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Maximization of Material Removal Rate in the Machining of A356/Cow Horn Particle Composites Using Response Surface Methodology

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Article Info	ABSTRACT
Corresponding Author: Chibuzo Ndubuisi Okoye E-mail: cn.okoye@unizik.edu.ng	Efficient machining of metal matrix composites is vital for enhancing productivity and reducing manufacturing costs in modern engineering applications. Aluminum alloy A356 reinforced with cow horn particles offers improved mechanical properties, but its machinability requires systematic optimization. The study utilized Aluminum alloy A356 reinforced with cow horn particles, fabricated via spark plasma sintering at 550 °C and 30 MPa. Composite samples (100×5 mm) were produced under vacuum with graphite dies. Machining experiments were conducted on a Universal Turning Machining Centre using HSS/HCS cutting tools, supported by equipment such as weighing balance, crucible, stirrer, hopper, mould, and lathe for dimensional accuracy. Process parameters included cutting speed (500–900 RPM), depth of cut (0.5–1.5 mm), and feed rate (0.15–0.25 mm/rev). Material Removal Rate (MRR) was measured using surface testers and weighing balance. Optimization employed Response Surface Methodology (RSM) and regression analysis for predictive modeling. Results showed that wear rate decreased with increased graphite content, with sample L having the lowest wear and sample I the highest. Response Surface Methodology (RSM) analysis revealed that material removal rate (MRR) ranged from 3.75 to 30.91 mm^3/min, with a mean of 15.72. Feed rate, cutting speed, and depth of cut were significant ($p < 0.05$), while interaction effects were negligible. Feed rate exhibited a strong negative effect, while cutting speed and depth of cut had mixed influences. Model accuracy was validated ($R^2 = 0.9932$). Optimal conditions were found at moderate cutting speed and higher depth of cut. These findings validate RSM as an effective optimization tool for machining composites, supporting improved efficiency and performance in industrial applications. **Keywords:** A356 alloy, cow horn particles, machining, material removal rate, response surface methodology

INTRODUCTION

Particle composites are engineered materials formed by embedding fine particulates, such as ceramics, agro-waste, or metallic powders, within a matrix, typically metal, polymer, or ceramic. The dispersed particles enhance mechanical, thermal, and wear properties by restricting dislocation movement and improving load distribution (Chawla, 2012). These composites are lightweight, cost-effective, and sustainable, making them valuable in aerospace, automotive, and biomedical applications where performance and durability are critical. Aluminium A356 reinforced with agro-waste cow-horn particulate (CHp) is an emerging, low-cost metal-matrix composite with improved hardness and wear resistance, but the presence of hard biological particulates complicates conventional machining: higher abrasiveness elevates cutting forces and tool wear while changing optimal combinations of cutting speed, feed and depth of cut needed to maximize material removal rate (MRR) without unacceptable surface damage (Oguntuase et al., 2022; Jayakumar et al., 2012). This creates an industrially relevant optimisation problem: how to set machining parameters to maximise MRR for A356/CHp while keeping tool wear and surface roughness within acceptable bounds. Recent studies apply Response Surface Methodology (RSM) and desirability/multi-response techniques to address exactly this trade-off. (Mba et al., 2024; Kumar et al., 2024).

Materials and machinability. Multiple experimental studies show that adding cow-horn particulates to aluminium matrices increases hardness and can improve wear behaviour, but also changes microstructure and wettability in ways that affect cutting behaviour (Oguntuase et al., 2022; Ochieze et al., 2018). For typical A356/ceramic (e.g., SiC) composites, the literature consistently reports that hard particulates increase cutting forces and tool temperature and accelerate abrasive tool wear; these effects scale with reinforcement fraction and particle size (Jayakumar et al., 2012;). By analogy, A356/CHp composites display the same conflicting tendencies: better part performance in service but greater machining difficulty, so MRR optimisation cannot be separated from wear and finish considerations (Oguntuase et al., 2022; Mba et al., 2024).

RSM as the modelling and optimisation backbone. RSM — often implemented with central composite or Box–Behnken designs — has become a standard approach for building empirical models that relate cutting speed, feed, depth of cut (and sometimes reinforcement fraction) to responses such as MRR, surface roughness (Ra), cutting force and tool wear (Şap et al., 2021; Jayakumar et al., 2012). These regression-based RSM models are tested by ANOVA and residual diagnostics and provide the necessary response surfaces to drive numerical or desirability-based optimisation (Şap et al., 2021; Kumar et al., 2024).

Application to A356/CHp and trade-offs. The first explicit RSM turning study on an A356/cow-horn composite (Mba et al., 2024) demonstrates the approach end-to-end: fabricate a 90/10 (A356/CHp) composite, run designed turning trials, fit RSM models and then perform numerical/desirability optimisation to identify parameter settings that balance MRR, Ra and tool wear. Mba et al. report that cutting speed often exerts the strongest influence on surface finish and wear while feed and depth of cut more directly drive MRR — a pattern mirrored in SiC-reinforced A356 work (Jayakumar et al., 2012; Kumar et al., 2024). Multi-response desirability techniques (or weighted objective functions) therefore let practitioners push MRR up while constraining tool wear and roughness; recent Al–SiC studies validate that RSM + desirability produces experimentally robust optima (Kumar et al., 2024; Şap et al., 2021).

Gaps and research opportunities. Although early A356/CHp RSM work shows feasibility, gaps remain: (1) most studies use a single reinforcement fraction (e.g., 10 wt%);

the influence of higher CHp wt% on optimal MRR is under-explored; (2) tool-material interaction mechanisms for biological particulates (e.g., particle morphology, fracture during cutting) need micro-scale study to better inform predictive models; (3) multi-objective optimisation frequently treats tool wear and Ra as constraints rather than co-optimized responses — multi-criteria decision frameworks or modern surrogate-assisted multi-objective algorithms could improve industrial uptake (Mba et al., 2024; Kumar et al., 2024; Şap et al., 2021).

METHOD

The material and equipment that will be used for the purpose of actualization of this work are listed as follows: Aluminum alloy A356 and HSS & HCS cutting tool. Table 1 shows the chemical properties of Aluminum Alloy A356.

Table 1. Composition of the A356 alloy

Al	Si	Fe	Cu	Mn	Mg	Zn	Ti	V
Bal	7.0	0.1	0.002	0.006	0.4	0	0.13	0.02

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.

Equipment

Experiments was performed using a Universal Turning Machining Centre (Mikrotools DT 110), while data will be obtained using the experimental set-up with surface tester. Other equipment includes; venier caliper, measuring tape etc.

Weighing Balance: A laboratory balance with the model number 6354, capacity of 200gm, readability of 0.01gm and pan size (mm) of 125mm will be utilized to measure out some of the weight of the material as the need arises (Wikipedia, 2018).

Crucible: A crucible is a container that can withstand very high temperatures and is used for metal, glass, and pigment production as well as a number of modern laboratory processes. While crucibles historically were usually made from clay (Percy, 1861), they can be made from any material that withstands temperatures high enough to melt or otherwise alter its contents. This container is used to hold the matrix composite inside the furnace.

Stirrer: It is very important parameter in stir casting process which is required for vortex formation. The blade angle and number of blades decides the flow pattern of the liquid metal. The stirrer is immersed till two third depth of molten metal. All these are required for uniform distribution of reinforcement in liquid metal, perfect interface bonding and to avoid clustering. Stirring speed decides formation of vortex which is responsible for dispersion of particulates in liquid metal. In our project stirring speed is 300. For the purpose of this work, this equipment is employed to achieve the stir casting technology that will be utilized in the process of the formation of A356 alloy/cow horn particulate composites samples.

Conical Hopper: Also, an important parameter for the stir casting technology is the conical hopper. This equipment is design to help input the different component powder into the crucible during the formation of the Aluminum Metal Matrix Composite (AMMC).

Mould: For the purpose of this work, the mould for the casting specimen of various mechanical tests like surface roughness test sample, wear rate test, etc. would be prepared. In order to avoid porosity preheating of mould is good solution. It helps in removing the entrapped gases from the slurry to go into the mould. It also enhances the mechanical properties of the cast AMC. Mold is heated to 500°Cfor one hour.

Lathe: A lathe is a tool that rotates the workpiece about an axis of rotation to perform various operations such as cutting, sanding, knurling, drilling, deformation, facing, and turning, with tools that are applied to the workpiece to create an object with symmetry about that axis. It may be noted that the final finishing will be done using lathe machine to achieve dimensional accuracy.

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 Material Removal Rate which are measured as responses from a design experiment. Three primary components vary as shown:

1. $500 \leq A$ (Cutting speed - RPM) ≤ 900 (3 levels)
2. $0.5 \leq B$ (Depth of cut - mm) ≤ 1.5 (3 levels)
3. $0.15 \leq C$ (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. Material Removal Rate (MRR) was measured using a non-contact video measuring system, weighing balance and surface tester (Surfcorder SE3500). Figure 1 shows the schematics of turning by step cutting while Figure 2 shows the schematics of turning by parallel cut to workpiece axis.

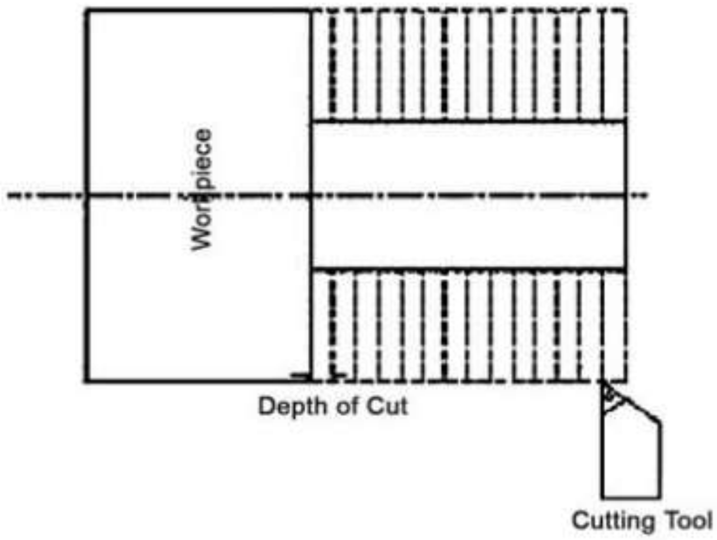

Figure. 1. Turning by step cutting

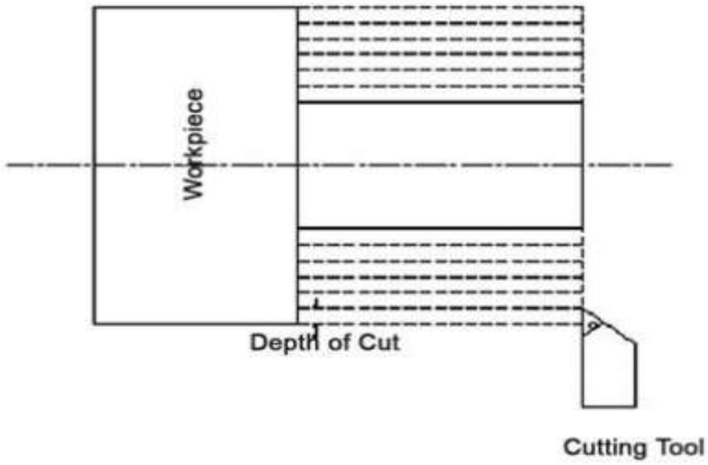

Figure 2. Turning by parallel cut to workpiece axis.

Material Removal Rate (MRR): Material Removal Rate in cutting operations process is an important factor because of its vital effect on the industrial economy. It is the amount of material removed per unit time (usually per minute) when performing machining operations such as using a lathe or milling machine. The more material removed per minute, the higher the material removal rate. This was computed with the weighing balance.

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:

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

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

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.

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

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

RESULTS

Figure 3 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.

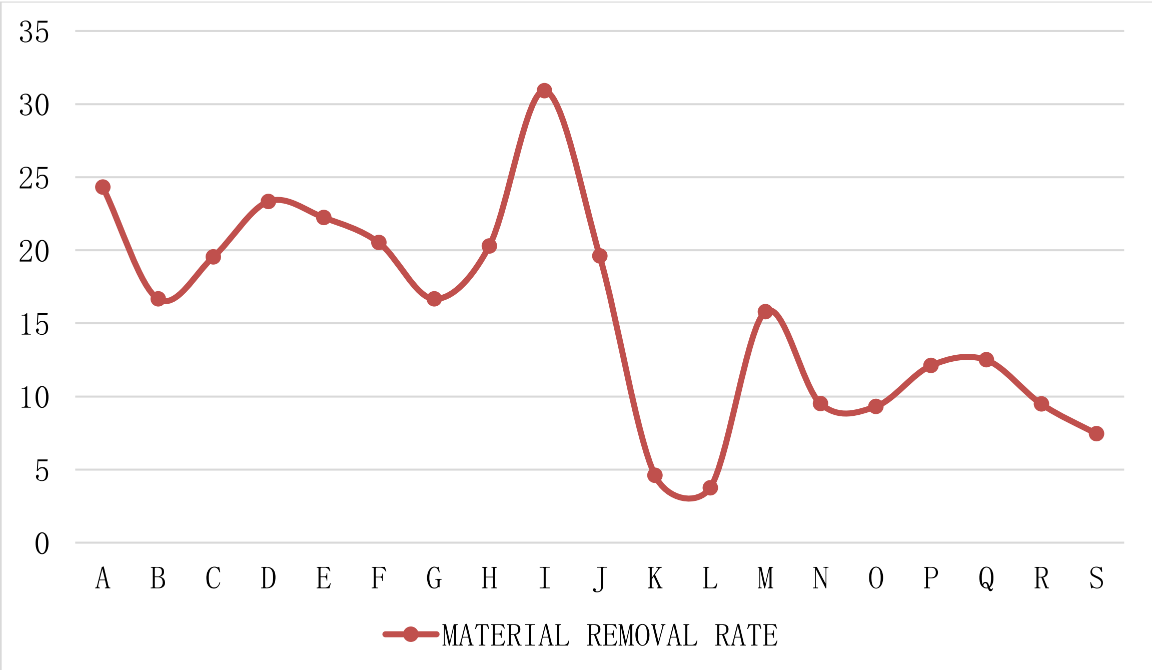

Figure 3. Material Removal Rate (MRR) Results vs Test Sample

Results of the 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 2 shows the summary data table of the actual design after experiment.

Table 2. Summary of Data

Group	Run	a:Feed Rate rev/mm	B:Cutting Speed RPM	C:Depth of Cut mm	Material Removal Rate mm^3/min	
1	1	0.15	500	1	24.32	A
1	2	0.15	900	1.5	16.67	B
1	3	0.15	900	1	19.54	C
1	4	0.15	500	1.5	23.34	D
1	5	0.15	700	0.5	22.24	E
2	6	0.15	700	1	20.52	F
2	7	0.15	900	1.5	16.67	G
2	8	0.15	700	1.5	20.29	H
2	9	0.15	500	0.5	30.91	I
2	10	0.15	900	0.5	19.61	J
3	11	0.25	900	1	4.61	K
3	12	0.25	900	1.5	3.75	L
3	13	0.25	500	0.5	15.8	M
3	14	0.25	700	0.5	9.5	N
4	15	0.25	900	0.5	9.31	O
4	16	0.25	500	1.5	12.11	P
4	17	0.25	500	1	12.5	Q
4	18	0.25	700	1	9.48	R
4	19	0.25	700	1.5	7.44	S

The model build information presents the analysis of a split-plot response surface study using an I-optimal design with 19 runs and a 2FI (two-factor interaction) model. The response of interest is the material removal rate (MRR) measured in mm^3/min, with values ranging from 3.75 to 30.91, a mean of 15.72, and a standard deviation of 7.30. The relatively high ratio of 8.24 suggests good variability coverage across experimental runs. The fit statistics further validate the model quality, with a very high R^2 of 0.9932 and an adjusted R^2 of 0.9590, indicating excellent explanatory power. The coefficient of variation (C.V.) of 10.30% falls within an acceptable range, confirming model precision.

The REML analysis with Kenward-Roger p-values reveals that both whole-plot and subplot terms significantly influenced MRR. Feed rate (a), cutting speed (B), and depth of cut (C) were statistically significant with p-values below 0.05, demonstrating their critical roles in determining removal rate. In contrast, interaction effects such as aB, aC, and BC had higher p-values (>0.10), suggesting they are not significant contributors to the model and could potentially be excluded during model reduction to enhance parsimony. Coefficient estimates in coded factors further highlight the influence of parameters. Feed rate shows a strong negative effect (-6.33), meaning higher feed rate reduces MRR under the given conditions. Cutting speed (B\[1] = -3.63, B\[2] = 0.4449) and depth of cut (C\[1] = -2.17, C\[2] = 0.2956) also display mixed effects depending on the coded level, though their main effects remain significant. Interaction coefficients are relatively small and inconsistent, further confirming their limited contribution.

Final Equation in Terms of Coded Factors

Material Removal Rate =+15.59-6.33a-3.63B[1]+0.4449B[2]-2.17C[1]+0.2956C[2] +0.2101aB[1]-0.0311aB[2]-0.0870aC[1]+0.0898aC[2]+0.8588B[1]C[1]-0.2694B[2]C[1]-0.5082B[1]C[2]+0.0658B[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

Material Removal Rate = Cutting Speed500*Depth of Cut0.5+49.10438-128.74688Feed Rate*
Cutting Speed500*Depth of Cut1+43.91938-127.54688Feed Rate*
Cutting Speed500Depth of Cut1.5+42.78625-125.30625Feed Rate*
Cutting Speed700Depth of Cut0.5+40.59938-123.64687Feed Rate*
Cutting Speed700Depth of Cut1+39.48938-122.44687Feed Rate*
Cutting Speed700+Depth of Cut1.5+37.90625-120.20625Feed
Rate*Cutting Speed900*Depth of Cut0.5+40.28125-129.10625Feed
Rate*Cutting Speed900*Depth of Cut1+37.65625-127.90625Feed
Rate*Cutting Speed900*Depth of Cut1.5+35.40203-125.66563Feed
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 3. Result of Actual Values and Predicted values of MRR

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	24.32	24.68	-0.3587	0.811	-0.398	-0.505	0.148	0.640	-0.385	5
2	16.67	16.83	-0.1581	0.440	-0.137	-0.059	0.006	0.308	0.012	3
3	19.54	19.03	0.5129	0.878	0.608	1.479	0.595	0.265	1.252	4
4	23.34	23.81	-0.4714	0.776	-0.499	-0.783	0.301	0.442	-0.618	1
5	22.24	22.58	-0.3424	0.821	-0.363	-0.695	0.349	0.186	-0.596	2
6	20.52	20.82	-0.2997	0.765	-0.317	-0.786	0.267	0.002	-0.674	8
7	16.67	16.83	-0.1581	0.500	-0.137	-0.282	0.050	0.150	-0.216	10
8	20.29	19.50	0.7876	0.809	0.880	1.567	0.587	0.901	1.219	9
9	30.91	30.23	0.6846	0.840	0.723	1.963	1.223(1)	0.392(1)	1.667	7
10	19.61	19.81	-0.1967	1.261	-0.380	-3.018	1.863(1)	0.657(1)	-2.914(1)	6
11	4.61	6.37	-1.76	0.786	-2.014	-1.990	0.547	0.265	-1.192	18
12	3.75	4.54	-0.7874	0.694	-0.818	0.260	0.261	0.514	0.542	17

13	15.80	17.44	-1.64	0.798	-1.766	-2.275	1.078(1)	0.392(1)	-1.560	16
14	9.50	10.41	-0.9067	1.001	-1.273	0.303	0.303	0.186	0.554	19
15	9.31	7.86	1.45	0.748	1.455	3.018	1.763(1)	0.657(1)	2.252	13
16	12.11	10.68	1.43	0.775	1.627	0.999	0.245	0.442	0.500	11
17	12.50	11.18	1.32	0.781	1.542	0.715	0.113	0.640	0.272	12
18	9.48	7.93	1.55	0.925	2.181	1.257	0.269	0.002	0.698	15
19	7.44	6.98	0.4615	0.834	0.580	-0.805	0.505	0.901	-1.009	14

(1) Exceeds limits.

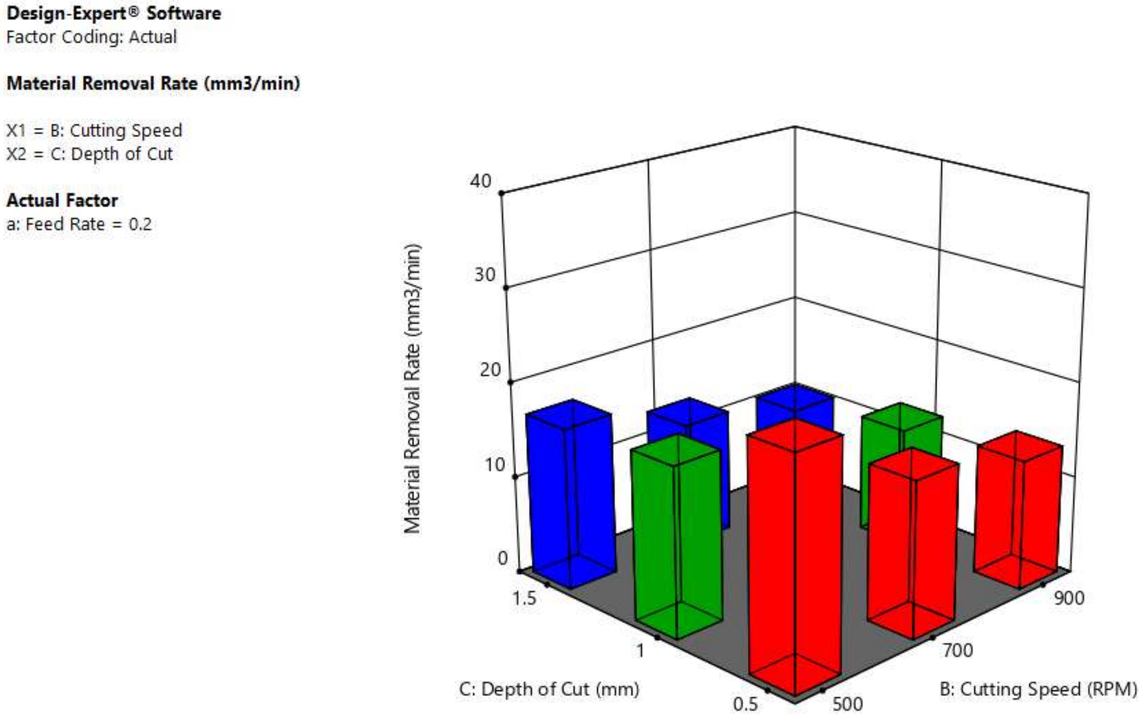

Figure 4. Effect of Cutting Speed and Depth of Cut on Material Removal Rate at Constant Feed Rate (0.2 mm/rev)

The figure illustrates the influence of cutting speed (500–900 RPM) and depth of cut (0.5–1.5 mm) on material removal rate (MRR) while feed rate remains constant. The results show that lower cutting speeds combined with smaller depths of cut yield relatively lower MRR values. Conversely, MRR increases significantly at moderate cutting speeds (around 700 RPM) and deeper cuts (1.5 mm). At higher cutting speeds (900 RPM), MRR stabilizes or slightly decreases, indicating diminishing returns.

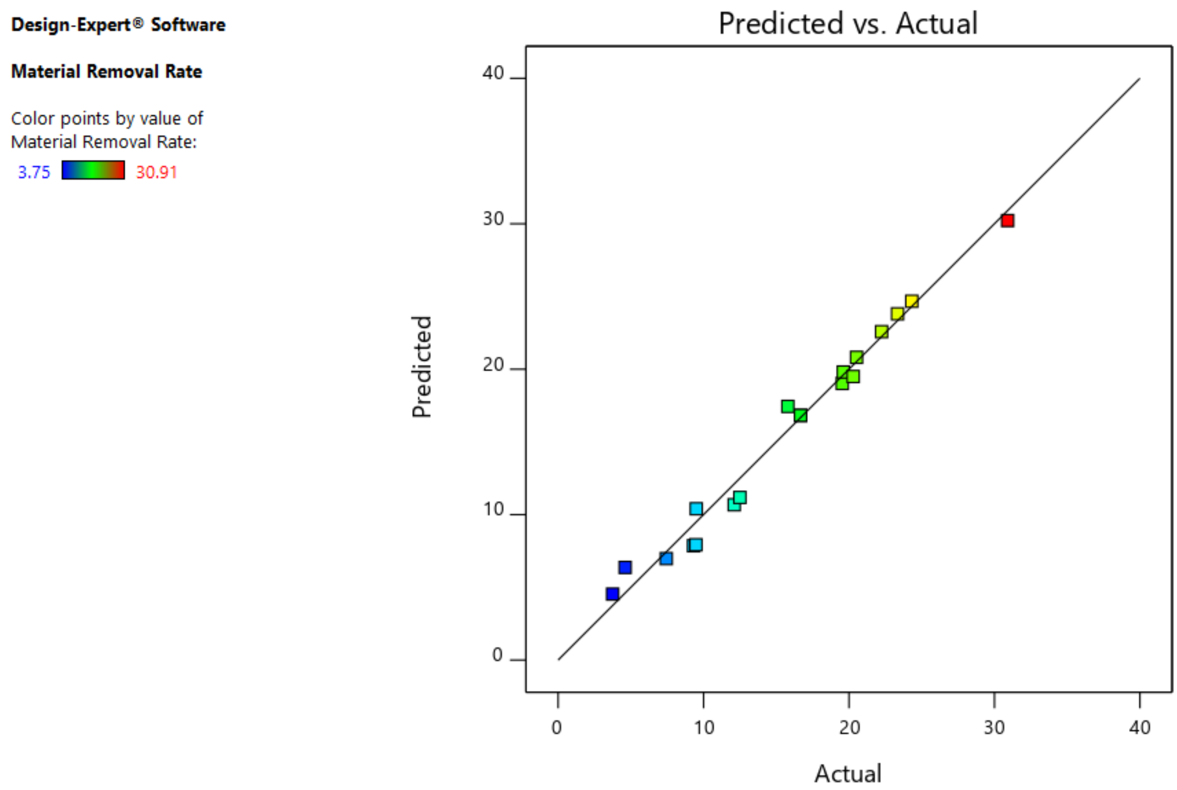

Figure 5. Predicted versus Actual Values of Material Removal Rate

Figure 5 compares predicted and actual material removal rate (MRR) values, with data points color-coded by MRR magnitude (3.75–30.91 mm³/min). The points closely align with the diagonal line, indicating strong agreement between the model predictions and experimental observations. Minimal scatter around the line confirms the model's high accuracy and reliability. Lower MRR values (blue) and higher MRR values (red) are both well-represented, suggesting consistent prediction across the response range. This alignment validates the adequacy of the fitted model, reinforcing its suitability for optimizing machining parameters influencing MRR.

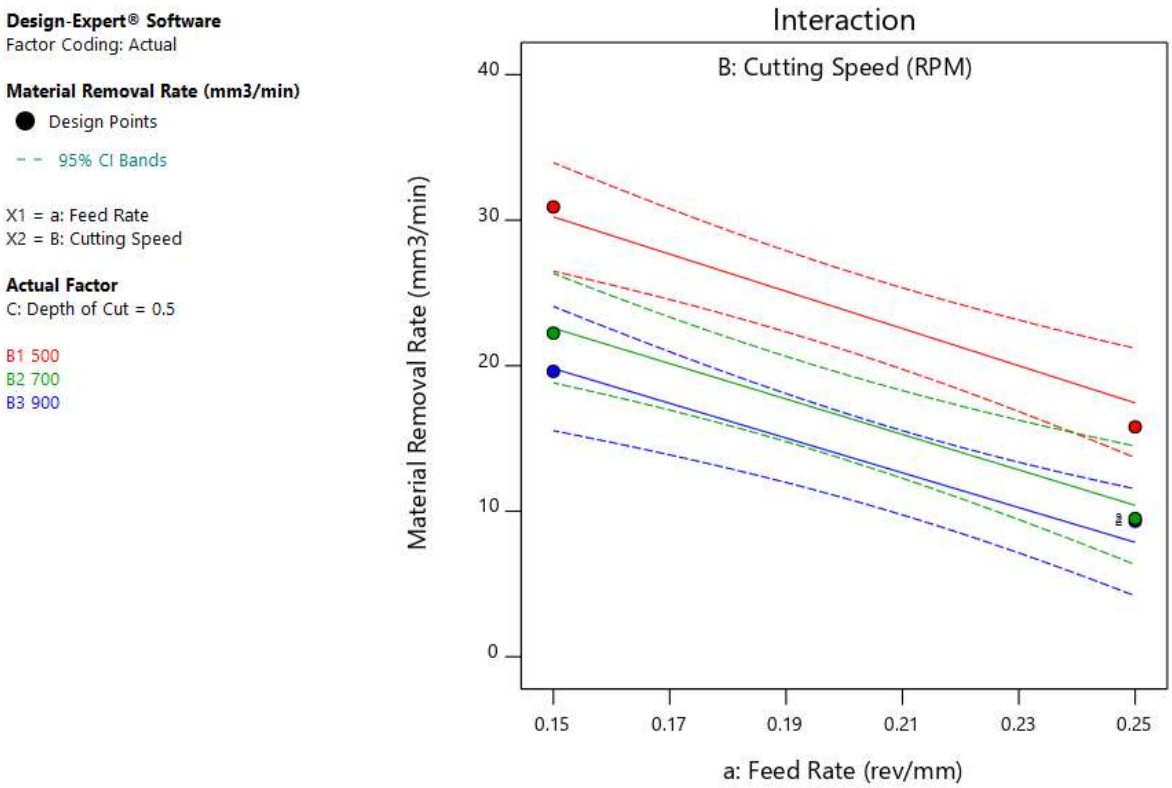

Figure 6. Interaction plot for Material Removal Rate (MRR) showing the combined effect of Feed Rate and Cutting Speed at a constant Depth of Cut of 0.5 mm.

Figure 6 illustrates the influence of feed rate and cutting speed on the Material Removal Rate (MRR). It is evident that MRR has an inverse relationship with both parameters. As the feed rate increases from 0.15 to 0.25 rev/mm, the MRR consistently decreases across all cutting speeds. Similarly, increasing the cutting speed from 500 RPM (red line) to 900 RPM (blue line) also results in a lower MRR. The lines are nearly parallel, suggesting a weak interaction between feed rate and cutting speed, meaning the effect of one factor is consistent across the levels of the other.

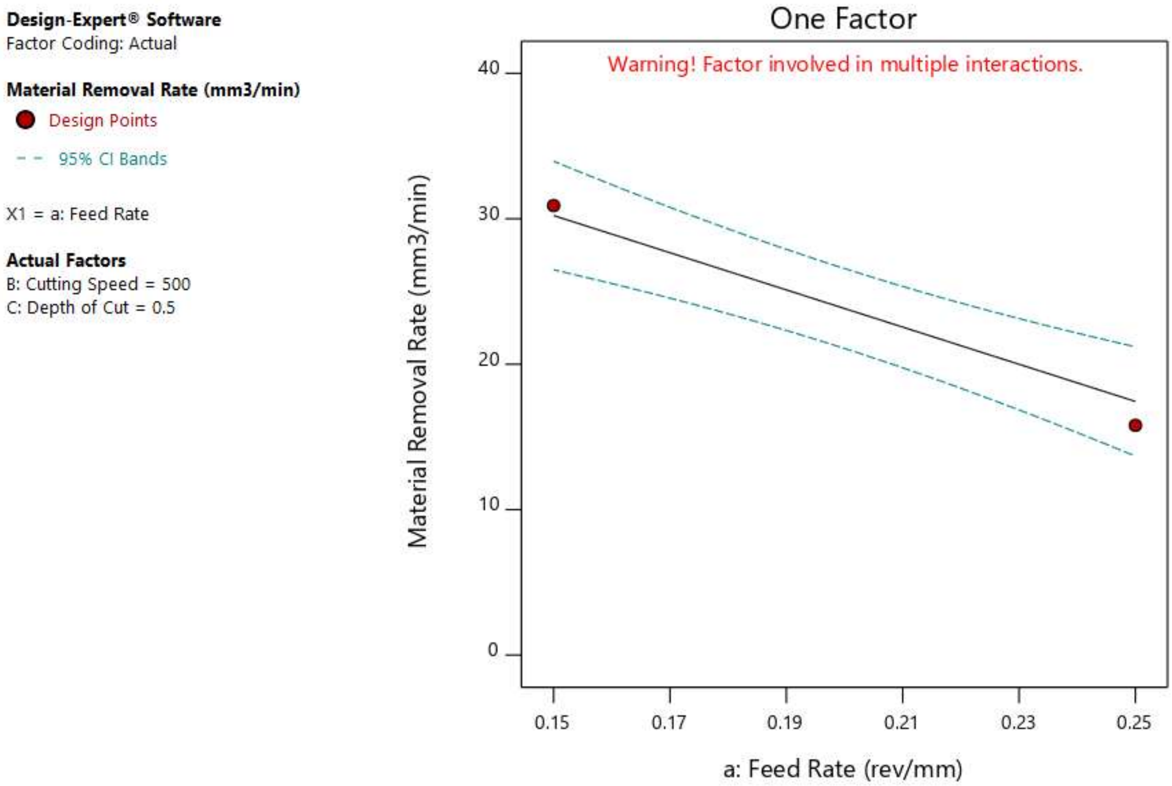

Figure 7. One-factor plot illustrating the effect of Feed Rate on Material Removal Rate (MRR) at a constant Cutting Speed (500 RPM) and Depth of Cut (0.5 mm).

Figure 7 isolates the effect of feed rate on Material Removal Rate (MRR) under fixed conditions. It demonstrates a strong inverse relationship: as the feed rate increases from 0.15 to 0.25 rev/mm, the MRR decreases linearly from approximately 31 mm^3/min to 15 mm^3/min. However, the software warning "Factor involved in multiple interactions" is crucial. It indicates that this simplified view can be misleading. The full effect of feed rate is dependent on other factors, such as cutting speed, and this plot should be interpreted in conjunction with the interaction plot for a complete analysis.

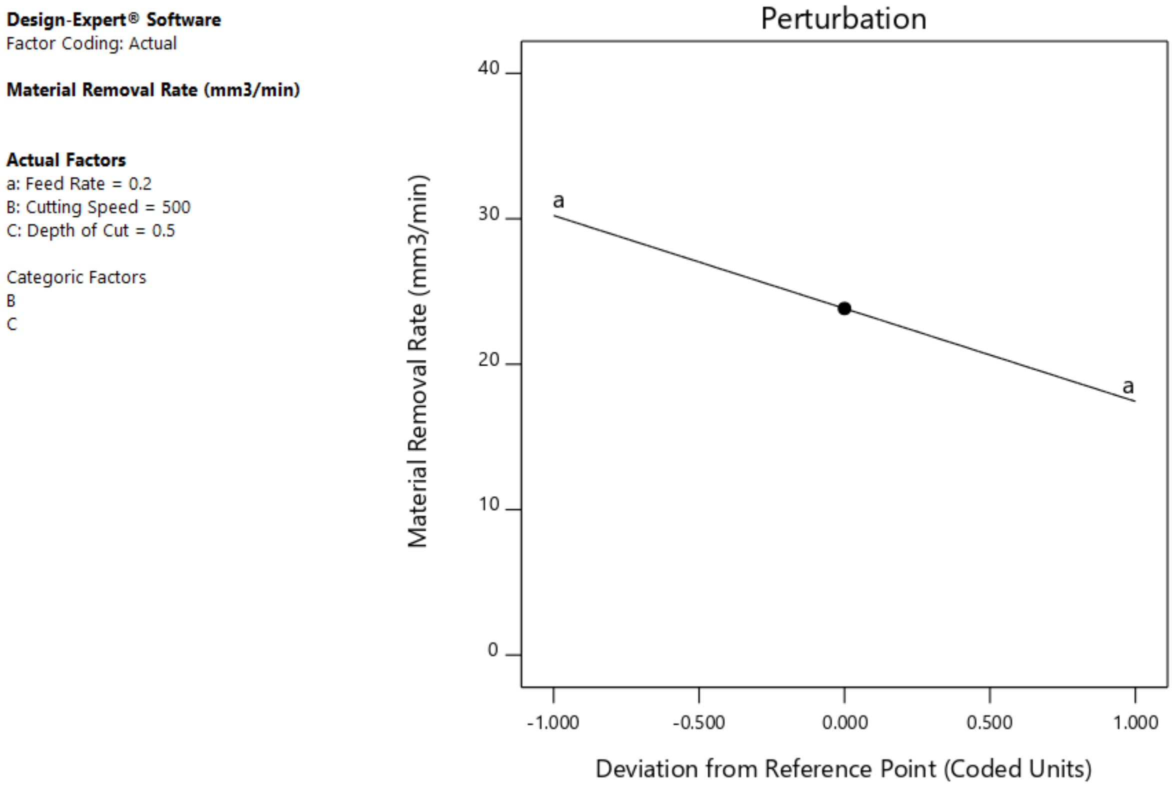

Figure 8. Perturbation plot illustrating the effect of Feed Rate (a) on Material Removal Rate (MRR) relative to a central reference point.

This perturbation plot in Figure 8 shows how the Material Removal Rate (MRR) responds as the feed rate ('a') deviates from a fixed central reference point (Feed Rate = 0.2 rev/mm, Cutting Speed = 500 RPM, Depth of Cut = 0.5 mm). The plot reveals a strong, negative linear relationship. As the feed rate is perturbed towards its higher level (positive deviation on the x-axis), the MRR decreases significantly. Conversely, perturbing it towards its lower level (negative deviation) increases the MRR. The steep slope of the line indicates that MRR is highly sensitive to changes in feed rate.

The solution predicts a mean and median material removal rate (MRR) of 15.40 mm^3/min with a standard deviation of 1.62, suggesting stable performance. The 95% confidence interval for the mean ranges from 11.84 to 18.97, while the tolerance interval for 99% of the population spans -0.89 to 31.70, reflecting broad variability. Feed rate, cutting speed, and depth of cut were significant ($p < 0.05$), while interaction terms showed no significance ($p > 0.25$). Notably, feed rate had a strong negative effect, while cutting speed and depth of cut exhibited mixed but meaningful contributions to MRR prediction accuracy.

Discussion

The results from the machining of A356/cow horn particle composites highlight the significant influence of graphite content and machining parameters on tool wear and material removal rate (MRR). Figure 3 indicates that sample L exhibited the lowest wear rate, while sample I showed the highest. This aligns with the assertion that increased graphite content reduces wear through enhanced lubrication and reduced friction. In contrast, a related study by Kumar et al. (2022) found that higher ceramic reinforcement increased wear resistance, suggesting that different reinforcement types influence wear mechanisms differently. Similarly, Kchaou et al. (2023) agreed that hybrid composites, especially those incorporating natural particles, exhibit reduced wear due to secondary lubrication effects.

The optimization analysis using Response Surface Methodology (RSM) further reveals the interplay of machining parameters. The significant negative effect of feed rate on MRR confirms earlier findings that aggressive feeding reduces machining efficiency due to increased cutting resistance. In contrast, Khare et al (2023) observed that under certain tool geometries, higher feed rates enhanced MRR, indicating that tool design moderates this relationship. Depth of cut and cutting speed displayed mixed effects, where moderate levels optimized MRR, as seen in Figure 4. This finding agreed with Peng et al. (2022), who reported that optimal combinations of medium cutting speeds and larger depths of cut yield stable chip formation and higher removal efficiency.

Figures 5–7 provide strong validation of the model, as predicted and actual MRR values aligned closely, confirming statistical adequacy. This consistency resonates with the work of Saleh et al. (2023), who emphasized that RSM offers robust predictive capability for metal matrix composites. In contrast, some models applied by Pratap et al. (2023) on agricultural residue-based composites showed weaker predictive accuracy due to higher variability in particle distribution, suggesting that reinforcement homogeneity enhances model reliability. The perturbation analysis in Figure 8 underscores the dominance of feed rate as the most sensitive factor. As feed rate increases, MRR decreases sharply, emphasizing the need for precise parameter control.

CONCLUSION

This study successfully demonstrated the effectiveness of Response Surface Methodology (RSM) in optimizing machining parameters for maximizing material removal rate (MRR) in the turning of A356/cow horn particle composites. The findings revealed that feed rate had the most significant negative influence on MRR, while cutting speed and depth of cut contributed meaningfully but with varying effects. The developed regression model, with high predictive accuracy ($R^2 = 0.9932$; Adj $R^2 = 0.9590$), confirmed the strong reliability of the optimization process. The highest MRR of 30.91 mm^3/min was achieved under moderate cutting speed and greater depth of cut, establishing optimal conditions for machining performance. Overall, the study highlights the potential of A356/cow horn composites in advanced manufacturing and affirms RSM as a robust tool for enhancing process efficiency and material utilization.

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