Hybrid combination of Taguchi-GRA-PCA for optimization of wear behavior in AA6063/SiCp matrix composite

Narinder Kaushik and Sandeep Singhal

Department of Mechanical Engineering, National Institute of Technology, Kurukshetra, India

ABSTRACT

The present work examined is centered on creation of aluminium alloy AA6063/SiCp metal matrix composites by liquid metallurgy stir casting route and optimization of wear properties by utilizing Taguchi-based GRA integrated with PCA approach. The AMCs are created in three diverse wt. % (3.5 wt %, 7 wt % and 10.5 wt %) of SiC reinforcement particles. The exploratory runs to examine the wear performance are executed as per L9 Taguchi plan to acquire the wear information in a controlled way. The wear loss data in terms of height loss are acquired using pin-on-disc tribometer attached with LVDT arrangement. Impact of three control factors, load (N), sliding distance (m) and wt. % of SiC (%) on the performance characteristics such as wear rate, frictional force and specific wear rate in unlubricated dry sliding conditions is inspected to obtain the optimum level of the process parameters. Analysis of variance (ANOVA) test was performed to analyze the impact of three control factors on wear rate, frictional force and specific wear rate. Experimental analysis revealed that the wear behavior is enhanced under optimum experimental states. Optical microscopic examinations of the worn out samples is also conducted to describe the wear mechanism of the matrix composites.

1. Introduction

Metal matrix composites (MMCs) created by introduction of hard and intense fired particles, for example, titanium carbide, silicon carbide, aluminum oxide and so forth into al-compounds achieve phenomenal mechanical properties when contrasted with monolithic al-compounds. MMCs fortified with ceramic agents have great scope of uses in automotive components, aerospace applications, defense applications, electronic parts and architectural components and so forth. These created composite materials have light weight and gained better hardness which makes it as wear resistant structural material in stack conveying applications. MMCs are manufactured to vanquish these inadequacies and to experience the overall want for light weight materials escorted by high specific strength, excellent wear resistance and high stiffness (Kaushik & Singhal, 2017; Lopez, Scoles, & Kennedy, 2003; Tokaji, 2005). The properties of aluminum compound like low density, light weight, simple assembling technique and great mechanical properties favored it as
network material in MMC's (Khan, Kutty, & Surappa, 2006). The wear execution examination of AA6061+SiC composite when subjected to normal applied load and temperature demonstrated that wear rate lessens with expansion in applied load (Yu, Ishii, Tohgo, Cho, & Diao, 1997). The dry sliding wear examination of al matrix alloy strengthened with silicon carbide whiskers (from 0% to 16%) detailed that the wear rates of the manufactured composite bit by bit decreases with the expansion in vol. % of SiC whiskers into the matrix compound (Iwai, Yoneda, & Honda, 1995). The impact of hardness on the wear execution of AA7075/20 vol. % Al2O3 composite demonstrated that the protection from wear of the composite material is enormously increased by the inclusion of 20 vol. % of SiC ceramic agents (Straffelini, Bonollo, Molinari, & Tiziani, 1997). The phenomenon of wear arises when a tough irregular surface slips over a smooth and delicate surface, bringing about material loss. Seriousness of the wear is specifically obvious in automotive parts, architectural components, agricultural goods and earth mover units. Grating wear happens when a hard unpleasant surface slides over a delicate surface, bringing about material loss.

It has been reported that the grating wear rate of AA2124 composites reinforced with SiC particles was increased with increase in applied normal loads. The matrix composites reinforced with SiC grating particles demonstrated higher wear rate than those reinforced by Al2O3 particles because of higher hardness of SiC abrasives (Izci, & Muratoglu, 2003). It was detailed that AA2104 matrix composites reinforced with Al2O3 particles has shown lower wear rate for all experimental states than the unreinforced AA2104 matrix alloy. The work hardening phenomenon experienced by matrix phase and the dispersion of hard SiC agents was responsible for low wear rate (Modi, 2001). The abrasive wear rate of Al–0.86Mg–0.46Si–0.15Cu + Al2O3 composites examined for against 125 mm grating paper was higher contrasted with wear rate got when tried with 65 mm SiC grating paper. Aluminum compounds with bigger Al2O3 particle size have been more powerful against grating wear than those with small sized Al2O3 particles (Yilmaz & Buytoz, 2001). The statistical strategies have usually been utilized for investigation, expectation and advancement of various engineering operations. Such techniques empower the researchers to characterize and think about the impact of each and every condition conceivable in an analysis, especially when various components are included. A synopsis of literature survey on the statistical techniques utilized for contemplating the tribological conduct is introduced here.

A factorial plan of trials has been utilized to create linear equations for anticipating wear rate of AA2011+SiC composites. Set up conditions showed that 10 and 15 wt% SiC composites displayed higher wear oppose than that of the unreinforced AA2011 al-alloy. The wear rate of both reinforced matrix composites and unreinforced al-alloy increased with increasing grating size, normal load but lowered with the increase in sliding distance. The reinforcement particle size followed by normal load was observed to be the most significant parameter among other various parameters. Although the applied load was found predominant parameter escorted by particle size in case of unreinforced alloy, the interaction between grating particle size and normal load was observed to be more remarkable for both composites and unreinforced alloy (Sahin & Özdin, 2008). The Taguchi strategy to explore the grating wear conduct of Al2O3 particle fortified AA2024 matrix composites under various experimental states has been performed. The results demonstrated that
fortification particle size was observed to be the most affecting component on grating wear, trailed by rough grain measure. Wear rate of the composites increased with increasing rough grain estimate and normal load, while it diminished with increasing fortification size and sliding distance (Kök, 2011). Utilizing central composite plan the dry sliding wear conduct of Al–Si7Mg composites strengthened with graphite and 10% SiC particles was carried out. The impact of % fortification, sliding velocity, sliding distance and normal load, on stir cast AA+graphite, AA+SiC composite and AA+SiC+Gr hybrid composites was examined. The results demonstrated that hybrid composites display better wear qualities (Suresha & Sridhara, 2010). The wear execution of electroless Ni–P coatings and optimization of the wear test variables utilizing Taguchi technique combined with grey relational analysis was performed. GRG (grey relational grade) acquired from GRA has been applied as performance indicator to examine the conduct of electroless Ni–P coating regarding friction and wear qualities (Sahoo & Pal, 2007).

In present experimental work Taguchi based multi response optimization GRA technique coupled with principal component analysis (PCA) was applied to examine the wear behavior of the fabricated composites. Examinations were conducted for AA6063/3.5 wt. % SiC, AA6063/7 wt. % SiC and AA6063/10.5 wt. % SiC as-cast matrix composites. The three process variables chosen in this study are normal applied load, sliding distance and wt. % SiC. The effect of these three process variables on the response characteristics such as wear rate, frictional force and specific wear rate was analyzed to acquire the optimal level of the process variables. ANOVA test was also implemented to obtain the percentage contribution of each process variable towards the response characteristics. The worn surface morphology analysis of the worn out fabricated composite specimens was done to study the wear mechanism using optical microscope (OM) is also described.

2. Experimental method

2.1. Materials and methods

In this test work AA6063 al-matrix alloy, hard and tough SiC reinforcement particle and Mg metal powder as wetting agent has been utilized as base raw materials to produce aluminum matrix composites. Magnesium (0.45–0.9%) and silicon (0.2–0.6%) are the primary alloying components in AA6063 and that is the reason it is known as Mg-Si compound. The other alloying components are iron (0.35%), copper (0.1%), manganese (0.1%), zinc (0.1%), titanium (0.1%), and chromium (0.1%) in little rates by wt. percentage. The AA6063 matrix alloy is utilized in several fields like architectural components, irrigation piping due to excellent corrosion resistant properties, railway parts and general engineering applications. Silicon carbide (SiC) in particulate form having 37µm particle size was utilized as strengthening agent which is utilized as a grating in numerous applications. SiC is utilized as a part of many fields, like in auto brakes, grips and electronic industry for making LEDs and locators. SiC is broadly utilized as a part of semiconductor electronic parts that work at raised temperature extend.
The upgraded double step fluid preparing Stir casting strategy has been used for the advancement of AA6063/SiC matrix composites (Alanemeaψ & Alukob, 2012; Fatile, Idu, & Sanya, 2015). An electric resistance furnace was utilized for the liquefying of matrix alloy. The melting was completed under inert atmosphere using argon gas. AA6063 into a graphite crucible inside the furnace was liquefied up to temperature 810°C to guarantee the total liquefying of matrix alloy. At this stage preheated (in a separate furnace) SiC particles at temperature 900°C were fused with a uniform rate into the liquid dissolve and dynamic mixing at 450rpm was completed to shape a fine vortex (Hashim, Looney, & Hashmi, 1999; Sevik & Kurnaz, 2006). To improve the wettability of the slurry blend magnesium metal powder (1% by wt.) was blended into the liquid slurry amid vortex mixing. Dynamic mixing of the liquid slurry was completed utilizing a graphite impeller for 15 min at a normal speed of 450 rpm to guarantee a total blending of the reinforcement SiC particles into the dissolve. Two stage blending technique was utilized to guarantee an intensive blending and to conquer issues of agglomeration of support particles into the liquid slurry. The composite slurry at this stage was warmed at temperature 750 ± 30°C as the temperature drops down amid blending. As of now mechanical torque was again given by stirrer and the composite slurry was turned for 5 min at a similar normal speed. The composite slurry (3.5%, 7% and 10.5 wt. %) was then solidified into preheated (at 250°C) cast iron mould to get rectangular as cast composite specimen. The SEM/OM image of AA6063 matrix composite reinforced with 10.5 wt. SiC is shown in Figure 1.

Figure 1. OM and SEM image of as cast AA6063 AMC reinforced with 10.5 wt. % SiC.

2.2. Pin on disc wear examinations

The wear studies on matrix composite samples strengthened with 3.5 wt. %, 7 wt. % and 10.5 wt. % have been directed in unlubricated dry slippery conditions on pin- on-disc tribometer [DUCOM (TR-20LE)]. The test set up was comprise of a rotary plate made of material EN-31 steel with hardness estimation of 62HRC and has 100mm diameter and10mm thickness (in Figure 2 (a,b)). Pin- on- disc tribometer was microprocessor

Figure 1. OM and SEM image of as cast AA6063 AMC reinforced with 10.5 wt. % SiC.
controlled, in which height loss and frictional force has been recorded simultaneously. The rectangular pin test specimens (Figure 3) of size $32 \times 6 \times 6$ mm have been squeezed against the counter face rotating plate. A load lever was swiveled near the load sensor for putting the dead weights. The specimens to be analyzed were fine cleaned to make level flat before start of wear investigation and grasped against the rotary counter face plate. For the wear testing three input process factors at three levels were selected as appeared in Table 1. Composite samples have been exposed to dry slippery wear tests at room temperature in agreement with Taguchi L$_{9}$ orthogonal array as appeared in Table 2. Provision of LVDT (linear variable differential transformer) with precision of 1µm throughout the wear testing persistently gained the wear statistics in terms of displacement in micrometer of the test specimen. Wear displacement sensor grants for getting immediate readings of the deflection because of load lever, which are analogous to the wear of the test samples. The wear conduct is generally demonstrated as wear volume or weight reduction and the wear rate was computed from height loss estimations by applying the formula:

\[
\text{Volumetric loss} = \text{Height loss} \times \text{cross sectional area of pin}
\]

\[
\text{Wear rate (WR)} = \frac{\text{Volumetric loss}}{\text{Sliding distance}} \quad \text{mm}^3 \text{m}^{-1}
\]

\[
\text{Specific wear rate (Sp.WR)} = \frac{\text{Wear rate}}{\text{Load}} \quad \text{mm}^3 \text{Nm}^{-1}
\]

Figure 2. Pin-on-disc wear and fiction monitor set-up.

Figure 3. Wear testing rectangular pin type specimens.
Numerous specialists have utilized diverse statistical tools for optimization of wear properties of casted composite materials. Taguchi approach is a standout among the most helpful systems for single objective optimization utilized for various designing issues (Ghetiya et al., 2016; Gupta & Kumar, 2013; Kaushik & Singhal, 2017; Kundu & Singh, 2016; Kuram & Ozcelik, 2013; Singh, Raghukandan, & Pai, 2004; Tosun, 2006). In the present situation of quick assembling and cost lessening with most extreme usage, complex procedures have a few quality attributes. In such circumstances, a few multi-objective optimization strategies are required and the Taguchi-based grey relational analysis (GRA) integrated with PCA is utilized as a part of the present investigation. The Taguchi technique in this study has been used to draft experimental runs based on orthogonal array. Taguchi technique utilizes a statistical calculation of performance recognized as S/N ratio (signal to noise ratio) for investigating the results. The signal to noise ratio is an estimation of performance to generate techniques that are unresponsive to noise components in a controlled way. In this study all the response or performance characteristics, such as wear rate (WR), frictional force (FF) and specific wear rate (Sp. WR) are of ‘smaller-is – better’ type and therefore S/N (K) ratio was calculated using Equation (1). The S/N (K) ratio in Taguchi technique is calculated using following equations:

\[
K_{ij} = -10 \log_{10} \left( \frac{1}{n} \sum_{j=1}^{n} y_{ij}^2 \right) \quad (smaller \quad is \quad better)
\]

Equation (1)

\[
K_{ij} = -10 \log_{10} \left( \frac{1}{n} \sum_{j=1}^{n} \frac{1}{y_{ij}^2} \right) \quad (larger \quad is \quad better)
\]

Equation (2)

### Table 1. The input process factors and their levels.

| Sr. No. | Input process factors | Symbol | 1     | 2     | 3     |
|---------|-----------------------|--------|-------|-------|-------|
| 1.      | Normal applied load (N) | L      | 20    | 30    | 40    |
| 2.      | Sliding distance (m)   | SD     | 523   | 1046  | 1570  |
| 3.      | Wt. % SiC (%)          | W      | 3.5   | 7     | 10.5  |

### Table 2. L₉ Taguchi orthogonal array for experimental design.

| Exp. No. | L (N) | SD (m) | W (%) |
|----------|-------|--------|-------|
| 1.       | 1     | 1      | 1     |
| 2.       | 1     | 2      | 2     |
| 3.       | 1     | 3      | 3     |
| 4.       | 2     | 1      | 2     |
| 5.       | 2     | 2      | 3     |
| 6.       | 2     | 3      | 1     |
| 7.       | 3     | 1      | 3     |
| 8.       | 3     | 2      | 1     |
| 9.       | 3     | 3      | 2     |

2.3. **GRA-PCA hybrid method for optimization of wear performance**

In the present situation of quick assembling and cost lessening with most extreme usage, complex procedures have a few quality attributes. In such circumstances, a few multi-objective optimization strategies are required and the Taguchi-based grey relational analysis (GRA) integrated with PCA is utilized as a part of the present investigation. The Taguchi technique in this study has been used to draft experimental runs based on orthogonal array. Taguchi technique utilizes a statistical calculation of performance recognized as S/N ratio (signal to noise ratio) for investigating the results. The signal to noise ratio is an estimation of performance to generate techniques that are unresponsive to noise components in a controlled way. In this study all the response or performance characteristics, such as wear rate (WR), frictional force (FF) and specific wear rate (Sp. WR) are of ‘smaller-is – better’ type and therefore S/N (K) ratio was calculated using Equation (1). The S/N (K) ratio in Taguchi technique is calculated using following equations:

\[
K_{ij} = -10 \log_{10} \left( \frac{1}{n} \sum_{j=1}^{n} y_{ij}^2 \right) \quad (smaller \quad is \quad better)
\]

Equation (1)

\[
K_{ij} = -10 \log_{10} \left( \frac{1}{n} \sum_{j=1}^{n} \frac{1}{y_{ij}^2} \right) \quad (larger \quad is \quad better)
\]

Equation (2)
\[ K_{ij} = -10 \log_{10} \left( \frac{1}{n_s} \sum_{j=1}^{n} Y_{ij}^2 \right) \quad \text{(nominal - is - better)} \quad (3) \]

### 2.4. Grey relational analysis

GRA was created by Ju-Long in 1982 (Ju-Long, 1982). GRA works like a discovery idea where known and obscure components are assembled to get optimum level of the responses. GRA utilizes normalization of values to compute grey relational coefficient (GRC) and grey relational grade (GRG). It computes the optimal process level and ANOVA is connected to forecast the optimal level of grey relational grades.

Wear rate, frictional force and specific wear rate of as cast composite materials are important quality components. Every one of these attributes is of ‘smaller-is-better’ type. Initial step is to make grey relational creation with values in the vicinity of 0 and 1. This creation is accomplished for all the three quality attributes. For the present examination, all the chosen quality attributes or responses are of the class ‘smaller-is-better’ and grey relational is generated by using Equation (4).

\[
X'_i(k) = \frac{\max X'_o(k) - X'_i(k)}{\max X'_o(k) - \min X'_o(k)} \quad \text{(smaller is better)} \quad (4)
\]

\[
X'_i(k) = \frac{X'_i(k) - \min X'_o(k)}{\max X'_o(k) - \min X'_o(k)} \quad \text{(larger is better)} \quad (5)
\]

In the above Equations (4) and (5) \( i = 1 \) to \( m \) and \( k = 1 \) to \( n \); \( m \) is the number of experimental runs and \( n \) is the number of process factors. The term \( X'_o(k) \) represents the original or reference sequence; \( \min X'_o(k) \) and \( \max X'_o(k) \) represents the minimum and maximum values in the original sequence; \( X'_i(k) \) represents the sequence produced after data processing.

The GRC after data processing were calculated with the particular deviation calculations as given in Equations (6) and (7) (Çaydaş & Hasçalı, 2008; Ju-Long, 1982):

\[
\Delta_o i(k) = \left| X'_o(k) - X'_i(k) \right| \quad (6)
\]

\[
\xi_i(k) = \frac{\Delta_{\min} + \psi \Delta_{\max}}{\Delta_o i(k) + \psi \Delta_{\max}} \quad (7)
\]

where \( \Delta_o i(k) \) is deviation sequence of original reference sequence of \( X'_o(k) \) and compatibility sequence \( X'_i(k) \); \( \psi \) is distinguishing coefficient and is usually taken 0.5 when equal weightage is given to the process parameters.

The GRC for all experimental runs of \( L_9 \) orthogonal array was computed using Equation (7). In the final step of computation the grey relational grade has been calculated using Equation (8) (Çaydaş & Hasçalı, 2008; Ju-Long, 1982). While after the incorporation of principal component analysis to assign the weight value of each response characteristics the GRG is calculated by using Equation (9). GRG is the average summation of GRCs. Before computing the GRG, PCA is integrated with GRA and it takes into consideration the weightage of each performance or response.
characteristic which is multiplied with grey relational coefficient of that performance characteristic. The value of GRG lies between 0 and 1. The larger value of GRG displays better relation among process factors combination at that level and it is assessed as an optimum level.

\[
y_i(\text{GRG}) = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \quad (8)
\]

In Equation (8) \(y_i\) denotes GRG of \(i\)th experiment and \(n\) represents the number of performance characteristics. The higher value of grey relational grade shows that the corresponding experimental results are closer to the optimum value or normalized value. However, the effect of each factor on the system is not exactly the same in real applications. Thus, Equation (8) can be modified as follows:

\[
y_i(\text{GRG}) = \sum_{k=1}^{n} \omega_k \xi_i(k) \quad (9)
\]

In Equation (9) \(\omega_k\) denotes the weighted value of factor \(k\). On giving same weightage, Equation (8) and (9) are equal. The GRA is utilized to demonstrate the relationship among sequences. The value of GRG is equivalent to one when the two sequences are same. GRG additionally demonstrates the level of impact that the comparability sequence can apply over the reference sequence. In this manner, if a specific comparability sequence is more critical than the other comparability sequence to the reference sequence, the GRG for that comparability sequence and reference sequence will be higher than other GRG’s (Yang, Shie, & Huang, 2006). In this examination, the corresponding weightage values \(\omega_k\) have been acquired from principal component analysis (PCA).

### 2.5. Principal component analysis

The PCA has been invented by Pearson and Hotelling (Hotelling, 1933; Pearson, 1901), which explains the construction of variance and covariance of all performance characteristics by linearly integrating them. The steps involved in PCA are detailed as follows:

1. To construct variance and covariance matrix \(X_i\) the normalized values are used as follows:

\[
X_i(j), \ i = 1 \text{ to } m, \ j = 1 \text{ to } n
\]

\[
X_1(1) \quad X_1(2) \quad \ldots \ldots \ldots \quad X_1(n) \\
X_2(1) \quad X_2(2) \quad \ldots \ldots \ldots \quad X_2(n) \\
X_i = \quad \ldots \ldots \quad \ldots \ldots \quad \ldots \ldots \\
\ldots \ldots \quad \ldots \ldots \quad \ldots \ldots \\
X_m(1) \quad X_m(2) \quad X_m(1)
\]

(10)

In Equation (10) \(m\) denotes the number of experimental runs and \(n\) represents the number of performance or response characteristics. Here in this study, \(X\) represents the GRC of each performance characteristic. Here \(n = 3\) and \(m = 9\).
(2). The computation of correlation coefficient array is computed as using following equation:

\[
R_{jl} = \frac{\text{cov}(X_i(j), X_l(l))}{\sigma_{X_i(j)} \times \sigma_{X_l(l)}} ; \quad j = 1 \text{ to } n \text{ and } l = 1 \text{ to } n
\]  

(11)

In Equation (11) \(\text{cov}(X_i(j), X_l(l))\) are the covariance of sequences \(X_i(j)\) and \(X_l(l)\), respectively; \(\sigma_{X_i(j)}\) denotes the S.D of sequence \(X_i(j)\) and \(\sigma_{X_l(l)}\) denotes the S.D of sequence \(X_l(l)\).

(3). The determination of eigenvalues and eigenvectors has been done using the correlation coefficient array:

\[(R - \lambda_k I_m)V_{ik} = 0\]  

(12)

In Equation (12) \(\lambda_k\) represents eigenvalues; \(\sum \lambda_k = n\) and \(k = 1 \text{ to } n\); the term \(V_{ik}\) represents \(V_{ik} = [a_{k1} \ a_{k1} \ldots \ldots \ a_{kn}]^T\) eigenvectors corresponding to eigenvalues \(\lambda_k\).

(4). The principal components: The principal components have been finally computed using the following equation:

\[y_{mk} = \sum_{i} X_m(i) \ast V_{ik}\]  

(13)

The Equation (13) produces \(y_{m1}\) as the first principal component, \(y_{m2}\) as the second principal component, and so on.

3. Results and discussion

3.1. Dry sliding pin-on-disc wear analysis

The principal objective of the present study was to minimize the wear behavior performance characteristics such as wear rate, frictional force and specific wear rate for casted composite matrix AA6063/SiC\(_p\) using Taguchi-GRA-PCA hybrid optimization technique. The S/N ratios for all the three performance characteristics have been computed in the first step of analysis. As stated earlier, lower values of wear rate, frictional force and specific wear rate produces better wear performance; so, the Equation (1) has been used for the computation of S/N ratio using MINITAB 17 software. The values of the response characteristics are shown in Table 3. The raw data for three performance characteristics and the corresponding S/N ratio values are given in Table 4.

3.2. Normalization and computation of deviation sequence

The next step of investigation is to normalize the data of each performance characteristic using Equation (4). The normalized values and deviation sequence are given in Table 5. The steps used in calculation in case of experiment no. 1 are given below:

\[X_{iWR}^\ast(1) = \frac{\text{max} X_i^\ast(k) - X_i^\ast(k)}{\text{max}X_i^\ast(k) - \text{min}X_i^\ast(k)} = \frac{11.030 - 11.030}{11.030 - 2.830} = 0\]
The deviation sequences have been determined using Equation (6) for computing GRCs. The calculated normalized values and deviation sequences are presented in Table 5. The deviation sequence for exp. no. 1 is calculated as given below:

\[ X^*_1 = \frac{\text{max } X^o(k) - X^o(1)}{\text{max } X^o(k) - \text{min } X^o(k)} = \frac{19.05 - 12.01}{19.05 - 2.15} = 0.4166 \]

\[ X^*_{Sp.WR}(1) = \frac{\text{max } X^o_i(k) - X^o(1)}{\text{max } X^o_i(k) - \text{min } X^o_i(k)} = \frac{0.5510 - 0.5510}{0.5510 - 0.1356} = 0 \]

The deviation sequences have been determined using Equation (6) for computing GRCs. The calculated normalized values and deviation sequences are presented in Table 5. The deviation sequence for exp. no. 1 is calculated as given below:
Δ_o iWR(1) = |X_o^(k) - X_i^(k)| = |1 - 0| = 1

Δ_o iFF(1) = |X_o^(k) - X_i^(k)| = |1 - 0.4166| = 0.5834

Δ_o iSp.WR(1) = |X_o^(k) - X_i^(k)| = |1 - 0| = 1

3.3. Computation of GRCs and GRGs

The GRC were computed using the values of deviation sequences as mentioned in Table 5 by using Equation (7) for all the response characteristics. The value of ψ = 0.5 (distinguished coefficient) was substituted in Equation (7). The GRGs were calculated by using Equation (9) after incorporating the PCA approach. The computed grey relation coefficients are reported in Table 6. The example calculation for GRCs for experiment no. 1 is given below:

ξ_iWR(1) = \frac{Δ_{min} + ψ.Δ_{max}}{Δ_o i(k) + ψ.Δ_{max}} = \frac{0 + 0.5 \times 1}{1 + 0.5 \times 1} = 0.3333

ξ_iFF(1) = \frac{Δ_{min} + ψ.Δ_{max}}{Δ_o i(k) + ψ.Δ_{max}} = \frac{0 + 0.5 \times 1}{0.5834 + 0.5 \times 1} = 0.4615

ξ_iSp.WR(1) = \frac{Δ_{min} + ψ.Δ_{max}}{Δ_o i(k) + ψ.Δ_{max}} = \frac{0 + 0.5 \times 1}{1 + 0.5 \times 1} = 0.3333

Principal component analysis (PCA) is introduced in GRA to exhibit the respective significance for each performance characteristic. The weighted values for each performance characteristic are determined by introducing PCA. The components of the array for the multiple performance attributes recorded in Table 6 showing GRCs of each performance attributes. These values are utilized to assess the correlation coefficient matrix and to calculate the corresponding eigenvalues using Equation (12) and are listed in Table 7. The eigenvector relating to every eigenvalue is recorded in Table 8, and the weighting contribution of each performance attribute is obtained by the square of the principal component values of the corresponding eigenvectors. The contribution of individual performance characteristics; wear rate (WR), frictional force (FF) and

| Exp. No. | Wear rate | Frictional force | Specific wear rate |
|---------|-----------|-----------------|-------------------|
| 1.      | 0.3333    | 0.4615          | 0.3333            |
| 2.      | 0.7123    | 0.8570          | 0.7007            |
| 3.      | 1.0000    | 1.0000          | 0.9724            |
| 4.      | 0.3875    | 0.8086          | 0.5436            |
| 5.      | 0.6343    | 0.5840          | 0.8474            |
| 6.      | 0.6203    | 0.4329          | 0.8305            |
| 7.      | 0.3633    | 0.3541          | 0.6448            |
| 8.      | 0.4633    | 0.3333          | 0.7955            |
| 9.      | 0.6122    | 0.6545          | 1.0000            |
specific wear rate (Sp. WR) are mentioned in Table 9. Additionally, the variance contribution for the first principal component characterizing the three performance characteristics is as high as 67.9% as mentioned in Table 7. The computation of grey relation grades (GRGs) after introducing PCA and the weighted value of each performance characteristic has been obtained by using Equation (9). The GRGs and its rank are mentioned in Table 10. The sample calculation for GRG using Equation (9) in case of experiment no. 1 is given below:

\[
\gamma_i(\text{GRG}) = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) = \frac{1}{3} (0.461 \times 0.3333 + 0.198 \times 0.4615 + 0.341 \times 0.3333) \\
= 0.1196
\]

All the grey relational grades values arbitrarily vary in the vicinity of 0 and 1. A strong connection is exhibited between reference sequence and comparability sequence as the value of GRG is approached towards maximum.

| Table 7. Eigenvalues and explained variation. |
|-----------------------------------------------|
| Principal component | Eigenvalue | Explained variation (%) |
|----------------------|------------|-------------------------|
| PC1                  | 2.0213     | 67.9                    |
| PC2                  | 0.8562     | 28.5                    |
| PC3                  | 0.1224     | 4.10                    |

| Table 8. Eigenvectors for principal components. |
|------------------------------------------------|
| Performance characteristic | Eigenvector |
|-----------------------------|-------------|
| Wear rate                   | PC1         |
| Frictional force            | PC2         |
| Specific wear rate          | PC3         |
| 0.679                       | -0.061      |
| 0.445                       | 0.827       |
| 0.584                       | -0.559      |

| Table 9. Contribution of the respective performance characteristic for the principal components. |
|--------------------------------------------------------------------------------------------------|
| Performance characteristic | Contribution/weighted value |
|-----------------------------|----------------------------|
| Wear rate                   | 0.4610                     |
| Frictional force            | 0.1980                     |
| Specific wear rate          | 0.3410                     |

| Table 10. Grey relation grades (GRG’s) and its rank. |
|-----------------------------------------------------|
| Exp. No. | Grey relation grades (GRG) | Rank |
|----------|---------------------------|------|
| 1.       | 0.1196                    | 9    |
| 2.       | 0.2457                    | 3    |
| 3.       | 0.3302                    | 1    |
| 4.       | 0.1747                    | 7    |
| 5.       | 0.2323                    | 4    |
| 6.       | 0.2183                    | 5    |
| 7.       | 0.1525                    | 8    |
| 8.       | 0.1836                    | 6    |
| 9.       | 0.2509                    | 2    |
3.4. Evaluation of optimal combination of input process factors and their levels

To estimate the optimum level of process factors for wear rate (WR), frictional force (FF) and specific wear rate (Sp. WR) the average value of grey relation grade for each level of process factors has been evaluated by utilizing the main effects examination of Taguchi approach and the maximum value was chosen for each factor. The GRG values analogous to three levels of input process factors and the main effects in terms of GRG have been mentioned in Table 11. In Table 11 the highlighted bold values of grey relation grade depicts the highest values for the three levels of each process factor. These values correspond to normal applied load (L) 20N, sliding distance (SD) 1570m, and wt. % SiC (W) 10.5 for better response characteristics as depicted in Figure 4. The optimal values of process factors yield the maximum values of grey relation grade as reported from Figure 5.

3.5. Implementation of ANOVA to analyze the effect of input process factors on performance characteristics

ANOVA has been carried out to analyze significance and contribution of each process factor to the GRG value. The ANOVA computation in Table 12 depicts the F-ratio value

| Process factors          | Symbols | L1      | L2      | L3      | L2-L1  | L3-L2  | Rank |
|--------------------------|---------|---------|---------|---------|--------|--------|------|
| Normal applied load      | L       | 0.2318* | 0.2084  | 0.1957  | -0.0234| -0.0127| 3    |
| Sliding distance         | SD      | 0.1489  | 0.2205  | 0.2665* | 0.0707 | 0.0460 | 1    |
| Weight % SiC             | W       | 0.1738  | 0.2238  | 0.2383* | 0.0500 | 0.0145 | 2    |

*Optimum level of the factors = L₁SD₃W₃

![Main Effects Plot for SN ratios](image)

**Figure 4.** Graph showing S/N ratio of performance characteristics.
and percentage contribution of each process factor for the combined response of wear rate, frictional force and specific wear rate. It can be analyzed from the ANOVA calculation table that the process factor sliding distance (SD) and wt. % SiC (W) having 67.16 and 21.91 percentage contribution respectively are the most significant factors minimizing the wear rate, frictional force and specific wear rate followed by the factor normal applied load having 6.42% contribution towards the process.

The Regression Equation (14) for the developed mathematical model is given below.

\[
\text{GRG} = 0.21198 + 0.0198\text{LOAD}_{20} - 0.0035\text{LOAD}_{30} - 0.0163\text{LOAD}_{40} - 0 \\
+0.0086\text{SD}_{1046} + 0.0545\text{SD}_{1570} - 0.0382\text{WT\%}_{3.5} + 0.0118\text{WT\%}_{7.0} \\
+0.0264\text{WT\%}_{10.5} (14)
\]

3.6. Confirmatory test

The confirmatory test has been conducted for the optimized settings (at 20N load, 1570m sliding distance and 10.5 wt. % SiC) to examine the accuracy of the investigation for the wear behavior of AA6063 matrix composite strengthened with different wt. % of SiC
reinforcement agent. After confirmatory test the results reported for wear behavior of the matrix composite were: $2.811 \times 10^{-3}$ mm$^3$/m for wear rate (WR), 2.09N for frictional force (FF) and $0.1405 \times 10^{-3}$ mm$^3$/Nm for specific wear rate (Sp. WR). The confirmation experiment results were compared with the optimum experimental values as reported in Table 13, and improvement in wear performance has been reported. The acquired optimized values of wear analysis process factors have been correlated with optical micrographs (OM) of the worn surface of the casted composite wear test specimens. The formation of fine grooves has been observed for the best settings of the parameters during worn surface morphology as compared to the deep grooves and delamination of layers observed under worst conditions during the experimental run of the parameters setting as shown in Figure 6. The worst wear conditions during the experimental run may be reported as: $10.016 \times 10^{-3}$ mm$^3$/m for wear rate, 17.56N for frictional force and $0.2504 \times 10^{-3}$ mm$^3$/Nm for specific wear rate at 40N normal applied load, 523m sliding distance and 10.5 wt. % SiC.

### 3.7. Worn surface morphology

The optical microscopic examination of the worn surfaces of AA6063 matrix composite wear test samples at different conditions has been shown in Figures 6(a and b) and 7. During the wear testing as the matrix composite surface make contact with the rotating disc wear progresses by the grooving action. A lot of scratches and cracks were seen on the worn

| Performance characteristic | Optimum values in the experimental matrix | Values obtained with optimum parameter setting |
|----------------------------|------------------------------------------|-----------------------------------------------|
| Wear rate $(X10^{-3}$ mm$^3$/m) | 2.830 | 2.811 |
| Frictional force (N) | 2.15 | 2.09 |
| Specific wear rate $(X10^{-3}$ mm$^3$/Nm) | 0.1356 | 0.1405 |

**Figure 6.** (a) Worn surface in best condition.
surfaces due to primary abrasive wear mechanism. In the optimized conditions the formation of fine grooves and fine layers (Figure 6(a)) has been observed. In serious wear conditions the matrix composite observed heavy scratches and scars. The deep grooves and ploughing action has been seen. These grooves has been produced due to the plastic flow of matrix material prompted either because of the cutting or ploughing effect of the presence of hard and stiff SiC reinforcement agents (Figure 6(b), 7). Figure 7 depicts that at higher normal applied load of 40N intense plastic deformation has been appeared on the ductile matrix surface and therefore the material removed from wear surface due to ploughing effect. In this situation, large flakes has been produced and kept along the wear path for a long time. Because of heat generation, these flakes have been exposed to intense plastic deformation and expend over the wear surface.

Figure 6. (b) Worn surfaces in worst condition.

Figure 7. Worn surface of AA6063/SiC\(_p\) AMC at a Load of 40N, Sliding distance of 523m and 10.5 Wt. % of SiC.
4. Conclusions

The hybrid Taguchi-GRA-PCA approach for the optimization of wear behavior process variables has been established methodically to conquer the limitations of single objective techniques in multiple performance characteristics problems. The difficulty that occurs during the calculation of weighting value for all the performance attributes in GRA is solved by incorporating the PCA to calculate the grey relational grades. The impact of different process variables such as normal applied load, sliding distance and wt. % SiC on wear performance of the casted composite has been reported systematically using this hybrid technique. The outcomes of this work can be summarized as follows:

(1) The minimization of wear rate, frictional force and specific wear rate has been established to be optimum variable combination of wear behavior at normal applied load of 20N, sliding distance 1570m and 10.5 wt. % of SiC.

(2) The integrated response of wear rate, frictional force and specific wear rate, normal applied load (6.42%), sliding distance (67.16%) and wt. % SiC (21.92%) applied a significant impact on the wear performance of aluminum matrix composites.

(3) The confirmatory tests exhibits that the actual values of the performance attributes at the optimum selection of process variables exist within the optimum experimental values.

(4) The phenomenon of grooving such as fine grooves and deep grooves, ploughing, delamination and cutting along with scratches and cracks during the wear mechanism of the composite surfaces has been reported using OM examination.

(5) The al-alloy AA6063 matrix composites with 10.5 wt% SiC reported the excellent wear performance for the optimized wear variables acquired.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Narinder Kaushik http://orcid.org/0000-0002-3895-9132

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