OPTIMIZATION OF MRR & RA IN CNC MILLING PROCESS PARAMETERS OF STIR CASTED ALUMINIUM 6061 HYBRID COMPOSITES

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Abstract:

A change in research from evaluation of merely metallic constituents into light weight composite constructions has occurred over the past few years as a result of the global demand for materials that are affordable, effective, and of great quality. When a non-metallic ceramic is manufactured and tested under standard conditions, the reinforcement materials utilized, such as SiC, Al2O3, and SiO2, considerably influence the structural behaviour. Silicon carbide and Graphene nanoparticles are used as reinforcement materials. CNC milling is distinguished by its ability to cut a wide variety of materials and manufacture custom-designed products significantly faster than traditional machining. In this project, Al6061 alloy reinforced with SiC and Gr nanoparticles will be cast with fixed SiC content of 0.5 weight percent and variable Graphene content of 0.25, 0.5, and 0.75 weight percent in stir casting machine. CNC milling parameters like feed rate, speed, and depth of cut will be researched. Stir Casting, a liquid processing technique, was used to cast an Al-based metal matrix composite. To evaluate the tensile strength, impact resistance, and hardness of the metal matrix composites. Using a Taguchi L16 Orthogonal array and a design of experiments, the process parameters Material Removal Rate (MRR) and Surface Roughness (Ra) are evaluated.

Keywords: Stir Casting Machine, Metal Matrix Composite, CNC Milling, Machining Parameters, Taguchi Design of Experiments, Material Removal Rate, Surface Roughness.

1. Introduction

Materials with greater strength, lower cost, and lighter weight are required for engineering applications. Due to their exceptional mechanical qualities, such as hardness, high strength, light weight, heat resistance, low cost, wear resistance, and weight ratio to strength, Metal Matrix Composites (MMC) have been used for over thirty years. The most typical MMC consists of an aluminium matrix supplemented with SiC and nanoscale Graphene particles. The composite is then challenging to machine. These Al-based Sic-Graphene nanoparticle composites are being employed more and more in drive shafts, turbocharger impellers, space structures, automotive pistons, bearings, cylindrical liners, connecting rods, and piston rings. The production of MMCs can be done in a variety of ways. Of all the techniques, The Stir Casting Technique is the most well-liked. It is ideal because it is less expansive, achieves high mechanical properties, and makes it simple to manage variables like stirring speed and pouring temperature. By adding SiC and Graphene to Al alloy, mechanical qualities have been improved. Variable weight percentages of Graphene and fixed weight percentages of SiC are used for all castings. The casting’s mechanical characteristics, the stir casting technique revealed characteristics including tensile strength, BHN hardness, and impact test. Due to their severe abrasiveness, MMCs are very challenging to machine, making them tough to turn, mill, drill, thread, etc. Because these studies largely focused on improving key influencing parameters and it can regulate the output quality features, researchers have been paying increasing attention to the machinability of MMCs. The Taguchi method is employed for optimization, and the Regreation equation and ANOVA were used to estimate the ideal machining conditions.

Studying machinability and enhancing machining performance of the aluminium hybrid composite are the goals of the current effort. Variable SiC weight % addition [0.5wt%] is fixed and Graphene weight percent [0.25wt%, 0.5wt%, 0.75wt%] reinforcement and Al6061 alloy was made by using stir casting technique. Among them Al6061 with 0.5wt% SiC & 0.75wt% Graphene reinforcements have better mechanical properties. The End Milling Process is used to assess the machinability of the Al hybrid metal matrix composite. High-speed end milling operations are performed with Solid Carbide tool with 6mm Dia, 4 flute spiral is used. Feed Rate, Speed, and Depth of Cut are the factors that have the greatest impact. The optimization is done in MINITAB- 21 and experiments are carried out by design of experiments in Taguchi L16 Orthogonal array with three parameters and each with four levels. By using ANOVA and Regression of the machining parameters of Ra and MRR. To find out the S/N ratios, percentage contribution and minimum Ra and Maximum MRR optimized predicted parameters.

2. Literature Review

In this study [1] three different reinforcement materials including ZrO_2, $ZrO_2 + Al_2O_3$, and 40FZA with varying propositions as 5,10 and 15 % were used. On both experimental and computational analysis, it is clear that the presence of 15% particles reinforced with 40FZA in Al6061 results in better strength, toughness, and strong resistance to wear and corrosion. It is found [2] that one of the most basic processes is stir casting. for Al castings and Al6061 is reinforced with Al Oxide particles (0-4wt%) gives the hardness, tensile strength and compression tests are conducted. The values are compared with pure Al alloy casting. So that the wt% of Al Oxide increases the mechanical properties also increases in metal matrix composites. In this paper [3] he used stir casting technique to prepare the MMC's with 0.33%, 0.55%, and 0.77% of Graphene nano particles. It is tested for mechanical properties then 0.77wt% of graphene nano particles composite is recommended of obtaining optimum results. It is found [4] The Stir casting method is being used to build Al MMC enhanced with Al2O3 and fly ash. The use of fly ash increases micro hardness and Rockwell hardness while decreasing density. The microstructures of Al6061 metal matrix composite reveal the uniform dispersion of reinforcing particles. It is found [5] Al6061 reinforced with Al2O3 in (5, 10, 15 & 20wt%) in stir casting. The microstructures show the Reinforcement particles are distributed uniformly. The reinforced particles increased the micro hardness and ultimate tensile strength of the material. In this paper [6] Stir Casting process is employed to create the SiC/ Al alloy MMC's. The technical challenges of achieving uniform dispersion, good wettability between compounds, and low porosity materials are discussed. This paper [7] deals with the Al6061 nano composites reinforced with Silicon and Graphite and to find out the wear rate and wear debris and to find out the improved mechanical properties and wear rate. In this study [8] to maximize MRR and minimize erosion rate and Ra while also optimizing the settings for Taguchi-based GRA analysis is used when milling ZE41A Mg alloy on a CNC machine to determine the tool rotation, cutting speed, feed rate, and depth of cut. In this paper [9] Al6061 alloy is reinforced with Tic particles are used to fabricate the casting by using stir casting machine. End mills are used in machining to optimize factors such as spindle speed, feed rate, and depth of cut. TWR is analysed by SEM analysis. In this study [10] The effect of Ra and MRR parameters in ENDMILL on the ability of the LM6/SiC metal matrix composite to be machined under wet cutting conditions. The experiments are conducted in 5 factor and 3 level in Taguchi design of experiments with L27 orthogonal array. ANOVA, Percentage Contribution, Prediction of optimum values of Ra and MRR.

The literature review mentioned above leads to the conclusion that a lot of research is being done on the manufacturing and machining of Al MMCs with silicon carbide and graphene as reinforcements. This study uses the design of experiments to investigate the impact of CNC factors on MRR and surface roughness of Al6061 reinforced with SiC and Graphene particles.

3. Materials and Methodology

There are two phases in every composite material. While the reinforcing phase gives the composite more strength, the matrix phase acts as a supporting material. The aluminium 6061 alloy was used in this study to mix silicon carbide (SiC) and graphene nanoparticles.

3.1 Methodology

Initially, Al6061 alloy was introduced into a graphite crucible with electrical furnace assistance and melted at 800°C. 3 grams of C_2Cl_6 was added to the melt after it had melted in order to release any trapped gases. 2 grams of potassium Hexa Fluoro Titanate (K_2TiF_6) was mixed with the reinforcement in the proper ratio before being heated in a preheater die for 2 hours to eliminate any foreign particles, minimize moisture content, and enhance wettability. Flux powder or molten salts, such as K_2TiF_6, are utilized to enhance the wettability of the matrix and the reinforcement materials. Throughout 4 phases of stirring with the Aluminium alloy melt while the stirrer was moving at 400 rpm, preheated reinforcement was added. Step-by-step reinforcement addition enhances the matrix's distribution and produces better properties. To ensure that reinforcement is distributed evenly all through melt, stirrer was stirred within the melt for 10 minutes. After stirring, the molten material was allowed to rest for 5 minutes in the furnace to allow the particles to settle before being Figure 1 depicts the pour into the heated die casting.

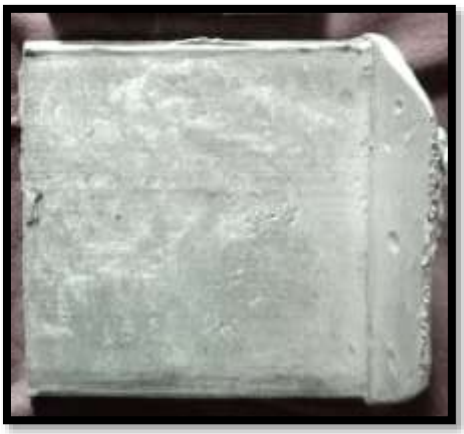

Fig. 1: Casted Aluminium SiC/Gr Composite

3.2 Design of Experiments

In every sector, it is challenging to produce high-quality and productive goods. To achieve this, the design of experiments (DOE) method is primarily utilized to generate efficient combinations of process parameters while simultaneously minimizing the number of trials. In this work, a mathematical model based on Taguchi and 16 trials was created to investigate how process factors affect machining features. One of the greatest techniques for developing the mathematical model is this one. Speed, depth of cut, and feed rate—which are employed as input variables—are the elements that, according to the literature, have the greatest impact on machining characteristics. Ra and MRR are used as output variables. Table 1 lists the input variables along with their values. Level values are taken into consideration based on machine capacity. L16 orthogonal array, which consists of 3 columns and 16 rows, is taken into consideration in this project. If you want accurate findings from any optimization method, you need run more experiments.

Three levels of values are specified for each parameter. For calculating the relation between parameters, MINITAB-21 was implemented. Particularly for DOE applications, this is utilized. Investigated were the interactions between input and output variables. Each experiment's MRR and Ra are determined, and then The S/N ratio is extended to the complete set of data.

Table 1: Levels and Parameters for Machining

S.No	Parameter	Units	Level1	Level2	Level3	Level4
1	Speed *N*	RPM	750	1000	1250	1500
2	Feed Rate *f*	mm/min	75	100	125	150
3	Depth of Cut *d*	mm	0.4	0.6	0.8	1

It is the difference between the signal mean and the standard noise deviation. This ratio will be applied in order to rank the input variables. It has 3 separate quality parameters: smaller is better, larger is better, and nominal is best. Because surface roughness should be less in any machining process, smaller is desirable for Ra. However, the MRR situation is completely the reverse, where larger is better.

Larger the better for MRR-

$$\frac{S}{N} = -10 \times Log10\left(\frac{sum\left(\frac{1}{y^2}\right)}{n}\right) \text{....... Eq (1)}$$

Smaller the better for Ra-

$$\frac{S}{N} = -10 \times Log10\left(\frac{sum(y^2)}{n}\right) \text{....... Eq (2)}$$

To determine the relative influence of one parameter on another, analysis of variance is utilized. Utilizing this statistical method, the experimental data were analysed. The optimal results were determined by comparing the mean square of the outcome as well as the standard error of the sample mean i.e. max MRR and min Ra.

4. Experimental setup

4.1 SELECTION OF CUTTING TOOL

Solid Carbide tools are chosen for cutting these composites based on the literature. It has exceptional fracture toughness, fatigue resistance, and shock resistance and is easily formable. In Fig. 2, the Endmill's geometry specifications for conducting experiments are shown. A smaller number of flutes allow for more or big chip space allowing for faster material removal but it make the tool weaken. A higher number of flutes will increase the strength of the tool and are better suited for cutting harder material. We take the four flute because it can produce small chips and less flute space so it can allow for faster feed rates.

Fig.2 SELECTION OF CUTTING TOOL

4.2 Experimental procedure

In Fig.3, the milling experiment was conducted out at the PBR Visvodaya Institute of Technology and Science (PBR VITS), Kavali, utilizing a BFW CHANDRA+ vertical milling machine. This experimental investigation's goal is to evaluate the importance and effects of the cutting parameters on the Ra and MRR of Al6061 SiC/Graphene MMC during end milling machining under wet cutting circumstances. For this experiment, a DOE based on Taguchi's technique was used. Three factors and four levels are used. The levels of the experimental variables or cutting parameters are shown in Table 1.

There will be research into the interactions or correlations between the variables since this is a Taguchi L16 orthogonal array. The following three variables are taken into consideration: Feed Rate (mm/min), Depth of Cut (mm), and Speed (rpm). The MRR is measured by the equation eq… (3). A contact-type Metrix+ MICROSURF 10A Digital Ra Tester was used to measure the surface roughness value (Ra). The average of at least five surface roughness measurements for each experiment was calculated and documented for subsequent examination. To determine the most important elements affecting the Ra and the percentage contribution of each parameter, a statistical analysis will be carried out using an ANOVA with a 95% confidence interval. By using linear regressions, a mathematical model of surface roughness will be developed. The optimum cutting parameters will be determined based on the S/N ratio, with lower values obtaining the lowest surface roughness and larger values achieving the highest Material Removal Rate. To determine the percentage error between the experiment and Taguchi technique, a confirmation test will be conducted.

$$\mathrm{MRR}(gm/hr) = \frac{\text{Work piece weight loss(grams)} \times 1000 \times 60}{\text{Density (gm/cm3)} \times \text{machining time (seconds)}} \quad \text{.........eq (3)}$$

Fig. 3 CNC VERTICAL MILLING MACHINE SETUP

4.3 Experimental Setup

The experiments of end mill process and setup of tool, work piece and surface checking was shown in fig.4.

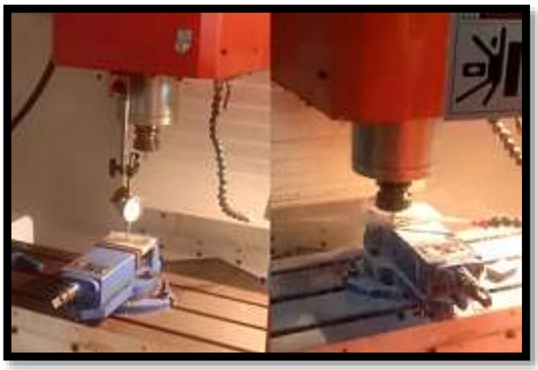

Fig.4 Experimental Setup of END Milling

5. Results and Discussion:

The input variables are determined on response, The S/N ratio and ANOVA tools were used to analyse the data. Table 2 provided all of the results for the various experimental setups.

Table 2: S/N ratio and ANOVA tools

S.No	SPEED	FEED RATE	DEPTH OF CUT	MRR	S/N for MRR	Ra	S/N for Ra
1	750	75	0.4	236.656	47.4824	**0.262**	11.6340
2	750	100	0.6	393.626	51.9017	0.362	8.8258
3	750	125	0.8	597.895	55.5325	1.128	-1.0462
4	750	150	1	**911.980**	59.1997	1.976	-5.9157
5	1000	75	0.6	314.203	49.9442	0.438	7.1705
6	1000	100	0.4	306.362	49.7247	0.320	9.8970
7	1000	125	1	809.189	58.1610	1.325	-2.4443
8	1000	150	0.8	793.094	57.9865	1.872	-5.4461
9	1250	75	0.8	427.415	52.6170	0.672	3.4526
10	1250	100	1	641.843	56.1486	0.749	2.5104
11	1250	125	0.4	417.122	52.4053	0.455	6.8398
12	1250	150	0.6	647.173	56.2204	1.234	-1.8263
13	1500	75	1	482.165	53.6639	0.642	3.8493
14	1500	100	0.8	520.265	54.3245	0.729	2.7454
15	1500	125	0.6	535.362	54.5730	0.567	4.9283
16	1500	150	0.4	503.268	54.0360	0.975	0.2199

5.1 Machine parameters' impact on MRR

The S/N ratios response table for MRR in Table 3 indicates that Feed Rate(f) has the biggest influence, followed by Depth of Cut(d) and Speed (N).

Table 3: Response Table for MRR and S/N Ratios (Larger is better)

Level	**Speed**(*N*)	**Feed Rate**(*f*)	**Depth of Cut**(*d*)
1	53.53	50.93	50.91
2	53.95	53.02	53.16
3	54.35	55.17	55.12
4	54.15	56.86	56.79
Delta	0.82	5.93	5.88
Rank	3	1	2

The MRR major impacts plot in Figure 5 shows that MRR improves as feed rate values rise. An increase in material removal rate follows an increase in input rate. However, increase in depth of cut and speed results in lower MRR. The ideal machining settings were identified from the major effects plot for SN ratios, and they are

Depth of Cut(d)- 1 mm; Speed(N)-1250 rpm; Feed Rate(f)- 150 mm/min;

Figure 5 shows the main effect plots for S/N ratios and data mean graphs for MRR Signal to Noise Ratios, which state that larger is better.

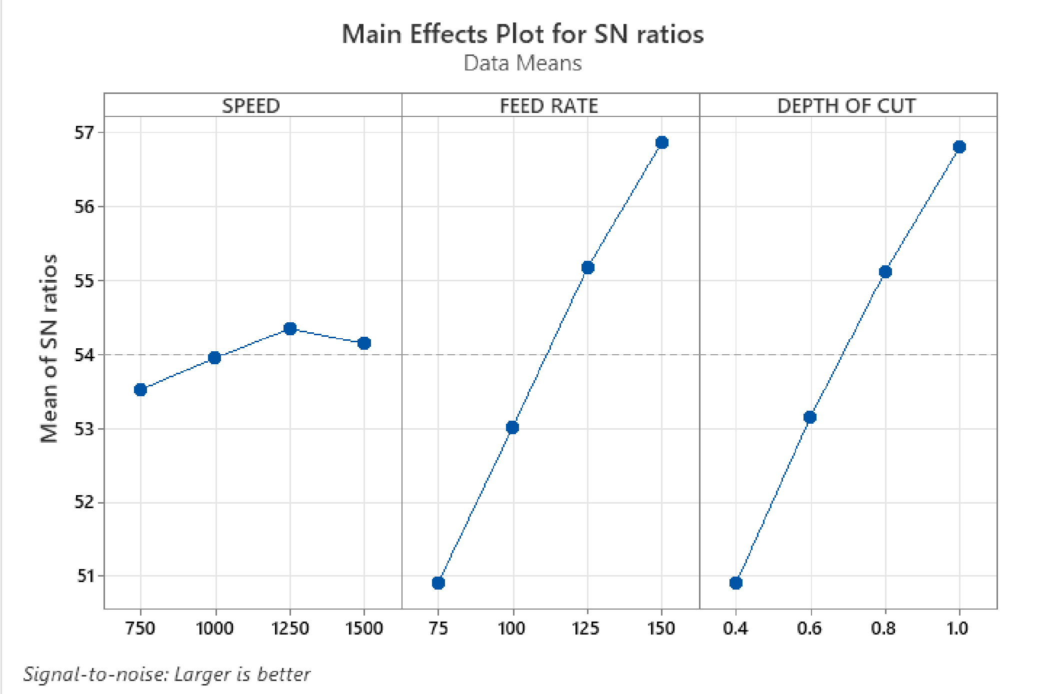

Fig. 5: MRR's Main Effect Plot

5.2 Effect of Machine Parameters on Surface Roughness

According to Table 4's S/N ratios response table for Ra, Feed Rate(f) has the greatest influence on Ra, followed by Depth of Cut(d) and Speed (N).

Table 4: Response Table for S/N Ratios- MRR (Smaller is better)

Level	**Speed**(*N*)	**Feed Rate**(*f*)	**Depth of Cut**(*d*)
1	3.37447	6.52660	7.14766
2	2.29427	5.99466	4.77460
3	2.74411	2.06940	-0.07356
4	2.93575	-3.24206	-0.50010
Delta	1.08020	9.76866	7.64776
Rank	3	1	2

It can be seen from the Ra main effects plot in fig. 6 that Ra rises with better feed rate values. Therefore, a higher feed rate causes a rougher surface. However, increasing cut speed and depth causes Ra to decrease. The ideal machining settings were identified from the major effects plot for SN ratios, and they are

Speed(*N*)-1000 rpm; Feed Rate(*f*)- 150 mm/min; Depth of Cut(*d*)- 1.0 mm;

Figure 6 displays the S/N Ratios Smaller is Better and S/N Ratios Main Effects plots as well as data means graphs for Ra.

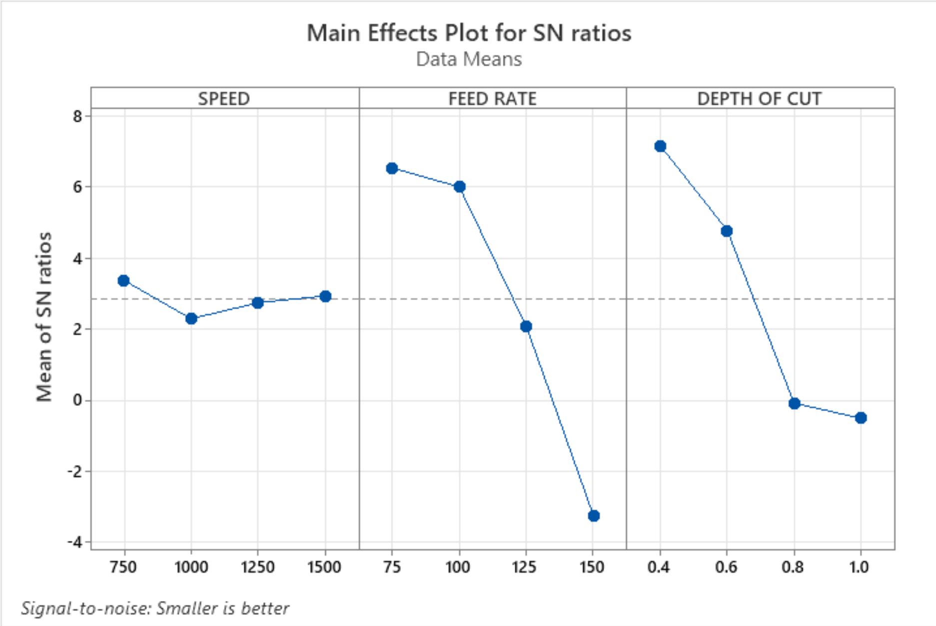

Fig. 6: Main Effect Plot for Ra

5.3 ANOVA FOR MRR

The main factors that significantly effecting the MRR is Feed Rate and Depth of Cut. ANOVA was done to study the effect of the end milling process variables. The results obtained from ANOVA are shown in table 5. From the Analysis of variance results it concludes the Residual error is 0.23% of total contribution and the most influencing parameter is Feed Rate and Depth of Cut followed by Speed.

Table 5: Analysis of Variance for MRR

Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**	**Contribution%**
SPEED	3	1.468	1.4683	0.4894	8.03	0.016	0.92%
FEED	3	79.769	79.7692	26.5897	436.10	0.000	50.24%
DEPTH OF CUT	3	77.148	77.1484	25.7161	421.77	0.000	48.59%
Residual Error	6	0.366	0.3658	0.0610			0.23%
Total	15	158.752					100.00%

Note: DF-Degrees of freedom; Seq SS-Sequential sum of squares; Adj SS-adjusted sum of squares; Adj MS-Adjusted mean squares; P-Percentage of Contribution.

5.4 ANOVA for Surface Roughness

The main factors that significantly effecting the Ra is Feed Rate and Depth of Cut. ANOVA was done to study the effect of the end milling process variables. The results obtained from ANOVA are shown in table 6. From the Analysis of variance results it concludes the Residual error is 1.3% of total contribution and the most influencing parameter is Feed Rate and Depth of Cut followed by Speed.

Table 6: Analysis of Variance for Ra

Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**	**Contribution%**
SPEED	3	2.407	2.407	0.8024	0.82	0.529	0.59%
FEED	3	244.513	244.513	81.5043	83.12	0.000	58.13%

DEPTH OF CUT	3	167.775	167.775	55.9249	57.03	0.000	39.89%
Residual Error	6	5.883	5.883	0.9805			1.39%
Total	15	420.578					100.00%

Note: DF-Degrees of freedom; Seq SS-Sequential sum of squares; Adj SS-adjusted sum of squares; Adj MS-Adjusted mean squares; P-Percentage of Contribution.

5.5 Regression Analysis

The MRR and Ra dependent variables as functions of speed, feed rate, and depth of cut, respectively, are predicted using mathematical models. Each response has not undergone any modification. Below are the predicted equations obtained from the regression analysis. R^2's coefficient of determination is used to evaluate the efficacy of proposed model. Between zero and one is the range for the coefficient of determination. It indicates that the dependent and independent variables fit together well if it is close to one. Therefore, that if R^2 = 95%, new observations had an estimated variability of 95%. The generated regression models for MRR and Ra in the latest research showed high R^2 values of 97.89% and 86.90%, respectively. The accuracy of the coefficients in the predicted model was evaluated by using residual plot. If the residual plot is linear, the model's residual errors are normally distributed, and the model's coefficients are essential. Figures 7 and 8 exhibit the residual plots that were produced for MRR and Ra, respectively. The residuals for both MRR and Ra were found to be similar to the straight line in Figs. 7 and 8, which suggests that the created model coefficient models are significant.

Regression Equation for MRR (R^2 = 97.89%)

MRR = - 351.7 - 0.0387 SPEED + 4.683 FEED RATE + 574.2 DEPTH OF CUT

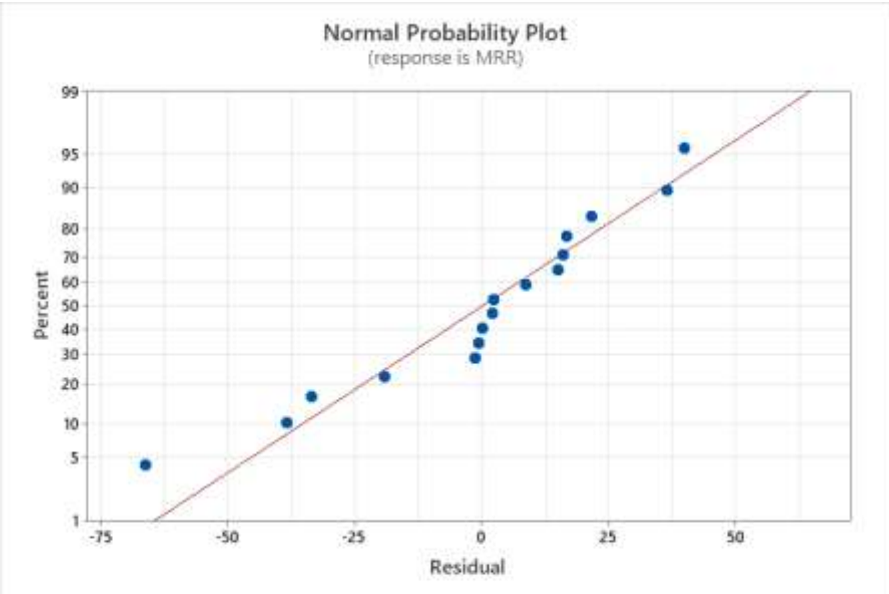

Fig. 7: Regression Normal Probability Plot for MRR

Regression Equation for Ra (R^2 = 86.90%)

Ra = -1.147 - 0.000329 SPEED + 0.01344 FEED RATE + 1.230 DEPTH OF CUT

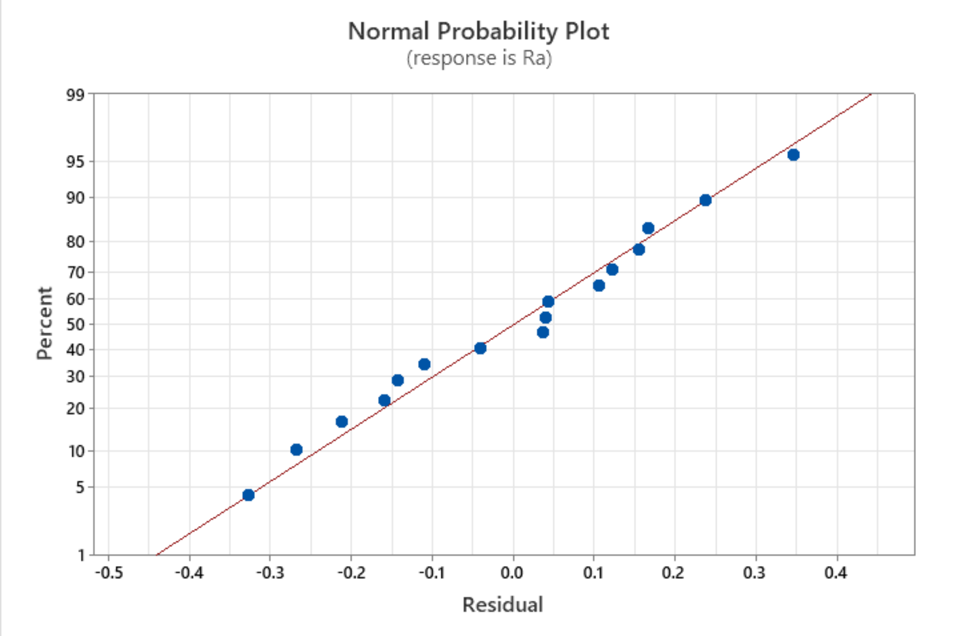

Fig. 8: Regression Normal Probability Plot for Ra

5.6 Optimum Predicted Values for MRR & Ra

The optimum predicted values are shown in the table 7 and table 8 for MRR & Ra.

Table 7: Optimum Predicted values for MRR

S.No.	Factor	Level	Value
1.	Speed *N*	2	1000
2.	Feed Rate *f*	4	150
3.	Depth of Cut *d*	4	1.0
PREDICTION			
4.	**S/N Ratio**	-7.12219	
5.	**Mean**	1.96275	

Table 8: Optimum Predicted values for Ra

S.No.	Factor	Level	Value
1.	Speed *N*	2	1000
2.	Feed Rate *f*	3	125
3.	Depth of Cut *d*	3	0.8
PREDICTION			
4.	**S/N Ratio**	-1.38419	
5.	**Mean**	1.2445	

6. Conclusion

An Al-based Metal Matrix Composite was casted by machining of Aluminium 6061 alloy reinforcement with 0.5- wt% SiC and 0.25-wt% Graphene, 0.5-wt% SiC and 0.5-wt% Graphene nano particles and pure Al6061, by using Stir Casting. Then to check the mechanical properties for the 3 castings and to take the 0.5-wt% SiC and 0.75-wt% Graphene nano particle casting which exhibits more tensile strength and hardness. The impact of process parameters on the machining characteristics, i.e. MRR & Ra, of produced composite, was investigated using Taguchi's Design of Experiments. According to the research, MRR is most affected by Feed Rate, followed by Depth of Cut and Speed. In the case of Ra, Feed Rate, Depth of Cut, and Speed are the main influencing factors. The anticipated response results and actual results showed a high degree of agreement from the perspective of the mathematical Regression Analysis and Optimum expected values for MRR and Ra. As a result, the generated models might be utilized to choose the best cutting parameters to evaluate product quality without the requirement to run test runs on materials that are challenging to cut.

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