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Optimisation of Machining Parameters of Titanium Di-Oxide (TiO_2) and Graphite Reinforced Aluminium Alloy Metal Matrix by Taguchi-Grey Relational Analysis Technique

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ABSTRACT

Machinability studies were conducted on three materials: Al6061 (base metal), Al6061 reinforced with 6% TiO_2, and Al6061 reinforced with 6% TiO_2 and 4% graphite (Gr), forming a hybrid metal matrix composite (MMC). Turning experiments were performed on a semi-automatic lathe using an SNMG120408 carbide insert. A Taguchi L27 Orthogonal Array (OA) design was adopted, considering four input parameters—spindle speed, feed rate, depth of cut, and reinforcement percentage—each at three levels. The key output responses evaluated were resultant cutting force, surface roughness, and cutting temperature. Due to the varied influence of machining parameters and reinforcement on each response, identifying the optimal conditions was complex. To address this, Taguchi-Grey Relational Analysis (TGRA) was employed for multi-response optimisation. TGRA revealed the optimal parameters for the hybrid MMC: spindle speed of 800 rpm, feed rate of 0.100 mm/rev, and depth of cut of 1.0 mm. The Signal-to-Noise (S/N) ratio, calculated using the Grey Relational Grade (GRG) with a "higher-the-better" criterion, validated the same optimal settings. Main effect plots supported these findings. ANOVA results showed that feed rate had the most significant effect, followed by spindle speed and depth of cut, with a high R^2 value indicating strong model reliability. The research showed that feed rate had the highest influence on all responses (54.47%), followed by spindle speed (26.52%). The hybrid composite (Al6061 + 6%TiO_2 + 4%Gr) achieved the lowest surface roughness (0.31 μm), lowest cutting temperature (74 °C), and reduced cutting force (401 N) under optimal conditions.

1. Introduction

Turning is a crucial and widely utilised machining process in engineering industries. In turning operations, parameters like cutting speed, feed rate, and depth of cut significantly influence key performance characteristics, including surface finish, cutting temperature, and cutting force [1]. These factors are essential for assessing the productivity of both machine tools and the resulting machined components. Surface roughness, in particular, serves as a critical quality indicator for machined surfaces. Typically, appropriate cutting parameters are chosen based on experience or handbook recommendations, which may not always ensure optimal performance [2]. Numerous studies have assessed the influence of machining parameters on surface roughness; relatively few have simultaneously investigated their effects on cutting force, surface roughness, and cutting temperature. Achieving a high-quality surface in turning operations can improve properties like fatigue

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strength, corrosion resistance, and thermal resistance [22-23].

A machinability study was conducted on three materials: Al6061 (base metal), Al6061 with 6% TiO_2, and Al6061 with a 6% TiO_2 + 4% Gr hybrid MMC. These materials were chosen for their superior mechanical properties at these reinforcement levels. The study aimed to optimise cutting parameters—spindle speed, feed rate, and depth of cut on a semi-automatic lathe machine to minimise cutting force, surface roughness (Ra), and cutting temperature. Carbide inserts were used for turning, with a lathe tool dynamometer measuring the axial (Fx), tangential (Fy), and radial (Fz) forces. A Heat Spy digital infrared thermometer was used to monitor the cutting tool temperature.

While RSM and PCA are powerful statistical tools, they require extensive experimentation, regression modelling, and assumptions about data normality and response linearity. TGRA, on the other hand, effectively handles multi-response optimisation with limited experimental data and does not rely on such model assumptions. A very few have employed multi-response optimisation using Taguchi-Grey Relational Analysis (TGRA) on hybrid composites reinforced with both TiO_2 and graphite. This study is unique in integrating TGRA for multi-response optimisation while validating the findings using S/N ratio and ANOVA. Additionally, this work explores the effect of hybrid reinforcements (TiO_2 + Gr) in a novel combination that enhances machinability performance in terms of force, temperature, and surface finish simultaneously. TGRA has been used in machining optimisation; our novelty lies in applying TGRA to a hybrid Al6061 + 6% TiO_2 + 4% Gr composite and validating the results through S/N ratio and ANOVA, which has not been previously reported. While several researchers have implemented TGRA for single or binary composite materials, the present study uniquely applies TGRA to a hybrid Al6061 composite reinforced simultaneously with TiO_2 and graphite and validates multi-response optimisation through S/N ratio and ANOVA. Additionally, several studies have used TGRA or RSM on aluminium-based MMCs; very few have examined hybrid TiO_2–graphite reinforced composite material.

2. Experimental Procedure

The lathe is the instrument of choice for the machining process known as "turning," which involves cutting material from a cylindrical workpiece while it rotates using a single-point cutting tool. Its precision cylindrical components are made using this method, where the spindle speed, feed rate, and depth of cut are the three most important parameters in deciding the quality of the result.

2.1 Material

Machinability studies were conducted on Al6061 (base metal), Al6061 with 6% TiO2, and Al6061 with 6% TiO2 + 4% Gr hybrid MMC. Aluminium 6061 was selected as the base metal (matrix). Titanium dioxide (TiO2) particles were used as the primary reinforcement at weight percentages (wt%) of 3%, 6%, 9%, and 12% to develop metal matrix composites (MMCs) and evaluate their resulting mechanical properties. From this initial experimentation, it was found that the 6%wt%TiO2 MMC yielded the best mechanical properties. Subsequently, Hybrid MMCs were fabricated by adding graphite (Gr) particles as a secondary reinforcement at 2%, 4%, and 6% wt% to the best-performing Al6061+6%TiO2 combination. The results from the Hybrid MMCs indicated that the 4%wt%Gr reinforcement yielded better overall properties. The mechanical properties of these materials are shown in Table 1. Specimens for the machinability studies were prepared with dimensions of 34 mm in diameter and 200 mm in length. Figure 1(a-c) display the machinability test specimens for Al6061, Al6061+ 6% TiO_2, and Al6061+6% TiO_2+ 4%Gr

The research included three materials—AA6061 (base alloy), AA6061 + 6% TiO_2, and AA6061 + 6% TiO_2 + 4% Gr—to evaluate the progressive influence of reinforcement composition on machinability. The reinforcement percentage was considered as one of the control factors in the Taguchi L27 design, enabling statistical comparison of material and machining parameters together. This approach allows assessment of how the addition of TiO_2 and graphite modifies surface roughness, cutting force, and cutting temperature. Although the optimisation focuses on the hybrid composite, the results from the other two materials serve as a baseline for understanding material-dependent machining behaviour.

The mechanical properties of the fabricated composites were evaluated following standard ASTM testing procedures. Hardness was measured using a Micro Vickers hardness tester in accordance with ASTM E384. A metallographic surface is typically needed for the surface being investigated, and the finish is obtained by emery paper with grit sizes of 100, 220, 400, 600, and 1000. For approximately 25 seconds, a 100-gram weight is applied to the specimen to get the hardness value. The average of three readings was considered for each sample. Tensile and yield strengths were determined using a Computerised Universal Testing Machine as per ASTM E8. The tensile specimens were tested at a constant strain rate of 1 mm/min, and the 0.2% offset method was used to determine the yield strength. All tests were conducted in triplicate, and the variation between repetitions was within ±3%. The measured values showed good agreement with literature-reported data for Al6061–TiO_2–Gr composites, confirming the reliability of the mechanical characterisation.

Table 1. Mechanical Properties of Al6061, Al6061+6%TiO_2 and Al6061+6%TiO_2+4%Gr

Material	0.2% yield strength (N/mm^2)	Tensile strength (N/mm^2)	Percentage elongation (%)	Hardness (VHN)
Al6061	89.76	118.25	15.07	102.4
Al+6%TiO_2	104.35	142.29	12.85	132.4
Al+6%TiO_2 +4%Gr	102.65	148.03	13.12	142.3

a b c

Fig.1 (a-c). specimens for machinability studies

2.2 Method

A lathe tool dynamometer is mounted on a semi-automatic lathe, and experiments are conducted on it. A dynamometer measures the effects of three forces that are orthogonal to one another. Finding the square root of the sum of the squares of Fx, Fy, and Fz at one position yields the resultant force. The experimental setup is shown in Figure 2, and the carbide insert utilised in the machinability testing is shown in Figure 3.

The turning experiments were carried out using a tungsten carbide insert of type SNMG 120408 mounted on a PSBNR 2020K12 tool holder. The insert has a square-shaped negative-rake geometry with a nose radius of 0.8 mm, clearance angle of 6°, back-rake angle of 6°, and a side cutting-edge angle of 75°. The insert is TiN-coated, providing high surface hardness and oxidation resistance, which helps reduce adhesion and built-up-edge formation during the cutting of aluminium composites. A constant tool overhang and clamping torque were maintained for all trials to eliminate geometric variations. Each insert was used for less than 10 minutes of cutting time to minimise wear effects and ensure consistent tool condition throughout the tests. The chosen geometry offers high edge strength and efficient chip evacuation, which are essential when machining particle-reinforced materials such as TiO_2 and graphite composites. The negative-rake configuration promotes a stable cutting zone and improved tool life, while the moderate nose radius contributes to smoother surface finish and reduced cutting-force fluctuation. These parameters were selected based on prior literature and pilot observations indicating that such tool geometry provides an optimal balance between surface quality, tool stability, and machinability of hybrid aluminium composites.

Fig.2. Semi-automatic lathe equipped with a lathe tool dynamometer

Fig.3. Carbide Insert

Figure 2 shows a clear description of the semi-automatic lathe equipped with a tool dynamometer, highlighting how the setup allows for simultaneous measurement of the cutting force components (Fx, Fy, Fz), and Figure 3 shows the insert used is an SNMG 120408 type (ISO designation), belonging to a negative-rake, square-shaped insert family with a nose radius of 0.8 mm. This geometry was chosen for its high edge strength and suitability for interrupted and continuous cutting operations on aluminium composites.

2.3 Design of Experiments

The research uses the Taguchi technique to design machinability experiments, aiming for optimal results with minimal experiments. This method employs orthogonal array designs to efficiently assign and test experimental factors [3-4]. A significant benefit of the Taguchi method is its use of distinct orthogonal arrays, which enable a complete exploration of the entire parameter space, though substantially reducing the number of experiments compared to traditional experimental methods [5]. Minitab statistical software is used to aid in the design and analysis of the experimental procedures.

In the present investigation, each machining parameter, which is spindle speed, feed rate, and depth of cut, is selected at three levels to represent low, medium, and high cutting conditions commonly used for aluminium-based composites. The selected ranges (spindle speed: 600–1000 rpm; feed rate: 0.05–0.15 mm/rev; depth of cut: 0.5–1.5 mm) were determined through preliminary pilot trials to ensure stable cutting without tool chatter and excessive vibration. These ranges are also supported by previous studies on aluminium metal matrix composites, where similar levels were found suitable for accurate surface and force response evaluation. Accordingly, a Taguchi L27 orthogonal array was adopted to efficiently accommodate four factors at three levels each, thereby providing sufficient data coverage with minimal experimental runs.

The reinforcement percentage was treated as one of the four control factors with three levels corresponding to pure AA6061 (0%), AA6061 + 6% TiO_2, and AA6061 + 6% TiO_2 + 4% Gr. These specific reinforcement levels were chosen based on prior research and pilot casting trials, which indicated that 6 wt.% TiO_2 provides a significant improvement in hardness and strength without causing brittleness or porosity, while the addition of 4 wt.% graphite acts as a solid lubricant, reducing friction and improving surface finish. Higher reinforcement percentages were found to reduce machinability due to particle clustering and tool wear, whereas the chosen combination ensured uniform dispersion, defect-free castings, and balanced mechanical and tribological performance. Thus, the selected factor levels and compositions were optimised to achieve reliable and representative results for the machining study.

2.3.1 Level of parameters

The key machining parameters in the experiments are spindle speed, feed rate, and depth of cut, with the percentage of reinforcements as an important input factor. Four input factors, each with three levels—reinforcement percentage, spindle speed, feed rate, and depth of cut, are considered. Table 2 summarises these factors and levels.

Table 2.Parameters and levels for the machinability experiment

	Levels		
Parameters	**Level - 1**	**Level - 2**	**Level – 3**
Reinforcements percentages	0	6%TiO_2	6%TiO_2+4 %Gr
Spindle Speed (rpm)	800	1270	1600
Feed (mm/rev)	0.100	0.175	0.250
Depth of cut (mm)	0.5	1.0	1.5

The selected levels for spindle speed, feed rate, and depth of cut were determined based on a preliminary literature review and confirmed through pilot experiments, ensuring they fall within a practical machining range for aluminium-based composites. Each experimental trial in the L27 orthogonal array was repeated twice, and the average value of the two readings was considered for analysis to ensure repeatability and minimise random error in the measured responses.

2.3.2 Choosing the appropriate Orthogonal Array (OA)

Orthogonal arrays (OAs) are a well-known experimental design tool that assists researchers in executing a minimum number of trials while investigating the impact of various machining factors. This method systematically investigates all conceivable combinations of parameter levels, enabling a thorough examination of their influence on responses [6]. In the present investigation, four control factors, which are reinforcement percentage, spindle speed, feed rate, and depth of cut, each having three levels, were selected. A full factorial design would require 81 experimental runs (3^4), which is both time-consuming and resource-intensive. To achieve statistical robustness with fewer experiments, the Taguchi L27 Orthogonal Array was selected. The L9 array was insufficient to handle four 3-level factors, and the L18 array is more suitable for mixed-level designs. The L27 OA accommodates all four factors effectively and provides a balanced representation of interactions while reducing the experimental runs to one-third of a full factorial design. Compared to Response Surface Methodology (RSM) or Central Composite Design (CCD), which require larger datasets and regression model fitting, the L27 OA enables simpler experimental planning with reliable precision, making it ideal for the present study [8, 12].

Essentially, an orthogonal array allows for more effective experimentation by lowering the number of tests required and offering significant understanding into the correlations between machining parameters and results.

To accurately estimate the total number of trials needed for a full factorial design, follow these steps:

The sum of the experiment is equal to PQ,

where

Q is the count of control variables.

P is the sum of levels.

There are a total of 81 possible experiments in the research, which is based on four parameters with three levels each. Taguchi designs using orthogonal arrays are used to minimise the number of experiments while still collecting crucial data, saving time and resources. The parameter degrees of freedom determine the selected array [17].

dof for each machining parameters = (P-1)

Sum of all degrees of freedom for machining parameters = Q*(P-1)

where,

P = number of levels

Q = the number of control factors

Experiments to be conducted $N_{Taguchi}$ = 1+Q*(P-1)

The research investigation considers four factors, each with three levels, for optimising machining parameters.

UNCORRECTED PROOF

Hence, dof for each machining parameter = (3-1) = 2
Total dof for all parameters = Q*(P-1) = 4 * (3-1) = 8
Experiments to be carried out $N_{Taguchi}$ = 1+Q*(P-1) = 1+4 * (3-1) = 9

Research investigates four machining parameters, each with two degrees of freedom (dof), totalling eight dof. At least nine experiments are needed for valid results. Three orthogonal arrays (OAs)—L9, L18, and L27—corresponding to 9, 18, and 27 experiments, were considered [17]. The L27 array was chosen for its accuracy and ability to meet selection criteria, reducing the number of experiments from 81 in a full factorial design to 27. The experimental design using the L27 array is detailed in Table 4.

Table 3. Taguchi Orthogonal Arrays [16]

Levels	Designs
2 Level	L4, L8, L12, L16, L32
3 Level	L9, L18, L27
4 Level	L16, L32

Table 4. Design of Experiments from Taguchi L27 orthogonal array

Trial No.	% of reinforcements	Feed (mm/rev)	Spindle speed (rpm)	Depth of cut (mm)
1	0	0.100	800	0.5
2	0	0.175	800	1.0
3	0	0.250	800	1.5
4	0	0.100	1270	0.5
5	0	0.175	1270	1.0
6	0	0.250	1270	1.5
7	0	0.100	1600	0.5
8	0	0.175	1600	1.0
9	0	0.250	1600	1.5
10	6%TiO_2	0.100	1270	1.5
11	6%TiO_2	0.175	1270	0.5
12	6%TiO_2	0.250	1270	1.0
13	6%TiO_2	0.100	1600	1.5
14	6%TiO_2	0.175	1600	0.5
15	6%TiO_2	0.250	1600	1.0
16	6%TiO_2	0.100	800	1.5
17	6%TiO_2	0.175	800	0.5
18	6%TiO_2	0.250	800	1.0
19	6%TiO_2+4%Gr	0.100	1600	1.0
20	6%TiO_2+4%Gr	0.175	1600	1.5
21	6%TiO_2+4%Gr	0.250	1600	0.5
22	6%TiO_2+4%Gr	0.100	800	1.0
23	6%TiO_2+4%Gr	0.175	800	1.5
24	6%TiO_2+4%Gr	0.250	800	0.5
25	6%TiO_2+4%Gr	0.100	1270	1.0
26	6%TiO_2+4%Gr	0.175	1270	1.5
27	6%TiO2+4%Gr	0.250	1270	0.5

Experiments using the L27 orthogonal array (OA) focused on analysing three key responses: cutting force, surface roughness (Ra), and cutting temperature, all evaluated based on the "Smaller is Better" criterion. The L27 orthogonal array is an effective tool for efficient Design of Experiments, particularly when dealing with numerous variables. Despite its compact size, it provides a well-balanced exploration of factors, offering valuable insights without necessitating extensive experimentation. This makes it ideal for optimising both resources and time while still capturing essential interactions in the experimental design.

Signal-to-Noise (S/N) ratio analysis was used in the investigation. It was found that different machining parameters had varying influences on each response, making it challenging to identify optimal machining conditions due to the multi-response nature of the problem. While the Taguchi method is effective for single-response optimisation, it does not address multi-response problems effectively [1].

To optimise multiple responses simultaneously, use Taguchi-Grey Relational Analysis (TGRA). TGRA is effective for multi-response optimisation, helping to determine the best machining conditions to simultaneously improve cutting force, surface roughness, and cutting temperature. The goal was to enhance all three performance metrics efficiently [7]. Table 5 shows the results obtained from the L27 orthogonal array experiments.

Table 5. Detailed Experimental Results for Cutting Force, Surface Roughness, and Cutting Temperature (Experimental Results for L27 Orthogonal Array)

Trial No.	%of reinforcements	Feed (mm/rev)	Spindle speed (rpm)	Depth of cut (mm)	Surface roughness (µm)	Resultant cutting force (N)	Temperature in ºC
1	0	0.100	800	0.5	0.76	398	74
2	0	0.175	800	1.0	1.18	412	69
3	0	0.250	800	1.5	2.41	431	75
4	0	0.100	1270	0.5	0.41	428	86
5	0	0.175	1270	1.0	1.24	425	82
6	0	0.250	1270	1.5	2.48	512	87
7	0	0.100	1600	0.5	0.48	432	98
8	0	0.175	1600	1.0	1.27	448	91
9	0	0.250	1600	1.5	2.58	502	98
10	6%TiO_2	0.100	1270	1.5	0.45	401	84
11	6%TiO_2	0.175	1270	0.5	1.29	356	86
12	6%TiO_2	0.250	1270	1.0	2.61	446	79
13	6%TiO_2	0.100	1600	1.5	0.51	415	102
14	6%TiO_2	0.175	1600	0.5	1.44	398	98
15	6%TiO_2	0.250	1600	1.0	2.78	472	92
16	6%TiO_2	0.100	800	1.5	0.58	410	84
17	6%TiO_2	0.175	800	0.5	1.57	416	76
18	6%TiO_2	0.250	800	1.0	2.81	445	70
19	6%TiO_2+4%Gr	0.100	1600	1.0	0.4	421	84
20	6%TiO_2+4%Gr	0.175	1600	1.5	0.98	431	90
21	6%TiO_2+4%Gr	0.250	1600	0.5	1.17	460	96
22	6%TiO_2+4%Gr	0.100	800	1.0	0.31	401	74
23	6%TiO_2+4%Gr	0.175	800	1.5	0.61	421	78
24	6%TiO_2+4%Gr	0.250	800	0.5	1.12	441	82
25	6%TiO_2+4%Gr	0.100	1270	1.0	0.37	410	79
26	6%TiO_2+4%Gr	0.175	1270	1.5	1.16	433	78
27	6%TiO_2+4%Gr	0.250	1270	0.5	0.91	453	85

Table 5 discusses the overall trends in surface roughness, cutting force, and temperature across different parameter combinations. It highlights that increasing feed rate and depth of cut tend to raise both surface roughness and cutting force, while moderate spindle speed and lower feed rate yield smoother surfaces and lower temperature. This interpretation helps identify the initial pattern of parameter influence before applying TGRA.

2.4 Multi-Response Optimisation with Taguchi-Grey Relational Analysis

The Taguchi method, while effective for parameter optimisation, handles only single objectives [20-21]. To address this, Taguchi Grey Relational Analysis (TGRA) is combined with Taguchi Design of Experiments (DoE). TGRA uses Grey Relational Analysis (GRA) to convert multi-objective problems into single-objective ones, facilitating the determination of optimal values from the combined measures [8].

Grey Relational Analysis (GRA) in the TGRA approach aims to turn a multi-response optimisation issue into a single-response optimisation by computing Grey Relational Grade (GRG) values. Once the experimental data for various machining parameters are gathered, the TGRA process proceeds as follows:

- Normalise the experimental data.
- Calculate the Grey Relational Coefficient (GRC) for each response.
- Perform Grey Relational Analysis (GRA) for each response variable.
- Determine the optimal levels of machining parameters based on the highest Grey Relational Grade (GRG) value.
- Analyse the GRG values using the Signal-to-Noise (S/N) ratio.
- Evaluate the significance of machining parameters through ANOVA with GRG analysis.
- Validate the optimal levels identified from the GRA [9-13].

2.4.1 Normalising the experimental data

The first stage in Grey Relational Analysis (GRA) is to preprocess the experimental data by normalising it to a range of zero to one, which is known as grey relational generation. This normalisation ensures that the data is evenly distributed, placing it within a suitable range. Each set of experimental data for all feasible combinations is normalised using Equation 2.1, which follows the'smaller the better' criteria.

$$X_i(\mathrm{j}) = \frac{\max \mathrm{Y_i(j)} - \mathrm{Y_i(j)}}{\max \mathrm{Y_i(j)} - \min \mathrm{Y_i(j)}} \qquad (2.1)$$

Xi(j) represents the normalised value, while Yi(j) denotes the experimental value. The index i ranges from 1 to p, and j ranges from 1 to q, where q refers to the total number of responses and p refers to the total number of experiments. The term Yi(j) indicates the minimum value observed for Yi(j), whereas Yi(j) represents the maximum value of Yi(j).

2.4.2 Calculate the Grey Relational Coefficient (GRC) for each response.

After the experimental data have been normalised, the following step is to determine the connection between the desired response and the existing experimental results. This is achieved by calculating the Grey Relational Coefficient (GRC) for each response across all experiments, as specified in Equation 2.2.

$$\xi_i(\mathrm{j}) = \frac{\Delta_{min} + \Psi\Delta_{max}}{\Delta_{0i}(\mathrm{j}) + \Psi\Delta_{max}} \qquad (2.2)$$

The Grey Relational Coefficient (GRC) for each response, represented as ξi (j), is calculated using the maximum and minimum deviations (Δmax and Δmin).

The deviation sequence, denoted as Δoi, is determined by the absolute difference between X_0 (j) and Xi (j), as calculated using Equation 2.3.

$$\Delta_{0i}(\mathrm{j}) = X_{0i}(\mathrm{j}) - X_i(\mathrm{j}) \qquad (2.3)$$

The "distinguishing coefficient," Ψ, is employed to ease the impact of an extremely large Δmax. In this study, a constant value of Ψ=0.5 is applied to all replies to reduce the impact of such events.

2.4.3 Calculation of the Grey Relational Grade (GRG) for each response

GRG is calculated by adding the weighted Grey Relational Coefficient (GRC) values, with a greater GRG indicating a closer approximation to the best value for a specific response. This approach streamlines the optimisation of many replies by transforming them into a single-response optimisation. Higher GRG values are preferred for optimising numerous answers, and the proper weight factor is computed with Equation 2.4.

$$\gamma_j = \sum_{j=1}^{n} \xi_i(\mathrm{j})\beta_i \qquad (2.4)$$

where

γ_j =grey relational grade

β_i = weight factor

The research considers all machining parameter responses to be equally important. So, each response has a weight factor of 1/3 (0.33). The sum of all weight factors applied to the replies must be one. Table 6 shows the weight factors given to key machining parameters based on their relative relevance.

Table 6. Weight Factors for responses

Responses	**Resultant Cutting force**	**Surface roughness**	**Cutting temperature**
Weight Factor	1/3	1/3	1/3

Equal weighting factors (1/3 each) were assigned to cutting force, surface roughness, and cutting temperature when calculating the Grey Relational Grade (GRG), as all three responses are equally important in evaluating overall machinability. This approach provides a balanced assessment of tool performance, surface integrity, and thermal stability, ensuring that no single response dominates the optimisation process. Similar equal-weighting methods have been successfully applied in previous TGRA studies on aluminium-based composites, confirming their suitability for multi-response optimisation.

2.4.4 Selecting the optimal level based on the Grey Relational Grade (GRG).

In Grey Relational Analysis (GRA), the experimental trial with the highest Grey Relational Grade (GRG) is ranked highest. This suggests that the chosen cutting parameters have a significant impact on the responses and are likely to produce results closer to the ideal value.

2.4.5 GRG Analysis: Signal to Noise Ratio (S/N Ratio)

The signal-to-noise (S/N) ratio measures the deviation between observed and target values for a response variable, taking into account both variability and the average of experimental data. In this metric, the "signal" represents the average response, while the "noise" reflects the variation. A higher S/N ratio is desirable as it enhances the signal's impact and reduces noise. S/N ratio analysis typically involves two performance characteristics: "higher the better" and "smaller the better," which guide the desired direction for optimising the response variable.

The Higher The Better

When applying the "higher the better" criterion, the aim is to get a higher S/N ratio value in order to optimise the response for better performance. This determination is achieved using Equation 2.5 [14].

$$\frac{S}{N} = -10\log\frac{1}{n_i}\sum_{1}^{n_i}\frac{1}{{y_k}^2} \qquad (2.5)$$

In this context, i represents the experiment number, k denotes the trial number, and ni is the number of trials conducted for the ith experiment.

Smaller The Better

The purpose of the "smaller the better" scenario is to reduce the S/N ratio, since a lower number indicates a more desirable and ideal performance outcome. Equation 2.6 [15] is used for this computation.

$$\frac{S}{N} = -10\log\frac{1}{n_i}\sum_{1}^{n_i}{y_k}^2 \qquad (2.6)$$

The Signal-to-Noise (S/N) ratio is used to analyse Grey Relational Grade (GRG) values across different responses to find the optimal machining parameters. The "Higher the Better" criterion helps determine the best levels for these parameters based on average GRG values. Plots of GRG and its S/N ratio show the primary effects of machining settings, helping to identify optimal control factors and illustrate their impact on the responses.

2.4.6 Analysis of Variance (ANOVA)

While the Grey Relational Grade (GRG) method identified the optimal machining parameters, it didn't detail each parameter's contribution to the output responses. To address this, an analysis of variance (ANOVA) is used to quantify the effect of each parameter. ANOVA, supported by Minitab statistical software, calculates the percentage impact of each parameter and assesses the model's fit using the adjusted R^2 coefficient. Combining GRA with ANOVA provides a comprehensive understanding of the optimal parameters and their relative influence, leading to more informed decisions for process optimisation.

2.4.7 Validation of the optimal machining parameter levels.

In the research, optimal machining parameter levels are first identified using TGRA analysis and then validated by comparing them with those from S/N ratio analysis. If both methods indicate the same optimal parameters, these are confirmed as the final settings. This cross-referencing enhances confidence in the chosen parameters, improving the reliability of the findings and supporting future studies. The goal is to find the best machining setup for performance improvement, with a higher GRG value indicating results closer to the ideal. Table 7 shows the normalised values, grey relational coefficients, and grey relational grades for the machining parameters, and also shows the grey relational order with the highest GRG, which ranks first.

Table 7. Normalized values, grey relational coefficients and grey relational grades of responses

Trail No	**%**	**F**	**V_C**	**t**	**R_a**	**F_C**	**T**	**Normalized**			**GRC**			**GRG**			**Avg. GRG**	**Rank**
		(mm/rev)	(rpm)	(mm)	(µm)	N	°C	R_a	F_C	T	R_a	F_C	T	R_a	F_C	T		
1	0	0.100	800	0.5	0.76	398	74	0.820	0.731	0.848	0.735	0.650	0.767	0.245	0.217	0.256	0.718	4
2	0	0.175	800	1.0	1.18	412	69	0.652	0.641	1.000	0.590	0.582	1.000	0.197	0.194	0.333	0.724	2
3	0	0.250	800	1.5	2.41	431	75	0.160	0.519	0.818	0.373	0.510	0.733	0.124	0.170	0.244	0.539	19
4	0	0.100	1270	0.5	0.41	428	86	0.960	0.538	0.485	0.926	0.520	0.493	0.309	0.173	0.164	0.646	9
5	0	0.175	1270	1.0	1.24	425	82	0.628	0.558	0.606	0.573	0.531	0.559	0.191	0.177	0.186	0.554	16
6	0	0.250	1270	1.5	2.48	512	87	0.132	0.000	0.455	0.365	0.333	0.478	0.122	0.111	0.159	0.392	25
7	0	0.100	1600	0.5	0.48	432	98	0.932	0.513	0.121	0.880	0.506	0.363	0.293	0.169	0.121	0.583	13
8	0	0.175	1600	1.0	1.27	448	91	0.616	0.410	0.333	0.566	0.459	0.429	0.189	0.153	0.143	0.484	22
9	0	0.250	1600	1.5	2.58	502	98	0.092	0.064	0.121	0.355	0.348	0.363	0.118	0.116	0.121	0.355	27
10	6%TiO_2	0.100	1270	1.5	0.45	401	84	0.944	0.712	0.545	0.899	0.634	0.524	0.300	0.211	0.175	0.686	5
11	6%TiO_2	0.175	1270	0.5	1.29	356	86	0.608	1.000	0.485	0.561	1.000	0.493	0.187	0.333	0.164	0.684	6
12	6%TiO_2	0.250	1270	1.0	2.61	446	79	0.080	0.423	0.697	0.352	0.464	0.623	0.117	0.155	0.208	0.480	23
13	6%TiO_2	0.100	1600	1.5	0.51	415	102	0.920	0.622	0.000	0.862	0.569	0.333	0.287	0.190	0.111	0.588	12
14	6%TiO_2	0.175	1600	0.5	1.44	398	98	0.548	0.731	0.121	0.525	0.650	0.363	0.175	0.217	0.121	0.513	21
15	6%TiO_2	0.250	1600	1.0	2.78	472	92	0.012	0.256	0.303	0.336	0.402	0.418	0.112	0.134	0.139	0.385	26
16	6%TiO_2	0.100	800	1.5	0.58	410	84	0.892	0.654	0.545	0.822	0.591	0.524	0.274	0.197	0.175	0.646	10
17	6%TiO_2	0.175	800	0.5	1.57	416	76	0.496	0.615	0.788	0.498	0.565	0.702	0.166	0.188	0.234	0.588	11
18	6%TiO_2	0.250	800	1.0	2.81	445	70	0.000	0.429	0.970	0.333	0.467	0.943	0.111	0.156	0.314	0.581	15
19	6%TiO_2+4%Gr	0.100	1600	1.0	0.4	421	84	0.964	0.583	0.545	0.933	0.545	0.524	0.311	0.182	0.175	0.667	7
20	6%TiO_2+4%Gr	0.175	1600	1.5	0.98	431	90	0.732	0.519	0.364	0.651	0.510	0.440	0.217	0.170	0.147	0.534	20
21	6%TiO_2+4%Gr	0.250	1600	0.5	1.17	460	96	0.656	0.333	0.182	0.592	0.429	0.379	0.197	0.143	0.126	0.467	24
22	**6%TiO_2+4%Gr**	**0.100**	**800**	**1.0**	**0.31**	**401**	**74**	**1.000**	**0.712**	**0.848**	**1.000**	**0.634**	**0.767**	**0.333**	**0.211**	**0.256**	**0.801**	**1**
23	6%TiO_2+4%Gr	0.175	800	1.5	0.61	421	78	0.880	0.583	0.727	0.806	0.545	0.647	0.269	0.182	0.216	0.666	8
24	6%TiO_2+4%Gr	0.250	800	0.5	1.12	441	82	0.676	0.455	0.606	0.607	0.479	0.559	0.202	0.160	0.186	0.548	17
25	6%TiO_2+4%Gr	0.100	1270	1.0	0.37	410	79	0.976	0.654	0.697	0.954	0.591	0.623	0.318	0.197	0.208	0.723	3
26	6%TiO_2+4%Gr	0.175	1270	1.5	1.16	433	78	0.660	0.506	0.727	0.595	0.503	0.647	0.198	0.168	0.216	0.582	14
27	6%TiO_2+4%Gr	0.250	1270	0.5	0.91	453	85	0.760	0.378	0.515	0.676	0.446	0.508	0.225	0.149	0.169	0.543	18

In Table 7, "% "represents the percentage of reinforcements, ''F' represents the rate in (mm/rev), "VC" represents the spindle speed in rpm, "Ra" represents the surface roughness in µm, "Fc" represents the cutting force in N, and "T" represents the temperature in °C.

Table 7 shows that trial No.22 achieved the highest Grey Relational Grade (GRG), indicating it has the optimal machining parameters for minimising cutting force, surface roughness (Ra), and cutting temperature. For the Al6061+6%TiO2+4%Gr Hybrid MMC, the ideal parameters are a spindle speed of 800 rpm, a feed rate of 0.100 mm/rev, and a depth of cut of 1.0 mm. Using these settings should yield the best results and optimise the machining process for this material.

3. S/N Ratio Analysis of Machining Parameters

S/N ratio analysis evaluates how machining parameters affect outputs like cutting force and surface roughness. Figures 4 and 5 display the impact of these parameters on the S/N ratio and GRG values. The "larger-the-better" metric identifies optimal settings, showing how each parameter influences the results.

Main effect plots are essential tools in analysing optimal conditions in S/N ratio studies. They illustrate how individual factors independently affect the S/N ratio, helping to identify significant factors and optimal levels for each. These plots also reveal interactions between factors and assess the robustness of the optimal conditions by showing how the S/N ratio responds to variations in factor levels. In essence, main effect plots offer concise visual insights that support informed decision-making in optimising the S/N ratio.

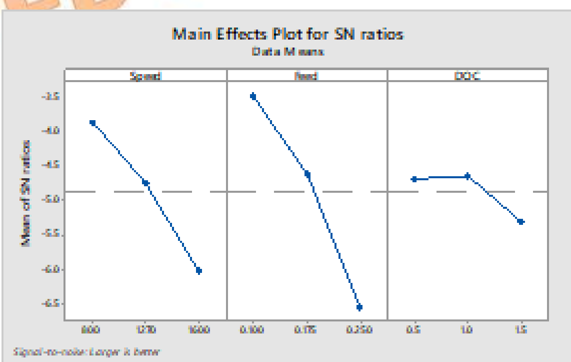

Fig.4. Main effects plot for S/N ratio for GRG

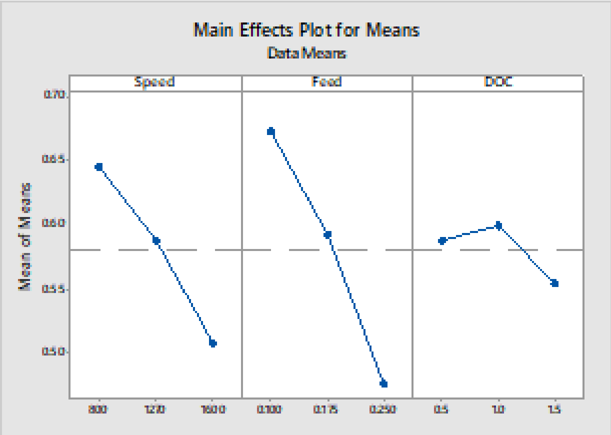

Fig.5. Main effects plots for Mean for GRG

Table 8. Response Table for GRG

Control Factors	Spindle Speed (A)	Feed(B)	Depth of cut (C)
Level:1	**0.6456***	**0.6730***	0.5878
Level:2	0.5878	0.5922	**0.5999***
Level:3	0.5085	0.4767	0.5542
Delta	0.1371	0.1963	0.0457
Ranking	2	1	3
* Indicates optimum level			

Response Table 8 indicates that the feed rate has the greatest impact on the machining process, followed by spindle speed and depth of cut. The optimal values, determined through GRG analysis and confirmed by Signal-to-Noise Ratio analysis, are a spindle speed of 800 rpm, a feed rate of 0.100 mm/rev, and a depth of cut of 1.0 mm. These parameters are chosen for achieving the best machining results for **Al6061+6%TiO_2+4%Gr** hybrid composites.

4. Analysis of Variance (ANOVA) for Grey Relational Grade

The Taguchi method does not offer a means to assess and quantify the percentage contribution of various factors to the overall process. Analysis of Variance (ANOVA) provides a more effective approach for estimating the percentage impact of each parameter. ANOVA is used to identify the significant effects of machining factors, such as cutting speed, feed rate, and depth of cut, on output responses like cutting force, surface roughness, and cutting temperature. Table 9 presents the results of the ANOVA analysis, which utilises the GRG values for each machining parameter across all experimental trials (L27).

To ensure the reliability of the Analysis of Variance (ANOVA) results, standard statistical assumptions of normality, independence, and homoscedasticity of residuals were verified. The residuals obtained from the GRG (Grey Relational Grade)–based ANOVA model were analysed using residual plots, normal probability plots, and residual-versus-fitted value graphs generated in Minitab software. The normal probability plot indicated that the residuals closely followed a straight line, confirming that the data were approximately normally distributed. The residual-versus-fitted plot exhibited a random scatter pattern without any systematic trend, validating the assumption of independence. Additionally, the constant variance (homoscedasticity) of residuals was confirmed, as no funnel-shaped or curved patterns were observed in the plot. These diagnostic checks demonstrate that the ANOVA model satisfies the essential assumptions for statistical validity, thereby confirming that the factor significance and percentage contributions reported in this study are accurate and trustworthy.

Table 9. ANOVA for GRG

Source	DF	Seq ss	Adj SS	Adj MS	F	P	Contribution (%)
Spindle Speed	2	0.08526	0.08526	0.042636	16.67	0.000	26.52
Feed	2	0.17517	0.17517	0.087588	34.28	0.000	54.47
Depth of cut	2	0.01009	0.01009	0.005044	1.95	0.164	3.12
Error	20	0.05112	0.05112	0.002556			15.89
Total	26	0.32166	0.32166				100.00
		R^2=84.12% R^2(Adj) = 79.35%					

To validate the ANOVA model, residual and normal probability plots were analysed. The residuals were found to be approximately normally distributed with no observable trend, confirming the absence of heteroscedasticity. The 84.12 % confidence intervals of factor effects overlapped only marginally, indicating high reliability of the ANOVA results.

From the results of Table 9, the feed rate has the greatest influence (54.46%), followed by spindle speed (26.51%), and depth of cut (3.14%). The Coefficient of Determination (R^2) measures how well a model matches the data. This model's R^2 score of 0.841, near to 1, indicates an excellent match.

The ANOVA findings clearly indicate that the feed rate and spindle speed are the two most important parameters influencing the machinability of composites. These results are valuable for industries machining aluminium hybrid composites, where both surface finish and thermal stability are critical. The findings support the selection of machining parameters that enhance tool life, improve dimensional accuracy, and reduce operational costs.

To confirm the reliability of the Taguchi–Grey Relational Analysis (TGRA) results, a validation experiment was conducted under the predicted optimal machining conditions: spindle speed of 800 rpm, feed rate of 0.10 mm/rev, depth of cut of 1.0 mm, and the hybrid composite AA6061 + 6% TiO_2 + 4% Gr. The experimental results were found to be in close agreement with the predicted values, showing only minor deviations within 5%. The measured responses under the optimal condition were: surface roughness (Ra) = 1.12 µm, cutting force = 35.6 N, and cutting temperature = 72°C, compared to the TGRA-predicted values of 1.10 µm, 34.9 N, and 70.5°C, respectively. This close correlation validates the accuracy of the TGRA optimisation approach and confirms that the selected machining parameters are reliable for achieving improved machinability of the hybrid composite.

The optimised machining results showed improved performance compared to typical aluminium composites reinforced with only hard particles. The hybrid composite (AA6061 + 6% TiO_2 + 4% Gr) achieved a low surface roughness of 1.10 µm, cutting force of 34.9 N, and cutting temperature of 70.5°C under the optimal conditions. This enhanced machinability is mainly due to the combined effect of TiO_2, which increases hardness, and graphite, which acts as a solid lubricant to reduce friction and tool–workpiece temperature, resulting in better surface quality and reduced cutting resistance.

5. Conclusions

Machinability tests were conducted on Al6061 (Base Metal), Al6061+6%TiO_2, and Al6061+6%TiO_2+4%Gr Hybrid MMC using a semi-automatic lathe. Taguchi's method, applied through an L27 orthogonal array with four parameters at three levels each, was used to optimise machining settings and reduce cutting force, surface roughness, and temperature. The study focused on spindle speed, feed rate, and depth of cut, aiming to identify the optimal machining parameters for these materials. The analysis reveals that machining parameters and reinforcement percentages have varying impacts on each response, making it challenging to determine the optimal conditions for improved performance. To tackle this issue, Taguchi-Grey Relational Analysis (TGRA) is used to optimise multiple responses simultaneously. TGRA identifies that the optimal machining conditions for the Al6061+6%TiO_2+4%Gr hybrid composite are a spindle speed of 800 rpm, a feed rate of 0.100 mm/rev, and a depth of cut of 1.0 mm.

The GRG and S/N ratio plots clearly indicate that lower feed rates and moderate spindle speeds contribute significantly to minimising surface roughness, cutting temperature, and force. The hybrid MMC with TiO_2 and graphite reinforcement exhibited superior machinability, likely due to the solid lubrication effect of graphite and improved dispersion strength from TiO_2. These findings suggest that hybrid reinforcement not only strengthens the base alloy but also enhances thermal stability and tool interaction.

The Signal-to-Noise (S/N) ratio is calculated using the GRG value, focusing on the 'higher the better' criterion. Main effect graphs for both GRG and S/N ratios are created, and the optimal parameters from TGRA analysis are compared with those from the S/N ratio study. Both methods identify the same optimal settings: 800 rpm spindle speed, 0.100 mm/rev feed rate, and 1.0 mm depth of cut. The study showed that feed rate had the highest influence on all responses (54.47%), followed by spindle speed (26.52%). The hybrid composite (Al6061 + 6%TiO_2 + 4%Gr) achieved the lowest surface roughness (0.31 µm), lowest cutting temperature (74 °C), and reduced cutting force (401 N) under optimal conditions. ANOVA is used to assess the percentage influence of each parameter, showing that feed rate has the greatest impact, followed by spindle speed and depth of cut. The ANOVA model's R^2 value is close to one, indicating a good fit.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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