Multi-Response Optimization of Mechanical Properties of Al reinforced by Al₂O₃ and/or SiC using Grey Relational Analysis

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ABSTRACT. Metal matrix composites (MMCs) combine attractive characteristics of ceramics and metals. Al- hybrid composites are a recent generation of MMCs and have the potential to satisfy new demands in advanced engineering applications. In this work, Al-MMC has been fabricated by mixing various percentages of Al₂O₃ and/or SiC reinforcement into the Al alloy, using stir casting. The mechanical properties (hardness, yield strength, tensile strength, elongation and flexural strength) have been measured for the fabricated MMCs. Grey relational analysis (GRA), based on the Taguchi method, is applied using three factors Al₂O₃, SiC and Al₂O₃+ SiC with three levels. Results show that the all reinforcement materials have a significant influence on the response. Results also show that the Taguchi-based grey relational approach improved the properties of output response of hybrid MMC.

Key word: Stir casting, hybrid composite, mechanical properties, optimization and grey relational analysis

1. Introduction

Metal matrix composites (MMCs) strengthened by ceramic particles are favorable materials for structural applications owing to their superior combination of properties. The properties of MMCs combine those of the metallic alloys (toughness and ductility) and the ceramic reinforcements (high modulus and high strength), leading to excellent profile of characteristics [1].

Hybrid metal matrix composites (HMCs) are characterized by toughness, impact strength, high specific strength and low sensitivity to changes of temperature. This makes them very attractive for use in in automobile and aerospace components. HMCs are made of discontinuous phase particle or fiber that is stiffer and stronger than the matrix (continuous phase). The desirable properties of these materials give them numerous potential applications in sectors such as aerospace, automotive and sporting goods industries [2]. Alumina (Al₂O₃), graphite (Gr), boron carbide (B₄C), Silicon carbide (SiC), (WC), (CNT) and (SiO₂) are some of the strengthening materials utilized, but SiC and Al₂O₃ are more typically used than other strengthening materials [3].

Aluminum MMCs have attracted great interest as engineering materials in recent decades. However, the use of a single reinforcement in Al matrix may sometimes lead to a decline in its physical properties. In order to overcome the drawback of single reinforced composites, the concept of using two different types of reinforcement in an Al matrix has been considered[4]. Al- MMCs enjoy widespread acceptance in aerospace, industrial and automotive applications due to their high strength, good structural rigidity and low density [5].

Researchers have studied and reported on aspects of the mechanical properties of MMCs with particulate reinforcement. Viswanatha B. M. et al [6] investigated the mechanical and physical properties and microstructure of an Al matrix supported with SiC and Gr particles. The addition of
silicon carbide particles made the tensile strength increase and decreased the percentage elongation. Vijaya R. B. et al [7] investigated mechanical properties and inferred that the TS of aluminum alloys are higher than in reinforced boron carbide samples, but the impact values of aluminum alloy are lower than the reinforced composite.

Raghavendra N. and Ramamurthy V. S. [8] developed a hybrid Al7075 metal matrix by using a varying weight percentage of Al2O3 and constant weight percentage of SiC. The results showed that when the weight fraction of reinforcement increased, this led to improve in the micro hardness. Rajesh A. M. et al [9, 10] experimentally studied the hardness, the behavior of wear at as-cast and conditions of age etc. on aluminum hybrid metal matrix composites. Al7075 was the matrix material and Al2O3 and SiC were reinforcement materials. The results showed that the HAMMCs have better properties as compared to unreinforced aluminum alloy.

Amit S. et al [11] used hybrid Taguchi-grey relational analysis (GRA)-entropy methodology to optimize the process parameters (reinforcement percentage, grain size and blade angle) on the response variables such as tensile strength and microhardness of Al2024/red mud MMC. Using ANOVA, the contribution of process parameters to the grey relational grades was evaluated. Confirmatory experiments were performed which showed that the proposed hybrid methodology can be successfully applied for enhancing performance of the stir casting process.

Muhammad H. S. et al [12] used a Box-Behnken experimental design which contained three process parameters (squeeze pressure, melt temperature and SiC wt.%) to optimize the squeeze casting process for fabricating Al 6061-SiC composite. The results indicated that squeeze pressure, melt temperature and SiC wt.% significantly affected the responses, whereas ductility was drastically reduced at higher concentrations of SiC reinforcement. The desirability analysis revealed optimum setting of process parameters, which was confirmed to have improved the ultimate tensile strength by 1.61%, hardness by 1.56%, and percentage elongation by 11.11% as compared to the initial setting.

In this paper, a Taguchi method is applied to conduct the experiments and a grey relational analysis (GRA) approach is used for development of a second-order polynomial model and optimize of hardness (BHN), yield strength (YS), ultimate tensile strength (UTS), ultimate compressive strength (UTC), elongation (e) and flexural strength (FS) of Al alloy reinforced with Al2O3 and/or SiC, with the type of reinforcement material (RM) and percentage of reinforcement particle (RM %) as input parameters.

2 Materials and method

2.1 Materials Used

Pure Al wire was used to establish the aluminum base composite. The chemical composition is presented in Table 1.

| Material | Si | Fe | Cu | Mn | Mg | Zn | Ti | B | V | Cr | Al |
|----------|----|----|----|----|----|----|----|---|---|----|----|

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To enhance the wettability of Al₂O₃ and SiC particles, Mg was included to the preparation of the composite by reducing its surface tension. Al₂O₃ and/or SiC with an average particle size of (25.88 μm) and (51.94 μm) respectively were used as reinforcement, as shown in Figure 1.

![Particle size distribution](image)

Fig. (1) shows particle size distribution of (a) Al₂O₃ and (b) SiC.

2.2 Material fabrication

The stir-casting method was used to produce the composite materials designed as in Table 2. The required amount of Al base material was poured into the crucible of graphite and the temperature raised to 750 °C, which was sustained until the base material had entirely melted. After melting of the aluminium base the reinforcement particles (SiC, Al₂O₃, and SiC + Al₂O₃) with various percentages of strengthening material (2, 4 and 6 % by wt) were covered with Al foil and preheated to 300 °C and then added step by step into the liquid metal. With the particles, 2.81 % of magnesium was also added to the molten aluminium, as a wetting agent. The influence of Mg diminished the surface tension of the aluminium and also increased the wetting properties between the Al and reinforcement materials in the molten stage. In this way, mixing and time of dispersion were also reduced to a large extent. The particles were dispersed uniformly in the molten aluminium alloy after 5 minutes of stirring at 650 °C and the mixing process was carried out in the presence of argon gas.

| Parameter | Designation | Unit | Coded/Actual levels |
|-----------|-------------|------|---------------------|
| Reinforcement material | A | --- | Al₂O₃, SiC, Al₂O₃ + SiC |
| Reinforcement Percentage | B | % | 2, 4, 6 |

2.3 Hardness test

Hardness testing was conducted using a Brinell hardness testing machine, and carried out according to ASTM E10-07 standards with a 500 Kg load and 10 mm ball indenter for 30 s. For each sample, the hardness measurement was taken at five different places, in order to get an average value for BHN.

2.4 Tensile test

Tensile testing of cylindrical specimens of composites was carried out in accordance with the ASTM E08-8 standard. To diminish the scratches of machining and the influences of defects on surface of the sample, SiC paper from a 1200 grit grinding was utilized to smooth the specimens. To conduct the tensile test, the universal testing machine (WDW instrument) was used and loaded with 10 KN load cell. At 2 mm/min cross head speed, tensile strength was calculated.
2.5 Compression test
Testing of compression was done at room temperature with a computerized universal testing machine (WDW instrument) and the ultimate compression strength was obtained according to ASTM E9-09 standards. The UTC was recorded carefully because it is a computerized machine. At 0.1 mm/min cross head speed, UTC was conducted.

2.6 Three-point bending test
This test investigated the particle-reinforced MMCs, because the particulate reinforcement makes the notch influence through testing. As machining of the surface of Al-MMCs is an extremely subtle and specialist process, the structure might be weakened. High speed diamond tools were used for machining.

Testing was carried out to discover the FS of aluminium with 2, 4 and 6 wt. % of Al$_2$O$_3$ and/or SiC composite: the maximum load of bending was estimated. This value of load was converted into flexural strength (MPa) value according to Equations (1–5).

The formula of FS is given as:

$$\sigma = \frac{M \times y}{I}$$  \hspace{1cm} (1)

Where \(\sigma\): the stress of the flexural; M: the moment of bending; y: the distance from the natural axis and I: the moment of inertia. The maximum flexural surface stress happens in the mid-point of the specimen.

Therefore:

$$M = \frac{P \times L}{4}$$  \hspace{1cm} (2)

$$y = \frac{t}{2}$$  \hspace{1cm} (3)

$$I = \frac{b \times t^3}{12}$$  \hspace{1cm} (4)

$$\sigma_{\text{max}} = \frac{(3 \times P \times L)}{(2 \times b \times t^3)}$$  \hspace{1cm} (5)

Where P: the load applied by the machine used in the test; t: the specimen thickness; b: the specimen breath, and L: the span length.

3. Results and discussion

3.1 Parametric Analysis of Responses
Parametric analysis of each variable on BHN, YS, UTS, UTC, e and FS tabulated in Table 3 and its corresponding analysis depicted in Figures 2 – 7.

| S. No | Reinforcement Material | Reinforcement Percentage | Brinell hardness BHN | Yield Strength MPa | Ultimate Tensile Strength MPa | Ultimate Compressive Strength MPa | Elongation % | Flexural strength MPa |
|-------|------------------------|--------------------------|----------------------|-------------------|-----------------------------|-----------------------------|--------------|---------------------|

Table 3. Matrix and assessed mechanical properties.
The behaviour of hardness of the composites is shown in Figure 2. The BHN increased when weight percentage of reinforcements increased and reached a maximum at 4 wt. % reinforcement, then decreased with increase in the addition percentage of the reinforcement for Al reinforced by Al$_2$O$_3$ and/or SiC. Also, hardness increased with the addition of reinforcement materials, because the hardness of SiC is higher than the hardness of Al$_2$O$_3$.

The increase in the percentage of the reinforcements and reinforcement materials (Al$_2$O$_3$ and/or SiC) caused increases in YS, as shown in Figure 3. The improved YS was due to the energy dissipation mechanism of SiC & Al$_2$O$_3$ fillers. The ultimate tensile strength behaviour of the composites was similar to the yield strength behaviour in terms of materials and the percentage of reinforcement for the same reason, as shown in Figure 4. The UTC behaviour of the MMCs was similar to the hardness behaviour in terms of materials and the percentage of reinforcement. This may be due to the fact that the base and reinforcement materials will resist the compression to the amount of 4% and thus will increase the UTC. Thereafter, will break down reinforcement materials due to their brittleness, and this leads to decrease in the UTC. Figure 5 illustrates.

The behaviour of the elongation for MMCs is quite opposite to the yield strength behaviour in terms of the percentage of the reinforcement, but it decreases then increases with reinforcement materials (decreases from Al$_2$O$_3$ to SiC then increases with Al$_2$O$_3$ + SiC) due to increased hardness with the increase of reinforcing materials, as mentioned above, in addition to increasing the brittleness with increasing the percent of reinforcing materials which reduces the elongation as shown in Figure 6.

Finally, the behaviour of the FS is similar to the YS and UTS behaviour in terms of materials and the percentage of reinforcement for the same reason and as shown in Figure 7.
3.2 Modelling of Performance characteristics

Performance characteristics like BHN, YS, UTS, UTC, e and FS have been utilized to estimate the influence of input parameters (reinforcement material and reinforcement percentage) according to a Taguchi design orthogonal array (OA). The acquired results of total 9 runs are shown in Table 3. Equations 6–11 shown below are the predicted regression models for calculating output (BHN, YS, UTS, UTC, e and FS). Equations of output are developed with 95% confidence levels.

\[
BHN = 26.3276 + 5.1477 \times A + 18.9733 \times B + 0.1487 \times A^2 - 3.8393 \times B^2 - 1.0175 \times A \\
\times B ........................................................ (6)
\]

\[
YS = 98.0339 - 6.6557 \times A + 3.5098 \times B + 2.6902 \times A^2 - 0.1323 \times B^2 + 0.8918 \times A \\
\times B ........................................................ (7)
\]

\[
UTS = 106.067 + 2.582 \times A + 1.892 \times B - 0.185 \times A^2 - 0.135 \times B^2 + 0.755 \times A \\
\times B ........................................................ (8)
\]

\[
UCS = 111.060 + 4.672 \times A + 21.827 \times B - 0.225 \times A^2 - 5.070 \times B^2 + 0.125 \times A \\
\times B ........................................................ (9)
\]

\[
e\% = 5.86333 - 0.91333 \times A - 1.75333 \times B + 0.19500 \times A^2 - 0.23500 \times B^2 - 0.01750 \times A \\
\times B ........................................................ (10)
\]

\[
FS\% = 144.167 + 7.917 \times A + 42.500 \times B + 0.250 \times A^2 - 8.000 \times B^2 - 0.500 \times A \\
\times B ........................................................ (11)
\]
3.3. Checking the sufficiency of the model

The adequacy of the model so developed is then assessed by use of the analysis of variance technique (ANOVA). Using the ANOVA technique, it can be noted that, as illustrated in Table 4, all of the quadratic regression models are important (0 < p-value < 0.05) and thus, every one of the models adequately illustrates the experimental data.

| Source                  | DF | Seq SS  | Adj SS  | Adj MS  | F      | P      |
|-------------------------|----|---------|---------|---------|--------|--------|
| For hardness            |    |         |         |         |        |        |
| A                       | 2  | 82.510  | 82.510  | 41.255  | 38.81  | 0.002  |
| B                       | 2  | 44.478  | 44.478  | 22.239  | 20.92  | 0.008  |
| Residual Error          | 4  | 4.252   | 4.252   | 1.063   |        |        |
| Total                   | 8  | 131.241 |         |         |        |        |
| For yield stress        |    |         |         |         |        |        |
| A                       | 2  | 222.521 | 222.521 | 111.260 | 110.53 | 0.000  |
| B                       | 2  | 136.209 | 136.209 | 68.105  | 67.66  | 0.001  |
| Residual Error          | 4  | 4.027   | 4.027   | 1.007   |        |        |
| Total                   | 8  | 362.756 |         |         |        |        |
| For Ultimate Tensile Strength | |         |         |         |        |        |
| A                       | 2  | 67.470  | 67.470  | 33.735  | 44.34  | 0.002  |
| B                       | 2  | 49.171  | 49.171  | 24.585  | 32.32  | 0.003  |
| Residual Error          | 4  | 3.043   | 3.043   | 0.760   |        |        |
| Total                   | 8  | 119.685 |         |         |        |        |
| For Ultimate Compressive Strength | |         |         |         |        |        |
| A                       | 2  | 97.144  | 97.144  | 48.572  | 44.51  | 0.002  |
| B                       | 2  | 70.778  | 70.778  | 35.389  | 32.43  | 0.003  |
| Residual Error          | 4  | 4.365   | 4.365   | 1.091   |        |        |
| Total                   | 8  | 172.287 |         |         |        |        |
| For Elongation          |    |         |         |         |        |        |
| A                       | 2  | 0.13407 | 0.13407 | 0.06703 | 30.94  | 0.004  |
| B                       | 2  | 3.74527 | 3.74527 | 1.87263 | 864.29 | 0.000  |
| Residual Error          | 4  | 0.00867 | 0.00867 | 0.00217 |        |        |
| Total                   | 8  | 3.88800 |         |         |        |        |
| For Flexural strength   |    |         |         |         |        |        |
| A                       | 2  | 590.17  | 590.17  | 295.083 | 885.25 | 0.000  |
| B                       | 2  | 921.50  | 921.50  | 460.750 | 1382.25 | 0.000  |
| Residual Error          | 4  | 1.33    | 1.33    | 0.333   |        |        |
| Total                   | 8  | 1513.00 |         |         |        |        |

The coefficient of determination (R²) is another criterion that is generally used to explain the adequacy of a predicted regression model. For the models, the calculated R² values are 96.80%, 98.9%, 97.5%, 97.5%, 99.8% and 99.9% for BHN, YS, UTS, UTC, e and FS respectively, as shown in Table 5. Values indicate that the regression models are quite adequate.

Table 5: R² Test for BHN, YS, UTS, UTC, e and flexural strength regression model.

| Output            | hardness | yield stress | Ultimate Tensile Strength | Ultimate Compressive Strength | Elongation | Flexural strength |
|-------------------|----------|--------------|__________________________|______________________________|------------|------------------|
| R² (%)            | 96.8     | 98.9         | 97.5                      | 97.5                        | 99.8       | 99.9             |

3.4 Optimization by Grey Relational Analysis Method
In this part, the Taguchi design orthogonal array (OA) was utilized with the grey relation analysis (GRA) in order to get the optimal parameters. The process is given in the following sections.

### 3.4.1 Data Pre-Processing

In grey relation analysis, data pre-processing is helpful because the unit and range in one data sequence might vary from others. Data pre-processing is important when the target directions in the sequence are various, or when the range of sequence scatter is too large. Data pre-processing is a transferring procedure, of the original to a similar sequence. For that reason, experimental results are normalized in the range between zero and one. Based on the data sequence characteristics, data pre-processing has various methodologies that can be presented for the GRA.

Response or output can be converted into the comparative series according to equations 12 “larger-the-better” characteristics.

\[ x_i^*(k) = \frac{X_i(k) - \min X_i(k)}{\max X_i(k) - \min X_i(k)} \]  

(12)

where, \( x_i^*(k) \) and \( x_i(k) \) are the sequence after the data pre-processing and comparability sequence respectively, \( \min x_i(k) \) is the smallest value of \( x_i(k) \) for the \( k^{th} \) response, and \( \max X_i(k) \) is the largest value of \( X_i(k) \) for the \( k^{th} \) response, \( k=1,2,3,4,5 \) and 6 for hardness, YS, UTS, UCS, e and flexural strength; \( i=1,2,3,..,9 \) for the numbers of experiment 1 to 9. Every one of the sequences of each performance characteristic after data preprocessing utilizing Equation 6 is shown in Table 6.

| S. No. | BHN (MPa) | YS (MPa) | UTS (MPa) | UCS (MPa) | e (%) | fs (MPa) |
|-------|-----------|----------|-----------|-----------|-------|----------|
| Reference Sequence | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| 1     | 0         | 0        | 0         | 0         | 1     | 0        |
| 2     | 0.488064  | 0.216709 | 0.230769  | 0.346667  | 0.414894 | 0.435294 |
| 3     | 0.376274  | 0.369331 | 0.346535  | 0.230476  | 0.132979 | 0.517647 |
| 4     | 0.336754  | 0.142144 | 0.269612  | 0.269841  | 0.787234 | 0.211765 |
| 5     | 0.73377   | 0.340938 | 0.461538  | 0.654603  | 0.292553 | 0.670588 |
| 6     | 0.570815  | 0.538144 | 0.654227  | 0.461587  | 0.013297 | 0.752941 |
| 7     | 0.701601  | 0.468886 | 0.423458  | 0.423492  | 0.867021 | 0.435294 |
| 8     | 1         | 0.719612 | 0.685453  | 1         | 0.329787 | 0.917647 |
| 9     | 0.781659  | 1        | 1         | 0.685714  | 0.037234 | 1        |

Now, \( \Delta_0(k) \) is the deviation sequence of the reference sequence \( x_0^*(k) \) and the comparability sequence \( x_i^*(k) \), i.e.

\[ \Delta_0(k) = |X_0(k) - X_i^*(k)| \]  

(13)

Using Eq. 13 the deviation sequence \( \Delta_0(k) \) can be computed and the outcomes are clear in Table 7.

| S. No. | \( \Delta_0(1) \) | \( \Delta_0(2) \) | \( \Delta_0(3) \) | \( \Delta_0(4) \) | \( \Delta_0(5) \) | \( \Delta_0(6) \) |
|-------|------------------|------------------|------------------|------------------|------------------|------------------|
| Reference Sequence | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Exp. No. 1 | 1 | 1 | 1 | 1 | 0 | 1 |
| Exp. No. 2 | 0.511936 | 0.783291 | 0.769231 | 0.653333 | 0.585106 | 0.564706 |
Exp. No. 3 0.623726 0.630669 0.653465 0.769524 0.867021 0.482353
Exp. No. 4 0.663246 0.857856 0.730388 0.730159 0.212766 0.788235
Exp. No. 5 0.266230 0.659062 0.538462 0.345397 0.707447 0.329412
Exp. No. 6 0.429185 0.461856 0.345773 0.538413 1 0.247059
Exp. No. 7 0.298399 0.531114 0.576542 0.576508 0.132979 0.564706
Exp. No. 8 0 0.280388 0.314547 0 0.670213 0.082353
Exp. No. 9 0.218341 0 0 0.314286 0 0

3.4.2 Grey Relational Coefficient (GRC) and Grey Relational Grade (GRG)

After data pre-processing is performed, GRC is computed from the normalized data to establish a relationship between the preferred and real data. The GRC is known as follows:

\[ \xi_i(k) = \frac{\Delta_{\min} + \xi \Delta_{\max}}{\Delta_0(k) + \xi \Delta_{\max}} \]

The identification or distinguishing coefficient, (ξ), has been utilized to make up for the influence of the data series and is characterized between zeros to one. (ξ) Value has been taken equal to 0.5. The GRC for each experiment OA is shown in Table 8.

Table 8: Grey relational grade and its order in the optimization.

| S. No. | Grey Relational Coefficient | Grey Relational Grade |
|-------|-----------------------------|-----------------------|
|       | BHN | YS | UTS | UCS | e | fs | \[ \xi_i = \frac{1}{n} (\xi_i(1)+ \xi_i(2)+ \xi_i(3)+ \xi_i(4)+ \xi_i(5)+ \xi_i(6)) \] |
| 1     | 0.333333 | 0.333333 | 0.333333 | 0.333333 | 1 | 0.333333 | 0.444444 | 7 |
| 2     | 0.494102 | 0.389623 | 0.393939 | 0.433526 | 0.460784 | 0.469613 | 0.440265 | 8 |
| 3     | 0.449498 | 0.442216 | 0.433477 | 0.393848 | 0.365759 | 0.508982 | 0.431538 | 9 |
| 4     | 0.429832 | 0.368228 | 0.406376 | 0.406452 | 0.701492 | 0.388128 | 0.450085 | 6 |
| 5     | 0.652546 | 0.431383 | 0.481481 | 0.591438 | 0.414097 | 0.602837 | 0.528964 | 4 |
| 6     | 0.538106 | 0.519828 | 0.591715 | 0.481504 | 0.333333 | 0.699291 | 0.522206 | 5 |
| 7     | 0.626253 | 0.484912 | 0.46445 | 0.464465 | 0.789916 | 0.469613 | 0.549935 | 3 |
| 8     | 1 | 0.640707 | 0.613838 | 1 | 0.427273 | 0.858586 | 0.756734 | 2 |
| 9     | 0.696048 | 1 | 1 | 0.614035 | 0.341818 | 1 | 0.775317 | 1 |

After getting the GRC, and by averaging the GRC corresponding to every response, the GRG is calculated. The overall evaluation of the multiple responses (output) is dependent on the GRG, that is:

\[ \gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \]

Where \( \gamma_i \) the GRG for the \( i^{th} \) experiment and \( n \) is the output number or responses. Table 8 displays the GRG for each experiment. When the GRG higher it is explained that the corresponding response is close to the optimum normalized value. Thus, because the experiment number 9 has the highest GRG it is the optimal among nine experiments.

Then it is simple to isolate the impact of every input parameter on the GRG at various levels since the design of experiments is orthogonal, as shown in Table 9.
Figure 8 displays the GRG obtained for different conditions. The mean of the GRG for principally, the larger the GRG is, the quality of the product will be nearer to the optimum value. So, the larger GRG is coveted for optimum performance. Therefore, A3B3 as presented in Table 9 denotes the optimum parameters which signify large percentages of reinforcement material and reinforcement. The level with the maximum GRG is an optimal level of the process parameters.

Table 9: Response table for the grey relational grade.

| Symbol | Parameters       | Grey Relational Grade | Main effect (max.-min.) | Rank |
|--------|------------------|------------------------|-------------------------|------|
|        |                  | Level 1 | Level 2 | Level 3 |                  |      |
| A      | Reinforcement material | 0.438749 | 0.5004183 | 0.6939953 | 0.2552463 | 1     |
| B      | Reinforcement percentage | 0.481488 | 0.575321 | 0.5763537 | 0.094866 | 2     |

Total mean value of the grey relational grade $\gamma^m = 0.544388$

* Levels for optimum GRG

3.4.3 Confirmation test

Testing was done to prove the enhancement in the performance characteristics in mechanical properties of Aluminium strengthened by Al2O3 and/or SiC. The optimum parameters are chosen for the test as shown in Table 10. The assessed grey relational grade $\hat{\gamma}$ utilizing the optimal level of the parameters can be obtained utilizing this equation.

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q} (\gamma_i - \gamma_m)$$

Where $\gamma_m$ the grey relational grade total mean, $\gamma_i$ is the mean of the grey relational grade at the optimal level and q is the process parameter number that will significantly influence multiple-performance characteristics.
The input parameters that were obtained, which give greater grey relational grade, are shown in Table 10. The predicted BHN, YS, UTS, UTC, e, FS and GRG for the optimal parameters are acquired utilizing Equation 16 and also displayed in Table 10, which gives the comparison of the experimental results and predication optimal (grey theory prediction design, A3B3) input parameters. Table 10 shows that the BHN, YS, UTS, UTC, e and FS are enhanced from 56.400, 119.995, 123.730, 143.520, 1.870, and 230.000 to 59.312, 120.858, 125.130, 146.210, 2.185 and 232.230. The corresponding improvements in BHN, YS, UTC, e and FS are 6.5%, 3.11%, 3.43%, 4.45%, 14.4% and 2.22% respectively. In the process, it has obviously been demonstrated that the characteristics of multiple performances have been highly improved during this study.

Table 10: Improvements in grey relational grade with optimized parameters.

| Condition description                  | Optimal mechanical properties |
|----------------------------------------|-------------------------------|
|                                        | Experimental | Prediction         |
| Hardness (BHN)                         | 59.312       | 56.400             |
| Yield Strength (MPa)                   | 120.858      | 119.995            |
| Ultimate Tensile Strength (MPa)        | 125.130      | 123.730            |
| Ultimate Compressive Strength (MPa)    | 146.210      | 143.520            |
| Elongation %                           | 2.185        | 1.870              |
| Flexural Strength (MPa)                | 232.230      | 230.000            |
| GRG                                    | 0.423401     | 0.544384           |

Improvement in grey relational grade = 0.120987

4. Conclusions
1. The stir casting process can be successfully used to produce single or hybrid metal matric composites.
2. Better mechanical properties (BHN, YS, UTS, UTC, e and FS) were obtained with the stir casting fabricated with reinforcement material (Al2O3 + SiC) and reinforcement percentage (6%).
3. The relationships between input parameters for reinforcement material and reinforcement percentage have been established. We adopted GRA methodology to improve the models of regression, which were tested for their adequacy using scatter diagrams and ANOVA test and found to be satisfactory.
4. The experiment reveals the best combination of factors and anticipated values were close to the observed values.
5. Multiple performance characteristics can be easily converted into the GRG by this approach, thus simplifying the analysis.
6. The outcomes show that the optimal condition, dependent on the method, can offer better overall quality.

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