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AN INVESTIGATION ON DRY SLIDING WEAR BEHAVIOR OF ALUMINUM BASED METAL MATRIX COMPOSITES USING GREY RELATIONAL ANALYSIS COUPLED WITH PRINCIPLE COMPONENT ANALYSIS

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Abstract

The current study reports on the wear properties of aluminum 6061-T6 reinforced with titanium carbide and graphite hybrid metal matrix composite using principal component analysis based grey relational analysis. Experiments were carried out using Taguchi's L9 orthogonal array. The dry sliding wear properties of composite samples are evaluated using a Pin-on-Disc apparatus. The effects of wear parameter input variables such as load, sliding speed, and sliding distance on different output responses, namely wear rate, friction force, and coefficient of friction, were investigated in this work. Using grey relational analysis in conjunction with principal component analysis, three output responses from each experiment were normalized into a weighted grey relational grade. According to the analysis of variance, the most influential parameter is sliding velocity (45.51%), followed by load (26.75%) and sliding distance (2.94%), all of which contribute to the quality characteristics. Additional experiments have confirmed optimal results. Finally, a scanning electron microscopic analysis was performed to investigate the wear mechanism.

Keywords: aluminum matrix composites; titanium carbide; graphite; taguchi method; grey relational analysis; principal component analysis; analysis of variance.

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Introduction

Due to their superior mechanical properties, composite materials are important engineering materials. Because of their superior properties such as high strength, hardness, stiffness, wear and corrosion resistances, metal matrix composite materials have become necessary materials in various engineering applications such as aerospace, marine, and automobile engineering applications. Aluminium and its alloys are gaining popularity due to their reputation as stronger, stiffer, corrosion-resistant, and low-cost materials. These materials have poor high temperature performance and have a lower load carrying capacity [1]. To address these concerns, researchers are attempting to incorporate various types of reinforcements such as silicon carbide, aluminum oxide, boron carbide, and titanium carbide into aluminum metal matrix composites [2-6].

Shorowordi et al. [7] studied the tribo-surface properties of Al-B_4C and Al-SiC composites worn at various contact pressures. The results showed that as contact pressures increased, the wear rate and surface roughness of Al-B_4C and Al-SiC MMCs increased. However, at high contact pressure, the coefficient of friction decreases. *Raghunath et al.* [8] investigated the tribological behavior of an aluminum alloy LM25 reinforced with SIC and TiO_2 particles. They discovered that the wear rate of the composites increases with increasing sliding distance and load conditions and decreases with increasing reinforcement volume content. With increasing load and Silicon carbide and Titanium oxide particle reinforcement, the friction coefficient decreases. The wear parameters of AA336 aluminum alloy-boron carbide and fly ash reinforced hybrid composites were investigated by *Arunachalam et al.* [9]. The results of the wear tests revealed that weight loss increases with increasing load and sliding distance. However, as the sliding velocity increased, the weight loss of the samples decreased. *Chelladurai et al.* [10] investigated the mechanical properties and wear behavior of LM13 Aluminium Alloy reinforced with copper coated steel wires in a squeeze cast. They concluded that reinforcing LM13 aluminum alloy with copper coated steel wires improves hardness, tensile strength, and wear resistance. The results of dry sliding wear tests show that increasing the number of copper coated steel wires reinforcement in the LM13 matrix reduces weight loss, wear rate, and coefficient of friction. However, as the sliding distance and load increased, so did the weight loss of the samples.

İjlal ŞİMŞEK [11] investigated the effects of B_4C content on the wear properties of Al-Graphite/B_4C hybrid composites. They discovered that increasing the amount of B_4C increases the hardness and decreases the density of the prepared composite. The results of wear tests revealed that the non-reinforced Al-Gr matrix alloy had the greatest weight loss, while the 9% B_4C reinforced composite materials had the least weight loss. However, they discovered that as the amount of reinforcement increased, the friction coefficient decreased. *Alaneme et al.* [12] investigated the corrosion and wear characteristics of aluminum composites reinforced with rice husk ash and alumina. They concluded that when aluminum alloy was reinforced with alumina alone, the corrosion resistance was much higher than when rice husk ash was added. The wear behavior of aluminum alloy reinforced with coconutshell ash particles was investigated by *Apasi et al.* [13]. They discovered that as the load increased, so did the wear rate of the composites, because the contact friction between the pin and the disc increased. The addition of ash reinforcement to the matrix was found to be beneficial because it reduced the wear rate.

Ravi et al. [14] investigated the dry sliding wear behavior of aluminum alloy 6061-redmud metal matrix composites and discovered that red mud particles in Al-6061 increase hardness while decreasing coefficient of friction as the weight percentage of red mud reinforcement increases. *Lokesh et al.* [15] used the Taguchi technique to investigate the dry sliding wear behavior of Al/Gr/SiC hybrid metal matrix composites. They discovered that the applied load had a greater impact on the wear rate of the composites than sliding distance and reinforcement. *Prathap Singh et al.* [16] used the Taguchi method to improve the dry sliding wear performance of a functionally graded Al6061 / 20% SiC metal matrix composite. The results revealed that the applied load had the greatest influence on dry sliding wear, followed by the region from the outer surface and sliding velocity. The dry sliding wear behavior of an Al alloy reinforced with SiC particles was investigated by *Rao et al.* [17]. The experiment was carried out with the aluminum alloys AA7010, AA7009, and AA2024, and the reinforcement volume fraction was varied from 10% to 25%. The test revealed that increasing the volume fraction of reinforcement reduced the wear rate. The growing demand for better metal matrix composites with desirable properties such as low wear rate, etc., prompted researchers to identify the parameters that may influence MMC performance. Fortunately, there are some optimization techniques in the literature that can be used to predict the performance characteristics of MMCs.

The Taguchi method is the most widely used optimization approach. Previously, the Taguchi method was used to determine and analyze the best process parameters for a single quality response [18]. However, some processes require more than one quality response to be considered. The traditional Taguchi approach is incapable of resolving complex interrelationships between multiobjective optimization problems into a single-objective function. As a result, an attempt was made to combine Grey relational analysis (GRA) based on Grey system theory with the Taguchi method to solve multi-performance characteristics [19]. *Al-Refaie* [20] used the Grey grade to determine the best factor levels. An attempt was made in this work to optimize multiple quality responses using Taguchi-based Grey relational analysis. *Tarng et al.* [21] used Grey-based Taguchi methods to optimize submerged arc welding process parameters while taking multiple weld qualities into account.

It is recommended to use Principal Component Analysis (PCA) to eliminate response correlation by converting correlated responses into uncorrelated quality indices known as principal components, which are then used as response variables for optimization. As a result, principal component analysis has recently been considered as an analytical tool for optimizing a system with multiple performance characteristics [22-24]. According to the literature review, no research has been done on Al6061-T6 reinforced with titanium carbide and graphite. As a result, in this study, an attempt was made to investigate the wear behavior of the Al6061-T6 reinforced with titanium carbide and graphite hybrid metal matrix composite under varying load, sliding speed, and sliding distance using taguchi based grey relational analysis coupled with principal component analysis and find the optimum parameters.

Experimental method

Selection of materials and fabrication of composite

In this study, Al6061-T6 was selected as matrix material for preparation of test samples of the composite. The table 1 shows the chemical composition of the Al6061-T6 in percentage. The hybrid metal matrix composite was prepared by adding 5% of titanium carbide and 5% of graphite with Al6061-T6.

Table 1. Chemical composition of Al6061-T6

Si	Fe	Cu	Mn	Mg	Cr	Zn	Al
0.4-0.8	0.1-0.7	0.04-0.15	0.1-0.25	0.8-1.2	0.04-0.35	0-0.25	Remainder

The Stir-casting technique (Figure 1) was used to create composite samples in this study. In the electrical furnace, a weighed amount of Al6061-T6 was melted at a temperature of 800 ± 10 °C. The titanium carbide and graphite were preheated for 30 minutes at 400°C to improve wettability before being slowly added to the molten metal with continuous stirring. After adding the reinforcements, the stirring was extended for fifteen minutes. After that, the molten mixture was poured into a metallic mold and allowed to solidify. Following solidification, the cast samples were removed from the mold and machined to 10 mm diameter and 30 mm length in accordance with American Society for Testing Materials G99-95 (2010).

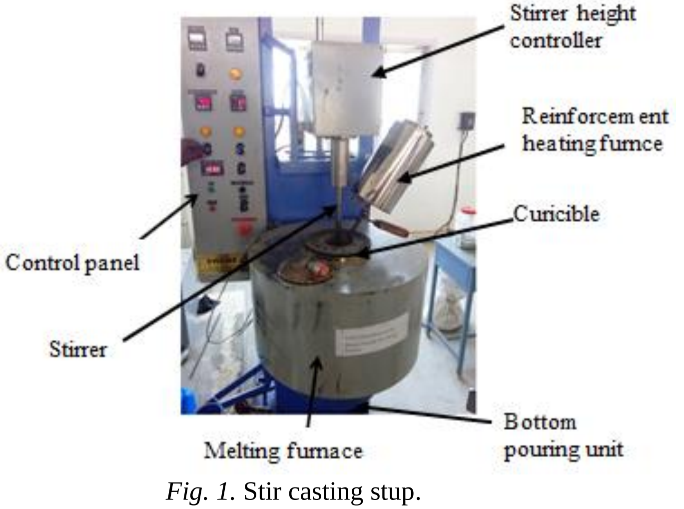

Fig. 1. Stir casting stup.

Taguchi Approach

Dr. Genichi Taguchi`s Design of experiments approach [25] was used to analyze wear parameters and to find out the combination of optimum parameters which would result in a lower wear rate. The experimental plan consisting of L9 was set by a technique based on the Taguchi's techniques, considering different variables at different levels like load, sliding velocity, and sliding distance and is shown in Table 2.

Table 2. Chemical composition of Al6061-T6

Level	Load (N)	Sliding Velocity (m/s)	Sliding Distance(m)
1	10	4	2000
2	20	6	2500
3	30	8	3000

The applied load (A) was assigned to the second column, the sliding velocity (B) to the third, and the sliding distance to the fourth (C). As response variables, the wear rate, friction force, and coefficient of friction of composites were used. The experiments were carried out in a sequence generated according to Taguchi design, and the experimental data was investigated using the software package MINITAB 16. The obtained results were converted into Signal to Noise (S/N) ratios. A performance characteristic is represented by the signal-to-noise (S/N) ratio, and the highest value of S/N ratio is required. Equation can be used to calculate the S/N ratio with lower-the-better characteristics (wear rate, coefficient of friction) (1).

$$\eta_{ij} = -10\log\left(\frac{1}{n}\right)\sum_{j=1}^{n} y_{ij}^{2} \qquad (1)$$

where η_{ij} is the j^{th} S/N ratio of the i^{th} experiment, y_{ij} is the i^{th} experiment at the j^{th} test, n is the total number of the tests.

Experimental procedure

The wear tests on the prepared composites are carried out using a pin-on-disc wear testing machine (Model: TR-20, DUCOM) (Figure 2). The test samples are 10 mm in diameter and 30 mm in length, and are prepared in accordance with ASTM G99-95 standards. The samples were pushed against a steel disc (EN-31), which had a hardness of RC 65 and a surface roughness of 0.1. (Ra). Before testing, each specimen is polished with 240 grit silica carbide emery paper and then 600 grit. The specimens' ends were then metallographically polished. The specimen's initial weight was determined using an electronic weighing machine with a minimum count of 0.0001 g. During the test, the pin was pressed against the counterpart while rotating against an EN31 steel disc with a hardness of 65HRC. The specimens were removed after running through a fixed sliding distance, cleaned with acetone, dried, and weighed to determine the weight loss due to wear.

The results for various parameter combinations were obtained by running the experiment as an average of at least three orthogonal array runs. The initial and final volume of the specimen are calculated using the initial and final weight of the specimen. The wear rate and friction coefficient are then calculated using Equations (2) and (3), as shown in Table 3.

$$\text{Wear rate} = \frac{\text{Loss in Volume}}{\text{Sliding distance}} \ \frac{\text{mm}^3}{\text{m}} \qquad (2)$$

$$\text{Coefficient of friction (COF)} = \frac{\text{Frictional force}}{\text{Normal force}} \quad (3)$$

Fig. 2. Pin on disc apparatus.

Table 3.Experimental plan and results.

Expt no	Load (N)	Sliding Speed (m/s)	Sliding Distance (m)	Wear rate (mm^3/m)	Friction force (N)	Coefficient of friction
1	10	4	2000	0.000982275	5.54	0.554
2	10	6	2500	0.002279245	5.89	0.589
3	10	8	3000	0.002113208	4.97	0.497
4	20	4	2500	0.000875472	8.28	0.414
5	20	6	3000	0.006163522	8.54	0.427
6	20	8	2000	0.011283918	8.36	0.418
7	30	4	3000	0.014188679	12.39	0.413
8	30	6	2000	0.002622642	13.26	0.442
9	30	8	2500	0.010249057	12.57	0.419

Optimization steps

Grey Relational Analysis

The grey relational analysis is a technique which is used for handling the uncertainty of multiple variables and discrete data. The steps of grey relational analysis are as follows:

Data pre-processing

To reduce inconsistency, the Grey Relational Analysis first normalizes the signal to noise ratio of quality characteristics. Data preprocessing is the process of converting the original sequence to a comparable sequence. For this purpose, the experimental results are normalized from 0 to 1. The quality characteristics of the process/product to be optimized are normalized in GRA using three different criteria: higher-the-better, lower-the-better, and nominal-the-better. This investigation's primary goal is to reduce the quality characteristics. As a result, the lower-the-better criterion was chosen for experimental data normalization, which is performed by Equation (4).

$$X_i^*(k) = \frac{\max X_i^0(k) - X_i^0(k)}{\max X_i^0(k) - \min X_i^0(k)} \tag{4}$$

where $X_i^0(k)$ is the value after the grey relational generation (data preprocessing), max $X_i^0(k)$ is the largest value of $X_i^0(k)$, min $X_i^0(k)$ is the smallest value of $X_i^0(k)$, and X^0 is the desired value.

Grey relational coefficient and grey relational grade

After data pre-processing is carried out, the grey relational coefficient might be calculated to express the relationship between the ideal and actual normalized experimental results. The grey relational coefficient can be calculated using Equation (5).

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

where $\zeta(\epsilon\ 0,1)$ = distinguished coefficient, ς=0.5 is generally used $\xi_i(k)$ is the grey relational coefficient, Δ_{min} is the smallest value of $\Delta_{oi}(k)$, Δ_{max} is the largest value of $\Delta_{oi}(k)$ $\Delta_{oi}(k)$ is the deviation sequence of the reference sequence $X_o^*(k)$, and the comparability sequence $X_i^*(k)$, namely

$$\Delta_{oi}(k) = \left|X_o(k) - X_i(k)\right|$$

$$\Delta_{max} = \max_{\forall j \epsilon \varepsilon} \max_{\forall k} \left|X_o^*(k) - X_j^*(k)\right|$$

$$\Delta_{min} = \min_{\forall j \epsilon \varepsilon} \min_{\forall k} \left|X_o^*(k) - X_j^*(k)\right|$$

Finally, the grey relational grade is evaluated in each experiment using the corresponding average-GRCs, as shown in Equation (6). GRG is used to show the connection between experimental data. The higher the GRG, the more effective the experimental strategy.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \tag{6}$$

where γ_i is the weighted grey relational grade for the i^{th} experiment, n is the number of performance.

However, since in real applications the effect of each factor on the system is not exactly same, the above equation can be modified as

$$\gamma_i = \sum_{k=1}^{n} w_k \xi_i(k) \quad \text{where} \sum_{k=1}^{n} w_k = 1 \tag{7}$$

where, w_k represents the normalized weighting value of factor k. Equations 6 and 7 are equal when the weights are the same. The grey relational grade is used in the grey relational analysis to show the relationship between the sequences. If the two sequences are identical, the grey relational grade value is 1. The grey relational grade also indicates how much influence the comparability sequence has over the reference sequence. As a result, if one comparability sequence is more important to the reference sequence than another, the grey relational grade for that comparability sequence and reference sequence will be higher than other grey relational grades. The corresponding weighting values, i.e., wk, are obtained from the principal component analysis in this study.

Principal component analysis (PCA)

Principal Component Analysis (PCA) was proposed by *Pearson* [26], and evolved as a statistical tool by *Hotelling* [27]. Initially, this technique was used to quantify and identify phenomena in social sciences where direct measurement of the phenomenal changes was difficult. PCA is useful for data reduction and interpretation of multi-objective data sets. PCA is currently finding widespread use in a variety of scientific fields. The procedure is detailed below [28].

The original multiple performance characteristic array

$$X = \begin{bmatrix} x_1(1) & x_1(2) & \ldots\ldots & \ldots\ldots x_1(n) \\ x_2(1) & x_2(2) & \ldots\ldots & \ldots\ldots x_2(n) \\ . & . & \ldots\ldots & \ldots\ldots\ . \\ . & . & \ldots\ldots & \ldots\ldots\ . \\ x_m(1) & x_m(2) & \ldots\ldots & \ldots\ldots x_m(n) \end{bmatrix} \tag{8}$$

$$x_i(j),\ i = 1,2,\ldots\ldots\ \ldots m; \quad j = 1,2,\ldots\ldots\ \ldots n$$

where m is the number of experiment and n is the number of the performance characteristic. In this study, X is the grey relational coefficient of each performance characteristic and m=9 and n=3.

Correlation coefficient array

The correlation coefficient array is evaluated as follows:

$$R_{jl} = \left(\frac{Cov(x_i(j), x_i(l))}{\sigma_{x_i}(j) \times \sigma_{x_i}(l)} \right) \tag{9}$$

$$j=1, 2, 3\ldots\ldots n, \quad l=1, 2, 3\ldots\ldots n$$

where $Cov(x_i(j), x_i(l))$ is the covariance of sequences $x_i(j)$ and $x_i(l)$, $\sigma_{xi}(j)$ is the standard deviation of sequence $x_i(j)$ and $\sigma_{xi}(l)$ is the standard deviation of sequence $x_i(l)$.

Determining the eigenvalues and eigenvectors

The eigenvalues and eigenvectors are determined from the correlation coefficient array,

$$\left(R - \lambda_k I_m\right)V_{ik} = 0 \tag{10}$$

where λ_k = eigen values, $\sum_{k=1}^{n} \lambda_k = n$, k=1,2……n; V_{ik}= $[a_{k1}ak\ a_{k2}\ ....\ a_{kn}]^T$ eigen vectors corresponding to the eigen value λ_k.

Principal components

The principal component is formulated as:

$$Y_{mk} = \sum_{i=1}^{n} X_m(i).V_{ik} \tag{11}$$

where Y_{m1} is called the first principal component, Y_{m2} is called the second principal component, and so on. The principal components are aligned in descending order with respect to variance, and therefore, the first principal component Y_{m1} accounts for most variance in the data.

Analysis and discussion of experimental results

In this study, the wear rate, the friction force and coefficient of friction of titanium carbide and Graphite based aluminium metal matrix composite for different combination of wear parameters of nine experimental runs is considered. The following sequential steps are adopted to determine the optimal combinations of the wear parameters based on grey relational analysis coupled with principal component analysis:

1. The signal to noise ratios for the experimental data was calculated.
2. The signal to noise ratios was normalized.
3. The corresponding grey relational coefficients were calculated.
4. Principal component analysis was used and the grey relational grades were calculated.
5. The optimal levels of wear parameters were obtained.
6. Finally, the confirmation experiments were conducted.

As per the optimization procedure, the signal to noise ratio and normalized signal to noise ratio for the wear rate, the friction force and the coefficient of friction were calculated and the results are tabulated in Table 4.

The principal component analysis is adopted to determine the corresponding weighting values for each performance characteristic to reflect its relative importance in the grey relational analysis. The elements of the array for multiple performance characteristics listed, Table 5 represent the grey relational coefficient of each performance characteristic. These data were used to evaluate the correlation coefficient matrix and to determine the corresponding eigenvalues from Eq.10. The eigenvalues are shown in Table 6.

Table 4. Signal to noise ratio and normalized signal to noise ratio values.

Ex no	Signal to noise ratio			Normalized signal to noise ratio		
	Wear rate (mm^3/m)	Friction Force (N)	Coefficient of friction	Wear rate (mm^3/m)	Friction Force (N)	Coefficient of friction
1	60.155338	-14.870195	5.129805	0.041325	0.110640	0.827422
2	52.844179	-15.402306	4.597694	0.343514	0.173067	1.000000
3	53.501157	-13.927128	6.072872	0.316359	0.000000	0.521559
4	61.155158	-18.360607	7.659993	0.000000	0.520133	0.006813
5	44.203421	-18.629157	7.391442	0.700659	0.551639	0.093911
6	38.950802	-18.444126	7.576474	0.917763	0.529931	0.033900
7	36.961161	-21.861426	7.680999	1.000000	0.930847	0.000000
8	51.625221	-22.450870	7.091555	0.393897	1.000000	0.191173
9	39.786322	-21.986706	7.555720	0.883229	0.945544	0.040632

Table 5. Grey relational co-efficient.

Ex. no	Grey relational coefficient		
	Wear rate	Friction Force	Coefficient of friction
1	0.923659351	0.81881295	0.376669968
2	0.592758322	0.742868154	0.333333333
3	0.612475264	1	0.489447782
4	1	0.49013222	0.986557656
5	0.416438046	0.475448285	0.841876878
6	0.352668244	0.485469289	0.936504641
7	0.333333333	0.349443428	1
8	0.559348729	0.333333333	0.723407985
9	0.361473093	0.345890431	0.924844303

Table 6. The eigenvalues and explained variation for principal components.

Principal components	Eigenvalues	Explained variation (%)
First	1.1077	36.92
Second	0.9692	32.31
Third	0.9231	30.77

Table 7 shows the eigenvector associated with each eigenvalue. The square of the eigenvalue matrix represents the performance characteristic's contribution to the principal component. Table 8 shows the contribution of wear rate, friction force, and coefficient of friction.

Table 7. The eigenvectors for principal components.

Performance characteristics	First principal component	Second principal Component	Third principal component
Wear rate	-0.5554	-0.658	-0.5085
Friction force	-0.5249	-0.7517	-0.3994
Coefficient of friction	-0.645	0.0451	0.7629

Table 8. The most variance contribution of each individual performance characteristic for the principal component.

Performance characteristics	Contribution/weighted value
Wear rate	0.30846916
Friction force	0.27552001
Coefficient of friction	0.41602500

The contributions of each individual performance characteristic for the principal component are 0.30846916, 0.27552001 and 0.416025. Furthermore, the variance contribution for the first principal component characterizing the three performance characteristics can reach 36.92%. As a result, the squares of its corresponding eigenvectors were chosen as the weighting values of the related performance characteristic for this study, and coefficients w1, w2, and w3 in Eq.7 were set to 0.30846916, 0.27552001, and 0.416025, respectively. The grey relational grades were calculated and shown in Table 9 using Eq.7 and data from Table 5.

Table 9. Grey relational grade and its rank.

Ex no	Grey relation grade	Rank
1	0.222407967	3
2	0.175399234	9
3	0.222690751	2
4	0.284647681	1
5	0.20323188	6
6	0.210717708	4
7	0.205042237	5
8	0.188445881	8
9	0.197187129	7

As a result, rather than complicated performance characteristics, the optimization design was performed with respect to a single grey relational grade. Table 9 clearly shows that the wear parameters setting of experiment number 4 has the highest grey relational grade based on the performed experimental design. Thus, among the nine experiments, the fourth provides the best multi-performance characteristics.

Table 10. Main effects on grey relational grades.

Level	Load	Sliding velocity	Sliding distance
1	0.2068	0.2374	0.2072
2	0.2329	0.1890	0.2191
3	0.1969	0.2102	0.2103
Delta	0.0360	0.0483	0.0119
Rank	2	1	3

**Optimum level*

The main effects are tabulated in Table 10 and the factor effects are plotted and shown in Figure 3 based on the value of grey relational grade in Table 9. According to Table 10 and Figure 3, the optimum factors for both the wear rate and the coefficient of friction obtained for the hybrid composite are a combination of 20 N load (level 2), 4 m/s sliding speed (level 1), and 2500 m sliding distance (level 2).

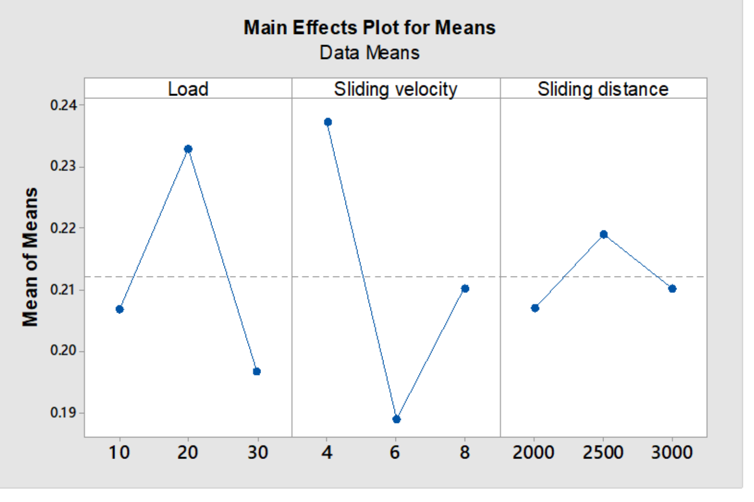

Fig. 3. Main effects plot for grey relational grade.

Analysis of variance

The goal of the analysis of variance is to determine which wear parameters have a significant impact on the performance characteristic. This is accomplished by dividing the total variability of the grey relational grades, measured as the sum of the squared deviations from the total mean of the grey relational grade, into contributions from each wear parameter and the error. This analysis was performed with a level of significance of 5% and a level of confidence of 95%.

Table 11. Results of analysis of variance on grey relational grade.

Source	DF	Adj SS	Adj MS	F	P	%C
Load	2	0.002071	0.001035	1.08	0.481	26.754
Sliding velocity	2	0.003523	0.001762	1.84	0.353	45.511
Sliding distance	2	0.000228	0.000114	0.12	0.894	2.945
Residual Error	2	0.001919	0.000960			24.790
Total	8	0.007741				100

From the results of analysis of variance on grey relational grade, it is clear that the sliding velocity is the most predominant factor (P=45.511%) on the multi-performance characteristics of Al6061-T6/Titanium carbide/Graphite hybrid composite than load (P=26.754%) and sliding distance (P=2.945%) (Table 11).

Confirmation Experiment

The aim of the confirmation experiment is to establish and confirm the progress of the quality characteristics using the optimum level of the design parameter. The confirmation experiment is conducted by setting the wear parameter at the optimum level. The predicted grey relational grade ($\hat{\gamma}$) at its optimum level of the wear parameter can be found out by using Equation (12).

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q}\left(\overline{\gamma_i} - \gamma_m\right) \tag{12}$$

Where γ_m is the total mean grey relational grade, $\overline{\gamma_i}$ is the mean grey relational grade at the optimum level, and 'q' is the number of main parameters that significantly affect the coefficient of friction and wear rate. Table 12 shows the comparison of the predicted grey relational grade with the actual grey relational grade obtained in the experiment using the optimal wear parameters.

Table 12. Results of confirmation experiment.

	Initial testing parameters	Optimum testing parameters	
		Prediction	Experiment
Combination of testing parameters	A1B1C1	A2B1C2	A2B1C2
Wear rate	0.000982275		0.000875472
Friction force	5.54		8.28
Coefficient of friction	0.554		0.414
Grey relational grade	0.23496379	0.264916295	0.284647681

The optimal data obtained from the confirmation test with the level settings parameters of load 20 N (level 2), sliding speed 4 m/s (level 1), and sliding distance 2500 m (level 2) had good agreement with the predicted model. As a result, the grey relational analysis based on the Taguchi method for multi-response problem optimization is a very useful tool for predicting the wear rate and coefficient of friction of Al6061-T6/Titanium carbide/Graphite hybrid metal matrix composites.

Surface morphology

Composite scanning electron micrograph (SEM) images demonstrate the successful incorporation of hybrid reinforcements in the Al-matrix. Figure 4 shows a scanning electron microscopy image of the prepared Aluminum 6061-T6/Titanium carbide/Graphite hybrid metal matrix composite, and it is clear that the reinforcements are evenly distributed in the aluminum 6061-T6.

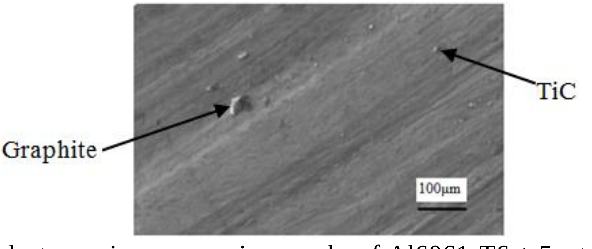

Fig. 4. Scanning electron microscope micrographs of Al6061-T6 + 5 wt percent titanium carbide + 5 wt percent graphite hybrid metal matrix composite.

The wear tests were carried out under ideal conditions (load of 20 N, sliding velocity of 4 m/s, and sliding distance of 2500 m), and scanning electron microscopy images of the worn surfaces of pure Aluminum 6061-T6, Aluminum 6061-T6 + 5 wt percent titanium carbide, Aluminum 6061-T6 + 5 wt percent graphite, and Aluminum 6061-T6 +5 wt. percent titanium carbide+5 wt. percent graphite are shown (a–d).

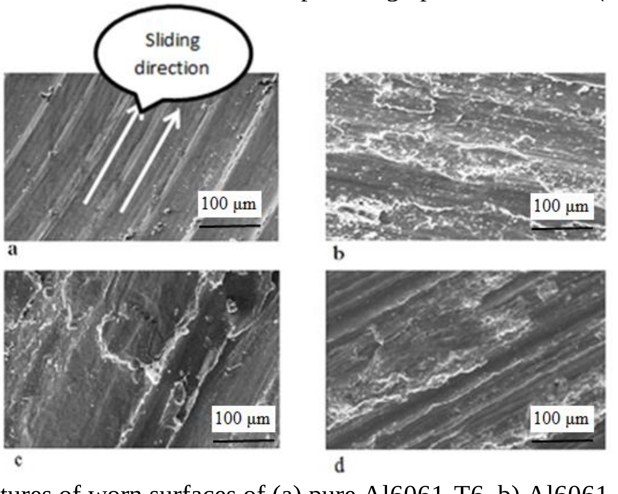

Fig. 5. Microstructures of worn surfaces of (a) pure Al6061-T6, b) Al6061-T6 + 5 wt percent titanium carbide, c) Al6061-T6 + 5 wt percent graphite d) Al6061-T6 + 5 wt percent titanium carbide + 5 wt percent graphite.

Figure 5(a-d) shows the presence of grooves of varying sizes on the worn surfaces of aluminum and its composites. It is formed as a result of extreme plastic deformation of materials. The scanning electron microscopy image of Al6061-T6 + 5% titanium carbide shows delamination type wear cracks propagating along longitudinal directions as a result of titanium carbide particle pull out (Figure 5b). The scanning electron microscopy images of Al6061-T6 + 5% graphite show mild grooves and mild delamination (Figure 5c). The degree of crack formation on the wear surface is minimal in the scanning electron microscopy image of Al6061-T6 + 5wt% titanium carbide + 5wt% graphite. The wear surface of the composite shows a mechanically mixed layer formed by material transfer from the steel disc's counterface. (See Figure 5d.) This leads to the conclusion that the Al6061-T6 -titanium carbide-graphite hybrid composite has a less worn surface than the unreinforced Al6061-T6. This analysis demonstrates that the addition of titanium carbide and graphite reinforcements improves the wear resistance of aluminum alloys.

Conclusions

The use of Taguchi's orthogonal array with grey relational analysis combined with principal component analysis was reported in this work to optimize the multiple performance characteristics of Al6061-T6/Titanium carbide/Graphite hybrid metal matrix composites such as wear rate, friction force, and coefficient of friction. Based on the present experimental work, the following conclusions have been drawn:

- The Al6061-T6/Titanium carbide/Graphite hybrid composites have been successfully produced by the stir casting route.
- Principal component analysis based grey relational analysis for the optimization of the multi response problems is a very useful tool for predicting the wear rate, friction force and coefficient of friction of Al6061-T6/Titanium carbide/Graphite hybrid metal matrix composites.
- From the grey relational analysis it is found that the optimum factors for both the wear rate and the coefficient of friction obtained for the hybrid composite are 20 N load (level 2), 4 m/s sliding speed (level 1), and 2500 m sliding distance (level 2) combination.
- From, ANOVA, it is revealed that the sliding velocity (45.511%) influences more on the multi-performance characteristics of hybrid composite followed by load (26.754%) and sliding distance (2.945%).
- From the study, it is concluded that the Grey relational analysis coupled with Taguchi method was proved to be a suitable method for optimization of multi-response characteristics, such as wear loss and co-efficient of friction of the prepared composites.

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