Jurnal Inovasi Teknologi dan Edukasi Teknik, 5(3), 2025

# EXPERIMENTAL AND PREDICTIVE MODELLING OF SURFACE ROUGHNESS IN MACHINING ALUMINIUM ALLOY A356/COW HORN PARTICLE COMPOSITE

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doi: 10.17977/um068.v5.i3.2025. 2

**Keywords**
Aluminium Alloy A356
Cow Horn Particles
Surface Roughness
Machining
Response Surface Methodology (RSM)

**Abstract**
The increasing demand for lightweight, cost-effective, and sustainable engineering materials has led to growing interest in natural particle-reinforced metal matrix composites. Aluminium Alloy A356, widely used in automotive and aerospace industries, was reinforced with cow horn particles to enhance mechanical performance while promoting waste utilization. The study utilized Aluminium Alloy A356 reinforced with cow horn particulates (0–20%) fabricated by spark plasma sintering at 550 °C under 30 MPa. High-Speed Steel (HSS) and High-Carbon Steel (HCS) cutting tools were employed for machining tests. Experiments were conducted on a Universal Turning Machining Centre with supporting equipment including surface testers, weighing balance, crucibles, stirrers, and moulds. Machining parameters cutting speed (500–900 RPM), depth of cut (0.5–1.5 mm), and feed rate (0.15–0.25 mm) were varied to study effects on tool wear rate, material removal rate, and surface roughness. Response Surface Methodology (RSM) was applied for optimization and process modelling. Results revealed that cutting speed and depth of cut significantly influenced surface roughness, while feed rate had minimal effect. Surface roughness ranged from 119.09 to 168.47 mm (mean 145.63 mm). Statistical analysis showed cutting speed ($p = 0.0039$) and depth of cut ($p = 0.0384$) significantly influenced roughness, while feed rate was insignificant. The predictive RSM model demonstrated strong accuracy ($R^2 = 0.9818$; Adj. $R^2 = 0.8907$), showing close agreement between predicted and actual values. The findings highlight the potential of A356/cow horn composites for sustainable manufacturing applications with optimized machinability.

## 1. Introduction

Aluminium A356 reinforced with agro-waste particulates such as cow-horn particles (CHp) has recently emerged as a promising class of light, low-cost, and environmentally sustainable metal–matrix composites (MMCs). The integration of agro-waste reinforcements not only provides an avenue for waste valorization but also enhances certain mechanical and tribological properties of the base alloy, making these composites attractive for applications in automotive, aerospace, and biomedical sectors. However, despite these advantages, machinability data—particularly predictive models for key performance indicators such as surface roughness (Ra)—remain scarce. This lack of empirical and modelling insights makes it challenging for practitioners to determine optimal cutting parameters that achieve functional surface integrity while minimizing tool wear, energy consumption, and overall production costs (Mba et al., 2024). Moreover, the heterogeneous microstructure of A356/CHp composites, characterized by the presence of hard, irregularly distributed particles and complex particle–matrix interfaces, significantly complicates chip formation, heat dissipation, and surface finish. These factors highlight the need for systematic experimental investigations coupled with robust predictive modelling approaches to establish reliable machinability guidelines, thereby bridging the gap between material development and industrial application.

Recent turning experiments on A356 composites reinforced with cow-horn particles (CHp) have increasingly utilized response surface methodology (RSM) to establish quantitative relationships between key machining parameters feed, cutting speed, and depth of cut and output responses such as surface roughness (Ra), material removal rate (MRR), and tool wear, in one representative study involving a 10 wt.% CHp–A356 composite, analysis of variance (ANOVA) revealed that cutting speed and depth of cut exerted statistically significant effects on Ra, whereas feed rate contributed less prominently within the tested ranges. The resulting regression model for Ra exhibited a high coefficient of determination ($R^2$) alongside an acceptable adjusted $R^2$ value, affirming its robustness and predictive capability (Mba et al., 2024). Interestingly, these findings diverge from the behavior commonly observed in conventional A356 metal–matrix composites reinforced with ceramic particulates such as silicon carbide (SiC). In A356/SiC systems, feed rate is often identified as the dominant factor governing Ra, with higher cutting speeds typically leading to smoother surfaces due to reduced chip load per tooth and thermal softening of the matrix (Palanikumar et al., 2008; Dabade et al., 2010). The contrasting factor hierarchies between A356/CHp and A356/SiC highlight the critical role of reinforcement type and particle–matrix interfacial mechanics in dictating machinability. Unlike hard, angular SiC reinforcements, CHp introduces a softer, more ductile organic-inorganic phase that modifies the tribological interactions at the tool–chip and tool–workpiece interfaces. As a result, the ranking of parameter influence on Ra shifts, underscoring the need for composite-specific machinability models rather than assuming direct transferability from ceramic-reinforced systems..

Beyond conventional turning operations, composite machining studies increasingly adopt statistically designed experiments such as Box–Behnken designs and D-optimal designs to develop parsimonious predictive models of surface roughness (Ra). These approaches allow researchers to incorporate not only main effects but also interaction and curvature terms, thereby capturing the complex, non-linear machinability behavior of reinforced metal–matrix composites. For instance, Box–Behnken designs have been applied to A356 systems reinforced with organic particulates during casting and processing stages (Nwafor et al., 2020), while D-optimal designs have been employed to model drilling responses in hybrid MMCs (Rajmohan & Palanikumar, 2013). Such a design of experiments (DOE) frameworks provide efficient data sampling strategies, reduces experimental burden, and yields statistically interpretable models with high predictive power. Furthermore, the integration of desirability functions enables simultaneous optimization of multiple machinability responses such as surface roughness, tool wear, and cutting forces, supporting decision-making in real-world manufacturing contexts (Palanikumar et al., 2008). Collectively, these methods highlight the importance of DOE-based modelling in bridging experimental machining studies with practical process optimization.

Polynomial RSM models remain common in MMC machining due to transparency and ANOVA-based diagnostics (Mba et al., 2024; Palanikumar et al., 2008). However, A356/CHp research on related processes (age-hardening) shows that machine-learning models, artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), can outperform pure polynomials and support multi-objective optimization with evolutionary methods (Nwobi-Okoye et al., 2019). The same toolkit is well-suited to Ra prediction, where nonlinearity, factor interactions (e.g., feed×speed), and microstructure-dependent effects are pronounced. A pragmatic strategy emerging from the literature is: (i) use DOE (Box–Behnken or D-optimal) to bound the design space efficiently; (ii) estimate an interpretable RSM for insight and screening; (iii) train ANN/ANFIS within the sampled space for higher-accuracy Ra prediction and couple it to global optimizers for trade-offs among Ra, MRR, and tool wear (Nwobi-Okoye et al., 2019; Rajmohan & Palanikumar, 2013).

For A356/CHp, experimental evidence indicates that factor importance for Ra can shift relative to ceramic-reinforced A356, making direct transfer of rules-of-thumb unreliable. Well-designed experiments and hybrid modelling (RSM + ML) provide both interpretability and accuracy, while microstructural knowledge clarifies why responses differ from SiC-based MMCs. The importance of studying experimental and predictive modelling of surface quality in machining Aluminium Alloy A356/Cow Horn Particle (CHp) composite lies in addressing knowledge gaps on the machinability of agro-waste reinforced MMCs. While extensive models exist for A356/SiC composites (Palanikumar et al., 2008), limited data capture how softer bio-reinforcements like CHp affect chip formation and surface roughness (Mba et al., 2024). Existing wear and microstructural studies (Ochieze et al., 2018) highlight altered tool–workpiece interactions, yet predictive machining models remain scarce. This study is vital to developing accurate Ra models, optimizing cutting conditions, and supporting sustainable, cost-effective composite applications.

## 2. Materials and methods

The materials employed in this study consisted of Aluminium Alloy A356 as the base matrix, in combination with High-Speed Steel (HSS) and High-Carbon Steel (HCS) cutting tools for machining trials. A356 is a widely used casting alloy, primarily due to its excellent strength-to-weight ratio and corrosion resistance, and it contains alloying elements such as silicon, iron, copper, manganese, magnesium, zinc, titanium, and vanadium in carefully controlled proportions that influence its mechanical and thermal properties. The choice of HSS and HCS cutting tools was motivated by their distinct alloying compositions: HSS is characterized by elements such as tungsten, molybdenum, and vanadium, which enhance hardness, hot-strength, and wear resistance, whereas HCS provides high edge retention at a relatively lower cost, making it suitable for comparative machinability assessment.

Composite specimens of A356 reinforced with varying proportions of cow-horn particles (xCHp, ranging from 0–20 wt.%) were fabricated using spark plasma sintering (SPS), a rapid consolidation technique that minimizes grain coarsening while ensuring strong particle–matrix bonding. Each specimen was produced with dimensions of 100 × 5 mm using graphite dies and punches, sintered at a temperature of 550 °C under an applied pressure of 30 MPa. The process was conducted in a closed vacuum chamber with controlled heating and cooling rates of 100 °C/min, ensuring uniform densification and reducing the likelihood of porosity or interfacial defects. This approach provided well-consolidated A356/CHp composites with tailored reinforcement fractions suitable for subsequent machinability evaluation.

### 2.1. Equipment

The experiments for this study will be conducted using a Universal Turning Machining Centre (Mikrotools DT 110), with data collected through a surface tester. Additional measuring tools such as vernier calipers and measuring tape will be used. A laboratory weighing balance, with 200 g capacity and 0.01 g readability, will measure material weights with precision. A crucible, capable of withstanding very high temperatures, will be used to hold the matrix composite in the furnace during melting and processing. The stirrer, an essential element in stir casting, will be applied to create a vortex that ensures uniform dispersion of reinforcement particles within the molten metal. Its design, including blade angle and number, influences flow patterns and bonding, with a stirring speed of 300 employed in this work. A conical hopper will facilitate the controlled input of component powders into the crucible during composite formation. Moulds will be prepared to cast specimens for various mechanical tests, with preheating at 500 °C for one hour to eliminate porosity and improve mechanical properties. Finally, a lathe machine will be used to finish the cast samples, ensuring dimensional accuracy and surface quality, which are critical for the performance evaluation of the developed composites.

To achieve the desired samples, the experiment was carefully designed and executed. A custom design, based on the surface response method (RSM), was adopted to study the effect of machining parameters on Aluminum Metal Matrix Composite (AMMC). The design focused on three machining attributes: cutting speed (500–900 RPM, three levels), depth of cut (0.5–1.5 mm, three levels), and feed rate (0.15–0.25 mm, two levels), with surface roughness measured as the primary response. Using DESIGN EXPERT SOFTWARE 11.0, a simplex lattice mixture design augmented with axial blend checks and the overall centroid was applied, reducing the experiment to 16 blends. The cutting operation involved turning a cylindrical rod (5 mm diameter, 150 mm length) using a cermet insert under varying conditions. The workpiece was fixed on the chuck, while the insert was clamped to the tool holder. Parameters such as cutting speed, feed, and depth of cut were systematically varied. Tool wear rate (TWR), material removal rate (MRR), and surface roughness (Ra) were evaluated using a video measuring system, weighing balance, and surface tester (Surfcorder SE3500). Surface roughness, defined by deviations from an ideal surface, was measured according to ASTM standards on A356 alloy/cow horn particulate composites.

## 2.2. Optimization using Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a statistical and mathematical approach used to design experiments, analyze results, and optimize processes. It is particularly valuable in improving product performance and reducing variability. RSM models can be expressed through first-order and second-order equations, which describe the relationships between independent variables and responses. In practice, RSM requires approximating models developed from observed data, making it an empirical method. Multiple regression techniques are central to constructing these models, as they help establish mathematical relationships between test factors and objective functions. Regression analysis allows researchers to determine the influence of different factors on responses, thereby identifying optimal solutions within the experimental space. RSM focuses on understanding the interactions among multiple variables (x1, x2, x3 … xk) and their combined effect on a response (y). To achieve accurate optimization, the functional relationship between responses and variables must first be defined. Once established, the appropriate factor settings are determined to yield the best possible outcome. Equations derived from regression, such as linear, interaction, and quadratic models, are commonly used to represent these relationships. Ultimately, RSM provides a systematic framework for process optimization, offering a practical balance between experimental efficiency and predictive accuracy.

# 3. Results and Discussion

## 3.1. Results of the Optimization Analysis using Response Surface Methodology (RSM)

An experimental investigation was carried out on A356 composites reinforced with cow-horn particles (CHp) to examine the influence of machining parameters on the performance of the developed material. In designing the study, three critical factors were identified as central to the composite formulation and machining process. Among these, two variables related to the A356/CHp formulation, together with feed rate, were selected as input parameters in a D-optimal custom experimental design, as they were expected to influence the machining responses significantly. The D-optimal approach, implemented through Design Expert software, was employed to efficiently explore the experimental space while minimizing the number of trials required. This method also allowed the definition of variable ranges and the generation of statistically robust models capable of capturing main effects, interactions, and curvature in the data. Table 1 presents the summary of the experimental design matrix, showing the actual combinations of parameters used and the corresponding responses measured during machining trials.

**Table 1: Summary of Data**

| Group | Run | a:Feed Rate rev/mm | B:Cutting Speed RPM | C:Depth of Cut mm | Surface Roughness mm | Tool wear mg/mm | |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 0.15 | 500 | 1 | 121.994 | 0.00074 | A |
| 1 | 2 | 0.15 | 900 | 1.5 | 157.78 | 0.00039 | B |
| 1 | 3 | 0.15 | 900 | 1 | 155.86 | 0.00041 | C |
| 1 | 4 | 0.15 | 500 | 1.5 | 122.211 | 0.00071 | D |
| 1 | 5 | 0.15 | 700 | 0.5 | 124.202 | 0.00065 | E |
| 2 | 6 | 0.15 | 700 | 1 | 127.289 | 0.00063 | F |
| 2 | 7 | 0.15 | 900 | 1.5 | 157.78 | 0.00039 | G |
| 2 | 8 | 0.15 | 700 | 1.5 | 133.484 | 0.00058 | H |
| 2 | 9 | 0.15 | 500 | 0.5 | 119.094 | 0.00092 | I |
| 2 | 10 | 0.15 | 900 | 0.5 | 136.311 | 0.00042 | J |
| 3 | 11 | 0.25 | 900 | 1 | 162.794 | 0.00014 | K |
| 3 | 12 | 0.25 | 900 | 1.5 | 168.47 | 0.00011 | L |
| 3 | 13 | 0.25 | 500 | 0.5 | 131.121 | 0.00037 | M |
| 3 | 14 | 0.25 | 700 | 0.5 | 149.205 | 0.00031 | N |
| 4 | 15 | 0.25 | 900 | 0.5 | 162.194 | 0.00026 | O |
| 4 | 16 | 0.25 | 500 | 1.5 | 158.032 | 0.00034 | P |
| 4 | 17 | 0.25 | 500 | 1 | 157.88 | 0.00036 | Q |
| 4 | 18 | 0.25 | 700 | 1 | 159.992 | 0.0003 | R |
| 4 | 19 | 0.25 | 700 | 1.5 | 161.213 | 0.00028 | S |

The build information reveals that a response surface methodology (RSM) split-plot design was applied using 19 experimental runs to evaluate the effect of feed rate, cutting speed, and depth of cut on surface roughness. Feed rate was treated as a hard-to-change numeric factor, while cutting speed and depth of cut were categorical with three levels each. Surface roughness values ranged from 119.09 to 168.47 mm, with a mean of 145.63 mm and a standard deviation of 17.17 mm. REML analysis showed that cutting speed ($p = 0.0039$) and depth of cut ($p = 0.0384$) significantly influenced surface roughness, while feed rate and interaction terms were statistically insignificant. The model demonstrated a strong fit with $R^2 = 0.9818$ and adjusted $R^2 = 0.8907$, suggesting reliable predictive capability. Coefficient estimates indicated that higher feed rate increased roughness, while certain levels of cutting speed and depth of cut improved surface quality. Insignificant interactions suggest limited combined effects among factors. Fit statistics, including low standard deviation (9.11) and C.V. (6.26%), further validate model precision. Overall, the study confirms cutting speed and depth of cut as dominant factors in determining surface roughness, providing useful guidance for optimizing machining conditions of the aluminum composite.

## 3.2. Final Equation in Terms of Coded Factors

Surface Roughness = +144.50+11.42a+12.16B[1]+1.77B[2]+5.43C[1]-1.09C[2]-1.87aB[1]
-0.9317aB [2]-0.4497aC [1] +0.2149aC [2] +3.24B [1]C[1] +2.45B [2]C[1]

-0.6823B [1]C[2]-1.08B [2]C[2]

The equation in terms of coded factors can be used to make predictions about the response for given levels of each factor. By default, the high levels of the factors are coded as +1, and the low levels are coded as -1. The coded equation helps identify the relative impact of the factors by comparing the factor coefficients.

## 3.3. Final Equation in Terms of Actual Factors

Surface Roughness = Cutting Speed500*Depth of Cut0.5+74.29615+254.05677 Feed Rate*
Cutting Speed500*Depth of Cut1+80.71898+296.09010 Feed Rate*

Cutting Speed 500*Depth of Cut1.5+82.68288+287.19312 Feed Rate*

Cutting Speed700*Depth of Cut0.5+84.75815+259.7267 Feed Rate*

CuttingSpeed500*DepthOfCut1+83.28848+301.76010FeedRate+Cutting

Speed700*Depth of Cut1.5+88.77588+292.86312 Feed Rate+Cutting

Speed900*Depth of Cut0.5+126.18321+115.34646 Feed Rate+Cutting

Speed900*Depth of Cut1+127.85104+157.37979 Feed Rate+Cutting

Speed900*Depth of Cut1.5+134.12148+148.48281 Feed Rate

The “Final Equation in Terms of Actual Factors” represents surface roughness (Ra) as a mathematical function of the primary machining parameters cutting speed, depth of cut, and feed rate expressed directly in their real-world units rather than in coded statistical values. Presenting the equation in this form allows practitioners to apply the model more intuitively when selecting or adjusting cutting conditions during machining. However, the current formulation of the equation appears somewhat fragmented and repetitive, with multiple terms redundantly pairing cutting speed and depth of cut alongside varying feed rate coefficients. This redundancy not only complicates interpretation but also obscures the underlying relationships between parameters. A more concise representation, achieved through algebraic simplification or reorganization, would enhance readability while preserving the predictive accuracy of the model. Such refinement would also make the equation more practical for industrial use, where clarity and direct applicability are critical..

The comparison between actual and predicted values demonstrates that the developed model provides a generally close fit, as evidenced by small residuals across several experimental runs (e.g., Runs 2, 3, 6, and 7), where deviations are negligible. This suggests that the regression equation captures the underlying trend of the data with reasonable accuracy. Nevertheless, certain runs specifically 5, 9, 10, 13, 14, and 15 exhibit relatively large residuals and externally studentized residuals that exceed conventional thresholds, indicating the presence of potential outliers or influential observations. For example, Run 13 recorded an actual surface roughness of 131.12 µm compared to a predicted value of 141.00 µm, resulting in a sizable negative residual of –9.88.

Similarly, Run 15 showed a marked positive residual of +8.45, highlighting localized model misfit. Diagnostic statistics such as Cook's Distance and DFFITS further reveal that these runs, particularly Runs 10 and 15, exert disproportionate influence on the regression estimates, thereby warranting closer scrutiny. Despite these deviations, the majority of data points exhibit strong agreement between observed and predicted values, lending support to the overall reliability and predictive validity of the model.

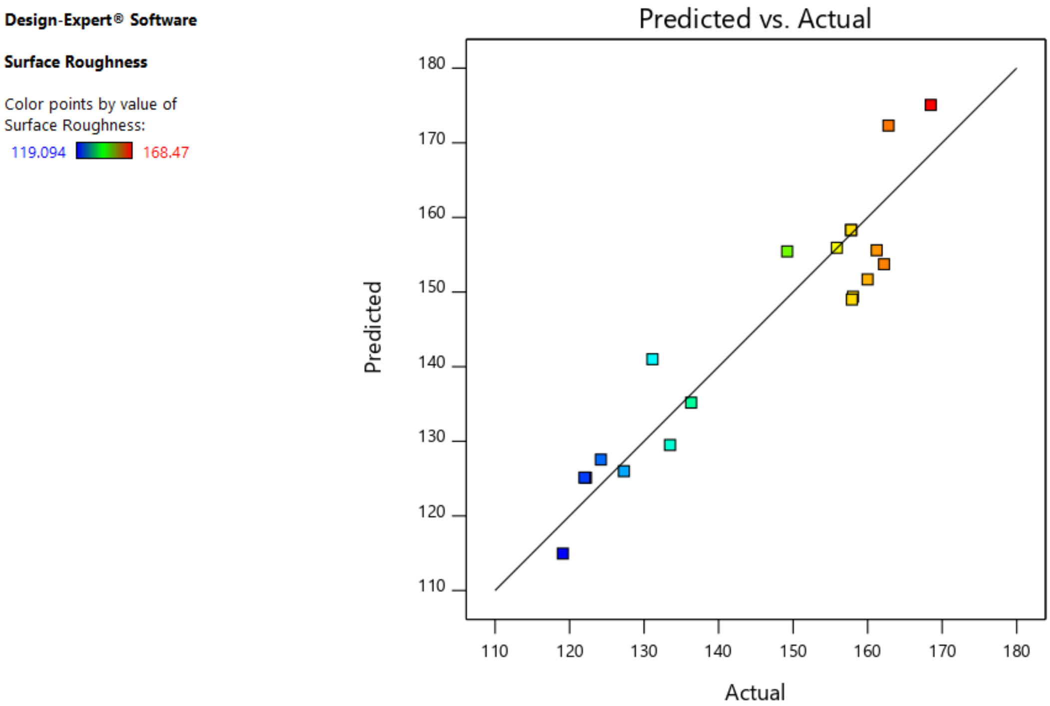

**Figure 1: Predicted versus actual plot for surface roughness showing strong agreement between experimental and model values.**

The Predicted vs. Actual plot compares model predictions of surface roughness with experimental values. Points close to the diagonal line indicate good agreement, showing the model's reliability. The color gradient, ranging from blue (low roughness, \~119) to red (high roughness, \~168), helps visualize variation across data. Most points cluster around the line, suggesting strong predictive accuracy, though slight deviations are visible at higher and lower values. This indicates minor under- or over-estimation in extreme cases. Overall, the model demonstrates good accuracy and robustness in predicting surface roughness within the tested range.

The solution output predicts a mean and median surface roughness of 160.26 mm, with a standard deviation of 9.11, indicating moderate variability. The 95% confidence interval for the mean ranges from 137.91 to 182.61, suggesting the prediction is reliable, while the 99% population tolerance interval (54.17–266.34) reflects the broader spread of possible values. The factors influencing this response include a low feed rate (0.1616 rev/mm), maximum cutting speed (900 RPM), and maximum depth of cut (1.5 mm). Statistical results show that cutting speed ($p = 0.0039$) and depth of cut ($p = 0.0384$) significantly affect roughness, while feed rate and interaction terms are not significant. Coefficient estimates indicate that increasing cutting speed and depth of cut raises surface roughness, while specific interactions reduce it slightly.

The optimization analysis using Response Surface Methodology (RSM) on Aluminium Alloy A356 reinforced with cow horn particles demonstrated that cutting speed and depth of cut significantly affected surface roughness ($p = 0.0039$ and $0.0384$). In contrast, feed rate and interaction terms were statistically insignificant. This observation is consistent with Abdallah et al (2014), who reported that cutting speed played a dominant role in reducing surface roughness during CNC milling of Aluminum 6061, while feed rate showed minimal effect, in contrast to depth of cut, which exerted a notable influence. Similarly, Haddad et al 2014) confirmed cutting speed as the most influential parameter in machining composites, with feed rate and depth of cut contributing to secondary effects.

In contrast, a review by Kiswanto et al (2014) identified feed rate as the most critical factor controlling surface quality across multiple aluminum alloy machining studies, thereby differing from the present result where feed rate was not significant. In a related study, Sulayman et al (2025) investigated LM13 aluminum alloy reinforced with rice husk ash using RSM. They observed similar trends, with cutting speed and depth of cut emerging as dominant factors influencing surface roughness, supporting the present findings.

Model performance in the present study was strong, with $R^2 = 0.9818$ and adjusted $R^2 = 0.8907$, alongside a low coefficient of variation (6.26%), suggesting high predictive reliability. This finding agreed with Putra et al. (2023), who employed Taguchi and ANOVA in machining Aluminum 6063 and achieved an $R^2$ of 0.9115, though with slightly lower precision. In addition, recent advances in predictive modeling, such as the ensemble learning approach applied to AlSi10Mg micro-milling, achieved high accuracy in forecasting surface roughness. Nevertheless, traditional RSM remains highly effective and offers clearer interpretability compared with complex machine learning models. The validated RSM model provides a robust framework for machining optimization, complementing both experimental findings and emerging AI-based predictive techniques.

## 4. Conclusion

This study successfully investigated the experimental and predictive modeling of surface roughness during the machining of Aluminium Alloy A356 reinforced with cow horn particles. Using Response Surface Methodology (RSM), the influence of cutting speed, feed rate, and depth of cut was systematically analyzed. Results revealed that cutting speed and depth of cut significantly affect surface roughness, while feed rate had minimal influence. The developed predictive model demonstrated strong reliability with high coefficient of determination and close agreement between experimental and predicted values. Future studies should investigate additional natural reinforcements and their hybrid combinations to enhance machinability and performance. Exploring advanced machining techniques, such as high-speed or cryogenic machining, could provide further improvements in surface finish and tool life. In addition, integrating artificial intelligence (AI) and machine learning approaches with experimental data may enhance predictive accuracy and enable real-time optimization of machining parameters for sustainable composite manufacturing.

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