Research Article

Journal of
Environmental
Nanotechnology

Enhancing the Surface Quality and Tool Life Using Nano MQL-assisted Machining Characteristics of Aluminium Composite

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Received: 20.11.2024 Accepted: 18.02.2025 Published: 30.03.2025

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ABSTRACT

This study investigates the effect of graphene nanoplatelets (GNPs) dispersed minimum quantity lubrication (MQL) for improving the turning characteristics of aluminium composite comprising of LM25 as matrix and 10 wt.% of titanium carbide (TiC) as reinforcement fabricated via stir casting technique. Turning studies are performed on the turning center attached with MQL setup where different weight proportions of GNPs (1, 3, and 5 wt.%) are mixed with canola oil and supplied at the cutting zone. Experiments are designed by Taguchi's method, an appropriate L_9 orthogonal array is considered. The surface roughness (SR), and flank wear outcomes are measured and analyzed using grey relational analysis (GRA). Observation shows, the MQL consisting of 3 wt.% of GNPs provided lower FW and SR as it lowers the interface temperature at cutting zone and easy dispersal of chips. Increases in FW and SR are mostly attributable to changes in the feed rate.

Keywords: Aluminium composite; Graphene; Minimum quantity lubrication; Flank wear; Surface roughness; Cutting zone.

1. INTRODUCTION

Machining aluminium composites reinforced with ceramic particles poses significant challenges owing to the ceramic reinforcement's abrasive and hard nature. During cutting, the interaction between the ceramic particles and the cutting tool generates high friction, leading to increased heat at the tool-workpiece interface (Nayak *et al*. 2022). This heat accelerates tool wear, particularly in conventional tools not designed for abrasive materials, resulting in rapid flank and crater wear. The hard particles can also chip or damage the cutting edge, reducing tool life and raising operational costs. Additionally, the uneven distribution of ceramic particles in the matrix often leads to inconsistencies in cutting force and cutting surface, which contributes to surface roughness and poor finish quality (Huo *et al.* 2021). The presence of ceramic particles makes it difficult to achieve fine surface finishes, as the particles tend to tear or plough through the matrix material, creating irregularities. These challenges necessitate careful selection of cutting tools (coated carbide or diamond tools), optimized cutting parameters, and effective cooling and lubrication techniques to reduce heat, minimize wear, and improve surface finish during the machining of these composites (Atkins 2009). The softening of the cutting tool at increased machining circumstances causes a link between cutting region temperature and flank wear. The most important component for cutting region temperature is nose radius, which in turn influences flank wear.

LM25 is an aluminium-silicon alloy prized for its advantageous mechanical qualities, high strength-to-weight ratio, and resistance to corrosion. With a density of 2.68 g/cm3, 570-580°C of melting point and a thermal conductivity of about 155 W/mK, making it suitable for applications requiring efficient heat dissipation (Govindan and Raghuvaran, 2019). LM25+nSiC+MoS_2 composites was prepared via ultrasonic assisted stir casting technique and found that higher quantities of nSiC produced higher strength and addition of MoS_2 influenced the mechanical strength of the hybrid composite considerably. The porosity decreases considerably with rise in density. Taguchi's technique was adopted for designing experiments and to optimize drilling parameters for lower thrust force and delamination. Drill diameter was shown to have the greatest impact on limiting thrust force, according to analysis of variance, whereas spindle speed was an extremely important component in lowering delamination (Raja *et al*. 2024). Machining studies on AA6061+ mica + boron carbide composite using response surface design was done and applied fuzzy logic to enhance the quality of output and optimized the outputs using metaheuristic algorithm and desirability function. Outcome shows that the induced thrust force and torque decreased with rising spindle speed because of softening of matrix constituents (Kayaroganam *et al*. 2021).

Titanium carbide (TiC) has a high modulus of elasticity and outstanding compressive strength, which can enhance the stiffness and load-bearing capacity of aluminium composites. It also possesses a low density of 4.93 g/cm³, compared to other ceramics, aiding in the creation of composites that are both lightweight and very strong-to-weight ratio (Srinivasan *et al.* 2024). Researchers found that the crater and scratch are the main defects in the machined surface of direct energy deposited Ti6Al4V-titanium carbide (TiC) composite. The machined surface flaws are reduced by the transfer of fine equiaxed TiC during cutting. Crush of coarse dendritic TiC particles causes tool coating peeling and adhesion. The additive manufacturing induced microstructure influences machinability (Qiao *et al*. 2022). The machinability of the AMCs was found to be enhanced when TiC and MoS_2 were included in AA7075, as compared to the basic material. Due of the lower ductility with reinforcing TiC and MoS_2 microparticles, the chip shape changes from uninterrupted sheared chips in AA7075 to discrete chips in composite. Because the composites included hard TiC particles, their surfaces were rougher than the base alloy (Dhulipalla *et al*. 2020). ZA37 composites with 5 wt.% and 10 wt.% TiC were made via stir casting, showing enhanced properties. Rising TiC content lowered sample density but increased hardness notably from 131 Hv to 155 Hv. From wear studies, at lower loads, abrasion dominated, shifting to a mix of abrasion and delamination at higher loads. The density was decreased, and the hardness was enhanced when the TiC concentration was increased (Sheikh and Khan, 2025).

A new MQL+LN_2 composite cooling equipment was developed after an analysis of the effects of various injection spots on cooling and lubrication. It was used to investigate the impacts of various cooling techniques on surface roughness, forces, and tool wear of cutting grey cast iron (GCI) and compacted graphite iron (CGI). Cutting CGI and GCI with composite cooling rather than MQL or LN_2 or a mix of the two produced the smoothest surfaces, longest tool life, and least cutting forces, as compared to the other cutting fluids (Meng *et al*. 2024). The effectiveness of Cryo-NMQL in machining of Hastelloy C276 is investigated. Cutting force decreased by 25.49%, cutting temperature by 29.84%, and roughness by 42.50% while using the Cryo-NMQL medium instead of dry cutting. Tool wear diminished by 44.55% with less adhesion and abrasion thanks to this lubricating fluid. Chip morphological examination revealed a less serrated, finer lamella shape with cryo-NMQL (Sen and Bhowmik, 2024). Turning operations on AISI1525 steel was conducted employing Taguchi L_9 arrays under different cooling circumstances by adjusting the machining parameters and simultaneously optimized surface roughness and cutting temperature. Across the board, the experimental trials for surface roughness demonstrated a substantial 68.04% enhancement for the jatropha oil lubricant compared to the mineral oil lubricant. First and foremost, spindle speed accounts for 28.14% of the total output reactions; second, depth of cut accounts for 24.40% (Kazeem and Jen, 2024). During the turning process of EN-24 steel, researchers looked at how different sustainable cooling methods affected the output properties. To create nanofluids, soluble oils were mixed with nanoparticles of SiC, Al_2O_3, and Al-SiC in various proportions of weight (0.5, 1, and 1.5wt.%). From the perspective of surface excellence, it is recommended to process EN-24 steel in a MQL atmosphere with Al-SiC/soluble oil hybrid NFs using a minimal feed rate along with a rapid cutting speed. By reducing the cutting speed and feed rate, tool wear may be minimized (Thakur *et al*. 2022).

To lower the temperature at the cutting zone during turning of aluminium composites, a variety of lubricating and cooling techniques may be used to enhance heat dissipation and reduce tool wear. Flood cooling, cryogenic cooling, minimum quantity lubrication (MQL), and high-pressure cooling (HPC) are used to direct the coolants directly at the cutting zone (Boothroyd and Knight, 1989). Solid lubricants such as graphite or molybdenum disulfide can be added to the coolant or applied as a coating to the tool, forming a low-friction layer that reduces heat generation. Unlike flood cooling, which requires larger quantity of coolants, MQL uses only a fine mist of lubricant, reducing coolant consumption, operational costs, and environmental impact associated with coolant disposal (Gupta and Davim, 2020). The oil mist in MQL effectively reduces friction and cutting forces at the interface of tool-workpiece, resulting in lower heat production directly at the source rather than relying on coolant to carry it away. This helps improve surface finish quality, minimizes thermal deformation, and prolongs tool life by reducing wear, particularly in abrasive or hard-to-machine materials (Ali *et al*. 2025).

The objective of this research work is to investigated the machining characteristics of aluminium composites, specifically LM25 reinforced with titanium carbide (TiC) particles, which presents unique challenges due to the hardness and abrasive nature of TiC, which tends to increase tool wear and surface roughness. To overcome this, nano-fluid assisted MQL system was considered to improve the surface integrity with lower tool wear and cutting forces. While considerable research has explored the effects of various coolants and lubrication methods on machining performance, a noticeable gap exists in understanding the specific impacts of MQL when used with uncoated carbide inserts on LM25-TiC composites. Previous studies have often focused on coated tools or alternative lubricants and coolants, leaving limited insight into the performance of uncoated carbide inserts under MQL conditions in this composite context. This gap suggests a novel opportunity to investigate how MQL can influence tool wear, surface finish, and temperature control in machining LM25-TiC composites with uncoated carbide inserts, which may offer cost-effective and sustainable benefits. The novelty of the present study is to incorporate graphene nanoplatelets (GNPs) in the canola oil to develop and nano-fluid based MQL system which can minimize the adverse effects during turning. Taguchi's technique is adopted for experimental design and the outputs are analysed and optimized with grey relational analysis to identify the most influential parameters and the optimal settings to produces better results.

2. MATERIALS AND METHODS

2.1 Matrix and Reinforcement Material

Aluminium alloy LM25 is used as the matrix which is supplemented with titanium carbide (TiC) 10 wt.%, developed by means of ultrasonic assisted stir casting method. LM25 is an aluminium-silicon alloy prized for its advantageous mechanical qualities, high strength-to-weight ratio, and resistance to corrosion (Govindan and Raghuvaran, 2019). With a density of 2.68 g/cm^3, 570-580°C of melting point and a thermal conductivity of about 155 W/mK, making it suitable for applications requiring efficient heat dissipation. LM25 is commonly used in automotive and aerospace applications, where lightweight and durable materials are essential, as well as in marine environments and heat exchangers, benefiting from its corrosion resistance and thermal conductivity. TiC is a ceramic material characterized by its high melting point (around 3100°C), excellent thermal stability, and impressive hardness 3000 HV (Srinivasan *et al*. 2024). TiC has a high modulus of elasticity and outstanding compressive strength, which can enhance the stiffness and load-bearing capacity of aluminium composites. It also possesses a low density of 4.93 g/cm^3, compared to other ceramics, aiding in the creation of composites that are both lightweight and very strong-to-weight ratio. Additionally, TiC offers good thermal conductivity, which helps improve heat dissipation in applications requiring thermal management suitable for high-performance uses in fields including aviation, automobiles, and military (Jiang *et al*. 2017).

2.2 Stir-casting Procedure for Fabrication of Composite

Initially, LM25 alloy is cut into pieces and is heated to a molten state subjected to 750°C, to ensure complete melting. Once the alloy is molten, the TiC reinforcements are preheated separately to 300°C to eliminate any surface wetness and to enhance their wettability with the molten aluminium (Upadhyay and Saxena, 2021; Kuttan *et al*. 2024). To achieve a uniform distribution of the nano clay and TiC particles, mechanical stirring at 500 rpm is applied to the melt to further promote uniform particle distribution which improves the connection of matrix to the reinforcements, leading to a more homogenous composite structure. After exhaustive mixing, the molten composite is dispensed into warmed moulds and allowed to solidify, yielding a composite with improved mechanical properties, ideal for high-performance applications requiring lightweight, wear-resistant, and durable materials.

2.3 Taguchi's Approach to Experiment Strategy

Taguchi's technique for designing experiments is a robust method that focuses on improving product quality by optimizing design and manufacturing processes (Taguchi *et al*. 2011; Hisam *et al*. 2024). Developed by Dr. Genichi Taguchi, this technique emphasizes reducing variability in a system's performance, making it less sensitive to external and uncontrollable factors, or noise (Muthukumar *et al*. 2015). Taguchi's approach involves using orthogonal arrays to systematically arrange experiments, allowing researchers to evaluate multiple variables with fewer experiments than traditional methods (Zubair *et al*. 2024). This design strategy enables efficient identification of the most influential factors and their optimal levels, thereby saving time and resources (Senthilkumar *et al*. 2024). In this study, 4 parameters are considered for experimentation with a range of values as given in Table 1.

Table 1. Input settings for experimentation

Parameter	Unit	Notation	-1	0	+1
Cutting Speed	m/min	CS	100	200	300
Feed Rate	mm/rev	FR	0.05	0.1	0.15
Depth of Cut	mm	DoC	0.2	0.4	0.6
Graphene Nanoplatelet	%	GNP	1	3	5

2.4 Grey Relational Analysis

One method under Grey System Theory for analysing connections and determining the level of resemblance or impact across numerous variables is grey relational analysis (GRA), especially when data is incomplete or uncertain (Tzeng *et al*. 2009). It's particularly helpful in decision-making, where it ranks alternatives based on their performance relative to a reference (ideal) sequence. To start, GRA requires normalizing the data to make it dimensionless and comparable (Gunasekaran *et al*. 2024). Normalization is typically done using one of the following equations depending on whether a higher value, lower value, or fixed target is preferred. Let $x_i(k)$ represent the value of the ith sequence at the k^{th} factor or attribute (Omoniyi *et al*. 2024). Higher-is-best normalization,

$$x_i'(k) = \frac{x_i(k) - \min(x_i(k))}{\max(x_i(k)) - \min(x_i(k))} \quad \ldots (1)$$

Lower-is-best normalization,

$$x_i'(k) = \frac{\max(x_i(k)) - x_i(k)}{\max(x_i(k)) - \min(x_i(k))} \quad \ldots (2)$$

Define a reference sequence x_0 based on the ideal or desired values for each attribute. The normalized value for the reference sequence is denoted as $x_0'(k)$, which is generally the best-performing sequence (e.g., the maximum values for higher-is-better attributes) (Sundara *et al*. 2020).

The grey relational coefficient (GRC) presents the relation amid the reference sequence and each alternative sequence. It is defined as:

$$\xi_i(k) = \frac{\Delta_{min} + \zeta \cdot \Delta_{max}}{\Delta_i(k) + \zeta \cdot \Delta_{max}} \quad \ldots (3)$$

Where $\Delta_i(k) = |x_0'(k) - x_i'(k)|$ is the absolute variance amid the normalized reference and alternative values, $\Delta_{min} = \min_{i,k} \Delta_i(k)$ is the smallest value of $\Delta_i(k)$, $\Delta_{max} = \max_{i,k} \Delta_i(k)$ is the largest value of $\Delta_i(k)$, ζ is the distinguishing coefficient, typically set between 0 and 1 (commonly, ζ=0.5) to control the sensitivity. The grey relational grade (GRG) reviews the complete relational degree between the reference and alternative sequences. It's calculated by averaging the GRC for each attribute of a given sequence (Kamis and Acar, 2024):

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \quad \ldots (4)$$

Where γ_i is the GRG for the ith sequence and n is the number of attributes. The alternatives are ranked based on the GRG γ_i. A higher Grey relational grade indicates a closer relationship to the reference sequence, meaning that alternative is more desirable (Shakeri *et al*. 2022).

2.5 Experimental Setup

A computer numeric control (CNC) based machining centre is used to turn the workpiece with an uncoated carbide cutting insert of nomenclature CNMG 120404. For each trial a separate workpiece is considered with an insert cutting edge. The workpiece size is Ø10mm of length 150mm. Minimum quantity lubrication (MQL) setup was attached to the turning centre to provide mist of coolant at the cutting region. The MQL coolant is comprised of canola oil mixed with different weight proportions of graphene nanoplatelets (GNPs). Canola oil, a base oil that is well-known for its stability, sustainability, and excellent lubricity for GNP dispersion (Sikdar *et al*. 2021). Canola oil has excellent biodegradability, superior lubricity, and high thermal stability compared to synthetic and mineral-based lubricants. Its natural ester content provides strong adsorption on metal surfaces, reducing friction and wear more effectively. Canola oil also has a higher flash point, making it safer for high-temperature machining applications. When combined with GNPs, canola oil ensures stable dispersion of nanoparticles. Compared to synthetic and mineral-based oils, canola oil demonstrates superior performance in MQL by offering better wetting characteristics, ensuring uniform lubricant distribution at the tool-workpiece interface. Additionally, its eco-friendly and non-toxic nature makes it a sustainable alternative, reducing health and environmental risks associated with petroleum-based lubricants. This combination of factors makes canola oil a highly effective choice for MQL applications, particularly when paired with GNPs to further enhance machining performance. The addition of GNPs; extremely thin, high-surface-area particles improves canola oil's lubricating and heat-conducting capabilities. To create a stable mixture, GNPs are dispersed in the oil using ultrasonic agitation or mechanical stirring, sometimes with a small amount of surfactant to prevent agglomeration (Banavathu *et al*. 2023). This GNP-enhanced MQL coolant is then applied in precise, minimal amounts to the cutting zone, where it reduces friction, improves heat dissipation, and creates a smoother chip flow. The improved lubricity and cooling effect can help extend tool life, improve surface finish, and reduce energy consumption, making the combination of graphene nanoplatelets and canola oil an efficient, eco-friendly choice for MQL in turning (Khadem *et al*. 2024). The experimental setup used is demonstrated in Fig. 1.

Using GNPs dispersed in canola oil for machining LM25-TiC composites under MQL offers several key benefits, including enhanced lubrication, reduced tool wear, improved heat dissipation, and eco-friendliness. GNPs, with their ultra-low friction coefficient, form a protective tribofilm at the tool-workpiece interface, minimizing direct metal-to-metal contact and reducing cutting forces. Their excellent thermal conductivity facilitates efficient heat transfer away from the cutting zone, preventing excessive temperature buildup and thermal damage to both the tool and workpiece. Additionally, GNPs exhibit superior mechanical strength, which helps resist abrasive wear caused by the hard TiC particles present in the composite. The use of canola oil as a biodegradable base fluid further enhances sustainability while ensuring effective nanoparticle dispersion. This synergistic combination of GNPs and canola oil in the MQL approach leads to improved machining performance, better surface quality, and extended tool life, making it an efficient and environmentally friendly alternative to conventional lubrication methods. The primary motivation for incorporating GNPs into minimum quantity lubrication (MQL) for machining lies in their exceptional tribological properties, including high thermal conductivity, superior lubricity, and excellent mechanical strength. GNPs form a protective layer at the tool-chip interface, reducing friction, minimizing tool wear, and enhancing heat dissipation, which leads to improved machining performance and surface quality. This approach distinguishes itself from other lubrication techniques, such as nanofluids containing TiO_2 or MoS_2 nanoparticles, by offering a unique combination of ultra-low friction and superior thermal management without excessive particle agglomeration or clogging issues commonly associated with spherical nanoparticles. Additionally, graphene's two-dimensional structure allows for effective load distribution and enhanced penetration into the cutting zone, making it particularly advantageous in high-speed and precision machining applications.

3. RESULTS AND DISCUSSION

3.1 Metallography Inference

The fabricated specimen (LM25+10%TiC) via stir casting technique is characterized for its microstructure as presented in Fig. 2. The uniform dispersal of TiC particles is seen from the micrographs which will enhance the mechanical strength of the composite. No crack, voids and discontinuities are visualized (Krishna *et al*. 2022).

3.2 Investigation of Input Parameters

Table 2 presents the input experimental design, and the output performance measures obtained from experiments. Surface roughness is tested using a Mitutoyo Surfboarder SJ1200, while flank wear is examined with a Mitutoyo create tool manufacturers microscope.

Observation from measured outputs present that, as the CS increases there is a substantial rise in FW and SR, similar is the case for FR also. At higher CS, the temperature at the cutting region rises significantly, leading to increased friction and thermal stress on the tool (Prvulovic *et al*. 2022). This elevated heat weakens the tool material and promotes faster wear along the tool's flank, a critical area that impacts tool longevity and machining precision. Similarly, an increase in FR elevates the forces exerted on both the tool and workpiece, which results in larger material removal per unit time but also exacerbates the load on the cutting tool (Ercetin *et al*. 2023).

The combined effect of higher CSs and FRs often leads to rougher surface finishes due to the aggressive cutting conditions and the more pronounced tool wear. The FW and SR tends to lower when the DOC is transformed from 0.2 mm to 0.4 mm, after which a rise in FW and SR is sensed when the DOC is further increased to 0.6 mm. A lower DOC may lead to excessive tool rubbing and increased contact with the workpiece, causing friction-induced wear and a rougher surface(Abellán *et al*. 2024). Conversely, higher DoC amplifies cutting forces and thermal stress, accelerating FW and potentially chipping the tool edge, which further deteriorates surface quality. Thus, an optimal, moderate DOC is crucial in achieving both lower FW and a reduced SR.

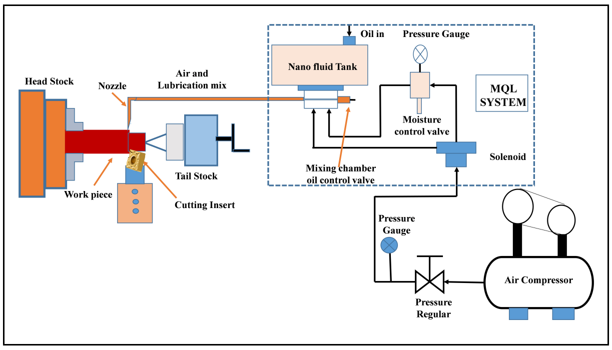

Fig. 1: MQL setup during machining

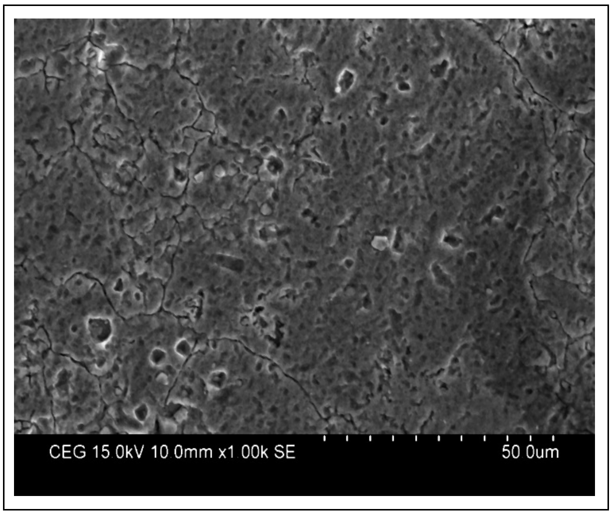

Fig.2: SEM micrograph of LM25+10%TiC

Table 2. Input array and experimental outputs

Trial No.	Cutting Speed (m/min)	Feed Rate (mm/ rev)	Depth of Cut (mm)	GNP %	FW (mm)	SR (microns)
1	100	0.05	0.2	1	1.44	1.144
2	100	0.1	0.4	3	1.21	0.966
3	100	0.15	0.6	5	1.78	1.526
4	200	0.05	0.4	5	1.46	1.249
5	200	0.1	0.6	1	1.78	1.136
6	200	0.15	0.2	3	2.45	1.513
7	300	0.05	0.6	3	2.08	1.413
8	300	0.1	0.2	5	2.14	1.551
9	300	0.15	0.4	1	2.72	1.629

The FR and CS significantly affect lubrication performance, influencing both SR and FW. At lower FRs and moderate CSs, the MQL system with GNPs performs optimally, as the lubricant effectively penetrates the tool-workpiece interface, forming a stable tribofilm that reduces friction and wear. However, at higher FRs, the increased material removal rate leads to higher cutting forces, limiting the lubricant's ability to maintain effective coverage, thereby increasing SR and FW. Similarly, at very high CSs, excessive heat generation can degrade the lubricant film, reducing its effectiveness and accelerating FW. Conversely, at extremely low CSs insufficient heat generation may hinder the activation of GNPs' lubricating properties. A general pattern observed is that moderate CS with low to medium FRs yield the best surface finish and lowest FW, while excessive FRs and CSs lead to deteriorating lubrication performance, resulting in higher SR and accelerated FW.

The inclusion of GNPs in the MQL system enhances the machinability of composite (Altaf *et al.* 2024). The FW tends to lower with higher GNP content in the MQL whereas the SR tends to lower until 3 wt.% addition of GNPs, when the inclusion of GNPs is at 5 wt.%, the SR tends to increase. inclusion of GNPs in MQL effectively reduce both FW and SR due to their outstanding lubricating capabilities and high thermal conductivity, create a protective layer between the tool and workpiece. GNPs have a high surface area to volume ratio and the developed layer reduces direct contact and friction at the interface, thereby decreasing FW. The high thermal conductivity of graphene also helps dissipate heat more efficiently from the cutting zone, preventing excessive temperature buildup that can accelerate wear and compromise surface quality (Ishfaq *et al.* 2022). The machining performance of LM25-TiC composites under MQL with GNPs peaked at 3 wt.% because this concentration provided the optimal balance between lubrication, thermal conductivity, and dispersion stability. At 5 wt.%, the performance decreased due to excessive GNPs leading to agglomeration, which led to uneven dispersion and clogging at the tool-workpiece interface. This agglomeration reduced the lubricating efficiency, increasing friction and tool wear instead of reducing it. Additionally, an overly thick tribofilm might have disrupted the cutting process, causing instability in chip formation and heat dissipation. Fig. 3 and Fig. 4 presents the contour plot showing the influence of input conditions over the FW and SR.

3.3 Multi-criteria Optimization of Outputs

For determining the optimal conditions, GRA is applied, and the procedure followed, and outputs are tabularized in Table 3. The investigational datasets (outputs) are initially normalized (converting between 0 and 1) for both FW and SR. The next step is to govern the deviation of the normalized value from the ideal value of 1 and subsequently the grey relational coefficient (GRC) for FW and SR is determined. Considering equal weightage (50%), the grey relational grade (GRG) is calculated. The lowest value of GRG is near to black (0) and the higher value is closer to 1 (white) (Anand *et al.* 2022).

By averaging the GRG values corresponding to individual level values of input parameters, the response table for GRG is formulated, as shown in Table 4. From the response table values, main effects plot (Fig. 5) is drawn to identify the ideal conditions which are: CS of 100 m/min, FR of 0.1 mm/rev, DOC of 0.4 mm and 3 wt.% GNP inclusions in MQL system. The impact of CS is higher, shadowed by FR, DOC, and % of GNPs.

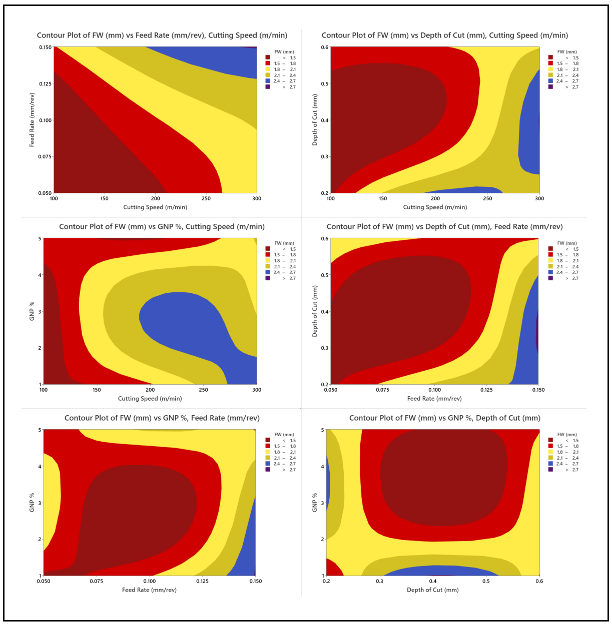

Fig. 3: Variation of FW for the inputs

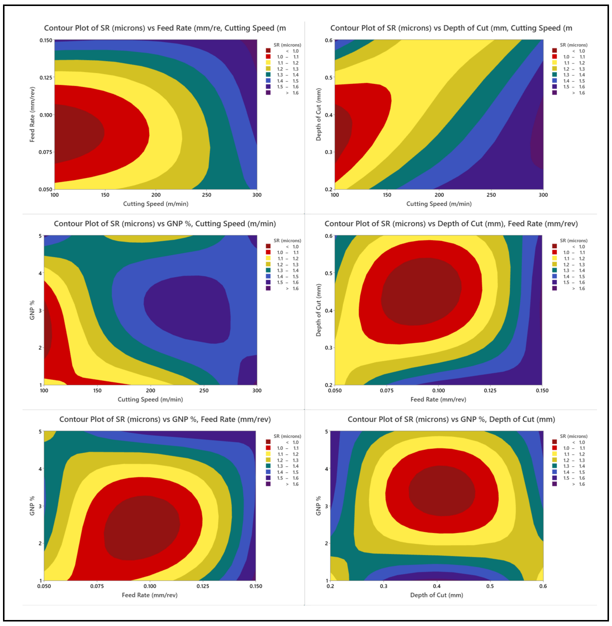

Fig. 4: Variation of SR for the inputs

To identify the influence of combined parameters, interaction plot is drawn as presented in Fig. 6. When two or more factors in an experiment interact, their combined effect on the response differs from the sum of their individual effects. Interaction plots visually depict these effects by plotting the levels of one factor on the x-axis and showing the response means for each level of another factor, often with lines representing different factor levels (Wakjira *et al*. 2019). There seems to be little to no interaction across the variables if their lines are parallel; if they cross or diverge, it indicates that the factors interact and their effects on the response are dependent on each other (Phadke, 2021).

Among CS and FR, there is considerable interaction for CS of 100 m/min and for a FR of 0.05 mm/rev, whereas for other values, there is no significant interaction. But among CS and DOC and CS and % GNPs there is a considerable relationship which significantly impacts the output responses. When FR combines with DOC and % GNPs, there is a significant interaction and among DOC and % GNP. This clearly illustrates that the combined influence is higher than the individual impact on the output responses.

3.4 Analysis of Variance (ANOVA)

Analysis of Variance (ANOVA) is a statistical technique used to analyze experimental datasets to determine the significance of dissimilar factors on a response variable. By partitioning the total variance in the dataset, ANOVA isolates the variability attributed to each factor, distinguishing it from random errors. A high F-ratio indicates a significant effect, suggesting that changes in that factor meaningfully impact the response, a p-value below a pre-determined threshold (often 0.05) confirms that the factor's influence is unlikely due to chance.

The ANOVA table for GRG is presented in Table 5, which shows that the table cannot be formulated as the error degrees of freedom (DoF) is zero. Hence pooling ANOVA desires to be done. ANOVA pooling is a technique used to improve the reliability of statistical tests when certain factor effects are deemed statistically insignificant. In ANOVA, each factor or interaction term contributes to the total variance in the dataset. However, when some factors or interactions show negligible influence on the response, pooling combines their mean squares with the residual error term to increase the degrees of freedom for error estimation. This process refines the analysis by reducing random noise and improving the accuracy of the F-ratio for the remaining significant factors (Harrer *et al*. 2021).

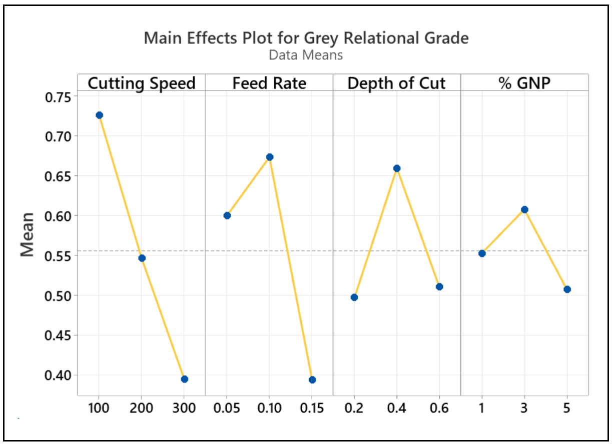

Fig. 5: Main effects plot for GRG

Table 3. GRA table for outputs

Trial No.	Normalizing Sequence		Deviation Sequence		GRC		GRG
	FW	SR	FW	SR	FW	SR	
1	0.848	0.732	0.152	0.268	0.766	0.651	0.709
2	1.000	1.000	0.000	0.000	1.000	1.000	1.000
3	0.623	0.155	0.377	0.845	0.570	0.372	0.471
4	0.834	0.573	0.166	0.427	0.751	0.539	0.645
5	0.623	0.744	0.377	0.256	0.570	0.661	0.615
6	0.179	0.175	0.821	0.825	0.378	0.377	0.378
7	0.424	0.326	0.576	0.674	0.465	0.426	0.445
8	0.384	0.118	0.616	0.882	0.448	0.362	0.405
9	0.000	0.000	1.000	1.000	0.333	0.333	0.333

Table 4. Response table for GRG

Factors	Level 1	Level 2	Level 3	Max - Min	Rank
Cutting Speed	0.726	0.546	0.394	0.332	1
Feed Rate	0.600	0.673	0.394	0.279	2
Depth of Cut	0.497	0.660	0.510	0.162	3
% GNP	0.552	0.608	0.507	0.101	4

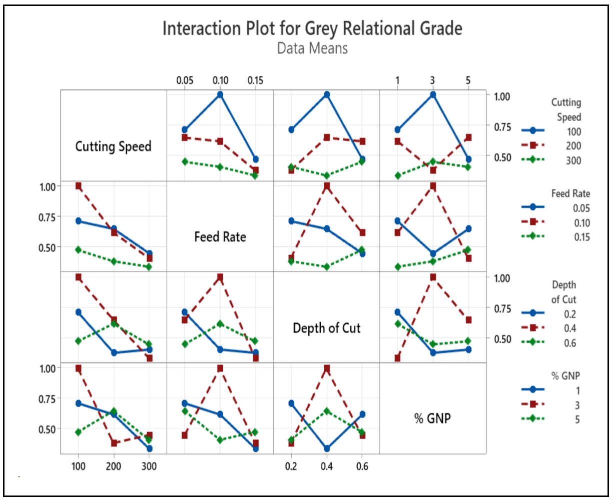

Fig. 6: Interaction plot for GRG

Table 5. ANOVA table for GRG

Source	DoF	Adj SS	Adj MS	F-Value	P-Value
Cutting Speed	2	0.16573	0.082864	*	*
Feed Rate	2	0.12582	0.062908	*	*
Depth of Cut	2	0.04879	0.024395	*	*
GNP %	2	0.01525	0.007627	*	*
Error	0	*	*		
Total	8	0.35559			

Pooling serves two main purposes: it strengthens the power of the ANOVA test by better estimating the error term, and it simplifies the model by excluding insignificant terms. This is particularly beneficial in experiments with limited data, as pooling increases the reliability of statistical conclusions (Last *et al*. 2008). The ANOVA table after pooling is presented in Table 6. The insignificant term (% GNP) is combined with the error term and analysis is done. A significant variance exists among all the variables, the F value for CS is higher showing that the influence of CS is maximum that the other input parameters. The R^2 value obtained during analysis is 95.71% with an R^2-adjusted value of 82.84%. The % contribution of each input parameter, excluding the insignificant term (% GNP) is presented in Figure 7. The CS contributes by 46.61%, FR by 35.38%, DOC by 13.72%, and error term by 4.29% which is within the 95% confidence interval (CI) (Bhushan, 2023).

Table 6. Pooled ANOVA for GRG

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Cutting Speed	2	0.16573	0.082864	10.86	0.084
Feed Rate	2	0.12582	0.062908	8.25	0.108
Depth of Cut	2	0.04879	0.024395	3.20	0.238
Error	2	0.01525	0.007627		
Total	8	0.35559			

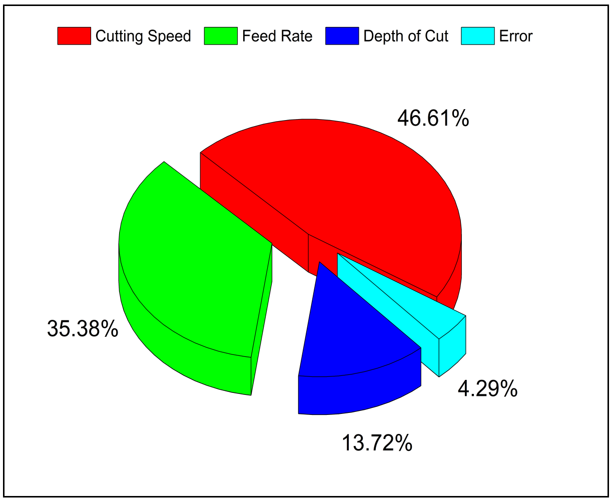

Fig. 7: % Contribution of individual parameters on GRG

Fig. 8 presents the tool insert flank face where the wear has occurred which clearly shows that the wear had occurred due to adhesion and delamination owing to increased friction and heat production at the cutting zone as a result of shearing (Ozkan *et al*. 2020).

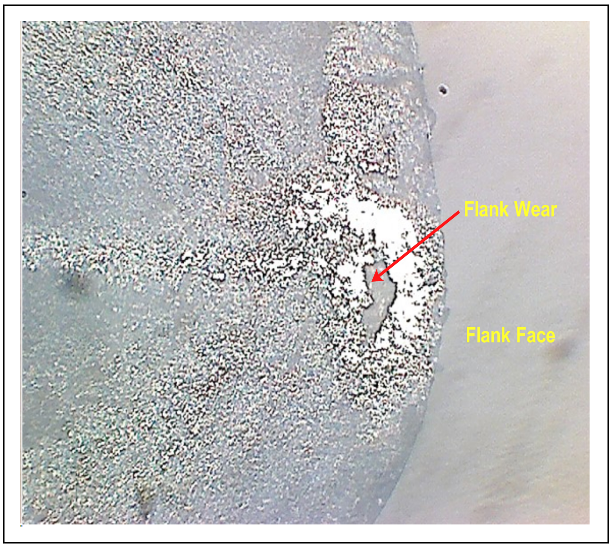

Fig. 8: Flank wear of optimal machining conditions

4. CONCLUSION

The MQL assisted machining studies on the LM25+10%TiC composite using GNPs dispersed in canola oil shows the following outcomes.

1. With stir casting technique, the SEM image shows uniform dispersal of TiC particles without any defects, which will enhance the mechanical strength of the composite.

2. Turning studies show that as the CS increases there is a substantial rise in FW and SR, similar is the case for FR also. Similarly, an increase in FR elevates

the forces exercised on equally the tool and workpiece. The combined effect of higher CSs and FRs often leads to rougher surface finishes due to the aggressive cutting conditions and the more pronounced tool wear. A moderate DOC favors the output.

3. The FW tends to lower with higher GNP content in the MQL whereas the SR tends to lower until 3 wt.% addition of GNPs, when the inclusion of GNPs is at 5 wt.%, the SR tends to increase.

4. From Mult objective GRA, the optimal conditions identified are CS of 100 m/min, FR of 0.1 mm/rev, DOC of 0.4 mm and 3 wt.% GNP inclusion in MQL system. ANOVA shows a contribution of CS by 46.61%, FR by 35.38%, and DOC by 13.72%.

5. A considerable correlation exists among CS and DOC and CS and % GNPs which significantly impacts the output responses. Similarly, among, FR with DOC and % GNPs, there is a significant interaction and also among DOC and % GNP.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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