Research Article

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Sustainable Nano-assisted Dry Turning of Hybrid Aluminium Matrix Composites: Process Parameter Optimisation via Grey Relational Analysis

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The sustainable machining issue has received additional consideration in recent years due to its social, economic, and environmental implications. The paper examines the performance optimisation of green nano-aided dry turning of the hybrid metal matrix aluminium alloy through the lens of Grey Relational Analysis (GRA). By adding a nanoparticle that minimizes a negative environmental impact, the tribological behaviours are enhanced and the cutting efficiency maximized. There are three key turning factors such as, cutting speed, feed rate and depth of cut which were systematically varied to establish the corresponding machining characteristics and sustainability aspect such as carbon emission, energy consumed, cutting force and surface topography. The findings of mean GRG and ANOVA revealed that the parameter that would exert the most impact in achieving sustainable machining is the depth of cut. The optimal set of parameter values that was identified using GRA was the combination of the following parameters, cutting speed of 200 m/min and feed rate of 0.05 mm/rev and depth of 0.2 5 mm. The employment of such parameters, along with the application of the nano-enhanced dry turning conditions led to a 72.84 percent reduction in carbon, 72.82 percent energy, 18.58 percent of cutting power, and 6.83 percent of the surface roughness. There was also an increase in performance by 0.1702 in total GRG. As was observed in this paper, nano-assisted machining strategies and parameter optimisation can play a very crucial role in facilitating sustainable manufacturing of the aluminium-based hybrid composites.

Keywords: Nano-assisted machining; Dry turning; GRA; Hybrid metal matrix aluminium alloy; Sustainable manufacturing.

1. INTRODUCTION

The need for sustainable machining has grown in relevance due to its environmental friendliness and economic benefits. The aluminium based hybrid generated composite finds wide application in the industries that need a high degree of accuracy in processing and environment friendliness. Nano-assistance dry turning has made it easier to achieve an enhanced tribological performance and less effect on the environment. This research paper aims to select parametric values that optimise machining operations, making them greener through the application of Grey Relational Analysis. The recent developments in the field of machining and sustainable farming also underline the use of nanotechnology, Minimum Quantity Lubrication (MQL) and nano-additives to promote better efficiency and environmental acceptability in a particular process. In the perspective of hard turning, two studies by (Bag *et al*. 2020; Rahman *et al.* 2024). The extension of tool life and improvement in surface quality were demonstrated using nano-cutting fluids and MQL in AISI 4340 steel machining, which understandably results in reduced cutting force and temperature. Equally, Khatai *et al.* (2024) have proved the better performance of a multi-nozzle MQL system on hardened AISI D2 steel, to give the optimal efficiency of energy consumption and machining results. Shaikh *et al*. (2021). have further confirmed the advantageousness of such benefits by orthogonal array experimenting using L9 on A105 material, comparing the dry, MQL, and nano-Al_2O_3 assisted MQL conditions and found nano assisted MQL to have an improved surface finish as well as tool wear reductions. Nano-additive-enhanced MQL was considered in as a potential method of enhancement of process control and reduction of defects on the microscale by Jagadeesha *et al.* (2024) in micromachining.

(Karmiris *et al.* 2022) trochoidal end milled Incoloy 800 and examined MQL effectiveness in milling activities by comparing the outcomes of dry and flood cooling. They realized that MQL produced remarkable improvements in the aspect of surface integrity. The results are consistent with the more general objectives of cleaner production, energy efficiency and lowered ecological footprint in production. Parallelly, the potential of nanotechnology in the agricultural front has picked up. (Dhanapal *et al.* 2024). Described nano-remediation methods as an approach to treat polluted agricultural soils, whereas (El-Ramady *et al.* 2023) supported the idea of nanofarming as the future of global farm challenges because it enhances the resilience of crops and the condition of the soil. In addition, Shafey, (2020) published the review of metal and metal oxide nanoparticles that can be synthesized using plant extract using green synthesis, which provides also environment-friendly alternatives to agriculture and machining.

Writing about AISI D2 tool steel, (Pradhan, 2013) utilized RSM and GRA in combination with PCA to investigate EDM using such parameters as MRR, TWR, and overcut, optimizing them. In a similar manner, (Selvaraj *et al.* 2014) primarily focused on optimizing of surface roughness, cutting force, and tool wear in dry turning duplex stainless steel via Taguchi method, which was proven to be effective in tuning parameters of the process. Jung and Kwon, (2010) Also confirmed the Taguchi-GRA methodology on EDM and obtained the optimum performance of the processes according to various measures. A thorough review of Inconel 718 machining, focusing on the Influence of cutting temperature and the issues it presents, was offered by Mahesh *et al.* (2021) in the field of thermal-resistant materials. Mia *et al*. (2019) and Younas *et al. (*2019) also broadened the study, incorporating environmental-related and sustainability issues into multi-objective machining optimization of Ti6Al4V with eco-friendly coolants and AHP-GRA hybrid models. (Khodabakhshi *et al.* 2017) investigated the process of friction stir welding of aluminium/polymer bi-materials that can be potentially utilised in the fabrication of lightweight aircraft and aerospace structures through bonding mechanisms. A review by Omiyale *et al.* (2022) covers the Wire Arc Additive Manufacturing (WAAM) of aluminium alloys and its potential about the aerospace and automotive industries. For composite materials and hybrid structures, Ajith *et al.* (2019) applied Taguchi-GRA, whereas Rajeswari and Amirthagadeswaran, (2017) applied RSM-GRA in predicting and optimising milling control parameters of aluminium hybrid composite to attain better dimensional accuracy and surface integrity.

Regarding non-conventional, (Kumar *et al.* 2015) explored Wire-EDM on aluminium composites and utilised GRA regarding parameter adjustment, to mitigate minimum wire wear and superior cut quality. Researchers such as (Aslani *et al.* 2020) stressed the adaptation of GRA and Taguchi techniques to enhance the quality of PLA pieces printed in 3D, which indicates the effectiveness of the method in terms of additive manufacturing. Furthermore, Taguchi-GRA techniques were successfully used in optimizing the working of absorption refrigeration systems (Canbolat *et al.* 2019) and Organic Rankine Cycle systems (Bademlioglu *et al.* 2020), thus demonstrating that their performance might apply to other energy systems as well.

Although numerous studies have been conducted on sustainable machining, few have focused exclusively on nano-assisted dry turning of aluminium-based hybrid composites under environment-friendly research conditions. The gap in the body of knowledge appears in the explanation of tribological and thermal effects of nano-coated tools in dry machining conditions. In contrast, most of the works available focus on MQL or wet machining. Also, there is limited work on the combination of optimisation tools such as Grey Relational Analysis (GRA) and nanotechnology on hybrid composites. Little research has been done to cover the synergistic effect of using multi-nano reinforcement (e.g., SiC, Ti, Zn) on machinability, surface integrity, and tool wear. Further, there is no detailed comparative study of hybrid material machining in conventional as well as nano-assisted machining environments. This research fills such gaps using nano-coated tungsten carbide inserts and utilizing GRA in the sustainable optimization of the process parameters. The innovation presents a new approach that associates nano-material behavior with dry machining working conditions and sustainability indicators to develop a strong and sustainable machining strategy.

2. MATERIALS AND METHOD

This paper was based on the topic of researching nano-assisted dry turning of a hybrid aluminium metal matrix composite to enhance the sustainability and performance of the machining process. It was through stir casting that the workpiece material was prepared, whereby the AA6061 aluminium alloy was used as the base material matrix, and it contained titanium (Ti) and zinc (Zn) as the reinforcing elements, as well as nano-sized silicon carbide (SiC) particles. A mechanical stirrer of 600 rpm was used to uniformly disperse the nano-reinforcements in the molten aluminium, which was subsequently transformed into rods of 600 mm in diameter, which were then chopped into 320 mm lengths.

Experiments to work in dry conditions (dry turning) were carried out on precision centre lathes without the application of cutting fluids to preserve ecologically sustainable conditions. Their high wear resistance and thermal stability led to the use of nano-coated carbide inserts. They chose a complete factorial design whereby cutting speed (150, 175, 200 m/min),

feed rate (0.05, 0.075, 0.1 mm/rev) and depth of cut (0.15, 0.20, 0.25 mm) were varied.

The output of performance was gauged in terms of surface roughness, energy use, ensemble cutting intensity, and carbon emissions, which were gauged and calculated through highly sensitive equipment. An analysis was conducted on the results, and further optimization was achieved using Grey Relational Analysis (GRA) to evaluate sustainability indicators. Additionally, ANOVA was employed to identify the most critical parameters.

Table 1. lists the detailed machining conditions and parameter levels

Parameter	Level 1	Leve l 2	Level 3	Units
Cutting Speed	150	175	200	`m/min
Feed Rate	0.05	0.075	0.10	mm/rev
Depth of Cut	0.15	0.20	0.25	mm
Tool Material	Nano-coated tungsten carbide insert	—	—	—
Machining Condition	Dry Machining	—	—	—

In this experimental study, a Sandvik nano-coated tungsten carbide insert (ISO SNMG08) was used due to the high wear resistance and thermal stability that would allow dry machining of nano-reinforced hybrid aluminium matrix composites. The conditions under which cuts were made were as stipulated by the tool manufacturers, cutting tool holder, lathe capacity, and ISO specifications of nano-aided machining.

The research on sustainable production utilized a total of 27 trials of dry turning, varying the cutting speed, feed rate, and depth of cut. The parameters were set within the specified tool and machine limits, and the knowledge of nano-assisted machining was used.

The experiments were also carried out on a Kirloskar Turnmaster 35 all-geared lathe(2.2 kW motor,800 mm centre distance, 175 mm centre height) using hybrid aluminium composites with 50 nm of SiC nanoparticles. The variables of cutting forces were measured with a Kistler quartz three-axis dynamometer (Type 9215A1) and linked with charge amplifiers (Type 5070) in data collection.

The roughness of the surfaces was measured by using a TR-100 surface tester, and the Material Removal Rate (MRR) was determined according to conventional volumetric calculations. Figure 1 displays the series of processes, which entailed preparation of the material, machining, and assessment of the performance and layout.

$$MRR = Depth\ of\ cut \times Feed\ rate \times Cutting\ speed \quad \ldots (1)$$

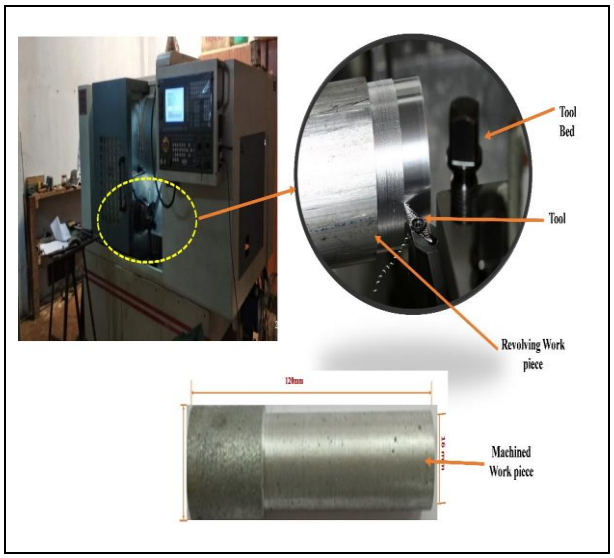


Fig. 1: Experimental setup and machined workpiece

Table 2. Outlines key tools and parameters

S. No.	Tool/Parameter	Details
1	Machining Time Quantity	Measured and recorded via the Kirloskar Turnmaster-35 lathe system
2	Machine Device	Kirloskar Turnmaster-35 all-geared lathe
3	Tool Material	Nano-coated tungsten carbide inserts (Sandvik, ISO SNMG08 specification)
4	Atmosphere	Dry Machining (Eco-friendly; no coolant used)
5	Size of Material	Φ60 mm × 320 mm (Machining length: 30 mm)
6	MRR Calculation	Based on volumetric removal (via weight difference)
7	Work Specimen Material	Hybrid Al alloy reinforced with nano SiC, Ti, and Zn via stir casting

The main instruments and settings utilized in the nano-assisted dry turning investigation are listed in Table 2. Nano-coated tungsten carbide inserts were machined in dry circumstances on a Kirloskar Turnmaster-35 lathe. A hybrid aluminum composite enhanced with nanoparticles of SiC, Ti, and Zn made up the workpiece. The weight difference before and after machining was used to calculate the material removal rate.

Table 3. Shows the chemical composition of the workpiece

Label	Aluminium (Base)	Titanium	Nano Silicon Carbide (SiC)	Zinc (Zn)
C-I	2 kg	10% – 200 g	5% – 100 g	2.5% – 50 g

The composition of Composite-I (C-I), which has 2 kg of aluminum as its base, is displayed in Table 3. By weight, it contains 60 g of zinc (2.5%), 120 g of nano silicon carbide (5%), and 240 g of bronze (10%).

2.1 Energy Depletion Calculation

Understanding a machine's energy consumption is essential for controlling its electrical energy use. Because energy accounts for approximately half of production costs, estimating energy consumption is crucial. In a larger sense, the continuous hunt for new energy sources is essential as energy use results in carbon emissions, which affect the ecosystem. Energy use in manufacturing accounts for a significant portion of total costs. Energy consumption (EC) in this investigation was determined using Equation (2).

$$E_C = \frac{F_c\,(N) \times V_c \times Machining\ Time}{1000} \quad \ldots (2)$$

In this context, VC stands for the machining speed in meters per minute (m/min), EC for the cutting energy in kilojoules (kJ), and FC for the cutting force (N) as determined by the cutting tool dynamometer. Manufacturing accounts for over 60% of the industry's energy consumption, with industrial sectors consuming an estimated 31% of the total energy. Furthermore, only 15% of the total energy spent is successfully used for manufacturing, indicating that energy efficiency in these sectors is below optimal. Therefore, in the quest for more ecologically friendly manufacturing in these procedures, it is crucial to minimize energy consumption in machining processes.

22 Estimate of Carbon Release

The industrial sector has been increasingly conscious in recent years of the significant environmental effects of its activities. In the past, companies have only just started to give minimizing their ecological effect top priority. Greenhouse gas concentrations are exacerbated by the use of fossil fuels in the production of many engineering goods, which significantly affects CO_2 emissions. One crucial contributing cause to climate change and heat waves is the abundance of CO_2 in these gases. As a result, cutting CO2 emissions as much as possible is essential. Alternative energy sources must be investigated and used in practical situations to address this problem. Carbon emissions may be predicted using Equation (3).

The formula for Cee is $EC \times Fe$ ... (3)

where Cee stands for the carbon emissions in kilograms of CO_2. Whereas Fe represents the carbon release factor specifically related to electrical energy consumption, EC denotes the total electrical energy consumption.

3. RESULTS AND DISCUSSION

3.1 Grey Relational Analysis Method

The Influence of the Cutting Speed on the Contact Pressure

$$P = \frac{F}{A} \quad \ldots (4)$$

Grey Relational Analysis, which involves several processes, is a component of this process. Normalizing the experimental data by correcting for variations in measurement units is the first step. Grey relations are created, and Grey coefficients are calculated to measure the relationships between datasets. Lastly, to measure the overall success of an experiment, the Grey Relational Grade (GRG) is computed by averaging the Grey relational coefficients. Depending on whether a "lower is better" or "higher is better" outcome is sought, different formulae normalize the data. The GRG and Grey relational coefficients are computed using other formulae. This approach offers a consistent and measurable way to evaluate the caliber of tests, which might improve industrial and technical procedures.

$$Zij = \frac{Yij - \min(Yij, i=1,2,3,\ldots n)}{(Yij, i=1,2,3,\ldots n) - \min(Yij, i=1,2,3,\ldots n)} \quad \ldots (5)$$

$$Z_{ij} = \frac{(Yij, i=1,2,3,\ldots\ldots n) - Yij}{(Yij, i=1,2,3,\ldots\ldots n) - \min(Yij, i=1,2,3,\ldots\ldots n)} \quad \ldots (6)$$

$$\gamma\,(Y_0(k), Y_i(k)) = \frac{\Delta + \xi\,\Delta max}{\Delta oj + \xi\,\Delta max} \quad \ldots (7)$$

$$\gamma_i = \frac{1}{k} \sum_{i=1}^{m} \gamma\ ij \quad \ldots (8)$$

The tests followed an organized method employing an L27 orthogonal array to assign different degrees of values to the process parameters.

Table 4 presents input control parameters and responses, including cutting speed, feed rate, depth of cut, surface roughness, cutting force, carbon emission, and energy consumption, for 27 trials. Those experiments evaluate the nano-aided dry turning performance of a hybrid aluminium alloy. Then, to be comparable across units and scales, zero through one normalization is performed in each output dimension. The normalized values can be used to determine the best machining conditions with the help of the Grey Relational Analysis. Better performance is observed when the normalized values are higher, particularly in terms of minimization requirements such as roughness, force, and emissions.

Table 4. Summarizes the results regarding surface roughness, cutting force, carbon emission and energy consumption.

Input Control Parameters				Output responses			
Trial NO	Cutting Speed (rpm)	Feed Rate (mm/min)	Depth of Cut (mm)	Surface Roughness (µm)	Cutting Force (N)	Carbon Emission kg-CO_2	Energy Consumption (kJ)
1	125	0.075	0.5	1.014	0.989	0.767	0.867
2	125	0.075	1	0.965	0.686	0.365	0.466
3	125	0.075	1.5	1.001	0.504	0.1	0.20
4	125	0.1	0.5	0.816	0.855	0.834	0.835
5	125	0.1	1	0.757	0.579	0.549	0.549
6	125	0.1	1.5	0.792	0.383	0.385	0.386
7	125	0.125	0.5	0.659	0.587	0.732	0.732
8	125	0.125	1	0.61	0.191	0.523	0.523
9	125	0.125	1.5	0.645	0.115	0.436	0.437
10	150	0.075	0.5	0.246	0.972	0.992	0.992
11	150	0.075	1	0.1	0.742	0.439	0.439
12	150	0.075	1.5	0.863	0.436	0.294	0.294
13	150	0.1	0.5	0.997	0.717	0.865	0.865
14	150	0.1	1	0.618	0.521	0.42	0.514
15	150	0.1	1.5	0.355	0.372	0.537	0.537
16	150	0.125	0.5	0.512	0.599	0.798	0.658
17	150	0.125	1	0.471	0.253	0.434	0.634
18	150	0.125	1.5	0.498	0.1	0.589	0.589
19	175	0.075	0.5	1.38	1.09	1.1	1.1
20	175	0.075	1	1.1	0.694	0.499	0.879
21	175	0.075	1.5	1.198	0.248	0.533	0.633
22	175	0.1	0.5	1.189	1.125	1.182	1.082
23	175	0.1	1	0.843	0.683	0.86	0.86
24	175	0.1	1.5	0.878	0.507	0.781	0.781
25	175	0.125	0.5	0.745	0.711	0.969	0.969
26	175	0.125	1	0.696	0.415	0.847	0.847
27	175	0.125	1.5	0.609	0.296	0.831	0.831

Similar to the previous case, for comparison or multi-criteria analysis, the table presents normalized surface roughness values, measured during the session and duplicated in four columns. To obtain normalized data for further calculations, such as grey relational analysis or optimization research, each value is normalized to fall between 0 and 1. An increase in normalized values (e.g., 0.801-1.000) depicts rougher surfaces whereas smaller normalized values (0.000-0.299) indicates more highly polished surfaces. Such a standardized course of actions supports the uniformity of further assessment of the machining performance per trial. The duplicated columns indicate the same sets of data that were generated during the different computing or analysis processes.

Table 5. Experimental results for L27 orthogonal array

Deviation Sequence			
Surface Roughness	Cutting Force	Carbon Emission	Energy Consumption
0.714	0.867	0.616	0.741
0.676	0.572	0.245	0.296
0.704	0.394	0.000	0.000
0.559	0.737	0.678	0.706
0.513	0.467	0.415	0.388
0.541	0.276	0.263	0.207
0.437	0.475	0.584	0.591
0.398	0.089	0.391	0.359
0.426	0.015	0.311	0.263
0.114	0.851	0.824	0.880
0.000	0.626	0.313	0.266
0.596	0.328	0.179	0.104
0.701	0.602	0.707	0.739
0.405	0.411	0.296	0.349
0.199	0.265	0.404	0.374
0.322	0.487	0.645	0.509
0.290	0.149	0.309	0.482
0.311	0.000	0.452	0.432
1.000	0.966	0.924	1.000
0.781	0.580	0.369	0.754
0.858	0.144	0.400	0.481
0.851	1.000	1.000	0.980
0.580	0.569	0.702	0.733
0.608	0.397	0.629	0.646
0.504	0.596	0.803	0.854
0.466	0.307	0.690	0.719
0.398	0.191	0.676	0.701

Surface Roughness, Cutting Force, Carbon Emission, and Energy Consumption are the four performance metrics for which normalized deviation sequences are shown in Table 5. Each row represents a distinct experimental or machining condition. The range of values is 0 to 1, with 1 denoting the most significant deviation and the minimum is 0. These sequences are likely used for performance comparison and evaluation through techniques such as Grey Relational Analysis. The goal is to find parameter configurations that maximize surface polish while lowering force, emissions, and energy consumption.

Table 6 presents Grey Relational Coefficients (GRC) for four key performance metrics: Surface Roughness, Cutting Force, Carbon Emission, and Energy Consumption. These coefficients measure the closeness of each response to the ideal value, with values closer to 1 indicating better performance. Each row corresponds to a different experimental run or machining condition. The Grey Relational Grade (GRG) is the average of the four GRCs, summarizing overall performance in a single

value. Higher GRG values suggest more optimal machining settings across all considered responses.

Table 6. Presents grey relational coefficients (GRC)

Grey Relational Coefficient				Grey Relational Grade
Surface Roughness	Cutting Force	Carbon Emission	Energy Consumption	
0.412	0.366	0.448	0.403	0.407
0.425	0.467	0.671	0.628	0.548
0.415	0.559	1.000	1.000	0.744
0.472	0.404	0.424	0.415	0.429
0.493	0.517	0.546	0.563	0.530
0.480	0.644	0.655	0.708	0.622
0.534	0.513	0.461	0.458	0.491
0.557	0.849	0.561	0.582	0.637
0.540	0.972	0.617	0.655	0.696
0.814	0.370	0.378	0.362	0.481
1.000	0.444	0.615	0.653	0.678
0.456	0.604	0.736	0.827	0.656
0.416	0.454	0.414	0.404	0.422
0.553	0.549	0.628	0.589	0.580
0.715	0.653	0.553	0.572	0.623
0.608	0.507	0.437	0.496	0.512
0.633	0.770	0.618	0.509	0.633
0.617	1.000	0.525	0.536	0.670
0.333	0.341	0.351	0.333	0.340
0.390	0.463	0.576	0.399	0.457
0.368	0.776	0.555	0.510	0.552
0.370	0.333	0.333	0.338	0.344
0.463	0.468	0.416	0.405	0.438
0.451	0.557	0.443	0.436	0.472
0.498	0.456	0.384	0.369	0.427
0.518	0.619	0.420	0.410	0.492
0.557	0.723	0.425	0.416	0.530

Table 7. Response for Grey Relational Grade

Factors	Level 1	Level 2	Level 3	Max - Min
Cutting speed (rpm)	0.567	0.584	0.450	0.134
Cutting speed (rpm)	0.540	0.495	0.565	0.070
Cutting speed (rpm)	0.428	0.555	0.618	0.190

Grey Relational Grades, which may be mislabeled but indicate different machining parameters, are displayed in Table 7 for various levels of three factors. The figures beneath Level 1, Level 2, and Level 3 are the average gray relational grade at each level, and each row represents a distinct factor. The range of values for each component, which means the degree of effect, is displayed in the "Max - Min" column. A wider range indicates greater impact on the production. Since all of the parameters are shown as "Cutting speed (rpm)," which might be inaccurate, they need to be labeled appropriately.

3.2 Surface Roughness analysis

Table 8. Analysis of variance for surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Cutting speed	2	0.9067	0.45335	9.69	0.001
Feed Rate	2	0.3516	0.17580	3.76	0.041
Depth of cut	2	0.1086	0.05430	1.16	0.334
Error	20	0.9360	0.04680		
Total	26	2.3029			

The ANOVA table 8 indicates that Cutting speed and Feed Rate significantly affect the response, with p-values of 0.001 and 0.041, respectively. Depth of cut shows no significant effect, as its p-value is 0.334.

$$\begin{aligned}\text{Surface Roughness} = {} & 0.7614 + 0.0452\ \text{Cutting speed_125} \\ & - 0.2436\ \text{Cutting speed_150} \\ & + 0.1984\ \text{Cutting speed_175} + 0.1127\ \text{Feed Rate_0.075} \\ & + 0.0436\ \text{Feed Rate_0.100} - 0.1564\ \text{Feed Rate_0.125} \\ & + 0.0784\ \text{Depth of cut_0.5} - 0.0769\ \text{Depth of cut_1.0} \\ & - 0.0015\ \text{Depth of cut_1.5}\end{aligned} \quad (1)$$

The regression equation (1) models surface roughness based on levels of cutting speed, feed rate, and depth of cut. Positive coefficients increase roughness, while negative ones reduce it, showing that Cutting speed_150 and Feed Rate_0.125 notably reduce roughness.

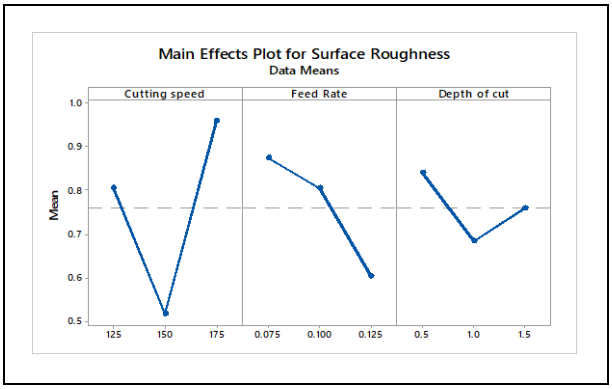


Fig. 2: Main effect plots for surface roughness

Figure 2 illustrates how variations in cutting speed, feed rate, and depth of cut affect surface roughness. At 150 rpm and 175 rpm, the surface roughness is at its lowest and maximum, respectively. Roughness steadily decreases as the feed rate increases. Out of the three levels, 1.0 mm produces the lowest surface roughness for depth of cut.

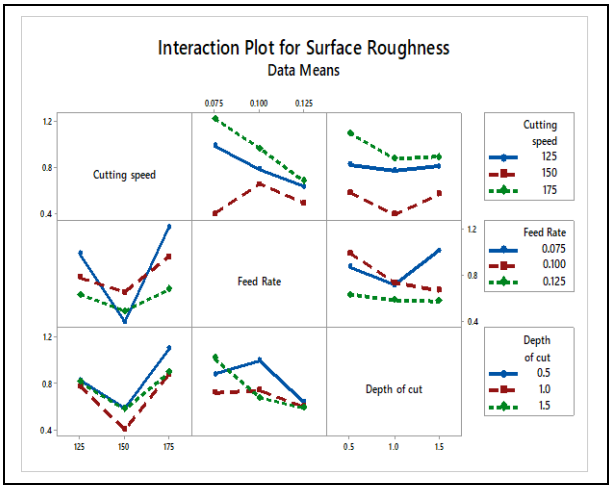


Fig. 3: Interaction plot for surface roughness

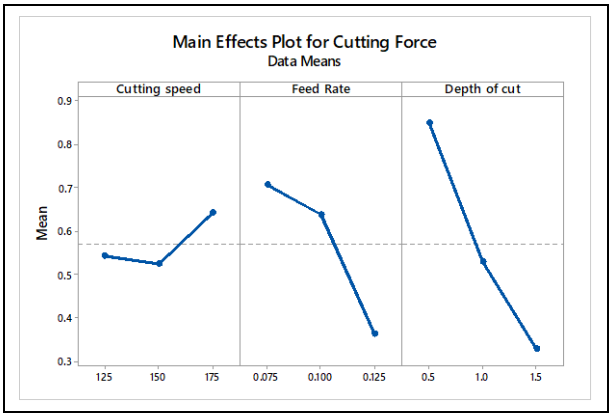


Fig. 4: Main effect plots for cutting force

Table 9: Analysis of variance for cutting force

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Cutting speed	2	0.07122	0.035611	3.93	0.036
Feed Rate	2	0.59562	0.297808	32.88	0.000
Depth of cut	2	1.24040	0.620200	68.48	0.000
Error	20	0.18114	0.009057		
Total	26	2.08838			

The interaction plot Figure 3 illustrates how surface roughness is influenced by cutting speed, feed rate, and depth of cut. Surface roughness tends to decrease at higher feed rates and lower cutting speeds. The lowest roughness is observed around 150 rpm with 0.100 mm/rev feed. Non-parallel lines indicate strong interaction effects between the parameters.

3.3 Cutting Force Analysis

The ANOVA table 13 shows that Feed Rate and Depth of Cut have a highly significant impact on the response with very low p-values (<0.001), while Cutting Speed also has a moderate effect (p = 0.036). Depth of Cut contributes the most, as indicated by its highest F-value of 68.48

$$\begin{aligned}\text{Cutting Force} = {} & 0.5693 - 0.0260\ \text{Cutting speed_125} \\ & - 0.0457\ \text{Cutting speed_150} \\ & + 0.0717\ \text{Cutting speed_175} + 0.1375\ \text{Feed Rate_0.075} + 0.0687\ \text{Feed Rate_0.100} \\ & - 0.2063\ \text{Feed Rate_0.125} + 0.2802\ \text{Depth of cut_0.5} - 0.0399\ \text{Depth of cut_1.0} \\ & - 0.2403\ \text{Depth of cut_1.5} \quad (2)\end{aligned}$$

The regression equation (2) estimates cutting force based on levels of cutting speed, feed rate, and depth of cut. Cutting force increases with lower feed rates and shallow depths, while it decreases significantly at higher feed rate (0.125 mm/rev) and greater depth (1.5 mm).

The Cutting force reduces with feed rate, increases somewhat with cutting speed, and declines dramatically with increasing depth of cut, as Figure 4 illustrates. When it comes to cutting force reduction, depth of cut has the most impact.

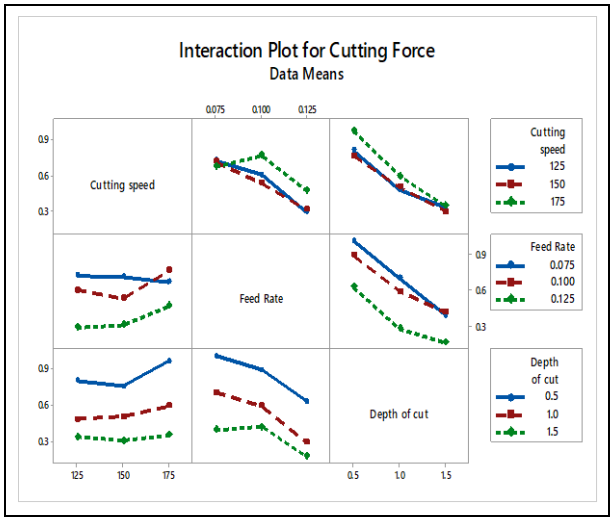


Fig. 5: Interation plot for cutting force

The plot of interactions. The relationship between cutting force and depth of cut, feed rate, and cutting speed is shown in Figure 5. As the feed rate and depth of cut rise, the cutting force significantly decreases. The force used is less for deeper cuts and at greater cutting speeds, particularly at 1.5 mm depth. The lines

are not parallel, showing combined parameter influence, demonstrating interaction effects

3.4 Carbon Emission Analysis

Table 10. Analysis of variance for carbon emission

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Cutting speed	2	0.5157	0.25783	20.60	0.000
Feed Rate	2	0.1097	0.05486	4.38	0.026
Depth of cut	2	0.9332	0.46662	37.29	0.000
Error	20	0.2503	0.01251		
Total	26	1.8089			

The ANOVA table 10 shows that cutting speed and depth of cut have a highly significant effect on cutting force, with p-values of 0.000. Feed rate also influences the response moderately (p = 0.026), while the low error value indicates a good model fit.

Carbon Emission = 0.6541
- 0.1329 Cutting speed_125
- 0.0577 Cutting speed_150
+ 0.1906 Cutting speed_175 - 0.0887 Feed Rate_0.075
+ 0.0584 Feed Rate_0.100 + 0.0302 Feed Rate_0.125 + 0.2613 Depth of cut_0.5
- 0.1057 Depth of cut_1.0 - 0.1557 Depth of cut_1.5..(3)

Regression equation (3) uses cutting speed, feed rate, and depth of cut levels to predict carbon emissions. Positive coefficients show that carbon emission is maximum at 175 rpm and 0.5 mm depth. A decrease in impact is observed for lower emissions at 125 rpm, particularly at deeper depths (1.0 mm and 1.5 mm).

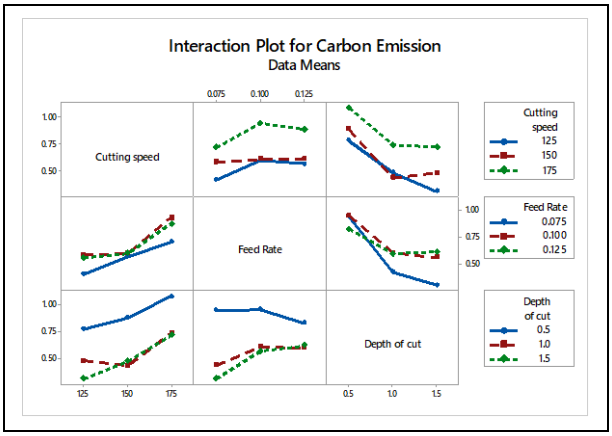


Fig. 6: Interaction plot for carbon emission

The plot of interactions. The relationship between cutting speed, feed rate, and depth of cut, and carbon output is depicted in Figure 6. Generally speaking, carbon emissions drop as cut depth increases, particularly at 125 rpm. Emissions often increase with higher feed rates, especially at 175 rpm. Non-parallel trends confirm interaction effects between the machining parameters.

3.5 Energy Consumption Analysis

Table 11: Analysis of variance for energy consumption

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Cutting speed	2	0.56487	0.282435	26.17	0.000
Feed Rate	2	0.01662	0.008310	0.77	0.476
Depth of cut	2	0.68132	0.340659	31.57	0.000
Error	20	0.21582	0.010791		
Total	26	1.47863			

With p-values of 0.000, ANOVA table 11 demonstrates that cutting depth and speed have a substantial impact on carbon emissions. The strong p-value (0.476) suggests that feed rate has no discernible effect. The most significant contribution is made by depth of cut, as indicated by the highest F-value of 31.57.

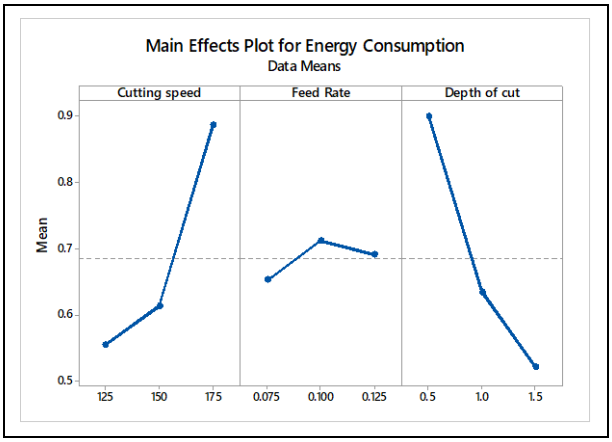


Fig. 7: Main effect plots for energy consumtion

Energy Consumption = 0.6851 - 0.1301 Cutting speed_125 - 0.0716 Cutting speed_150
+ 0.2017 Cutting speed_175 - 0.0329 Feed Rate_0.075
+ 0.0270 Feed Rate_0.100 + 0.0060 Feed Rate_0.125
+ 0.2149 Depth of cut_0.5 - 0.0506 Depth of cut_1.0
- 0.1643 Depth of cut_1.5..
(4)

Figure 7 illustrate are illustrates in the prim,awhich shows showing how energy consumption rises with cutting speed, changes little with feeand d rate,

and then falls off dramatically as cut depth increases. The two factors that most affect energy usage are cutting depth and speed.

According to the plot, energy use increases with cutting speed, peaks at a medium feed rate, and then sharply decreases as cut depth increases. The two factors that have the most Influence on mean energy values are cutting speed and depth of cut. Regression equation (4) uses cutting speed, feed rate, and depth of cut to forecast energy usage. At 175 rpm and a shallow depth of 0.5 mm, energy consumption noticeably rises; at lower speeds and deeper cuts, such as 1.5 mm, it falls. The effects of the feed rate are negligible, as seen by the modest coefficient values.

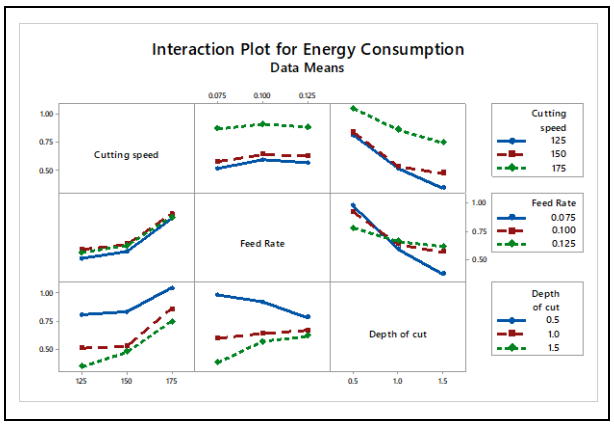


Fig. 8: Interaction plot for energy consumption

The interaction between cutting speed, feed rate, and depth of cut, and energy usage is shown in Figure 8. Particularly at higher levels, energy consumption rises with cutting speed and feed rate. However, as cut depth increases, energy consumption reduces; the lowest values are seen at 1.5 mm. The non-parallel lines show interactions between the parameters.

4. CONCLUSION

This study used the stir casting process to create a nano-reinforced hybrid aluminum alloy composite. The fundamental matrix was made of 2 kg of aluminum, and the reinforcements were 10% titanium (200 g), 5% nano-sized silicon carbide (100 g), and 2.5% zinc (50 g). Nano-SiC improves surface polish and wear resistance, while titanium increases mechanical strength and thermal stability. Zinc improves wettability, which helps with better particle distribution. This composite was created especially for coolant-free, environmentally friendly dry machining, which supports sustainable production objectives. Cutting forces, energy consumption, and surface roughness are all decreased when nano-reinforcements are uniformly distributed, improving machinability. Because of this, the material may be used in precise applications that call for high-performance qualities in dry turning.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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