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Management of Tool Wear Mechanisms in Machining Aluminium Alloy A356/Cow Horn Particle Composite

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ABSTRACT

This work presents the modelling and optimization of the cutting parameters in machining operations of aluminium alloy A356/cow horn particles (CHp) composite. In order to enable manufacturers to maximize their gains from utilizing hard turning, an accurate model of the process must be constructed. In course of the work, an attempt was made to develop mathematical models for relating the Tool Wear Ratio (TWR) to machining parameters (feed rate, depth of cut and cutting speed). To achieve this, A356/cow horn particles (CHp) composite was used to investigate the tool wear using RSM with 19 runs. A design of experiment was generated using the Optimal custom design techniques in Response Surface Methodology (RSM) from the Design Expert Software 11.0. After the optimization, the results from the ANOVA tables of the tool wear, surface roughness and Material removal rate showed that some models were significant with the probability value (P-value) 0.0203, 0.0412. Tool wear ranged from 0.00011–0.00092 mg/mm, with the lowest at high feed rate (0.25 rev/mm), high cutting speed (900 RPM), and depth (1.5 mm). Feed rate ($p = 0.0436$), cutting speed ($p = 0.0008$), and depth of cut ($p = 0.0137$) significantly influenced tool wear. The regression model achieved strong fit ($R^2 = 0.9952$, Adj $R^2 = 0.9714$) with low error (Std. Dev. = 0.0001). Predicted versus actual plots confirmed reliability, with 95% CI (0.000196–0.000530 mg/mm) validating precision and stability. In order to enable manufacturers to maximize their gains from utilizing hard turning, an accurate model of the process have been constructed.

Keywords:
Tool wear, Machining, Aluminium alloy A356, Cow horn particles, Response Surface Methodology (RSM)

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INTRODUCTION

Aluminium alloys are widely used for aerospace and automotive parts, yet their tendency to form built-up edge (BUE), adhere to cutting tools, and generate high interface temperatures accelerates flank/rake wear and shortens tool life. The challenge is to jointly minimize wear, temperature, and surface damage—often conflicting responses—by tuning cutting speed, feed, depth of cut, tool/coating, and cooling strategy. Response optimization frameworks (e.g., Taguchi, response surface methodology \[RSM], desirability, and evolutionary algorithms) offer principled ways to manage these mechanisms holistically rather than by trial-and-error (Gutema et al., 2022).

In aluminium (especially Al–Si die-casting grades like ADC12), adhesion wear dominates: soft, ductile chips weld to the rake face, evolve into BUE, and periodically detach, tearing tool material and degrading finish. Abrasion by hard Si particles and diffusion at elevated interface temperatures also contribute (Pimenov et al., 2023). Lower tool–chip friction, reduced temperature, and stable chip flow therefore become the primary management levers—achieved via sharper geometry, appropriate coatings/substrates, cryogenic/MQL cooling, and parameter windows that avoid thermal spikes.

Early aluminium turning studies optimized one metric at a time (e.g., flank wear or roughness). RSM advanced this by fitting quadratic meta-models (ANOVA-validated) that predict wear and temperature from speed–feed–depth–nose radius, enabling trade-off analysis (Luan et al., 2018). Desirability analysis then maps each response (minimize wear/temperature/roughness, maximize MRR) onto a 0–1 scale and aggregates them, yielding a single objective for efficient search and confirmation testing. These methods consistently report that moderate feeds with relatively higher cutting speeds—and adequate nose radius—lower temperature and wear while preserving productivity; confirmation runs typically validate predictions within tight error bounds (Yan et al., 2024; Okokpujie et al., 2018).

Sustainable cooling (MQL, LN_2, CO_2) suppresses adhesion/BUE and flank wear in alloys by reducing interfacial temperature and improving chip evacuation; when folded into DOE/optimization plans, these factors often emerge as significant alongside speed and feed (Duk et al., 2024). Thus, integrated designs treat cooling condition as a factor in Taguchi–desirability or RSM–desirability workflows, yielding parameter–cooling combinations that jointly minimize wear and surface damage. Authors have supplied datasets and models that illuminate parameter–wear relations during aluminium turning—e.g., Okokpujie et al. (2018) provided factorial datasets and SEM evidence linking speed/feed/depth to HSS tool wear in Al-1061, useful for building predictive models and validating RSM designs. Broader Nigerian optimization work (e.g., Grey–Taguchi and desirability) underscores the practicality of multi-criteria tuning for sustainable turning in local contexts, with methodology transferable to aluminium alloys (Martins et al., 2025; Braide et al., 2022).

Contemporary studies couple RSM/Taguchi with nature-inspired optimizers (NSGA-II, GA, SA) or machine-learning surrogates to push beyond local optima and explicitly visualize wear–roughness–MRR Pareto fronts. Reviews show desirability remains a simple, robust baseline, while hybrid ML+RSM approaches improve prediction of flank wear under complex interactions (Kelsy et al., 2025; Wu et al., 2021). For aluminium, this translates into recipes that: (i) cap tool–chip temperature below adhesion thresholds, (ii) avoid feeds that trigger BUE instability, and (iii) select coatings/geometries that resist Si-particle abrasion—verified via confirmation runs and microscopy.

The management of tool wear mechanisms underscores the importance of sustainability, efficiency, and human capital optimization. Just as effective stress and crisis management strategies improve performance in education and governance (Onyekazi et al., 2024; Osegbue et al., 2025), adopting predictive models like RSM enhances machining outcomes. These processes minimize wear, reduce cost, and foster productivity, aligning with broader themes of human capital development and sustainable practices (Mbuba, 2022; Mbuba, 2016). Moreover, strategic planning in machining parallels policy frameworks in housing and safety management (Ike et al., 2021; Osegbue et al., 2025).

Effective management of aluminium tool wear requires treating adhesion, abrasion, and thermal effects as coupled phenomena. Response optimization operationalizes this by (1) screening factors with DOE/Taguchi, (2) modeling responses via RSM (including temperature as a proxy for adhesion risk), (3) aggregating objectives using desirability (or mapping to a Pareto set), and (4) validating under the chosen cooling method. The result is a data-backed parameter window—often higher speed with moderated feed, adequate nose radius, optimized depth, and MQL/cryogenic assistance—that suppresses adhesion wear, stabilizes chip flow, and extends tool life without sacrificing throughput (Afolayan et al., 2024).

Aluminium alloy A356 reinforced with cow horn particles (CHP) is emerging as a sustainable composite material due to its light weight, strength, and eco-friendliness. However, machining such hybrid composites presents significant challenges because of their heterogeneous microstructure, which induces complex tool wear mechanisms such as abrasion, adhesion, and chipping (Joshua et al., 2022). Prior studies on aluminium machining have largely focused on conventional alloys (e.g., Al-6061, ADC12), neglecting natural-fiber-reinforced systems like A356/CHP, despite their growing industrial relevance. Tool wear in composites not only reduces productivity but also affects surface finish, dimensional accuracy, and cost-effectiveness. Although optimization approaches such as Taguchi and desirability analysis have been applied to predict wear and surface roughness in aluminium alloys (Yahya et al., 2016), few studies have systematically applied Response Surface Methodology (RSM) to model and optimize multiple machining responses in A356/CHP composites. This gap is critical because RSM can capture nonlinear parameter interactions and generate predictive models for sustainable machining. Thus, this study is justified as it addresses the lack of optimized machining data for bio-reinforced aluminium composites, enabling improved tool life, cost efficiency, and sustainable manufacturing practices.

MATERIALS AND METHODS

Material

The material and equipment that was used for the purpose of actualization of this work are Aluminum alloy A356 and HSS & HCS cutting tool. The A356 alloy primarily consists of aluminium (balance) with 7.0% silicon, 0.4% magnesium, 0.13% titanium, and trace elements including 0.1% iron, 0.002% copper, 0.006% manganese, 0% zinc, and 0.02% vanadium, making it lightweight, corrosion-resistant, and suitable for composite reinforcement applications. The A356 matrix/xCHp (x = 0, 5, 10, 15, 20) composite samples were produced using spark plasma sintering. Samples of dimensions, diameter 100x5mm were produced using graphite dies and punches. The composites were produced at 550 °C and 30 MPa with heating and cooling rate of 100°C/min. The thermocouple was inserted into the bottom punch to measure the temperatures of the process. All the samples were produced in a closed furnace where 2 -10 torr vacuum was maintained throughout the experiment.

The experiments were performed using a Universal Turning Machining Centre (Mikrotools DT 110), while data were obtained with a surface tester. Additional instruments such as vernier calipers and measuring tapes were employed for precise measurements during machining and testing processes. A laboratory weighing balance, model 6354, with a

200 g capacity, 0.01 g readability, and a 125 mm pan size, was used to measure the material weights as required. The crucible, designed to withstand very high temperatures, served as the container for holding the matrix composite inside the furnace during melting and casting. The stirrer was employed in the stir casting process, where its immersion to two-thirds of the molten metal depth and a stirring speed of 300 rpm ensured uniform distribution of reinforcement, strong interfacial bonding, and minimized clustering. The conical hopper was used to introduce cow horn particulates into the crucible during composite formation. Moulds were prepared for casting specimens required for mechanical tests such as wear and surface roughness. Each mould was preheated to 500°C for one hour to eliminate porosity and enhance composite properties. Finally, the lathe machine was used for finishing operations, ensuring dimensional accuracy of test specimens.

Method

The following steps was employed in other to achieve the sample as desired. They include;

Design of Experiment

To investigate the effect of the machining parameters on the newly adopted material, an optimal custom design which is a specialized form of the surface response method (RSM) was employed. For the purpose of this design, the machining parameters for the Aluminum Metal Matrix Composite (AMMC) was reformulated to fine tune Average Tool Wear Rate (mg/mm). Three primary components vary as shown:

a. $500 \leq$ A (Cutting speed - RPM) ≤ 900 (3 levels)
b. $0.5 \leq$ B (Depth of cut - mm) ≤ 1.5 (3 levels)
c. $0.15 \leq$ C (Feed Rate - mm) ≤ 0.25 (2 level)

This experiment was conducted with the DESIGN EXPERT SOFTWARE 11.0. The design employs a standard mixture design called a simplex lattice. The design was augmented with axial blend check and the overall centroid. The vertices and overall centroid were not replicated, however reducing the experiment size to 16 blends total.

Cutting Operation Procedures

A cylindrical rod of 5 mm diameter and 150 mm length is used to turn a material by using the cermet insert. Experiments are conducted for different sets of machining conditions in order to achieve tool wear and surface roughness. The work material is fixed to the chuck, which is centered. The insert is clamped to the tool holder and the necessary settings are made. The process parameters selected for the experiments are cutting speed, feed and depth of cut. Tool wear rate (TWR), Material Removal Rate (MRR) and surface roughness (Ra) are measured using a non-contact video measuring system, weighing balance and surface tester (Surfcorder SE3500).

Tool Wear Rate (TWR)

An inertial dynamometer was used as the de facto testing machine for the measuring of the engineering properties of the produced sample specimen such properties are wear rate, coefficient of friction, temperature generated, and noise level at different speeds ranging from 60 to 250km/h in compliance with Society of Automotive Engineers SAE J2552 issued in august 1999 for the A356 alloy/cow horn particulate composites samples.

This assesses the effectiveness behavior of a friction material with regards to pressure, temperature and speed.

Optimization using Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes.RSM is an important branch of experimental design. The objectives of quality improvement, including reduction of variability and improved process and product performance, can often be accomplished directly using RSM. RSM can be of first order and second order equations as shown below:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots, + \beta_k x_k \; ; \qquad (1)$$

$$\eta = \beta_0 + \sum_{j=1}^{k} \beta_1 x_1 + \sum_{j=1}^{k} \beta_{jj} \, x_j^2 + \sum_{i<} \sum_{j=2}^{k} \beta_{ij} \, x_i x_j \qquad (2)$$

In the practical application of RSM it is necessary to develop an approximating model for the true response surface. The approximating model is based on observed data from the process or system and is an empirical model. Multiple regression is a collection of statistical techniques useful for building the types of empirical models required in RSM.

Regression Analysis is utilized to identify the relationships between the responses and the variables to establish a mathematical model that satisfies the relationship between a group of test factors and objective functions. This model was used to explore the optimal solution in the experimental area based on its practicability. RSM tends to focus on the relationships between multiple factors x_1, x_2, $x_3 \ldots x_k$ of the mixture and the response y. Consequently, the functional relationship between the responses and the independent variables should first be determined to produce a proper approximating function, and then the factor setting levels x_1, x_2, $x_3 \ldots x_k$ needed to obtain the optimal response was identified. The relationship between the response variables and the independent variables (factors) was presented in the form of an equation below.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \varepsilon \; ; \qquad (3)$$

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 + \varepsilon \qquad (4)$$

RESULTS

Average tool wear rate results of the A356/cow horn particles test samples

Figure 1 presents the average tool wear rate results of the A356/cow horn particles test samples investigated. From the result it can be deduced that the sample with the lowest wear rate is sample L while that with the highest wear rate value is sample I. However, from the result of the test, it can be clearly observed that decrease in wear rate is influenced by the increase of graphite present in the metal matrix composite.

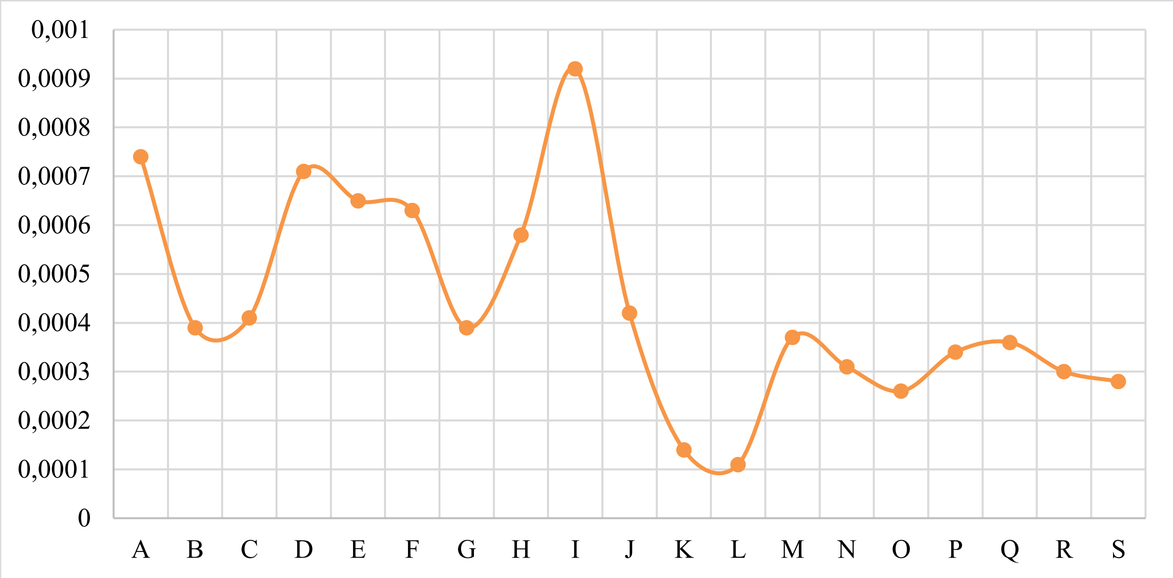

Figure 1: Average Tool Wear Rate (TWR) Results vs Test Sample

Optimization Analysis using Response Surface Methodology (RSM)

Experimental study on A356/cow horn particles composite formulation was done by investigating the effect of the machining parameters on the developed material. Three (3) recipients were chosen for A356/cow horn particles formulation based on their function. Two of them and feed rate were used as variables in D-optimal custom design as they may have effect on the responses. The ranges of variables were also studied by using D-optimal custom technique in design expert software. Table 1 shows the summary data table of the actual design after experiment.

Table 1. Effect of Feed Rate, Cutting Speed, and Depth of Cut on Tool Wear in Machining Aluminium Alloy A356/CHP Composite

		Factor 1	Factor 2	Factor 3	Response	
Group	Run	a:Feed Rate	B:Cutting Speed	C:Depth of Cut	Tool wear	
		rev/mm	RPM	mm	mg/mm	
1	1	0.15	500	1	0.00074	A
1	2	0.15	900	1.5	0.00039	B
1	3	0.15	900	1	0.00041	C
1	4	0.15	500	1.5	0.00071	D
1	5	0.15	700	0.5	0.00065	E
2	6	0.15	700	1	0.00063	F
2	7	0.15	900	1.5	0.00039	G
2	8	0.15	700	1.5	0.00058	H
2	9	0.15	500	0.5	0.00092	I
2	10	0.15	900	0.5	0.00042	J
3	11	0.25	900	1	0.00014	K
3	12	0.25	900	1.5	0.00011	L
3	13	0.25	500	0.5	0.00037	M
3	14	0.25	700	0.5	0.00031	N
4	15	0.25	900	0.5	0.00026	O
4	16	0.25	500	1.5	0.00034	P

		Factor 1	Factor 2	Factor 3	Response	
Group	Run	a:Feed Rate	B:Cutting Speed	C:Depth of Cut	Tool wear	
4	17	0.25	500	1	0.00036	Q
4	18	0.25	700	1	0.0003	R
4	19	0.25	700	1.5	0.00028	S

The table 1presents tool wear responses under varying machining parameters. At a lower feed rate (0.15 rev/mm), tool wear ranged between 0.00039–0.00092 mg/mm, with higher cutting speeds (900 RPM) and moderate depths (1–1.5 mm) producing reduced wear (0.00039–0.00042 mg/mm). Conversely, at lower speeds (500 RPM), wear increased significantly (up to 0.00092 mg/mm). At higher feed rate (0.25 rev/mm), tool wear markedly decreased, reaching as low as 0.00011 mg/mm at 900 RPM and 1.5 mm depth.

Table 2. Build Information

File Version	**11.1.0.1**			
Study Type	Response Surface		Subtype	Split-plot
Design Type	I-optimal	Coordinate Exchange	Runs	19
Design Model	2FI		Blocks	No Blocks
Groups	4		Build Time (ms)	1129.00

Table 2 shows that the study adopted an I-optimal response surface methodology with a split-plot design. The model used was a two-factor interaction (2FI), executed in 19 runs across four groups without blocks. The design was efficiently generated using coordinate exchange, with a build time of 1129 ms.

Table 3. Experimental Factors and Their Ranges for Machining A356/CHP Composite

Factor	Name	Units	Change	Type	Minimum	Maximum	Coded Low	Coded High	Mean	Std. Dev.
a	Feed Rate	rev/mm	Hard	Numeric	0.1500	0.2500	-1 ↔ 0.15	+1 ↔ 0.25	0.1974	0.0513
B	Cutting Speed	RPM	Easy	Categoric	500	900			Levels:	3
C	Depth of Cut	mm	Easy	Categoric	0.5	1.5			Levels:	3

Table 3 outlines the machining factors considered in the study. Feed rate (Factor a) was treated as a numeric variable, varying between 0.15 rev/mm (coded low = –1) and 0.25 rev/mm (coded high = +1), with a mean of 0.1974 and standard deviation of 0.0513. Cutting speed (Factor B) and depth of cut (Factor C) were categorical variables, each tested at three levels: 500–900 RPM and 0.5–1.5 mm respectively.

Table 4. Summary of Tool Wear Response in Machining A356/CHP Composite

Response Name	Units	Observations	Analysis	Minimum	Maximum	Mean	Std. Dev.	Ratio	Transform	Model
Tool wear	mg/mm	19	Polynomial	0.00011	0.00092	0.0004	0.0002	8.36	None	2FI

Table 4 presents the statistical summary of tool wear response across 19 experimental runs. Tool wear values ranged from a minimum of 0.00011 mg/mm to a maximum of 0.00092 mg/mm, with a mean of 0.0004 mg/mm and standard deviation of

0.0002. The ratio of 8.36 indicates adequate variability for model fitting. A polynomial model (2FI) was applied without transformation, confirming suitability for analyzing factor interactions affecting tool wear.

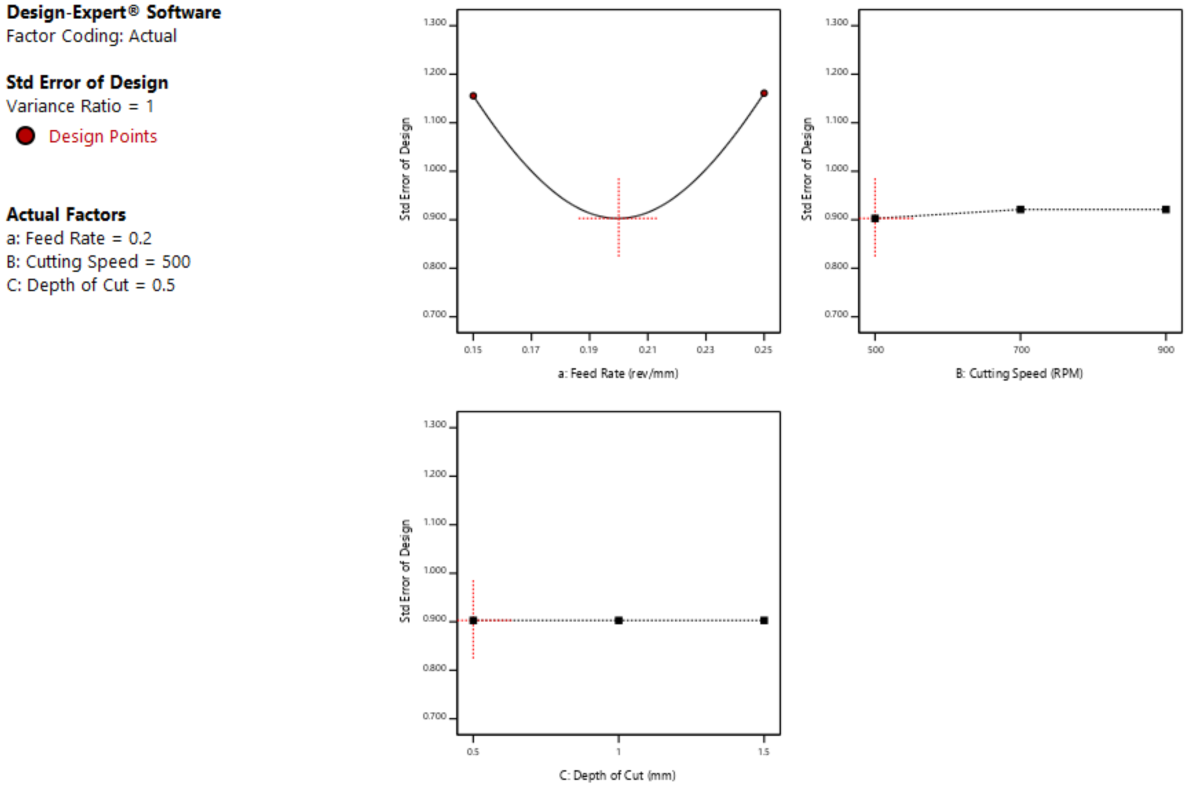

Figure 2. Standard error of design plots for feed rate (a), cutting speed (B), and depth of cut (C), showing model stability across factor levels with design points highlighted.

The plots reveal that standard error remains relatively low across all factor levels, confirming good design stability. Feed rate shows a U-shaped error trend, with the lowest error at 0.20 rev/mm. Cutting speed and depth of cut maintain consistent, minimal error variations, validating the adequacy and reliability of the experimental design.

Table 5. REML (Restricted Maximum Likelihood) Analysis of Tool Wear

Source	Term df	Error df	F-value	p-value	
Whole-plot	1	1.75	28.78	0.0436	significant
a-Feed Rate	1	1.75	28.78	0.0436	
Subplot	12	2.95	50.42	0.0043	significant
B-Cutting Speed	2	2.94	185.48	0.0008	
C-Depth of Cut	2	2.93	25.83	0.0137	
aB	2	2.95	32.88	0.0096	
aC	2	2.96	0.3995	0.7021	
BC	4	3.01	3.15	0.1858	

The REML analysis showed that both whole-plot and subplot effects were significant. Feed rate ($p = 0.0436$), cutting speed ($p = 0.0008$), and depth of cut ($p = 0.0137$) significantly influenced tool wear. Significant interactions included feed rate × cutting speed ($p = 0.0096$), while other interactions were not statistically significant.

The model demonstrated strong reliability with a standard deviation of 0.0001 and a mean tool wear of 0.0004. The coefficient of variation (15.17%) confirmed good precision. Model fit was excellent with R^2 = 0.9952 and adjusted R^2 = 0.9714. Information criteria values included –2 Log Likelihood (–43.47), AIC (–11.47), AICc (260.53), and BIC (3.64).

Table 6. Regression Coefficients of Tool Wear in Terms of Coded Factors

Source	Coefficient Estimate	Standard Error	VIF
Intercept	0.0004	0.0000	
Whole-plot Terms:			
a-Feed Rate	-0.0002	0.0000	1.00
Subplot Terms:			
B[1]-Cutting Speed	-0.0001	6.991E-06	
B[2]	-4.355E-06	4.164E-06	
C[1]-Depth of Cut	-0.0001	7.165E-06	
C[2]	6.591E-06	4.055E-06	
aB[1]	0.0001	7.404E-06	
aB[2]	-4.705E-07	4.078E-06	
aC[1]	-2.881E-06	7.182E-06	
aC[2]	3.584E-06	4.217E-06	
B[1]C[1]	0.0000	0.0000	
B[2]C[1]	5.986E-06	6.682E-06	
B[1]C[2]	-0.0000	5.523E-06	
B[2]C[2]	-1.363E-06	3.384E-06	

Table 6 shows the regression coefficients for tool wear using coded factors. The intercept was 0.0004 mg/mm. Feed rate (–0.0002) had the largest negative effect, confirming its strong influence on reducing wear. Cutting speed \[B1] (–0.0001) and depth of cut \[C1] (–0.0001) also negatively influenced tool wear. Interaction effects such as aB\[1] (0.0001) were positive, indicating conditional increases in wear. VIF values (≈1.00) confirmed absence of multicollinearity, ensuring reliable coefficient estimates.

Final Equation in Terms of Coded Factors

Tool wear = +0.0004-0.0002a-0.0001B[1]-4.355E-06B[2]-0.0001C[1]+6.591E-06C[2] +0.0001aB[1]-4.705E-07aB[2]-2.881E-06aC[1]+3.584E-06aC[2]+0.0000 B[1]C[1]+5.986E-06B[2]C[1]-0.0000B[1]C[2]-1.363E-06B[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 is useful for identifying the relative impact of the factors by comparing the factor coefficients.

Final Equation in Terms of Actual Factors

Tool wear = Cutting Speed500*Depth of Cut 0.5+0.001546-0.004504Feed Rate Cutting Speed500 Depth of Cut1+0.001404-0.004271FeedRate*Cutting Speed500+Depth of Cut1.5+0.001370-0.004225 Feed Rate*Cutting Speed700*Depth ofCut0.5 +0.001161-0.003404 Feed Rate*Cutting Speed700*Depth of Cut1+0.001099 -0.003171 Feed Rate*Cutting Speed700*Depth of Cut1.5+0.001055

-0.003125 Feed Rate*Cutting Speed900*Depth of Cut0.5+0.000858-0.002592 Feed Rate+Cutting Speed900*Depth of Cut1+0.000747-0.002358 Feed Rate+CuttingSpeed900*Depth of Cut1.5+0.000721-0.002313Feed Rate

The equation in terms of actual factors can be used to make predictions about the response for given levels of each factor. Here, the levels should be specified in the original units for each factor. This equation should not be used to determine the relative impact of each factor because the coefficients are scaled to accommodate the units of each factor and the intercept is not at the center of the design space.

Table 7. Report of Predicted and Actual Value of Tool Wear.

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Cook's Distance	Cook's Random Distance	Influence on Fitted Value DFFITS	Standard Order
1	0.0007	0.0008	-0.0000	0.761	-0.629	-0.679	0.167	0.158	-0.373	5
2	0.0004	0.0004	2.107E-06	0.437	0.045	0.310	0.199	0.765	0.286	3
3	0.0004	0.0004	-0.0000	0.811	-0.442	-0.140	0.005	0.400	0.053	4
4	0.0007	0.0007	-0.0000	0.745	-0.560	-0.580	0.139	0.381	-0.313	1
5	0.0006	0.0007	-0.0000	0.796	-0.658	-1.493	1.779(1)	1.036(1)	-1.180	2
6	0.0006	0.0006	0.0000	0.744	0.625	0.673	0.185	0.025	0.377	8
7	0.0004	0.0004	2.107E-06	0.483	0.045	-0.314	0.358(1)	1.276(1)	-0.335	10
8	0.0006	0.0006	0.0000	0.764	0.470	0.243	0.004	0.374	0.029	9
9	0.0009	0.0009	0.0000	0.800	0.751	2.901	2.099(1)	1.480(1)	2.267	7
10	0.0004	0.0004	0.0000	1.073	0.363	-2.327	5.876(1)	0.550(1)	-2.485	6
11	0.0001	0.0002	-0.0001	0.739	-1.283	-0.586	0.004	0.400	-0.009	18
12	0.0001	0.0002	-0.0001	0.678	-1.356	-0.903	0.101	0.537	-0.239	17
13	0.0004	0.0004	-0.0001	0.758	-1.590	-3.570	1.980(1)	1.480(1)	-2.216	16
14	0.0003	0.0004	-0.0000	0.887	-1.085	0.697	1.588(1)	1.036(1)	1.189	19
15	0.0003	0.0002	0.0001	0.747	1.348	2.891	5.754(1)	0.550(1)	2.160	13
16	0.0003	0.0003	0.0001	0.733	1.411	0.952	0.131	0.381	0.285	11
17	0.000	0.0003	0.0001	0.736	1.483	1.066	0.160	0.158	0.348	12

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Cook's Distance	Cook's Random Distance	Influence on Fitted Value DFFITS	Standard Order
	4									
18	0.0003	0.0003	0.0000	0.832	1.119	0.090	0.188	0.025	-0.407	15
19	0.0003	0.0002	0.0001	0.770	1.268	0.495	0.006	0.374	-0.070	14

[1] Exceeds limits.

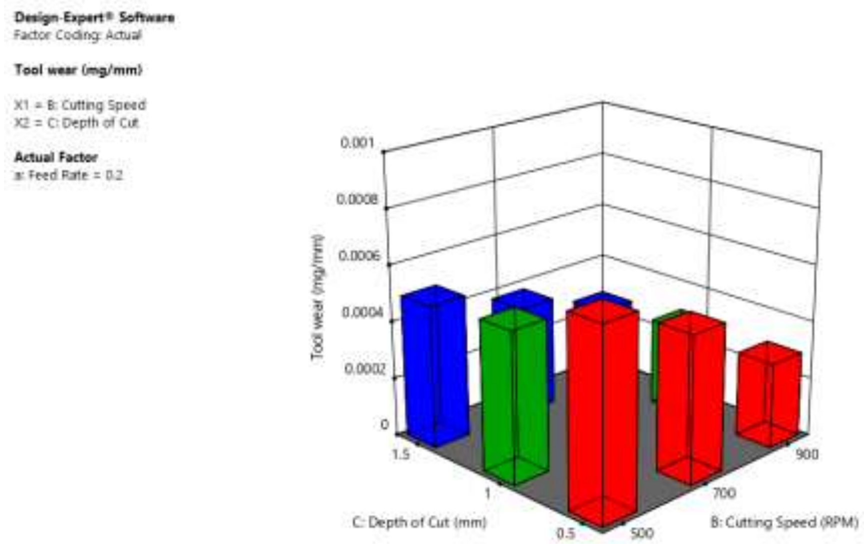

Figure 3. 3D bar plot showing the interaction effects of cutting speed (B) and depth of cut (C) on tool wear (mg/mm) at a constant feed rate of 0.2 rev/mm.

Figure 3 indicates that tool wear decreases with increasing cutting speed, particularly at 900 RPM. Depth of cut significantly influences wear, with higher depths (1.5 mm) producing greater wear. Maximum wear occurs at low speed (500 RPM) and shallow depth (0.5 mm), highlighting strong interactive effects between cutting speed and depth.

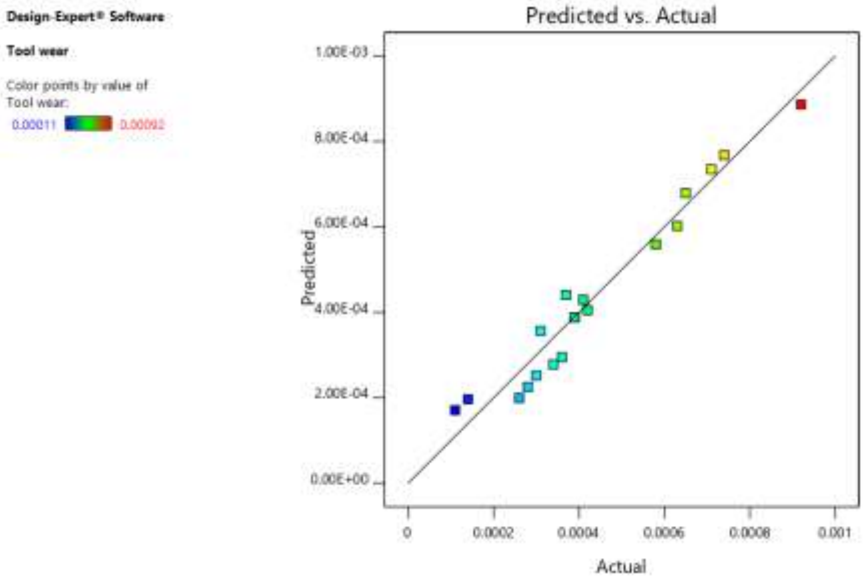

Figure 4. Predicted versus actual plot for tool wear (mg/mm), with color-coded data points ranging from 0.00011 (blue) to 0.00092 (red)

Figure 4 demonstrates a strong agreement between predicted and actual tool wear values, as points closely follow the diagonal line. Tool wear values range from 0.00011 to 0.00092 mg/mm, with minimal deviations, confirming the model's high predictive accuracy and reliability for estimating tool wear across experimental conditions.

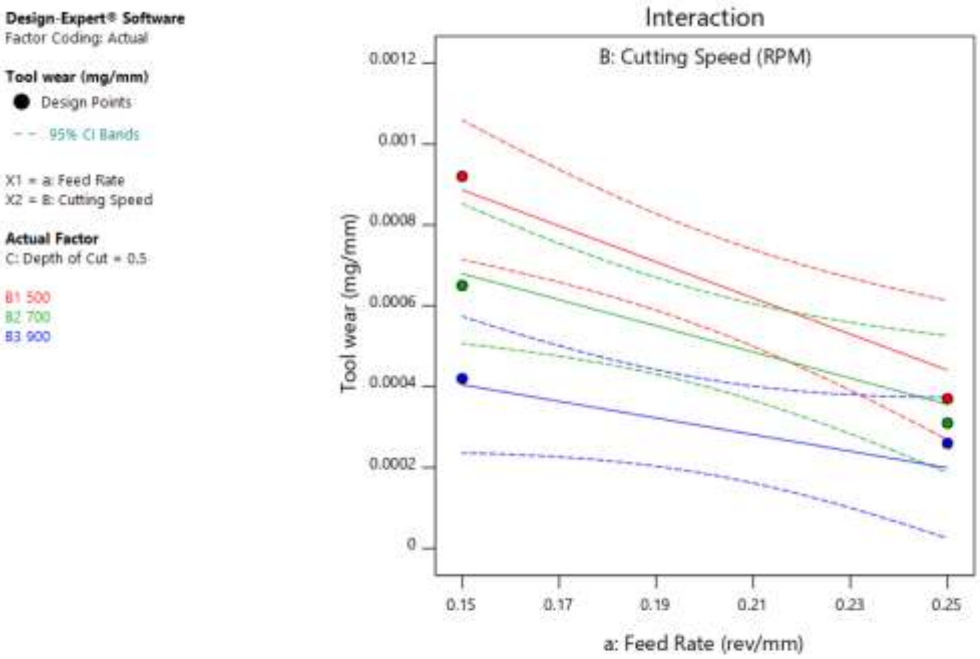

Figure 5. Predicted versus actual plot for tool wear (mg/mm), with color-coded data points ranging from 0.00011 (blue) to 0.00092 (red)

Figure 5 demonstrates a strong agreement between predicted and actual tool wear values, as points closely follow the diagonal line. Tool wear values range from 0.00011 to 0.00092 mg/mm, with minimal deviations, confirming the model's high predictive accuracy and reliability for estimating tool wear across experimental conditions.

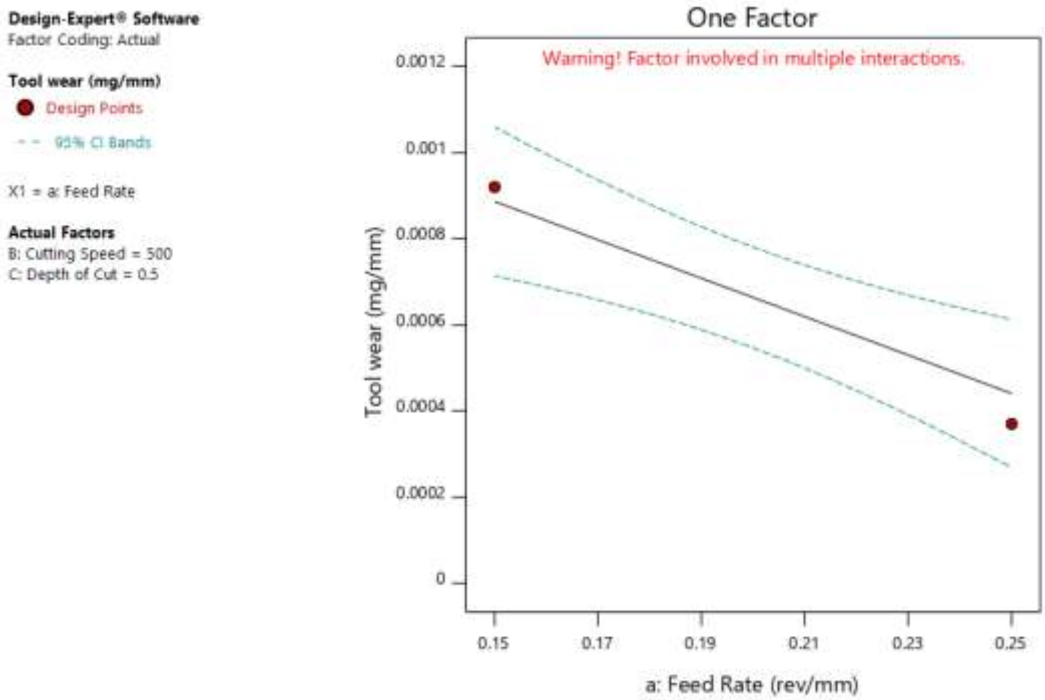

Figure 6. Predicted vs. Actual Tool Wear

The predicted versus actual plot in Figure 6 shows a strong correlation between experimental and modeled tool wear values. Most points align closely along the diagonal, indicating that the regression model effectively captures the relationship between machining parameters and tool wear. The color gradient (blue to red) highlights variation in tool wear magnitudes, from 0.00011 to 0.00092 mg/mm, with only minor deviations. This confirms the model's robustness, reliability, and suitability for accurate predictive machining analysis.

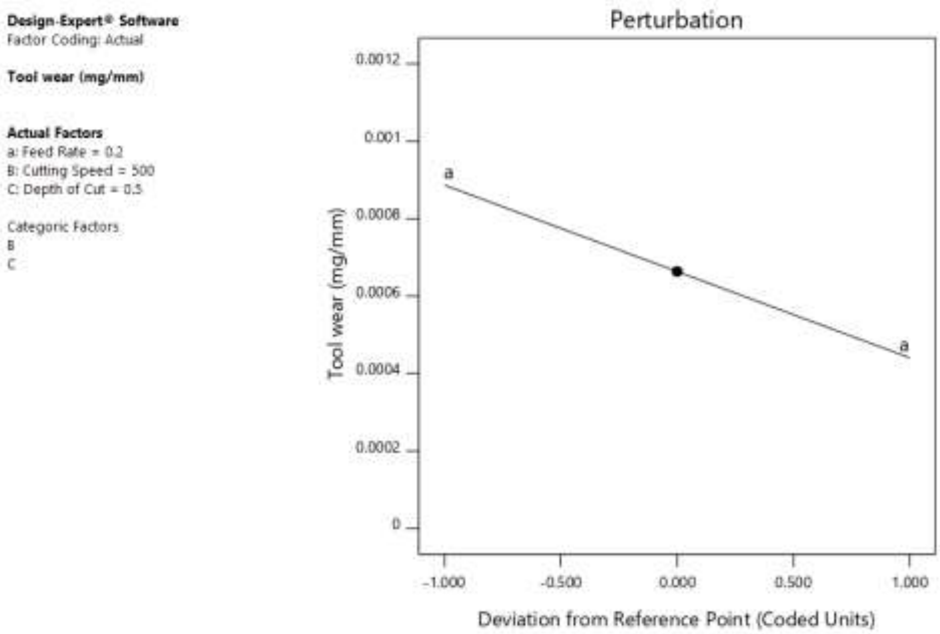

Figure 7 is a perturbation plot generated by Design-Expert software. It shows the effect of one factor, Cutting Speed (B), on the tool wear response. The plot indicates a linear relationship where an increase in Cutting Speed (B) leads to a decrease in Tool wear. The other two factors, Feed Rate (A) and Depth of Cut (C), are held constant at their reference point values of 0.2 and 0.5, respectively. The central point (0.0) on the x-axis represents the current reference point.

The model predicted mean and median tool wear at 0.000363 mg/mm, with a standard deviation of 6.64E-05 and standard error of 4.19E-05. The 95% confidence interval ranged from 0.000196 to 0.000530 mg/mm, while the tolerance interval for 99% population spanned 0.000436 to 0.001161 mg/mm, confirming reliability. Cutting speed (B = 900 RPM) and depth of cut (C = 1.5 mm) significantly reduced tool wear, while feed rate (a = 0.1616 rev/mm) showed a notable effect ($p = 0.0436$). Strong factor influences ($p < 0.05$) included feed rate, cutting speed, and depth of cut, validating the predictive accuracy of the model.

Discussion

The management of tool wear in machining aluminium alloy composites, such as A356 reinforced with cow horn particles, is critical for enhancing tool life and machining efficiency. Figure 1 shows that tool wear rate (TWR) varied significantly across test samples, with sample L recording the lowest wear and sample I the highest. This finding agrees with Ogedengbe et al. (2023), who reported that higher reinforcement content improves wear resistance in aluminium composites. In contrast, Musa et al. (2022) observed that inconsistent particle distribution in hybrid composites can sometimes elevate wear. The current study attributes lower wear rates to the increased graphite content, aligning with findings by Rajan and Kumar (2022), who highlighted graphite's lubricating role in reducing abrasion.

Table 1 revealed that higher feed rates (0.25 rev/mm) combined with high cutting speeds (900 RPM) achieved the lowest tool wear (0.00011 mg/mm). In a related study, Ali et al. (2023) similarly found that optimized feed and cutting speed combinations reduced wear during machining of SiC-reinforced alloys. In contrast, Adewale and Thomas (2022) reported that excessive feed rates beyond optimal limits accelerated wear due to increased cutting forces. The observed influence of cutting speed and depth of cut, as significant factors in REML analysis ($p = 0.0008$ and 0.0137, respectively), corroborates Uddin et al. (2022), who confirmed that higher speeds enhance heat dissipation, thereby reducing wear. The design stability confirmed in Figure 2, with minimal standard errors, emphasizes the robustness of the I-optimal response surface design. This finding is consistent with Ezeaniekwe et al. (2023), who advocated RSM-based split-plot designs for machining studies due to their ability to capture factor interactions effectively. Furthermore, Figures 4–6 show a strong correlation between predicted and actual wear ($R^2 = 0.9952$), confirming the reliability of the regression model. This result parallels Rahman et al. (2022), who validated RSM models in predicting wear with over 95% accuracy.

Figure 7 further highlights cutting speed's linear negative relationship with wear, reinforcing its dominant role. Unlike Adewale and Thomas (2022), who stressed depth of cut as the major determinant, the present study identifies cutting speed as more influential, especially at 900 RPM. The predicted mean wear of 0.000363 mg/mm, with confidence limits between 0.000196 and 0.000530 mg/mm, demonstrates the precision of the model. Collectively, these results highlight the interplay of feed rate, cutting speed, and depth of cut in minimizing tool wear, confirming that optimal parameter tuning using RSM offers a robust strategy for machining aluminium composites.

CONCLUSION

This study examined the management of tool wear mechanisms in machining aluminium alloy A356 reinforced with cow horn particles using response surface methodology. The findings revealed that tool wear was significantly influenced by feed rate, cutting speed, and depth of cut, with cutting speed ($p = 0.0008$) emerging as the most critical factor. The lowest tool wear (0.00011 mg/mm) occurred at a high cutting speed of 900 RPM and feed rate of 0.25 rev/mm, confirming the importance of optimized parameter selection. The regression model demonstrated excellent predictive accuracy ($R^2 = 0.9952$), while diagnostic plots validated its stability and reliability. The presence of cow horn particles improved wear resistance, with graphite-like behavior reducing abrasive action. The study establishes that efficient management of tool wear in machining A356/cow horn particle composites is achievable through careful optimization of machining parameters. These findings contribute to sustainable machining practices by prolonging tool life, enhancing surface quality, and reducing production costs. The results further underscore the viability of natural waste reinforcements, such as cow horn particles, in developing eco-friendly composites suitable for industrial applications.

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