials with heightened tensile strength, hardness, and decreased 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)	Brinell Hardness Number (BHN)	Density (D) Kg/m^3
1	115	55.84	2786.40
2	136	67.47	2816.90
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 Equation (5) and Equation (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 equation (5) and equation (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

After the grey relational coefficient calculations are finalized for each response, the corresponding grey relational grade is computed for each factor at various levels. This procedure facilitates pinpointing the optimal level for each factor by considering their associated grey relational grade values. In the context of Grey Relational Analysis (GRA), it is noted that the influential factor with the highest grey relational grade value among its assessed levels signifies the optimum level. The material factors are evaluated and prioritized according to their delta values, aiding in the identification of the most influential factor for achieving optimal properties.

The ranking and mean values are presented in Table 5 and Figure 7, respectively.

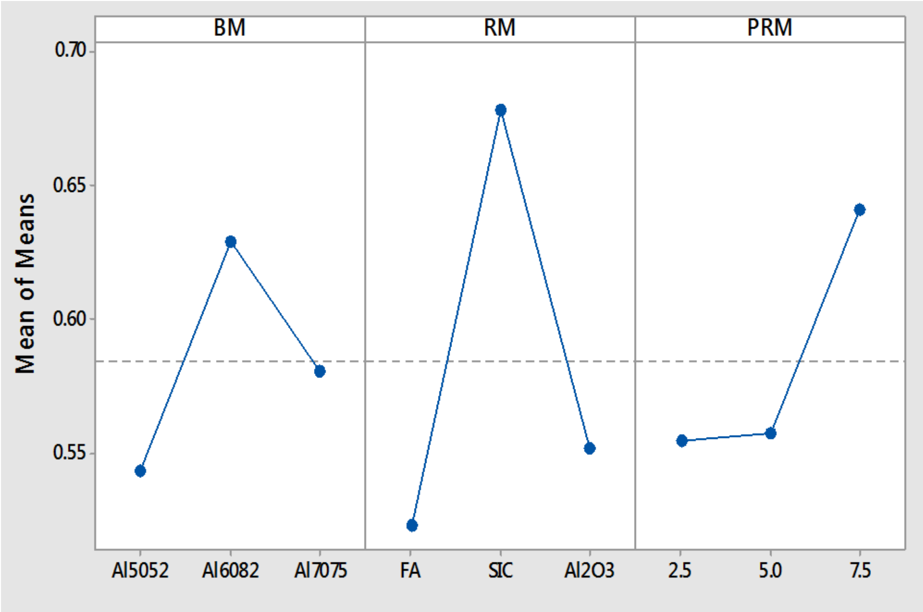

Fig 6. Grey relational grade values for each factor at each level

From the Figure 1 and Table 5, it is observed the optimum material combination for getting the optimal properties in aluminium metal matrix composites are:

Base Material at 3rd Level i.e., Al 6082

Reinforcement Material is at 2nd Level i.e., SiC

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

IV. Experiment Results

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 6, it can be observed that the confirmation results closely align with the original results.

Table 6. Confirmation test Results

Original experiment values				Confirmation results			
L_9 -Orthoganl combination	UTS	BHN	D	Optimum material combination	UTS	BHN	D
Al6082/7.5% SiC MMC	155	72.4	3007.5	Al6082/7.5% SiC MMC	149	74	3010

The surface of the fabricated AMMC sample, which possesses the optimal material combination, was examined through the utilization of scanning electron microscopy (SEM) images, as depicted in Figure 7. The observable phenomenon of reinforcement particle dispersion within the aluminium 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.

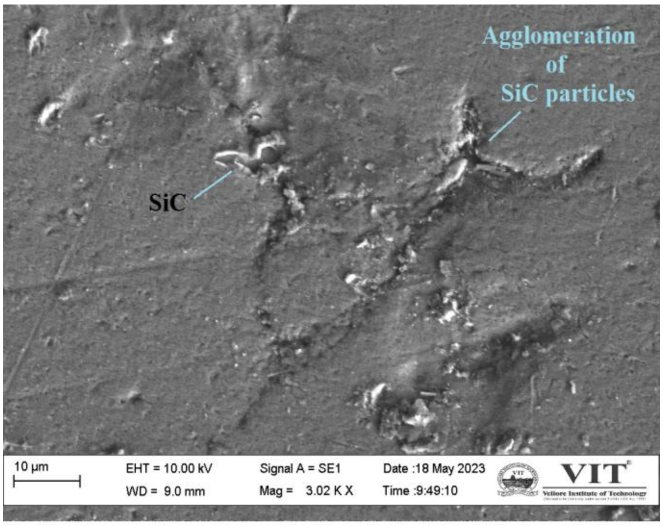

Fig 7. SEM image of fabricated AMMC sample

5. Conclusions

In summary, this study has extensively explored multiple aspects relevant to the subject under consideration. It intricately examined the procedure of enhancing material selection for aluminum metal matrix composites (AMMC) using the Grey Relational Analysis (GRA) methodology. The inquiry emphasized the significance of aluminum and its alloys in diverse sectors such as aerospace, marine, and automotive, showcasing their lightweight qualities and thermal attributes. Furthermore, the notion of Metal Matrix Composites (MMCs) was introduced, accentuating the integration of diverse metals, ceramics, or natural compounds to heighten material properties. Based on the findings from the confirmation results, it can be inferred that the stir casting process is a highly suitable method for the production of aluminium metal matrix composite samples. It obtained from the conducted experiments, it can be inferred that the incorporation of SiC particles leads to an enhancement in the properties of the aluminium alloy. 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 aluminium alloy. The GRA approach reveals that the reinforcement material has the most substantial impact on achieving optimal properties, followed by the percentage of reinforcement material and the base material. The presence of SiC particles contributes to an increase in the average hardness of the aluminum alloy, rendering it more brittle. The findings of this study suggest that incorporating SiC particles results in a higher density for the aluminum alloy. This emphasizes the significance of selecting optimal casting parameters to ensure a consistent dispersion of reinforcement materials. Furthermore, the research underscores that crucial factors in enhancing the properties of metal matrix composites (MMCs) include applying appropriate coatings to SiC particles, optimizing stirring speed, temperature, and particle feeding time.

References

[1] N. Fatchurrohman, I. Iskandar, S. Surya, K. John, "Sustainable analysis in the product Development of Al-Metal Matrix Composites automotive component" applied mechanics and materials, 2015 vol.695, pp.32-35.

[2] Mc. Danels, D. L. "Analysis of stress-strain, fracture and ductility behaviour of aluminium matrix composites containing discontinuous SiC reinforcement". Metall. Trans. A, 1985. Vol.16, pp. 1105-1115.

[3] Madhukar P, Selvaraj N & Rao C S P "Manufacturing of Aluminium Nano hybrid composites: a state of review", IOP Conf Series Mater. Sci. Eng, 2016, 149, 121-141.

[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, 38 484-494.

[5] Anand BABU Kumba, R. Jeyapaul, Bhiksha Gugulothu, S. Selvaraj, Varatharajulu M "A Retrospective Investigation on Hybrid Metal Matrix Composites: Materials, Processing Methods and Properties of Composites" Iranian journal of chemistry & chemical engineering (IJCCE), https://doi.org//10.30492/IJCCE.2022.553499.5327

[6] S.V.S. Narayana Murty, B. Nageswara Rao, B.P. Kashyap On the hot working characteristics of 6061Al–SiC and 6061–Al_2O_3 particulate reinforced metal matrix composites Composites science and technology 2003, 63, 119-135

[7] B. Vijaya Ramnath, C. Elanchezhian, RM. Annamalai, S.Aravind, T. Sri Ananda Atreya, V. Vignesh and C.Subramanian "Aluminium metal matrix composites - a review" Rev. Adv. Mater. Sci, 2014. 38 pp.55-60

[8] Shahin Soltani Rasoul Azari Khosroshahi Reza Taherzadeh Mousavian Zheng-Yi Jiang Alireza Fadavi Boostani Dermot Brabazon "Stir casting process for manufacture of Al–SiC composites Rare Metals, 2017, Volume 36, Issue 7, pp 581–590.

[9] D. C. Montgomery, Design and Analysis of Experiments, Wiley India, India.

[10] Bala Murgan Gopalsamy, Biswanath Mondal, Sukumal Ghosh "Taguchi method and ANOVA: An approach for process parameter optimization of hard machining while machining hardened steel", Journal of scientific and Industrial research, 2009, 68, p. 686.

[11] D. Philip Selvaraj, P. Chandramohan "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, p. 293.

[12] Anand Babu. K, Venkataramaiah. P, Saideepthi Yerrathota "Material Selection for Preparation of Aluminium Hybrid MMCs", Materials Today: Proceedings 5 (2018), 12209–12222.

[13] Pervez, M.N.; Shafiq, F.; Sarwar, Z.; Jilani, M.M.; Cai, Y. Multi-response optimization of resin finishing by using a taguchi-based grey relational analysis. Materials **2018**, 11, 426.

[14] Julong, D. Introduction to Grey System Theory. J. Grey Syst. **1989**, 1, 1–24.

[15] Prayogo, G.S.; Lusi, N. Application of Taguchi technique coupled with grey relational analysis for multiple performance characteristics optimization of EDM parameters on ST 42 steel. AIP Conf. Proc. **2016**, 1725.

[16] Pervez, H.; Mozumder, M.; Mourad, A.-H. 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, 710.

[17] Zou, S.Y.; Huang, R.; Chi, M.C.; Hsu, H.M. Factors affecting the effectiveness of inorganic silicate sealer material through multi-quality characteristics. Materials **2013**, 6, 1191–1204.

[18] Uthayakumar, M.; Kumaran, S.T.; Aravindan, S. Dry sliding friction and wear studies of fly ash reinforced AA-6351 metal matrix composites. Adv. Tribol. **2013**, 2013, 1–6.

[19] Ghosh, S.; Sahoo, P.; Sutradhar, G. Tribological Performance Optimization of Al-7.5% SiCp Composites Using the Taguchi Method and Grey Relational Analysis. J. Compos. 2013, 1–9.

[20] Kuram, E.; Ozcelik, B. Multi-objective optimization using Taguchi based grey relational analysis for micro-milling of Al 7075 material with ball nose end mill. Measurement **2013**, 46, 1849–1864.

[21] Kurt, M.; Hartomac, S.; Mutlu, B.; Köklü, U. Minimization of the Surface Roughness and Form Error on the Milling of Free-Form Surfaces using a Grey Relational Analysis. Mater. Technol. **2012**, 46, 205–213.

[22] Raykar, S.J.; Addona, D.M.D.; Mane, A.M. Multi-objective optimization of high speed turning of Al 7075 using grey relational analysis. Procedia CIRP **2015**, 33, 293–298.

[23] Lal, S.; Kumar, S.; Khan, Z.A.; Siddiquee, A.N. Multi-response optimization of wire electrical discharge machining process parameters for Al7075/Al2O3/SiC hybrid composite using Taguchi-based grey relational analysis. Proc. IMechE Part B J. Eng. Manuf. **2015**, 229, 229–237.

[24] Shivalingaiah, K.; Nagarajaiah, V.; Selvan, C.P.; Kariappa, S.T.; Chandrashekarappa, N.G.; Lakshmikanthan, A.; Chandrashekarappa, M.P.G.; Linul, E. Stir Casting Process Analysis and Optimization for Better Properties in Al-MWCNT-GR-Based Hybrid Composites. *Metals* 2022, *12*, 1297. https://doi.org/10.3390/met12081297.

[25] Kareem, A.; Qudeiri, J.A.; Abdudeen, A.; Ahammed, T.; Ziout, A. A Review on AA 6061 Metal Matrix Composites Produced by Stir Casting. *Materials* 2021, *14*, 175. https://doi.org/10.3390/ma14010175.

[26] S. S, A. S and K. D, "Optimization of Hardness and Tensile Strength of Stir Cast Hybrid Aluminum Metal Matrix Composite Using Grey Relational Analysis," *2022 International Conference on Computational Modelling, Simulation and Optimization (ICCMSO)*, Pathum Thani, Thailand, 2022, pp. 132-136, doi: 10.1109/ICCMSO58359.2022.00037.